ISSN 2543-6597

Bialystok University of Technology
Faculty of Engineering Management

sciendo

International Society for Manufacturing, Service and Management Engineering

# Engineering Management in Production and Services

Volume 15 • Issue 4 • 2023

## Frequency

ECONOMICS AND MANAGEMENT
is published quarterly since 1998

As of the beginning of 2017 the journal
is published under a new name:
ENGINEERING MANAGEMENT
IN PRODUCTION AND SERVICES

## Submission

Papers for submission should be prepared according to the *Authors Instructions* available at www.empas.pb.edu.pl

All papers should be submitted through the electronic submission system

## Publisher

Bialystok University of Technology
Wiejska 45A, 15-351 Bialystok, Poland

The International Society
for Manufacturing Service
and Management Engineering (ISMSME)

## Indexation

Journal is indexed in SCOPUS, Ei Compendex, EBSCO Business Source Ultimate (Complete), Norwegian Register for Scientific Journals, Series and Publishers, Index Copernicus, ERIH PLUS, Google Scholar, Central European Journal of Social Sciences and Humanities, Research Papers in Economics (RePEc), BazTech and BazEkon databases





## Editorial Office

Bialystok University of Technology
Wiejska 45A, 15-351 Bialystok, Poland
Phone: (+4885) 746 9825
Fax: (+4885) 663 1988
www.empas.pb.edu.pl

**DOFINANSOWANO ZE ŚRODKÓW BUDŻETU PAŃSTWA**

Program „Rozwój czasopism naukowych"

Projekt: Rozwój czasopisma naukowego Engineering Management in Production and Services

Kwota dofinansowania: 80 000,00 zł

Całkowita wartość zadania: 80 000,00 zł

Projekt ma na celu rozwój czasopisma naukowego Engineering Management in Production and Services, poprzez publikację ośmiu numerów w języku angielskim oraz upowszechnienie i zabezpieczenie oryginalności publikowanych w nim artykułów.

**PROJECT FUNDED FROM THE STATE BUDGET**

"Development of scientific journals" Programme

Project: Development of the Engineering Management in Production and Services scientific journal

Amount of funding: PLN 80,000.00

Total value of the task: PLN 80,000.00

The project aims at developing the Engineering Management in Production and Services scientific journal by publishing eight issues in English, disseminating and ensuring the originality of the published articles.

# Table of contents

Volume 15 • Issue 4 • 2023

received: 5 March 2023
accepted: 15 November 2023

pages: 128-143



# Smart fruit growing through digital twin paradigm: systematic review and technology gap analysis

Ilmars Apeinans
Lienite Litavniece
Sergejs Kodors
Imants Zarembo
Gunars Lacis
Juta Deksne

**Ilmars Apeinans**
Rezekne Academy of Technologies, Latvia
ORCID 0000-0001-6584-5176
Corresponding author: ilmars.apeinans@rta.lv

**Lienite Litavniece**
Rezekne Academy of Technologies, Latvia
ORCID 0000-0001-9859-7850

**Sergejs Kodors**
Rezekne Academy of Technologies, Latvia
ORCID 0000-0002-1066-1887

**Imants Zarembo**
Rezekne Academy of Technologies, Latvia
ORCID 0000-0001-7277-1750

**Gunars Lacis**
Institute of Horticulture, Latvia
ORCID 0000-0002-9877-8317

**Juta Deksne**
Rezekne Academy of Technologies, Latvia
ORCID 0000-0003-2062-0410

A B S T R A C T
This article provides a systematic review of innovations in smart fruit-growing. The research aims to highlight the technological gap and define the optimal studies in the near future moving toward smart fruit-growing based on a systematic review of literature for the period 2021–2022. The research object is the technological gap until the smart fruit-growing. The research question of the systematic review was related to understanding the current application of vehicles, IoT, satellites, artificial intelligence, and digital twins, as well as active studies in these directions. The authors used the PRISMA 2020 approach to select and synthesise the relevant literature. The Scopus database was applied as an information source for the systematic review, completed from 10 May to 14 August 2022. Forty-three scientific articles were included in the study. As a result, the technology gap analysis was completed to highlight the current studies and the research trends in the near future moving toward smart fruit-growing. The proposed material will be useful background information for leaders and researchers working in smart agriculture and horticulture to make their strategic decisions considering future challenges and to optimise orchard management or study directions. Considering the current challenges, authors advise paying attention to decision-making, expert, and recommendation systems through the digital twin paradigm. This study will help the scientific community plan future studies optimising research to accelerate the transfer to new smart fruit-growing technologies as it is not sufficient to develop an innovation, but it must be done at the appropriate time.

K E Y W O R D S
**artificial intelligence, digital twin, smart horticulture, orchard, remote sensing**

**10.2478/emj-2023-0033**

# Introduction

Modern horticulture faces a series of global challenges, such as climate changes and yield quality, thus leading to competitiveness and economy of production issues and the public's demand for sustainable and safe food. Often, the mitigation of these challenges requires contradictory solutions, e.g., the ability to limit the increasing disease pressure while ensuring environmentally friendly growing. Applying balanced cultivation solutions requires knowledge, a high level of expertise in growing the relevant

Apeinans, I., Litavniece, L., Kodors, S., Zarembo, I., Lacis, G., & Deksne, J. (2023). Smart fruit growing through digital twin paradigm: systematic review and technology gap analysis. *Engineering Management in Production and Services, 15*(4), 128-143. doi: 10.2478/emj-2023-0033

horticulture crop, and continuous access to timely environmental and market information. One of the solutions is smart horticulture, which includes management of publicly available data, locally collected sensor data, decision-making and advisory systems. An essential part of such a smart horticulture system is the development of a digital twin of orchards and the use of unmanned aerial vehicles (UAV) for their constant monitoring (Van Der Burg et al., 2021; Verdouw et al., 2021). This development direction can strengthen existing horticulture farms and promote their development and economic competitiveness while ensuring the environment's and society's requirements.

In the Green Deal of the European Union (European Commission, 2019), the Biodiversity Strategy (European Commission, 2020) defines future development perspectives, and both documents directly affect the agricultural sector. The achievement of strategic goals requires promoting innovations in the agricultural sector, ensuring the efficient use of resources, reaching the maximum harvest volumes and reducing the negative impact of weather conditions on the agricultural harvest. The application of information technology in the agricultural sector using innovative technologies will ensure the future development of this sector, obtaining the maximum amount of harvest with as few resources as possible (European Commission, 2019; 2020).

A comprehensive analysis-based systematic review of literature related to orchard management with small unmanned aerial vehicles (UAV) was presented by Zhang et al. (2021). All research related to UAV application in fruit growing was grouped into five categories: (1) resource efficiency, (2) geometric traits, (3) productivity, (4) disease, and (5) other applications. Each category was discussed in detail and analysed from four aspects, namely, (1) sensors, (2) methods, (3) decision indicators, and (4) orchard management activities, providing conclusions about future research and its relevance. Evaluating potential future research, Zhang et al. (2021) outlined challenges, some of them could face: (1) most research focused on specific fruit species at a certain growth stage under certain conditions; (2) despite the promising results in deep learning, further progress in improving the performance of proposed methods in various environmental and agronomic conditions with advanced deep learning algorithms need to be undertaken; (3) current achievements in indirect yield estimation are positive; however, there is abundant room for further progress in enhancing the robustness of the methods and performance for different crops and growing stages remain unanswered at present; (4) techniques like machine learning and deep learning have not been adequately employed in UAV orchard management; (5) UAVs are currently operated by persons with the skills of professional pilots; (6) powerful UAVs are generally more costly and not affordable for applications, especially in developing countries; and (7) real-time direct estimation of fruits is encouraged.

On the other hand, artificial intelligence application in orchard management has been presented in a review of deep learning application for fruit detection and yield estimation by Koirala et al. (2019). The review presents the description of vertical progress in deep learning: (1) architectures; (2) feature extraction; (3) training, tuning and testing; (4) transfer learning, augmentation, and datasets; and (5) yield estimation. It summarises that research is completed around R-CNN and YoLo architectures, applying a regression model for yield estimation. It is suitable to mention a review presented by Hasan et al. (2020), which grouped challenges into three categories: (1) public data availability and their quality improvement; (2) enhancement of deep learning methods; and (3) quality control. That coincides with research tasks outlined by the "Trustworthy AI" concept.

Two years later to the review by Hasan et al. (2020), it would be expected to find research progress and outline new state-of-the-art considering the rapidly growing global artificial intelligence market (Grand View Research, 2022), as well as the worldwide inclusion of artificial intelligence into research strategies and a list of key enabling technologies. Particular interest was expressed in applying the digital twin paradigm for autonomous orchard management based on key enabling technologies like artificial intelligence and robotisation.

Making an analogy to the most challenging research field, "autonomous cars", the automatisation of orchard management will be iterative. Six levels of driving automation are defined in "ISO/SAE PAS 22736:2021 Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles" starting from "Level 0: No Driving Automation" until "Level 5: Full Driving Automation". The evolution of orchard management may have a similar pattern, where traditional fruit growing is firstly supported by precise horticulture, followed by smart horticulture through iterative automatisation, solving technological and legal issues. For example, if the autonomy of a UAV is supported

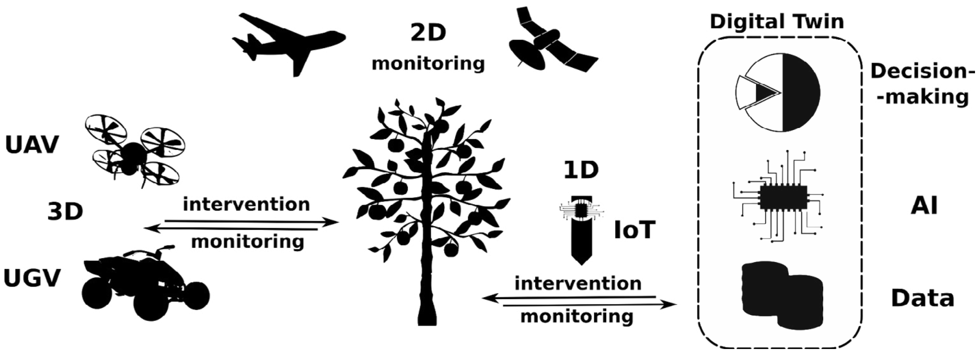



Fig. 1. Digital twin of smart fruit-growing

technologically, their application is restricted for safety reasons and social unreadiness to use these new technologies. Meanwhile, the digital twins have similar integration levels: (1) digital models; (2) digital shadows, which support monitoring of physical entities; and (3) digital twins, which provide bidirectional communication between virtual and physical entities (Botín-Sanabria et al., 2022).

The schematic presentation of a smart fruit-growing system is provided in Fig.1. Here, a digital twin is considered software for orchard management, which provides an interface between a fruit-grower, a virtual entity and a physical entity working like a decision-making tool or a command centre. The development of a digital twin of smart fruit growing depends on technological readiness. If yield estimation is a domain of precise horticulture related to monitoring and prediction, smart fruit growing implies interventions based on data-driven decision-making. Therefore, the authors reviewed the technology gap from yield estimation to smart fruit growing because each computer decision requires data before launching some interventions.

Thus, the main research question is, "How big is the technology gap between autonomous fruit yield estimation and smart fruit growing?".

Gap analysis has been applied to many different fields. Accordingly, there are various approaches to gap analysis, where core differences rest with the kinds of gaps in question. Gap analysis consists of four steps: (1) identifying key needs of the present situation, (2) determining the ideal future or desired situation, (3) highlighting the gaps that exist and need to be filled, and (4) modifying and implementing plans to fill the gaps (Kim & Ji, 2018).

As a result, the following research questions (RQ) must be answered first to achieve the main goal:

RQ1: What are the technological solutions and applications of vehicles, IoT and satellites?

RQ2: What are the trends and methods of artificial intelligence application?

RQ3: What are the technological solutions, applications, and challenges of digital twins?

Based on defined questions, the next tasks are identified: (1) to study the current application of vehicles; (2) to study the current application of IoT; (3) to study the current application of satellites; (4) to study the current application of artificial intelligence; (5) to study the current application of digital twins; and (6) to discuss the results.

Then, it will be possible to highlight research challenges to overcome the technology gap to achieve smart fruit-growing.

## 1. Research methods

To achieve the goal and answer research questions, the authors used the PRISMA 2020 approach. The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement was designed to help systematic reviewers transparently report why the review was done, what the authors did, and what they found. The PRISMA 2020 is an updated guideline for reporting systematic reviews, which includes reporting guidance that reflects advances in methods to identify, select, appraise, and synthesise studies. The structure and presentation of the items have been modified to facilitate implementation (Page et al., 2021).

The process of selecting and synthesising the relevant literature is shown in Fig. 2, that is, a PRISMA 2020 flow diagram.

Systematic literature reviews can be defined as a means of identifying, evaluating, and interpreting all available studies relevant to a specific research question, domain, or phenomenon of interest (Kitch-

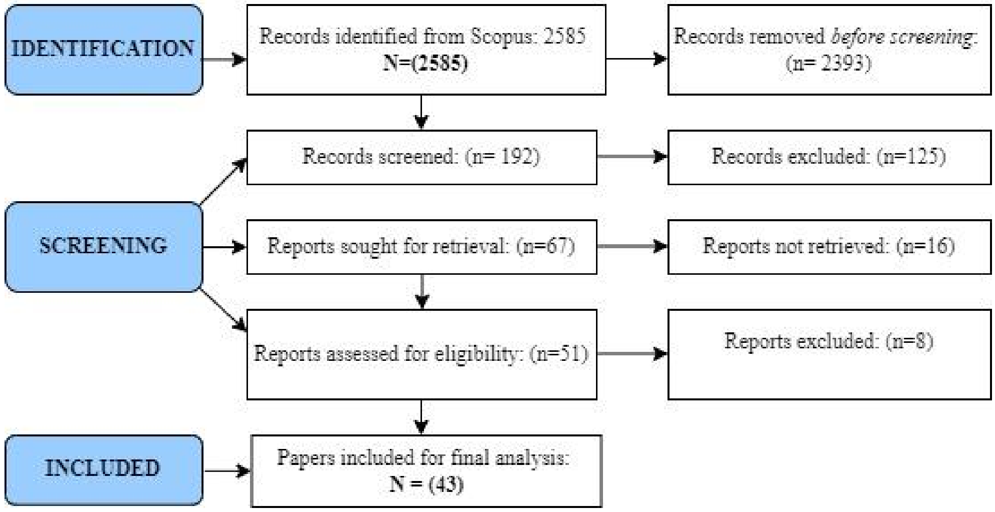


Fig. 2. PRISMA 2020 flow diagram for new systematic literature reviews

Tab. 1. Criteria and results of the relevant literature search

| Topic | Keywords | Selection criteria and results | |
|---|---|---|---|
| Vehicles | (horticulture OR precision AND agriculture OR smart AND farming OR orchard AND management OR yield AND estimation OR fruits) OR (uav OR ugv OR uuv OR usv OR artificial AND intelligence OR deep AND learning OR object AND detection OR digital AND twin OR digital AND shadow): 474 | 2021-2022: 144 | Review & articles: 42 |
| | | Records screened: 42 | Sought for retrieval: 17 |
| | | Eligible: 12 | Final analysis: 12 |
| IoT | (sensor OR sensors OR iot OR "Internet of Things" ) AND (orchard OR horticulture): 1370 | 2021-2022: 255 | Review & articles: 128 |
| | | Records screened: 79 | Sought for retrieval: 22 |
| | | Eligible:15 | Final analysis: 10 |
| Satellites | (satellite OR satellites) AND ("yield estimation" OR "yield prediction" OR "yield monitoring") AND (orchard OR horticulture): 318 | 2021-2022: 112 | Review & articles: 89 |
| | | Records screened: 10 | Sought for retrieval: 8 |
| | | Eligible: 7 | Final analysis: 4 |
| Artificial intelligence | (horticulture OR orchard) AND ("yield prediction" OR "yield estimation") AND ("artificial intelligence" OR "deep learning" OR "machine learning") AND fruit: 200 | 2021-2022: 94 | Review & articles: 84 |
| | | Records screened: 11 | Sought for retrieval: 10 |
| | | Eligible: 9 | Final analysis: 9 |
| Digital Twin | "digital twin" AND "smart farming": 223 | 2021-2022: 180 | Review & articles: 50 |
| | | Records screened: 50 | Sought for retrieval: 10 |
| | | Eligible: 8 | Final analysis: 8 |
| | **Total: 2585** | **2021-2022: 785** | **Review & articles: 393** |
| | | **Records screened: 192** | **Sought for retrieval: 67** |
| | | **Eligible: 51** | **Final analysis: 43** |

enham, 2004). A quality literature review takes time. Authors not only need to collect literature but also require in-depth understanding and relevant experience in the specific field because the interpretation of the results of the studies included in the literature review is more subjective (Fisch & Block, 2018).

The authors used the SCOPUS database to identify and select research papers. The authors chose this database because it has a large amount of indexed data, includes only well-performing, high-impact and peer-reviewed journals, and is convenient for data selection. Records identified in the Scopus database were sufficient to obtain a significant data sample size, so no additional databases were required.

In the first step, review topics based on research questions were assigned, and in the second step, the most appropriate keywords were selected for each topic (Table 1).

In total, 2585 results were found using the above-mentioned keywords. To identify all appropriate papers on the selected topics, the authors used the advanced search technique and selected "reviews" and "articles" from 2021 to 2022. Within each topic section, the titles and abstracts of the reviews and articles were examined, and duplicates and articles unrelated to the topic were excluded. Then, the authors read and evaluated the remaining 192 articles. As a result, 43 articles were selected for in-depth analysis.

# 2. Research results

The systematic review results are presented independently for each research question related to the current application of (1) vehicles, (2) IoT, (3) satellites, (4) artificial intelligence, and (5) digital twins.

## 2.1. Current application of vehicles

Tardaguila et al. (2021) completed an analysis of vehicle-mounted platforms: (1) ground vehicles, (2) aerial vehicles, and 3) portable platforms. Different sensors were mounted and researched, and such technologies as GPS and RTK provide a sufficient platform for vehicle navigation. Unmanned vehicles are discussed; however, monitoring of orchards as a whole autonomous system is not sufficiently studied.

Unmanned systems, such as unmanned ground vehicles (UGV) and UAVs, provide great support in different fields of application and environment. However, the type of vehicle and the field of application depend highly on the sensors and devices mounted on it. Each vehicle type has its benefits and disadvantages, e.g., UAVs are mostly limited in the weight of payload they can carry. UGVs can carry a heavier load but are limited in mobility compared to UAVs.

A review, "Sensors and Measurements for Unmanned Systems: An Overview" (Balestrieri et al., 2021), depicts fields of application for different vehicle types and environmental factors that can affect vehicle performance and longevity.

The use of UGV in agriculture has a wide range of applications. Most commonly, UGV is used as a device for fruit harvesting. It can be a claw that picks apples from trees (Chen et al., 2021b) and is controlled by AI or carefully designed scissors used for precise grape harvesting (Kolhalkar et al., 2021).

The use of UAVs in agriculture increases as demand for higher quality and higher productivity continues to rise. The main use of UAVs is depicted in articles:

- "Early Estimation of Olive Production from Light Drone Orthophoto, through Canopy Radius" (Ortenzi et al., 2021);
- "Estimating Evapotranspiration of Pomegranate Trees Using Stochastic Configuration Networks (SCN) and UAV Multispectral Imagery" (Niu et al., 2022);
- "An Automatic UAV Based Segmentation Approach for Pruning Biomass Estimation in Irregularly Spaced Chestnut Orchards" (Di Gennaro et al., 2022).

The main UAV application mentioned in the articles is data acquisition while performing the main UAV task, i.e., imaging or remote sensing (Ortenzi et al., 2021; Di Gennaro et al., 2022; Niu et al., 2022).

Images may differ from case to case based on UAV type and mounted sensors, as some UAVs can add special cameras, e.g., multispectral cameras (Niu et al., 2022). A more versatile UAV version is shown in "Identification of fruit tree pests with deep learning on an embedded drone to achieve accurate pesticide spraying" (Chen et al., 2021a), where an AI system is placed on a UAV, allowing it to do image analysis during flight. Based on analysis results made by AI, the path for pesticide spraying is marked for another UAV to do precise pesticide spraying while reducing pesticide effect on healthy trees. For more insight, review articles "Orchard management with small unmanned aerial vehicles: a survey of sensing and analysis approaches" (Zhang et al., 2021) and "A Review on Drone-Based Data Solutions for Cereal Crops" (Panday et al., 2020) show a possible use of a UAV that was not applied or considered in other articles. The review looked into different types of drones and areas of application. As a result, the number of articles reviewed is larger, and the scope of the review is much broader.

AV and UGV are types of vehicles with already defined common constructional designs. UAVs are designed on the same principle as helicopters or planes. UGV have wheels or caterpillar tracks. However, there are attempts in robotics to move away from common construction designs for UAVs and UGVs. A review, "Bio-Inspired Robots and Structures toward Fostering the Modernization of Agriculture" (Kondoyanni et al., 2022), looks into new designs of unmanned vehicles with designs inspired by nature's creations. In 2021, researchers created a miniature robot that mimicked bees, with the main task of miniature robot bees to complement work done by natural bees (Kondoyanni et al., 2022).

## 2.2. Current application of IoT

Even the slightest changes in the environment can influence yield in horticulture; thus, close monitoring of all potential factors is essential. As such, the Internet of Things (IoT) is a highly efficient solution to solving this task. In the context of this review, sensor technology was mainly investigated, as sensors are devices that can be applied in various situations. In a review, "A comprehensive review of remote sensing platforms, sensors, and applications in nut crops" (Jafarbiglu & Pourreza, 2022), the authors have researched various sensor technologies and applications. For example, the review mentions simple sensors planted on or in the ground, as well as, specialised platforms equipped with different sensors, or mobile platforms like UAVs and UGVs with sensors connected to the Internet to transmit data (Abdul Haleem et al., 2022).

Data received from sensors is analysed and used for further studies (Akhter & Sofi, 2021) and real-time adjustments (Rehman et al., 2022).

The range of sensors used in agriculture is wide, starting with clip-type cameras used to monitor plants and predict optional time for harvesting based on images (Lee et al., 2022) and ending with more unusual IoT solutions, like tilt sensors. They are not common in agriculture, but they can be used for danger warnings in locations with potential high-intensity storms or hurricanes (Hui et al., 2022).

One of the main factors that influence yield is irrigation, as plants require the correct amount of water, and it is highly inadvisable to deviate from that. Several different sensor types are used to monitor and react to changes in soil or air. The simplest solution to measure moisture in air is weather stations. They already support various sensors, including moisture, temperature, wind speed and direction sensors (Quezada et al., 2021). It is possible to react to high temperatures or strong winds using all these sensors. Of course, setting up a full meteorological station may not be the best solution for every orchard, so specific sensors can be set up for monitoring moisture, be those temperature sensors or moisture sensors in one form or another. A good example of a temperature sensor use is provided in the article "Intelligent Spraying Water Based on the Internet of Orchard Things and Fuzzy PID Algorithms", where the temperature difference between day and night was a factor for when and how much water should be sprayed for better sugar accumulation in fruits (Zhang et al., 2022). Other solutions that can be used for irrigation systems may contain a soil electrical conductivity sensor (Gao et al., 2021) or an air humidity sensor (Kun et al., 2021).

## 2.3. Current application of satellites

The traditional remote sensing approach used in agriculture is based on the application of satellites. Compared to UAVs, a satellite is a space-based platform suitable for surveying large areas and monitoring national and regional agricultural changes. Satellites provide useful information for assessing the monitored object and its ecosystem at a macro level using different indices. Indices are effective in the case of low spatial-resolution images. UAVs are the optimal remote sensing technique for local agricultural surveys and rapid handling of local agricultural production problems while directly monitoring objects, which must be extracted from the background using computer vision techniques. Thematic mapping is the keyword which best describes the applied purposes of satellites. Macro analysis through maps is interfaced with time-series analysis, change detection, anomaly detection, feature fusion and monitoring of phenology cycle information. For example, Toosi et al. (2022) presented an automatic citrus orchard mapping method using spectral satellites. The developed method was applied for 2016–2019 to analyse land-use changes. Macro monitoring is useful for the public sector when information about a large territory must be collected centrally, but crowdsourcing methods are not allowed or possible. Ali et al. (2022) presented a review of remote sensing applications in yield estimation and prediction. They discussed (1) satellites and spatial resolution, (2) spectral bands, and (3) grouped methods by sensor type. Four forms of vegetation reflectance were mentioned, each with its own set of works: (1) reflectance of individual plant parts (single organ pigments), (2) reflectance of sets (canopies), (3) plant presence and status, and (4) set structure and texture. In the meantime, Tardaguila et al. (2021) grouped smart viticulture applications in different study domains, which can be generalised for other cultures too: (1) soil properties and soil quality assessment; (2) vegetative growth, nutritional status and canopy architecture; (3) pest and disease detection and management; (4) water status; (5) yield components and crop forecasting; (6) fruit composition and quality attributes; (7) targeted management; and (8) selective harvesting. Maybe the principles and techniques for satellite imagery are well-known and researched. However, the development of monitoring systems is an actual research field because algorithms and methods must be tuned for each plant cultivar and its ecosystem. For example, Mwinuka et al. (2021) researched the assessment of canopy water status and yield prediction of irrigated African eggplant tuning prediction models using field survey data.

## 2.4. Current application of artificial intelligence

Speaking about yield estimation, Maheswari et al. (2021) presented a review of intelligent fruit yield estimation for orchards using deep learning-based semantic segmentation techniques. The review does not differ much from the situation mentioned in the review by Koirala et al. (2019), which mentions improvement of deep learning and quality of datasets as driving forces. A more comprehensive review was provided by Fu et al. (2022). The review included the analysis of (1) indirect yield prediction, which was divided into two parts: input features and regression algorithms, and (2) direct yield estimation, which was divided into three parts for analysis, which includes estimation platforms, method of fruit detection and fruit-counting approaches. It closed some significant information gaps, such as the application of the RGB-D sensor and LiDAR or more modern object detection algorithms, like YOLOv4. Additionally, it provided a good roadmap of research fields of AI-based yield estimation. Considering the more recent publications related to accuracy, confidence and recognition quality, Wang and He (2021) applied YoLov5 and experimentally compared it with state-of-the-art CNN architectures using natural dataset and tuning methods. As for specific domain problems, like double counting of fruits, Mirhaji et al. (2021) experimentally evaluated the impact of photographing locations and the number of images on accuracy results. They also applied augmentation that simulates shadows and sunshine. In the meantime, Gao et al. (2022) and Fu et al. (2022) presented research suitable for fruit harvesting: (1) real-time fruit detection from video using YOLOv4-tiny and Kinect V2; and 2) detection of banana stalks using YOLOv4. Meantime, Xia et al. (2022) applied CenterNet, which detects centre-points of objects, and the Kuhn–Munkres algorithm for object tracking. Anderson et al. (2021) analysed autonomous estimation of fruit load in complex terms of business processes in the field: distance to a tree, daytime, cultivars, and others, completing an experiment using a prototype of a UGV. For example, they conclude that a multi-view technique is recommended for fruit load estimation of orchards using the canopy management systems of conventional, hedge and single leader, but not trellised canopies. Summarising the above, the following development vectors can be identified: (1) experimentation with new CNN architectures; (2) if new CNN architecture is not published, the pre-processing or post-processing algorithms are applied to improve accuracy; (3) object tracking application to precise the fruit load; (4) searching for the optimal number and position of imaging points, including video application; (5) experimentation with different cultivars; and (6) designing autonomous vehicle movement and imaging process and its impact on fruit detection accuracy.

## 2.5. Current application of digital twins

The digitalisation level of food production management and the integrity of physical and virtual systems can be classified into three stages of its development: (1) a digital model — an approach with manual data transfer; (2) a digital shadow with automatic data transfer; and (3) a digital twin, providing a user with a possibility to control the physical system through its virtual representation (Botín-Sanabria et al., 2022). If the digital shadow is associated with precision agriculture, smart farming will be the next generation related to food production automation, in which management tasks are not only based on geospatial data but also on context data, situational awareness and event triggers, using a digital twin approach constructing a cyber-physical system for farm management (Verdouw et al., 2021).

Digital twin architecture has been introduced for Controlled Environment Agriculture applications to optimise productivity through the application of climate control strategies and treatments related to crop management (Chaux et al., 2021). A review of 300 publications on digital twin applications in the food industry concluded that the application of digital twins mainly focuses on the production and processing stages of agriculture, and only several publications consider autonomous control or providing recommendations to humans (Henrichs et al., 2021). A digital twin of a plant in combination with a conceptual ontological model for domain knowledge representation is used to model plant development stages and forecast crop yield considering weather conditions, climate and external events (Skobelev et al., 2021). Pylianidis et al. (2021) identified several use cases for prototyped or deployed digital twins in agriculture in publications dated from 2017 to 2020: digital twins of (1) picked mango fruit that captures its temperature variability and biochemical response throughout the cold chain to evaluate quality losses along the cold chain like firmness and vitamin content; (2) a field using data coming from ISOBUS sensors, other field related data, human expertise and machine learning to provide better field prognostics and act faster in the presence of predicted deviations; (3) to emulate the use of unmanned ground vehicles in fields. It contains a predefined selection of commercially available unmanned ground vehicles which a farmer can test on the virtual field to find the most efficient for their case; (4) a self-contained aquaponics production unit; the purpose of this digital twin is to balance the fish stock and plants in the unit by monitoring them and controlling the unit automatically; (5) a harvested potato to gain insight into harvester damage to potatoes; (6) a tree and its surroundings in an orchard; these digital twins allow the continuous monitoring of orchard production systems to predict stress, disease and crop losses, and develop a self-learning system; (7) any agricultural entity, using holographic devices, augmenting the world with camera-based imaging, placing 2D or 3D content in the real world, simulating them, and creating logs and maintenance events; (8) the cultivated landscape for supporting planners in designing agricultural road networks; (9) that allows users to identify pest and diseases in plants; (10) a field and its machinery, which allows the real-time monitoring of machines and their energy consumption and evaluation of the economic efficiency of the crop management treatment; (11) olive trees to monitor olive fly occurrence; (12) bee colonies, which allows the beekeepers to manage the food storage reserves, to identify disease and pest infections, to inspect if queenless and swarming states exist, it provides an anti-theft mechanism, and insight into the colony status and hygiene; (13) a vertical farm; the virtual and physical components are interconnected through sensors embedded in the materials of the farm structure that monitor temperature, humidity, luminosity, and CO2; (14) the world's agricultural resources; the digital twin will give instant access to critical data on the world's farmland; it will allow sharing insights, materials, and connection with the food supply chain; (15) an indoor garden that calculates the ideal conditions for plants to grow; (16) for aquaculture combining human intelligence and artificial intelligence to help fishermen develop accurate digital decision-making processes for production management. Sung and Kim (2022) proposed a three-layer (physical world, communication protocol and cyber world) architecture for digital twin-based smart farms and the realisation of the conceptual model at the laboratory level.

Several challenges in implementing digital twins have been identified: (1) combining multidisciplinary knowledge and providing enough data (Henrichs et al., 2021); (2) seamless access to object data while maintaining data integrity, respecting use rights, safety and security; (3) real-time synchronisation in rural areas; (4) granularity of digital twins: finer granularity (up to individual plant or animal) increases cost, but provide more value; (5) stakeholders can contribute different types of data and may need only a limited amount of information, which requires a secure and trusted way to access the digital twin (Verdouw et al., 2021); (6) data management, data privacy and security, data quality, real-time communication of data and latency, physical realism and future projections, real-time modelling, continuous model updates, modelling the unknown, transparency and interoperability, large scale computation, and interaction with physical assets (Rasheed et al., 2020).

Enabling technologies are employed to overcome the challenges. These have been categorised into five categories by Rasheed et al. (2020): (1) physics-based modelling, consisting of experimental modelling, three-dimensional modelling and high fidelity numerical simulators; (2) data-driven modelling, consisting of data generation, data pre-processing, management and ownership, data privacy and ethical issues, machine learning and artificial intelligence; (3) big data cybernetics, consisting of data assimilation, reduced order modelling, hardware and software in the loop, other hybridisation techniques, physics-informed ML, compressed sensing and symbolic regression; (4) infrastructure and platforms consisting of big data technologies, IoT technologies, communication technologies, computational infrastructures, digital twin platforms; (5) human-machine interface consisting of augmented and virtual reality, natural language processing, and gesture control.

# 3. Discussion of the results

Based on the systematic review results, this research team identified keywords for each topic (Appendix I). The keywords were grouped into two categories: “application” and “active research”. One category identifies the application of study results, another — actual problems and studies mentioned in the literature of 2020–2022.

A fishbone diagram is an effective tool for gap analysis to depict all impact factors, grouping them by categories. It was applied to visualise the review results mentioned in the table of Appendix I (Fig. 3). The keywords were determined using the brainstorming method when the authors completed the systematic review.

The fishbone diagram (Fig. 3) depicts current studies and problems which are already studied. However, it is important to make future forecasts for strategic development. The “research” industry is not an exception; therefore, actual challenges for research in increasing the capacity of smart fruit-growing must be investigated. In other words, the technological gap to the increased capacity of smart fruit-growing must be identified.

Jia (2021) raised the topic of methodology development to plan and design smart gardens because the construction of smart garden projects requires the coordination of multiple disciplines, relying on the support of advanced technologies like IoT. The methodology of smart garden planning and design must provide knowledge, tools and assistance to solve such tasks as (1) correctly selecting radio frequency modules; (2) selecting optimal locations of gateways; (3) data modelling, data processing and visualisation; (4) performance analysis and tuning of algorithms. Jia (2021) highlights five parts of smart garden architecture: (1) smart garden infrastructure, (2) smart garden perception platform, (3) smart garden cloud platform, (4) smart garden data platform, and (5) smart garden application system. Meanwhile, the industrial planning in the farmstead shall be based on the basic principle of ecological and environmental protection, considering economic and social benefits, constantly improving the industrial chain, realising the multiple values of products, promoting their synergistic development, and maximising overall benefits. This is similar to the principles of the “enterprise engineering” discipline. Therefore, it can be concluded that the design of a smart orchard is enterprise engineering of the fruit-growing domain. Kalyanaraman et al. (2022) presented a transdisciplinary coalition called the AgAID Institute, which proposes a new knowledge transfer model and fosters partnerships among agriculture and artificial intelligence researchers, educators, extension professionals, industry technology providers, growers, crop consultants, managers, and policymakers, creating an ecosystem for driving the Agriculture 4.0 revolution. The AgAID Institute is organised around three Ag-inspired research thrusts that work hand-in-hand with three foundational AI research thrusts: (1) forecasting intelligence, (2) farm operations intelligence, and (3) labour intelligence, supported by AI, respectively, (1) interactive data-driven modelling, (2) interactive decision and action support, and (3) Human–AI workflow. Additionally, the AgAID Institute supports knowledge society drivers: (1) circular learning, (2) early adopter network, and (3) adoption

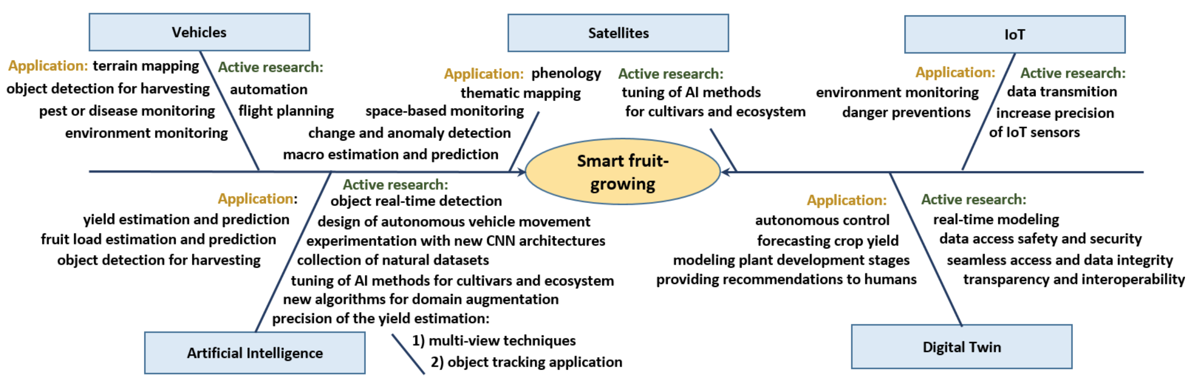



Fig. 3. Actual application and active studies in smart fruit-growing

amplification. Considering challenges, the AgAID Institute raises attention mainly to social, economic, and legacy barriers that coincide with the trustworthy AI concept. Indeed, smart farming technologies are advanced enough; however, the knowledge and innovations are researched independently, and their systematisation in a unified engineering discipline is required. For example, De Alwis et al. (2022) summarised knowledge about smart farming through the big data concept: (1) data types, (2) big data applications, and (3) big data techniques. Meantime, Mohamed et al. (2021) generalised research through IoT, looking at drones and robots like mobile IoT networks, but the application was grouped through sensors. They highlight the importance of Smart Decision Support System development, which can support the real-time analysis and mapping of soil characteristics, also helping to make proper decision management. Finally, they mention that smart agriculture in developing countries needs more support from governments at the level of small farms and the private sector. All these research efforts show the technological gap, which is expressed in the lack of data-driven decision-making systems and the mastership to design smart farming systems for them. Jerhamre et al. (2021) completed a semi-structured interview study in Sweden examining how different agricultural stakeholders regard smart farming technology. They identified the following challenges: (1) the agricultural sector is not researched homogeneously, there are open niches, which remain unexplored; (2) data collection, maintenance, sharing, interconnection and processing are not sufficiently developed; (3) stakeholders require customisation possibility to fit AI to their farm ecosystem and increase its precision; (4) stakeholders are more interested in decision-support systems than autonomous systems; (5) stakeholders worry about cyberattacks, which can cause destructions through autonomous systems; (6) additionally, they worry about dependency on technology, whose failure can cause losses, while manual maintenance is restricted due to autonomous system exploitation; (7) public data platform required for all agricultural data to be compiled; (8) upgrade of existing farm is restricted by finance, knowledge, experience and worry about security; (9) there is insufficient experience in how to integrate smart solutions into existing decision making system; (10) open systems are required for customisation needs; (11) smart solutions have to be directed to improve working conditions. O'Shaughnessy et al. (2021) discussed information on agricultural resources, challenges for sustainable crop production, frameworks for smart farming solutions and potential positive and negative technological and social aspects comparing the situations in the U.S. and South Korea. O'Shaughnessy et al. (2021) identified the important element of smart farming development: each cultural region and each farm have its policies and business rules, e.g., governance of water is different in each of the fifty states of the U.S. Therefore, the development of data-driven decision-support systems is a rational solution to investigate workflows and regional specifics, which can be gradually automated in the future. In the meantime, the complexity and diversity of ecosystems underline the demand for customisation and open solutions, which can be freely adapted for required workflow. Also, O'Shaughnessy et al. (2021) mentioned challenges caused by COVID-19, which disrupted agricultural distribution systems. That can be generalised in the demand for decision support systems, which can help humans in situations requiring fast decisions or quick changes in the workflow to save business competitiveness. In the 2020/2021 crop year, China was the leading producer of apples worldwide. Jin et al. (2021) indicated barriers to sustainable apple production in China. Considering that China aspires to be a leader in artificial intelligence, the indicated barriers can be equivalent to world-level challenges. Jin et al. (2021) mentioned the synergy of multiple environmental, economic, and social problems which affect the apple production system. Speaking about effective decision-making, Jin et al. (2021) identified similar problems: (1) low adoption of new technologies and practices; (2) limited access to trustworthy information and knowledge; (3) low resilience to climate shocks; (4) the lack of knowledge in orchard management; (5) uncertainty about market access routes; and (6) land fragmentation and limited collaboration among market players. Of course, smart technologies and artificial intelligence received more attention in terms of development, and much knowledge was collected. However, there is a vast knowledge accessibility gap between practice and research. Going back to the six levels of driving automation, smart fruit-growing is somewhere between Level 1, "Assisted Automation", and Level 2, "Partial Automation". IoT monitoring can be an example of assisted automation providing a warning system, but harvesting robots provide partial automation of some fruit-growing activities. Meanwhile, the paradigm of a digital twin can be aspired as the main driver for smart fruit-growing development in the future because it is suitable for a business process management that maps, monitors, and provides geospatial analysis, forecasts, simulates and optimises the workflows of a business. Verdouw et al. (2021) provided a comprehensive analysis of digital twin models, grouping them by control models: (1) imaginary, (2) monitoring, (3) predictive, (4) prescriptive, (5) autonomous, and (6) recollection where the decision-maker is identified as the important element of control model.

The described challenges were grouped into categories: "environment", "technology", "legislation", and "socio-economics" (Appendix II). To visualise the extracted knowledge, the Nadler-Tushman's Congruence Model was applied with category modifications considering PESTLE classification (Fig. 4). This diagram (Fig. 4) depicts the technological gap identified by the authors through the review of existing scientific literature. The keywords were determined using the brainstorming method.

The gap analysis showed that fruit growers are not ready to use fully autonomous systems for fruit growing because they do not trust artificial intelligence and robots. Autonomous systems can be attacked by intruders to cause destruction, or they can simply break down without the possibility of switching to manual control. Meanwhile, the fruit growers are interested in automatic orchard monitoring and AI-based recommendation systems, which can improve decision-making and optimise business processes. Additionally, fruit growers do not have sufficient knowledge required to integrate smart solutions into their native workflows, and the legacy and standards related to autonomous systems are only in the development stage. The independent fine-grained automation of fruit-growing activities and the development of recommendation systems through the digital twin paradigm can structure knowledge about smart solutions and tune the legacy and socio-economic situation for more effective use. Also, the open systems and a customisation possibility are not sufficiently developed to tune smart solutions to local legislation and existing workflows, let alone limited data sharing. Considering the wish of fruit growers, the human–robot collaborative paradigm of Industry 5.0 is well-suitable for them. Currently, the decision-making systems based on the digital twin paradigm are the most suitable development path going to smart fruit-growing based on the human-robot collaborative paradigm of Industry 5.0.

Carrying out a repeated assessment of the situation from November 2022 to April 2023, the keywords "digital twin" AND "smart farming" provided three publications in 2023. Lemphane et al. (2023) presented an article which discusses the smart farming digital twin concept for pasture management based on the artificial intelligence application. Thapa and Horanont (2023) propose the importance of the implementation of digital twin farming platforms to sustain food security based on the involvement of artificial intelligence, the Internet of Things, big data,

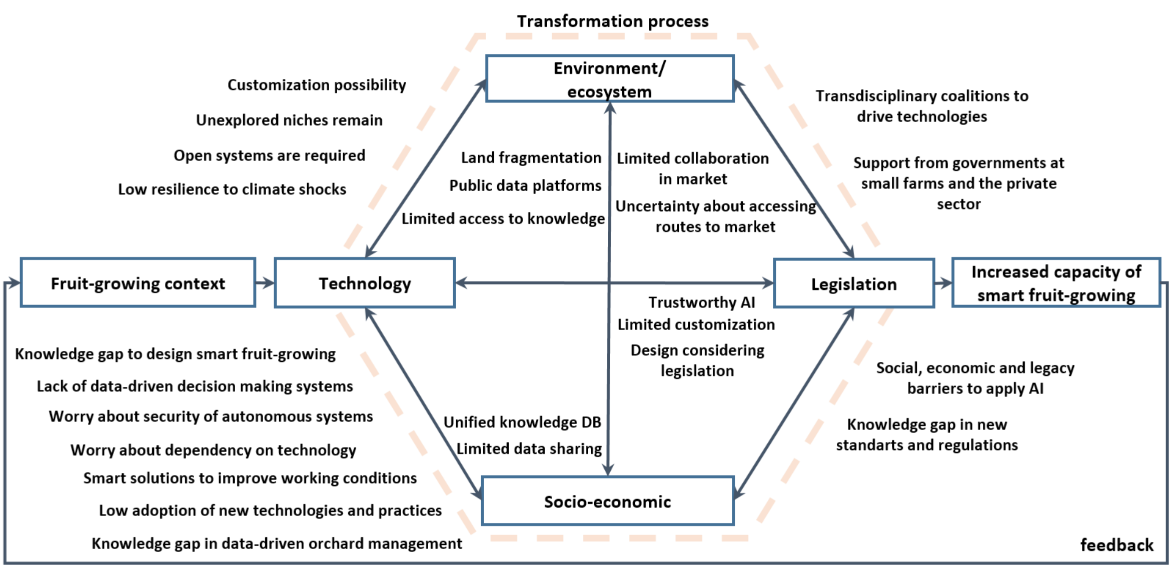



Fig. 4. Challenges or technological gap to increase the capacity of smart fruit-growing

and cloud services to excel in farming using simulation, analysis, and accurate planning for growth in agricultural sectors. Meanwhile, Alves et al. (2023) presented a digital twin of a smart irrigation system composed of an IoT platform and a discrete event simulation model. The articles are not directly related to horticulture; however, they confirm the identified interest of farmers in automatic monitoring, decision-making and AI-based systems and the increase of digital twin trends in the field of smart agriculture.

The authors assume that this study will help the scientific community to plan future studies to optimise research and accelerate the transfer to new smart fruit-growing technologies as it is insufficient to develop an innovation, but it must be done at the appropriate time.

# Conclusions

The amount and quality of developed smart solutions are increasing, and the research information supporting them accumulates in all areas of life, including fruit growing. Using the PRISMA 2020 method for the analysis of published scientific information, the following can be concluded:

- The current level of development of artificial intelligence, automatically controlled devices and decision-making systems limits their direct inclusion in daily fruit-growing practices. The existing achievements indicate the need to improve the structuring of available data, better adapt decision-making systems advice to the needs of the specific fruit-growing farm, environmental and market requirements, and ensure the safety of unmanned aerial vehicle (UAV) applications.
- Closer social and intellectual cooperation between developers of intelligent solutions and their potential end-users should be formed to promote innovative fruit-growing technologies and recognise and substantiate their usefulness.
- The analysis of the existing knowledge indicates the advantages and potential of the digital twin paradigm in developing smart fruit-growing and its future perspectives in creating a dialogue between the field of information technology and practical horticulture.

The study results can optimise research and development of smart fruit-growing technologies.

# Acknowledgement

This research is funded by the Latvian Council of Science, project “Development of autonomous unmanned aerial vehicles based decision-making system for smart fruit growing”, project No. lzp2021/1-0134

# Literature

Abdul Haleem, S., Kshirsagar, P. R., Manoharan, H., Prathap, B., Pradeep Kumar, K., Tirth, V., Islam, S., Katragadda, R., & Amibo, T. A. (2022). Wireless sensor data acquisition and control monitoring model for internet of things applications. *Scientific Programming*, *2022*. doi: 10.1155/2022/9099163

Akhter, R., & Sofi, S. A. (2021). Precision agriculture using IoT data analytics and machine learning. *Journal of King Saud University-Computer and Information Sciences*. doi: 10.1016/j.jksuci.2021.05.013

Ali, A. M., Abouelghar, M. A., Belal, A. A., Saleh, N., Younes, M., Selim, A., Amin, M. E. S., Elwesemy, A., Kucher, D. E., Magignan, S., & Savin, I. (2022). Crop Yield Prediction Using Multi Sensors Remote Sensing. *The Egyptian Journal of Remote Sensing and Space Science*. doi: 10.1016/j.ejrs.2022.04.006

Alves, R. G., Maia, R. F., & Lima, F. (2023). Development of a Digital Twin for smart farming: Irrigation management system for water saving. *Journal of Cleaner Production*, *388*, 135920. doi: 10.1016/j.jclepro.2023.135920

Anderson, N. T., Walsh, K. B., Koirala, A., Wang, Z., Amaral, M. H., Dickinson, G. R., Sinha, P., & Robson, A. J. (2021). Estimation of Fruit Load in Australian Mango Orchards Using Machine Vision. *Agronomy*, *11*(9), 1711. doi: 10.3390/agronomy11091711

Balestrieri, E., Daponte, P., De Vito, L., & Lamonaca, F. (2021). Sensors and measurements for unmanned systems: An overview. *Sensors*, *21*(4), 1518. doi: 10.3390/s21041518

Botín-Sanabria, D. M., Mihaita, A. S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. D. J. (2022). Digital twin technology challenges and applications: A comprehensive review. *Remote Sensing*, *14*(6), 1335. doi: 10.3390/rs14061335

Chaux, J. D., Sanchez-Londono, D., & Barbieri, G. (2021). A digital twin architecture to optimize productivity within controlled environment agriculture. *Applied Sciences*, *11*(19), 8875. doi: 10.3390/app11198875

Chen, C. J., Huang, Y. Y., Li, Y. S., Chen, Y. C., Chang, C. Y., & Huang, Y. M. (2021a). Identification of fruit tree pests with deep learning on embedded drone to achieve accurate pesticide spraying. *IEEE Access*, *9*, 21986-21997. doi: 10.1109/ACCESS.2021.3056082

Chen, W., Zhang, J., Guo, B., Wei, Q., & Zhu, Z. (2021b). An Apple Detection Method Based on Des-YOLO v4 Al-

gorithm for Harvesting Robots in Complex Environment. *Mathematical Problems in Engineering*, *2021*. doi: 10.1155/2021/7351470
De Alwis, S., Hou, Z., Zhang, Y., Na, M. H., Ofoghi, B., & Sajjanhar, A. (2022). A survey on smart farming data, applications and techniques. *Computers in Industry*, *138*, 103624. doi: 10.1016/j.compind.2022.103624
Di Gennaro, S. F., Nati, C., Dainelli, R., Pastonchi, L., Berton, A., Toscano, P., & Matese, A. (2020). An automatic UAV based segmentation approach for pruning biomass estimation in irregularly spaced chestnut orchards. *Forests*, *11*(3), 308. doi: 10.3390/f11030308
European Commission. (2019). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. The European Green Deal. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1576150542719&uri=COM%3A2019%3A640%3AFIN
European Commission. (2020). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. EU Biodiversity Strategy for 2030. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1590574123338&uri=CELEX:52020DC0380
Fisch, C., & Block, J. (2018). Six tips for your (systematic) literature review in business and management research. *Management Review Quarterly*, *68*(2), 103-106. doi: 10.1007/s11301-018-0142-x
Fu, L., Wu, F., Zou, X., Jiang, Y., Lin, J., Yang, Z., & Duan, J. (2022). Fast detection of banana bunches and stalks in the natural environment based on deep learning. *Computers and Electronics in Agriculture*, *194*, 106800. doi: 10.1016/j.compag.2022.106800
Gao, F., Fang, W., Sun, X., Wu, Z., Zhao, G., Li, G., Li, R., Fu, L., & Zhang, Q. (2022). A novel apple fruit detection and counting methodology based on deep learning and trunk tracking in modern orchard. *Computers and Electronics in Agriculture*, *197*, 107000. doi: 10.1016/j.compag.2022.107000
Gao, P., Xie, J., Yang, M., Zhou, P., Chen, W., Liang, G., Chen, Y., Han, X., & Wang, W. (2021). Improved soil moisture and electrical conductivity prediction of citrus orchards based on IOT using Deep Bidirectional LSTM. *Agriculture*, *11*(7), 635. doi: 10.3390/agriculture11070635
Grand View Research. (2022). *Artificial Intelligence Market Size Report, 2022-2030*. Retrieved from https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market
Hasan, R. I., Yusuf, S. M., & Alzubaidi, L. (2020). Review of the state of the art of deep learning for plant diseases: a broad analysis and discussion. *Plants*, *9*(10), 1302. doi: 10.3390/plants9101302
Henrichs, E., Noack, T., Pinzon Piedrahita, A. M., Salem, M. A., Stolz, J., & Krupitzer, C. (2021). Can a Byte Improve Our Bite? An Analysis of Digital Twins in the Food Industry. *Sensors*, *22*(1), 115. doi: 10.3390/s22010115
Hui, K. K. W., Wong, M. S., Kwok, C. Y. T., Li, H., Abbas, S., & Nichol, J. E. (2022). Unveiling Falling Urban Trees before and during Typhoon Higos (2020): Empirical Case Study of Potential Structural Failure Using Tilt Sensor. *Forests*, *13*(2), 359. doi: doi.org/10.3390/f13020359
Jafarbiglu, H., & Pourreza, A. (2022). A comprehensive review of remote sensing platforms, sensors, and applications in nut crops. *Computers and Electronics in Agriculture*, *197*, 106844. doi: 10.1016/j.compag.2022.106844
Jerhamre, E., Carlberg, C. J. C., & van Zoest, V. (2022). Exploring the susceptibility of smart farming: Identified opportunities and challenges. *Smart Agricultural Technology*, *2*, 100026. doi: 10.1016/j.atech.2021.100026
Jia, A. (2021). Intelligent garden planning and design based on agricultural internet of things. *Complexity*, *2021*. doi: 10.1155/2021/9970160
Jin, S., Li, W., Cao, Y., Jones, G., Chen, J., Li, Z., Chang, Q., Yang, G., & Frewer, L. J. (2022). Identifying barriers to sustainable apple production: A stakeholder perspective. *Journal of Environmental Management*, *302*, 114082. doi: 10.1016/j.jenvman.2021.114082
Kalyanaraman, A., Burnett, M., Fern, A., Khot, L., & Viers, J. (2022). Special report: The AgAID AI institute for transforming workforce and decision support in agriculture. *Computers and Electronics in Agriculture*, *197*, 106944. doi: 10.1016/j.compag.2022.106944
Kim, S., & Ji, Y. (2018). Gap analysis. *The International Encyclopedia of Strategic Communication*, 1-6. doi: 10.1002/9781119010722.iesc0079
Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University, 33*(2004), 1-26. Retrieved from https://www.researchgate.net/profile/Barbara-Kitchenham/publication/228756057_Procedures_for_Performing_Systematic_Reviews/links/618cfae961f09877207f8471/Procedures-for-Performing-Systematic-Reviews.pdf
Koirala, A., Walsh, K. B., Wang, Z., & McCarthy, C. (2019). Deep learning–Method overview and review of use for fruit detection and yield estimation. *Computers and Electronics in Agriculture*, *162*, 219-234. doi: 10.1016/j.compag.2019.04.017
Kolhalkar, N. R., Krishnan, V. L., Pandit, A. A., Somkuwar, R. G., & Shaaikh, J. A. (2021). Design and performance evaluation of a novel end-effector with integrated gripper cum cutter for harvesting greenhouse produce. *International Journal of Advanced Technology and Engineering Exploration*, *8*(84), 1479. doi: 10.19101/IJATEE.2021.874507
Kondoyanni, M., Loukatos, D., Maraveas, C., Drosos, C., & Arvanitis, K. G. (2022). Bio-Inspired Robots and Structures toward Fostering the Modernization of Agriculture. *Biomimetics*, *7*(2), 69. doi: 10.3390/biomimetics7020069
Kun, T., Sanmin, S., Liangzong, D., & Shaoliang, Z. (2021). Design of an Intelligent Irrigation System for a Jujube Orchard based on IoT. *INMATEH-Agricultural Engineering*, *63*(1). doi: 10.35633/inmateh-63-19
Lee, U., Islam, M. P., Kochi, N., Tokuda, K., Nakano, Y., Naito, H., Kawasaki, Y., Ota, T., Sugiyama, T., & Ahn, D. H. (2022). An Automated, Clip-Type, Small Internet of Things Camera-Based Tomato Flower and Fruit Monitoring and Harvest Prediction System. *Sensors*, *22*(7), 2456. doi: 10.3390/s22072456
Lemphane, N. J., Kuriakose, R. B., & Kotze, B. (2023). Designing a Digital Shadow for Pasture Management to

Mitigate the Impact of Climate Change. In: A. Joshi, M. Mahmud, & R. G. Ragel (Eds.), *Information and Communication Technology for Competitive Strategies (ICTCS 2021). Lecture Notes in Networks and Systems, 400*. Singapore: Springer. doi: 10.1007/978-981-19-0095-2_35

Maheswari, P., Raja, P., Apolo-Apolo, O. E., & Pérez-Ruiz, M. (2021). Intelligent fruit yield estimation for orchards using deep learning based semantic segmentation techniques—a review. *Frontiers in Plant Science*, *12*, 684328. doi: 10.3389/fpls.2021.684328

Mirhaji, H., Soleymani, M., Asakereh, A., & Mehdizadeh, S. A. (2021). Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. *Computers and Electronics in Agriculture*, *191*, 106533. doi: 10.1016/j.compag.2021.106533

Mohamed, E. S., Belal, A. A., Abd-Elmabod, S. K., El-Shirbeny, M. A., Gad, A., & Zahran, M. B. (2021). Smart farming for improving agricultural management. *The Egyptian Journal of Remote Sensing and Space Science*. 10.1016/j.ejrs.2021.08.007

Mwinuka, P. R., Mbilinyi, B. P., Mbungu, W. B., Mourice, S. K., Mahoo, H. F., & Schmitter, P. (2021). The feasibility of hand-held thermal and UAV-based multispectral imaging for canopy water status assessment and yield prediction of irrigated African eggplant (Solanum aethopicum L). *Agricultural Water Management*, *245*, 106584. doi: 10.1016/j.agwat.2020.106584

Niu, H., Zhao, T., Wang, D., & Chen, Y. (2022). Estimating Evapotranspiration of Pomegranate Trees Using Stochastic Configuration Networks (SCN) and UAV Multispectral Imagery. *Journal of Intelligent & Robotic Systems*, *104*(4), 1-11. doi: 10.1007/s10846-022-01588-2

Ortenzi, L., Violino, S., Pallottino, F., Figorilli, S., Vasta, S., Tocci, F., Antonucci, F., Imperi, G., & Costa, C. (2021). Early Estimation of Olive Production from Light Drone Orthophoto, through Canopy Radius. *Drones*, *5*(4), 118. doi: 10.3390/drones5040118

O'Shaughnessy, S. A., Kim, M., Lee, S., Kim, Y., Kim, H., & Shekailo, J. (2021). Towards smart farming solutions in the US and South Korea: A comparison of the current status. *Geography and Sustainability*. doi: 10.1016/j.geosus.2021.12.002

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Systematic Reviews*, *10*(89). doi: 10.1136/bmj.n71

Panday, U. S., Pratihast, A. K., Aryal, J., & Kayastha, R. B. (2020). A review on drone-based data solutions for cereal crops. *Drones*, *4*(3), 41. doi: 10.3390/drones4030041

Pylianidis, C., Osinga, S., & Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. *Computers and Electronics in Agriculture*, *184*, 105942. doi: 10.1016/j.compag.2020.105942

Quezada, C., Mercado, M., Bastías, R. M., & Sandoval, M. (2021). Data Validation of Automatic Weather Stations by Temperature Monitoring in Apple Orchards. *Chilean Journal of Agricultural & Animal Sciences*, *37*(1), 21-31. doi: 0.29393/CHJAAS37-3VDCQ40003

Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access*, *8*, 21980-22012. doi: 10.1109/ACCESS.2020.2970143

Rehman, A., Saba, T., Kashif, M., Fati, S. M., Bahaj, S. A., & Chaudhry, H. (2022). A revisit of internet of things technologies for monitoring and control strategies in smart agriculture. *Agronomy*, *12*(1), 127. doi: 10.3390/agronomy12010127

Skobelev, P., Mayorov, I., Simonova, E., Goryanin, O., Zhilyaev, A., Tabachinskiy, A., & Yalovenko, V. (2021). Development of digital twin of plant for adaptive calculation of development stage duration and forecasting crop yield in a cyber-physical system for managing precision farming. In *Cyber-Physical Systems* (pp. 83-96). Cham: Springer. doi: 10.1007/978-3-030-67892-0_8

Sung, Y. M., & Kim, T. (2022). Smart Farm Realization based on Digital Twin. *ICIC Express Letters, Part B: Applications, 13*(4), 421-427. doi: 10.24507/icicelb.13.04.421

Tardaguila, J., Stoll, M., Gutiérrez, S., Proffitt, T., & Diago, M. P. (2021). Smart applications and digital technologies in viticulture: A review. *Smart Agricultural Technology*, *1*, 100005. doi: 10.1016/j.atech.2021.100005

Thapa, A., & Horanont, T. (2022). Digital Twins in Farming with the Implementation of Agricultural Technologies. *Applied Geography and Geoinformatics for Sustainable Development: Proceedings of ICGGS 2022*, 121-132. doi: 10.1007/978-3-031-16217-6_9

Toosi, A., Javan, F. D., Samadzadegan, F., Mehravar, S., Kurban, A., & Azadi, H. (2022). Citrus orchard mapping in Juybar, Iran: Analysis of NDVI time series and feature fusion of multi-source satellite imageries. *Ecological Informatics*, *70*, 101733. doi: 10.1016/j.ecoinf.2022.101733

Van Der Burg, S., Kloppenburg, S., Kok, E. J., & Van Der Voort, M. (2021). Digital twins in agri-food: Societal and ethical themes and questions for further research. *NJAS: Impact in Agricultural and Life Sciences*, *93*(1), 98-125. doi: 10.1080/27685241.2021.1989269

Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021). Digital twins in smart farming. *Agricultural Systems*, *189*, 103046. doi: 10.1016/j.agsy.2020.103046

Wang, D., & He, D. (2021). Channel pruned YOLO V5s-based deep learning approach for rapid and accurate apple fruitlet detection before fruit thinning. *Biosystems Engineering*, *210*, 271-281. doi: 10.1016/j.biosystemseng.2021.08.015

Xia, X., Chai, X., Zhang, N., Zhang, Z., Sun, Q., & Sun, T. (2022). Culling Double Counting in Sequence Images for Fruit Yield Estimation. *Agronomy*, *12*(2), 440. doi: 10.3390/agronomy12020440

Zhang, C., Valente, J., Kooistra, L., Guo, L., & Wang, W. (2021). Orchard management with small unmanned aerial vehicles: A survey of sensing and analysis approaches. *Precision Agriculture*, *22*(6), 2007-2052. doi: 10.1007/s11119-021-09813-y

Zhang, P., Wang, S., Bai, M., Bai, Q., Chen, Z., Chen, X., Hu, Y., Zhang, J., Li, Y., Hu, X., Shi, Y., & Deng, J. (2022). Intelligent Spraying Water Based on the Internet of Orchard Things and Fuzzy PID Algorithms. *Journal of Sensors*, *2022*. doi: 10.1155/2022/4802280

## Appendix I

Tab. 2. Keywords describing application and actual research in smart fruit-growing

<table>
<tr><th colspan="2">Vehicles</th><th colspan="2">Satellites</th></tr>
<tr><th>Application</th><th>Research</th><th>Application</th><th>Research</th></tr>
<tr><td>– Object detection for harvesting;<br>– Pest or disease monitoring;<br>– Environment monitoring;<br>– Terrain mapping</td><td>– Automation;<br>– Flight planning</td><td>– Space-based monitoring;<br>– Thematic mapping;<br>– Macro estimation and prediction;<br>– Change and anomaly detection;<br>– Phenology</td><td>– Tuning of AI methods for cultivars and ecosystem</td></tr>
<tr><th colspan="2">IoT</th><th colspan="2">Digital Twins</th></tr>
<tr><th>Application</th><th>Research</th><th>Application</th><th>Research</th></tr>
<tr><td>– Environment monitoring;<br>– Danger prevention</td><td>– Data transmission<br>– increase;<br>– Precision of IoT sensors</td><td>– Autonomous control;<br>– Providing recommendations to humans;<br>– Modeling plant development stages;<br>– Forecasting crop yield</td><td>– Data access safety and security;<br>– Seamless access and data integrity;<br>– Real-time modeling;<br>– Transparency and interoperability</td></tr>
<tr><th colspan="4">Artificial Intelligence</th></tr>
<tr><th colspan="2">Application</th><th colspan="2">Research</th></tr>
<tr><td colspan="2">– Yield estimation and prediction;<br>– Fruit load estimation and prediction;<br>– Object detection for harvesting</td><td colspan="2">– Experimentation with new CNN architectures;<br>– Collection of natural datasets;<br>– Tuning of AI methods for cultivars and an ecosystem;<br>– Design of autonomous vehicle movement;<br>– New algorithms for domain augmentation;<br>– Real-time detection;<br>– Precision of the yield estimation:<br>1) multi-view techniques;<br>2) object tracking application</td></tr>
</table>

## Appendix II

Tab. 3. Keywords describing challenges in smart fruit-growing

| **Environment ↔ Legislation** | **Legislation ↔ Socio-economics** |
|---|---|
| – Transdisciplinary coalitions to drive technologies;<br>– Support from governments at small farms and the private sector | – Social, economic and legacy barriers to applying AI;<br>– Knowledge gap in new standards and regulations |
| **Socio-economics ↔ Technology** | **Environment ↔ Socio-economics** |
| – Knowledge gap to design smart fruit-growing;<br>– Lack of data-driven decision-making systems;<br>– Stakeholders worry about cyberattacks, which can cause destruction through autonomous systems;<br>– Stakeholders worry about dependency on technology as their failure can cause losses, while manual maintenance is restricted due to autonomous system exploitation;<br>– Smart solutions have to be directed to improve working conditions;<br>– Low adoption of new technologies and practices;<br>– Lack of knowledge about orchard management | – Unified database or roadmap to link knowledge and innovations;<br>– Data collection, maintenance, sharing, interconnection and processing are not sufficiently developed;<br>– Public data platform required for all agricultural data to be compiled;<br>– Limited access to trustworthy information and knowledge;<br>– Uncertainty about accessing routes to market;<br>– Land fragmentation and limited collaboration among market players |
| **Technology ↔ Environment** | **Technology ↔ Legislation** |
| – Unexplored niches remain;<br>– Customisation possibility to fit AI to farm ecosystem and increase its precision;<br>– Open systems are required for customisation needs;<br>– Low resilience to climate shocks | – Trustworthy AI;<br>– Each cultural region, as well as each farm, has its policies and business rules;<br>– Limited customisation |

Volume 15 • Issue 4 • 2023

Engineering Management in Production and Services

received: 2 May 2023
accepted: 25 October 2023

pages: 1-11



# Comparative study on workforce transformation strategy and SME policies in Indonesia and Malaysia

Ardian Adhiatma
Nurhidayati
Olivia Fachrunnisa
Najah Lukman
Md Noh Ab. Majid

ABSTRACT
This study aims to compare efforts to digitise SMEs in Indonesia and Malaysia, particularly in the Central Java and Kuala Terengganu regions, especially in the cultural context and perceptions of SME owners, in terms of workforce transformation. Data were collected on the creative industry SMEs in Central Java and Kuala Terengganu, with a sample size of 241 at each location. The collected data were then analysed using the ANOVA difference test and the SPSS regression test. This study's results prove differences in the levels of agile leadership, organisational ambidexterity and workforce transformation in SMEs in Central Java, Indonesia and Kuala Terengganu, Malaysia. Agile leadership and organisational ambidexterity have also been shown to positively and significantly affect workforce transformation. The results of this study contribute to improving the theoretical understanding of SME workforce transformation in Indonesia and Malaysia, particularly the development of academic science in management. In addition, this study also provides information, recommendations, and references to SME entrepreneurs related to strategic planning to optimise performance in maintaining the sustainability of their businesses. This study also provides a practical contribution as a reference for improving the performance of SMEs in Indonesia and Malaysia.

KEY WORDS
**workforce transformation, agile leadership, organisational ambidexterity**

**10.2478/emj-2023-0024**

**Ardian Adhiatma**

Universitas Islam
Sultan Agung, Indonesia
ORCID 0000-0003-4870-566X
Corresponding author:
e-mail: ardian@unissula.ac.id

**Nurhidayati**

Universitas Islam
Sultan Agung, Indonesia
ORCID 0000-0001-7881-3915

**Olivia Fachrunnisa**

Universitas Islam
Sultan Agung, Indonesia
ORCID 0000-0003-3298-6903

**Najah Lukman**

Universiti Teknologi MARA, Malaysia
ORCID 0009-0000-1905-6694

**Md Noh Ab. Majid**

Universiti Teknologi MARA, Malaysia
ORCID 0000-0001-8590-0849

## Introduction

Small and medium enterprises (SMEs) are the backbone of a resilient national economy in increasing domestic ultimatums (Hashim, 2015; Azam et al., 2023; Costa Melo et al., 2023; Nuryakin et al., 2022). In developing countries, SMEs play an important role due to the potential to increase income distribution and job creation, reduce poverty and export growth, and develop entrepreneurship, industry, and rural economics (Tambunan, 2008; Karmaker et al., 2023; Skare et al., 2023).

Adhiatma, A., Nurhidayati, Fachrunnisa, O., Lukman, N., & Ab. Majid, M. N. (2023). Comparative study on workforce transformation strategy and SME policies in Indonesia and Malaysia. *Engineering Management in Production and Services, 15*(4), 1-11. doi: 10.2478/emj-2023-0024

SMEs in Indonesia account for more than 90 % of all companies; therefore, they are the largest source of employment (Tambunan, 2008). Most SMEs in Indonesia are engaged in the agricultural sector, including livestock, forestry and fisheries. The second important sector for SMEs is trade, hotels and restaurants. SMEs in Indonesia do not yet have the maximum development capacity due to obstacles, including the lack of capital and the ease of technology implementation. According to Wignaraja (2013), the supply of communication technology to SMEs only reached 6.6 %, so marketing through technology was not optimal. In Malaysia, SMEs also play a very important role in national economic growth as well as in building social welfare (SME Corporation Malaysia, 2018). Malaysia has 662 939 SMEs, representing more than 97 % of total companies and contributing more than one-third of the total Malaysian GDP (Chin & Lim, 2018; SMEinfo, 2017). Many companies in Malaysia are family businesses; their traditional structure means the lack of literature on their leadership (PWC, 2016). Malaysian SMEs have shown remarkable changes in terms of economic contribution (Hussain et al., 2010; Khan & Khalique, 2014; Ghee et al., 2015) and national job opportunities (Islam, 2010; Schaper, 2014).

More specifically, the development of SMEs in Indonesia, especially in Central Java, intensified, and the growth reached 15 % in 2020, which is fairly large. The development of SMEs in Kuala Terengganu has also experienced a significant increase in technological developments that have facilitated their marketing and operational strategies. Across ASEAN, digital technology is actively transforming industries, enriching lives and driving progress. ASEAN has the opportunity to advance the forefront of the dynamic global digital economy as a community. Although still lagging behind other global peers, ASEAN has the potential to enter the top five digital economies globally by 2025 if all ASEAN members are committed to strengthening their local digital economy (Chua & Dobberstein, 2017).

The business world, both large and small, faces IR 4.0, which demands the ability to adapt and take advantage of digital technology availability. The availability of technology from IR 4.0, e.g., information technology during the post-pandemic period, provides opportunities and challenges in maintaining sustainability when facing dynamic, unpredictable change. Lockdown regulations put pressure on financial limitations and disrupted operational cash flows and physical communication with limited customers, resulting in a decreased ability to maintain business sustainability (Ali & Karimah, 2020). This phenomenon demands strengthening the ability of SMEs to manage the existing workforce transformation in adapting to the digital work environment. Digitalisation affects the development of SMEs in Indonesia and Malaysia, but the national cultural context sometimes makes implementation different. Digitalisation is more efficient if human resources or the workforce are ready to transform.

The workforce transformation is a fundamental change in circumstances and requires a change in culture, behaviour and mindset (Shaughnessy, 2018; Fachrunnisa et al., 2020). In other words, workforce transformation requires a change in human consciousness that truly transforms life and livelihoods (Verhoef et al., 2019). Several factors that determine the achievement of workforce transformation include organisational ambidexterity and agile leadership. Rapid changes in the external environment, such as new technologies and growing global competition, cause a short product life cycle and rising tensions between exploitation and exploration (Tai et al., 2019). Due to the rapid changes in the external environment, SMEs face difficulties with long-term survival. Solís-Molina et al. (2018) argued that organisations need competencies of ambidexterity. Several research efforts on organisational ambidexterity (O'Reilly & Tushman, 2013) showed that organisations that managed to create a balance between exploration and exploitation performed better in the short and long term. Rosing and Zacher (2017), Sudarti et al. (2019) and Adhiatma et al. (2019) also stated that ambidexterity is not only achieved at the organisational level but also at the individual level. Factors that affect ambidexterity at an individual level provide insights and new methods on how to develop ambidexterity in an organisation. This way, SMEs are expected to be able to adapt to the changing environment and digital technology to build digital transformation through increasing organisational ambidexterity capabilities. The successful workforce transformation in this digital era is determined by the existence of agile leadership. An agile leader can guide their team and continually influence its behaviours by defining, spreading and maintaining organisational vision (Perker et al., 2015). Marquest (2018) stated that maintaining performance in a current rapidly changing environment demands the ability to drive workforce transformation, and agility is the key to staying in a business game. Leadership agility means affecting people and making a change. Agility is considered a main skill for current managers.

The biggest challenge facing SMEs towards digitalisation is transforming their workforce by changing their mindsets and work patterns. Entrepreneurs need the right strategic orientation, e.g., learning and marketing orientation, creativeness and innovation, to support the transformation to maintain business continuity (Ejdys, 2015). In facing digital transformation challenges and the need to remain competitive in the industry, leaders must formulate and implement strategies that embrace the implications of digital transformation and drive better operational performance (Hess et al., 2016). The effective use of labour has often been a critical factor in a company's long-term success over its competitors, especially in highly competitive and technology-driven industries. This study examines a comparative study as an effort towards digitising SMEs in Indonesia and Malaysia, especially in the Central Java and Kuala Terengganu regions, especially in the cultural context and perceptions of SME owners in the field of workforce transformation. In addition, this research is also useful to encourage the strengthening of economic growth and development through collaboration or cooperation between SMEs in the two countries.

# 1. Literature review and hypothesis development

Agile leadership is the ability to guide and influence the team to always provide customer value by having the flexibility and speed skills that can facilitate organisational success (Adhiatma, Fachrunnisa, Nurhidayati et al., 2022; Grzesik & Piwowar-Sulej, 2018). An agile leadership-based approach can answer the industry's ability to adapt quickly to market needs (Faisal et al., 2007; Kot et al., 2018). Since SMEs in Indonesia are smaller companies, it is easier for leaders to make and implement decisions quickly (Hamdani & Wirawan, 2012). Research is still lacking on leadership knowledge and its impact on company performance, especially in the agile leadership style of business leaders in Malaysia (Sam et al., 2012). A study by Madanchian and Taherdoost (2019) shows a leadership effectiveness dimension consisting of the ability to inspire, facilitate and motivate an accountable and positive attitude, contributing to Malaysian SME performance improvement. Recent research also stated that the unpreparedness for facing IR 4.0 indicates that the leadership capability of Malaysian SMEs still needs improvement (Hamdan, 2020). The lack of understanding of leadership for business performance sustainability can lead to the lack of motivation of all SME members to produce optimal performance in their tasks. Meanwhile, recent research related to leadership for Malaysian SMEs shows that agile leadership becomes the key to success in implementing digital transformation (Fachrunnisa et al., 2020).

Hence, Hypothesis 1 of this study is as follows:
H1. There are different levels of agile leadership in SMEs in Kuala Terengganu and Central Java.

Ambidexterity is usually seen as a combination of two conflicting activities: exploration and exploitation (Rosing & Zacher, 2017). Ambidexterity is the company's ability to exploit existing capabilities to explore new opportunities (Adler & Heckscher, 2013). According to research by Chuen et al. (2018), SME owners and managers in Malaysia have not generated sufficient returns due to their current competitive abilities. Organisational capabilities, such as ambidextrous or balancing exploitation and exploration, will be useful to support the growth of SME performance in the long term. According to research by Ikhsan et al. (2017), the ambidexterity context already significantly impacts the performance of SMEs in Indonesia's creative industry. This can encourage companies to create and provide better value to maximise customer satisfaction through products and services. Other authors (Adhiatma, Fachrunnisa & Sudarti, 2022; Adhiatma, Fachrunnisa, Nurhidayati et al., 2022; Sudarti et al., 2019) also said that most SMEs in Indonesia have close relationships with customers.

Hence, Hypothesis 2 in this study is as follows:
H2. There are different levels of organisational ambidexterity in SMEs in Kuala Terengganu and Central Java.

Workforce transformation is a fundamental change from a situation and requires changes in culture, behaviour and mindset (Shaughnessy, 2018). In other words, workforce transformation requires a shift in human consciousness that can truly transform lives and livelihoods (Pan et al., 2019). Transformation is not just changing but has a more rational, cognitive and holistic perspective and can be spiritually oriented (Bertola & Teunissen, 2018). SMEs in Central Java have been transforming the workforce through entrepreneurship training to gain added value from the productivity of small and medium enterprises (Suminar et al., 2020). Meanwhile, many

SMEs in Malaysia still face domestic and global challenges to compete. The main obstacle Malaysian SMEs face is workforce transformation (Gunto & Alias, 2013).

Hence, Hypothesis 3 in this study is as follows: H3. There are different levels of workforce transformation in SMEs in Kuala Terengganu and Central Java.

Creating a transforming workforce in SMEs requires agile leadership and organisational ambidexterity. Workforce transformation is also closely related to increasing the productivity needed in business and public sectors. In the face of this digital era, workers who have been able to transform will be more agile so as to create an agile organisation (Sanatigar et al., 2017). Establishing agility in SMEs in Central Java and Kuala Terengganu is one of the key skills for today's managers. An agile manager with multiple skills, flexibility and speed to facilitate the achievement of greater organisational success is ready to meet the challenges of today's world (Buhler, 2010). Organisational ambidexterity is also important for the long-term success of SMEs (Laureiro-Martínez et al., 2015). One of the more persistent ideas in organisational science is that long-term success depends on how SMEs in Central Java and SMEs in Kuala Terengganu exploit their capabilities while simultaneously exploring fundamental new competencies. Previous studies have often considered that the reciprocal exchange between these two activities cannot be overcome, but more recent research has described organisational ambidexterity as being able to simultaneously exploit existing competencies and explore new opportunities (Raisch et al., 2009).

Hence, Hypothesis 4 in this study is as follows: H4. There is a positive and significant influence between agile leadership and organisational ambidexterity on workforce transformation in SMEs in Kuala Terengganu and Central Java.

## 2. Research method

### 2.1. Population and sample

A survey methodology is used in this research to collect primary data for empirical analysis. The samples used in this research were SMEs intensely using simple digital technology, such as social media marketing and partnership, to work with clients and customers. In this study, the high use of a simple digital technology by an SME was understood as the use of at least mobile phones with an Internet connection in running the business as the mobile phone is a simple digital technology supporting the use of the Internet and social media (e.g., Facebook, Instagram, Whatsapp, etc.) that facilitate access to information about various digital technology features.

The study population were SMEs in Indonesia and Malaysia with industrial classification, included in a homogeneous-specific section that falls under the classification of small and home industries. The study samples were SMEs with less than 300 employees, and the study sampling technique was non-random sampling with a purposive sampling method. Specifically for this research project, company data (e.g., industry type, number of employees and annual sales) were collected into an ad hoc database (Table 2).

Data was obtained from distributing questionnaires to owners/leaders/managers of 250 creative industries SMEs in Semarang, Central Java, Indonesia, and 250 SMEs in Terengganu, Malaysia, as they have a strategic position in decision-making related to information technology adoption. The questionnaire was submitted by a trained research assistant. The criteria of SMEs selected as study samples are based on the development and adoption of BPS (Badan Pusat Statistik, 2017; SME Corporation Malaysia, 2018), referring to SMEs by the World Bank's standard (World Bank Group, 2018) as business types with the annual sales turnover of USD 100 000 – < 15 000 000, and full-time employees of 10 – ≥ 300 people. Additionally, Semarang as the capital city of Indonesia, and Terengganu, the capital city of Malaysia, were selected as population targets since these areas have the potential for the development of creative industry-based small businesses (Halim & Mat, 2010; Wahyono & Hutahayan, 2020). Other selection criteria used in this research were SMEs using the Internet in part business, with the organisation's tenure of more than one year (i.e., SMEs have been operating for at least one year). SMEs in the creative industries sector were chosen as a sample because they use digital technologies (for business development, production and distribution, processes, and customer relationships) to develop innovation in their business (Li, 2018). In this research, SMEs in the creative industries sectors included fashion, retail, service, food and beverages, and handicrafts as a part of creative industries. According to the National Creative Industry Policy (DIKN, 2018) of Malaysia and Badan Ekonomi Kreatif Indonesia (2017) of

Indonesia, the creative industries definition follows the United Kingdom's Department of Culture Media and Sport (DCMS, 1998) "those industries which have their origin in individual creativity, skill and talent and which have a potential for wealth and job creation through the generation and exploitation of intellectual property". The questionnaire contained a detailed literature review on measurement scales and some questions that address workforce transformation, organisational ambidexterity and agile leadership. The questionnaire was supplemented with a cover letter requesting owners, senior managers or executives to complete the questionnaire.

An expert focus group was used to meet the face validity for agile leadership, organisational ambidexterity and workforce transformation and to validate the developed items before surveying. All the survey statement items were translated from English into Indonesian and Malaysian, then back-translated into English by an independent translator, and content analysis was also carried out on spoken and written material (Brislin, 1980). In addition, five SME owners had a personal interview, and the questionnaire was validated by several academics. The interview aimed to improve the quality of items and correct the wording issues. Finally, after three months, 482 out of 500 companies provided data, which represents a 96.4 % response rate.

In this study, the collection of data through the distribution of questionnaires arranged in stages based on a five-point Likert scale ranging from strongly disagree to strongly agree.

### 2.2. Measures

Agile leadership was defined as the ability to guide a team in influencing behaviour to always provide value to customers by having the flexibility and speed skills to facilitate organisational success. This variable was measured with four items: the sense of urgency and direction, sharing responsibility and mutual accountability, effectiveness in recognising problems and making decisions, and commitment and trust among members. These items were developed by Perker et al. (2015).

Organisational ambidexterity refers to a company's ability to exploit current opportunities while simultaneously exploring new opportunities for the future. The three items by Tuan (2016) were used for measuring: using new technology, the capability to get to know new technology, and increasing the role of consumers.

Workforce transformation was defined as the creation and change from one form to another that is new in function or structure, which includes fundamental changes from one state and culture. This variable was measured with four items, such as skills and qualities required for workforce, communication and reliability. These items were developed by Stevens (2018).

## 3. Results

The study's analysis technique used ANOVA to test hypotheses one to three. The fourth hypothesis used the multiple regression analysis and SPSS 25 as an analysis tool.

### 3.1. Demographic data

This study used 482 Indonesian and Malaysian SMEs as a sample. Demographic data included the country, business fields, the number of employees, and annual sales (Table 2).

In terms of the country, 50 % of SMEs were from Indonesia and 50 % from Malaysia. The majority of respondents were SMEs from the food and drinks businesses (40.2 % in Semarang and 31.9 % in Terengganu), followed by the fashion business sector (31.9 % in Semarang and 16.5 % in Terengganu). The crafts business sectors from Semarang and Terengganu comprised 17.8 % of SMEs. While the retail business SMEs from Terengganu amounted to 7.05 %, and 2.07 % were from Semarang. The remaining 7.8 % and 26.5 % were Semarang and Terengganu service business SMEs.

Most SMEs in Semarang (58.09 %) and Terengganu (56.43 %) had 5–10 employees. 31.12 % of Semarang SMEs had between ≥ 10–49 employees, and in Terengganu, such SMEs comprised 35.27 %. SMEs with 50–300 employees amounted to only 8.30 % in Terengganu and 10.79 % in Semarang. Judging from annual sales, the majority of Indonesian and Malaysian SMEs have an annual sales capability of ≤ USD 100 000 (68.46 % and 65.56 %, respectively). The annual sales capability between USD 100 000 and 3 000 000 was reported by 26.97 % of SMEs in Semarang and 31.54 % in Terengganu. SMEs with annual sales capabilities of more than USD 300 000 comprised only 4.56 % in Semarang and 2.90 % in Terengganu.

Tab. 1. Demographic data

| Detail<br>Total Sample (482) | Semarang, Indonesia (241) | | Terengganu, Malaysia (241) | |
|---|---|---|---|---|
| | Total | Percentage | Total | Percentage |
| **Semarang** | **241** | **50** | | |
| **Terengganu** | | | **241** | **50** |
| **Business Field** | Semarang | | Terengganu | |
| Foods/Drinks | 97 | 40.2 | 77 | 31.9 |
| Crafts | 43 | 17.8 | 43 | 17.8 |
| Fashion | 77 | 31.9 | 40 | 16.5 |
| Retailer | 5 | 2.07 | 17 | 7.05 |
| Service | 19 | 7.8 | 64 | 26.5 |
| Number of employees | Semarang | | Terengganu | |
| 5 – 10 | 140 | 58.09 | 136 | 56.43 |
| ≥ 10 – 49 | 75 | 31.12 | 85 | 35.27 |
| 50 – 300 | 26 | 10.79 | 20 | 8.30 |
| Annual Sales | Semarang | | Terengganu | |
| ≤ USD 100 000 | 165 | 68.46 | 158 | 65.56 |
| USD 100 000 – 3 000 000 | 65 | 26.97 | 76 | 31.54 |
| USD 3 000 000 - < 15 000 000 | 11 | 4.56 | 7 | 2.90 |

Tab. 2. Results of the validity and reliability test for Indonesian and Malaysian SMEs

| Country | Indonesia | | | | | Malaysia | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Corrected Item-Total Correlation | P-value | Note | Cronbach's Alpha | Note | Corrected Item-Total Correlation | P-value | Note | Cronbach's Alpha | Note |
| **Agile Leadership** | | | | | | | | | | |
| Sense of urgency and direction | 0.289 | 0.000 | Valid | 0.925 | Reliable | 0.313 | 0.000 | Valid | 0.804 | Reliable |
| Shares of responsibility and mutual accountability | 0.407 | 0.000 | Valid | 0.920 | Reliable | 0.175 | 0.000 | Valid | 0.803 | Reliable |
| Effectiveness in recognising problems and decision-making | 0.430 | 0.000 | Valid | 0.921 | Reliable | 0.332 | 0.000 | Valid | 0.804 | Reliable |
| Commitment and trust among members | 0.491 | 0.000 | Valid | 0.920 | Reliable | 0.154 | 0.000 | Valid | 0.804 | Reliable |
| **Organisational Ambidexterity** | | | | | | | | | | |
| Always using new technology | 0.528 | 0.000 | Valid | 0.917 | Reliable | 0.293 | 0.000 | Valid | 0.842 | Reliable |
| The capability to get to know new technology | 0.552 | 0.000 | Valid | 0.917 | Reliable | 0.310 | 0.000 | Valid | 0.805 | Reliable |
| Increase the role of consumers | 0.557 | 0.000 | Valid | 0.918 | Reliable | 0.402 | 0.000 | Valid | 0.808 | Reliable |
| **Workforce Transformation** | | | | | | | | | | |
| Skills required | 0.619 | 0.000 | Valid | 0.918 | Reliable | 0.183 | 0.000 | Valid | 0.812 | Reliable |
| Qualities required from the workforce | 0.666 | 0.000 | Valid | 0.916 | Reliable | 0.384 | 0.000 | Valid | 0.812 | Reliable |
| Communication | 0.599 | 0.000 | Valid | 0.916 | Reliable | 0.273 | 0.000 | Valid | 0.809 | Reliable |
| Reliability | 0.678 | 0.000 | Valid | 0.920 | Reliable | 0.293 | 0.000 | Valid | 0.819 | Reliable |

### 3.2. Validity and reliability test

Validity is defined as the extent to which a concept can be measured accurately in quantitative studies (Heale & Twycross, 2015). The validity test is used to measure the validity or invalidity of a questionnaire. The reliability test is related to the consistency of size (Heale & Twycross, 2015). Reliability testing is used to assess the consistency of objects and data, whether the instruments used to measure the same object several times will produce the same data. Based on Table 3, the significance level or p-value is below 0.05. The corrected item-Total Correlation (r-count) for all research variables ≥ r-table (0.1264), so it can be assumed that all statements on agile leadership, organisational ambidexterity, and workforce transformation are valid. Furthermore, the reliability test results show that the Cronbach's alpha value is > 0.6. Therefore, the instruments in this study are reliable and feasible to use.

### 3.3. ANOVA test

The one-way ANOVA test analysis was used to test the comparison of the average rate between several data groups. ANOVA test or F-test can be done in two ways: by looking at the level of significance or by comparing the F-count with the F-table. Testing with a significant level on the ANOVA table < $\alpha = 0.05$, then H0 is rejected (influential), while on the contrary if the significant level on the ANOVA table > $\alpha = 0.05$, then H0 is accepted (no effect).

Based on the ANOVA test analysis results (Tab. 4), agile leadership, organisational ambidexterity and workforce transformation have an F-count (5.423, 4.935 and 5.781) > F table (3.861) with their significance of 0.02, 0.026 and 0.016. The ANOVA test results show differences in the levels of agile leadership, organisational ambidexterity and workforce transformation in SMEs from Kuala Terengganu, Malaysia and Central Java, Indonesia.

Tab. 3. Anova analysis results

| Differences of SME levels in Central Java, Indonesia and SMEs in Kuala Terengganu, Malaysia | F | Sig |
|---|---|---|
| Agile leadership | 5.423 | 0.02 |
| Organisational ambidexterity | 4.935 | 0.026 |
| Workforce transformation | 5.781 | 0.016 |

### 3.4. Multiple linear regression test

Furthermore, the results of multiple linear regression tests were used to test the influence of agile leadership and organisational ambidexterity on workforce transformation in SMEs in Kuala Terengganu and Central Java. The results of the multiple regression test in SPSS are listed in Table 4 below.

Tab. 4. Multiple linear regression test

| Hypothesis | Regression | Std B | Unstand B | SE | p-value |
|---|---|---|---|---|---|
| H4 | Agile leadership → Workforce transformation | 0.325 | 0.355 | 0.054 | 0.000 |
| | Organisational ambidexterity → Workforce transformation | 0.560 | 0.698 | 0.062 | 0.000 |

Based on the table above, the multiple linear regression equation is as follows:

$Y = 0.325X1 + 0.560X2 + e$

Y = Workforce transformation

X1 = Agile leadership

X2 = Organisational ambidexterity

e = error term

Consequently, agile leadership and organisational ambidexterity have a positive and significant effect on workforce transformation. The higher level of agile leadership and organisational ambidexterity possessed by SMEs will increase their workforce transformation.

Based on the significance test for individual parameters, the statistical t-test in Table 6 shows that agile leadership has a significant effect on workforce transformation (t-count 6.573 > t table 1.969; p-value 0.000 < 0.05). Likewise, organisational ambidexterity (t-count 11.325 > t-table 1.969; p-value 0.000 < 0.05) shows a significant effect on workforce transformation. This means that the higher the agile leadership and organisational ambidexterity of SMEs, the higher

Tab. 5. Result of the t-statistic test

| Hypothesis | Regression | t count | p-value (Sig.) | VIF | Results |
|---|---|---|---|---|---|
| H4 | Agile leadership → Workforce transformation | 6.573 | 0.000 | 1.616 | Supported |
| | Organisational ambidexterity → Workforce transformation | 11.325 | 0.000 | 1.616 | Supported |

the level of workforce transformation for SMEs in Indonesia and Malaysia. The results of the multiple linear regression test and t-statistic test indicate that the fourth hypothesis is supported.

# 4. Discussion

The results of this study are in line with previous research that forming agility in SMEs in Central Java and Kuala Terengganu is one of the main skills for managers today. An agile manager with many skills, flexibility and speed to facilitate the achievement of greater organisational success is ready to meet the challenges of today's world (Buhler, 2010). Organisational ambidexterity is also critical for long-term success in SMEs (Laureiro-Martínez et al., 2015). One of the more persistent ideas in organisational science is that long-term success depends on how SMEs exploit their capabilities while simultaneously exploring fundamental new competencies. One of the competencies that need to be explored by SMEs is the adoption of Supply Chain Management (SCM) as a comprehensive strategic management application for the flow and transformation of raw materials into finished products or services for distribution to end users (Kot et al., 2018). Previous studies have often considered that the reciprocal exchange between these two activities cannot be overcome, but more recent research has described organisational ambidexterity as being able to simultaneously exploit existing competencies and explore new opportunities (Raisch et al., 2009).

Agility in Indonesian SMEs, including smaller companies, will make it easier for leaders to make decisions and implement them quickly, which is in line with previous research (Hamdani & Wirawan, 2012). Research is still lacking in knowledge about leadership and its impact on company performance, especially the agile leadership style of business leaders in Malaysia (Sam et al., 2012). Meanwhile, in line with previous research by Ikhsan et al. (2017), the context of ambidexterity already has a significant impact on the performance of SMEs in Indonesia's creative industries. SMEs in Central Java that have been able to implement organisational ambidexterity will strengthen their ability to survive and develop by producing superior performance in an increasingly dynamic market. Furthermore, the research results by Suminar et al. (2020) also state that SMEs in Central Java have been able to transform the workforce through entrepreneurship training, which can provide added value to the productivity of small and medium enterprises. However, there are still many SMEs in Malaysia who face domestic and global challenges to compete. The main obstacle faced by Malaysian SMEs is workforce transformation (Gunto & Alias, 2013).

Based on this research result, SMEs need agile leadership and ambidexterity to implement workforce transformation. This leadership style fosters a culture of agile transformation among members to strengthen performance and maintain business sustainability. Owners or leaders of SMEs that are able to react rapidly and agilely to business opportunities and barriers can establish a strategic culture that allows their workforce to adapt to the needs of a dynamic business environment. Furthermore, the developed agility allows for raising awareness, sharing duties with others, identifying obstacles to act, having adaptable and flexible structures, and anticipating business challenges. A leader's capacity to manage their SME's workers to transform depends on their flexibility in managing their workforce to change on a daily basis in terms of qualities and skills, adjusting to recent social principles, fluidity and agility, speed, and being more adaptive (Fachrunnisa et al., 2020; Stevens, 2018).

In addition, ambidextrousness in business organisations also contributes to realising the transformation of workers. The achievement of workforce transformation is marked by the skills and qualities required, communication, and reliability. An ambidextrous small business workforce is better prepared to face the dynamic business environment. An ambidextrous workforce tends to work exploratively and exploitatively to transform their work procedures into dynamic and flexible processes or system implementations, so they are always ready to transform to capture current and future opportunities to achieve higher performance. Organisational ambidexterity, in the sense of ambidexterity in their business company, means not only exploiting one or certain workforces but being able to maintain harmony between exploitation and exploration so that it is organisationally beneficial. This organisational ambidexterity can take advantage of new technologies to build work procedures into dynamic and flexible processes or a system to balance the exploitation and exploration of their workforce. Hence, the formed ambidexterity culture can organisationally transform the work of their workforce to be able to meet the needs of each workforce, leader, and customer (Tuan, 2016; Stevens, 2018; Adhiatma et al., 2022).

# Conclusions

The empirical research was performed to verify the differences in levels of agile leadership, organisational ambidexterity and workforce transformation in SMEs of Central Java, Indonesia and Kuala Terengganu, Malaysia. In addition, it also examined the effect of agile leadership and organisational ambidexterity on workforce transformation in Indonesian and Malaysian SMEs based on the literature review and hypothesis development. It allowed confirming:

- differences in the level of agile leadership, organisational ambidexterity and workforce transformation among SMEs of Central Java, Indonesia and Kuala Terengganu, Malaysia.
- a positive and significant effect of agile leadership and organisational ambidexterity on workforce transformation in Indonesian and Malaysian SMEs.

Hence, it seemed to be an essential conclusion that agile leadership and organisational ambidexterity were the factors determining the ability of SMEs to increase workforce transformation. SMEs will be able to achieve higher agility in dealing with an uncertain environment and rapid changes through several leadership roles so that the company would be able to achieve higher agility capabilities in an uncertain, rapidly changing environment. Such roles include leaders using foresight and strategic perspectives to make the best decision at the right time, direct goal setting and best planning, using their own initiative, and awareness of the application of modern scientific work methods. Agile leadership and organisational ambidexterity have a positive and significant effect on workforce transformation. Based on the calculation results of the t-statistical test, there are differences in the level of agile leadership, organisational ambidexterity and workforce transformation in SMEs in Indonesia and Malaysia.

This research contributes to increasing the theoretical understanding of workforce transformation among SMEs in Indonesia and Malaysia so that it can be used in the development of academic science, especially in the field of management. The study results also provide information, recommendations, and references to business actors, especially those in the SME scope. Thus, these small business actors will be able to plan a more solid strategy to be able to produce optimal performance for the sustainability of their business.

However, this study has the following limitations, so several stages are required for further research:

- This study analyses the influence of agile leadership and organisational ambidexterity as assessed from perceptions of the actors (leaders) of Indonesian and Malaysian SMEs. However, a more specific approach is needed to make a better contribution to each process to obtain different results (e.g., the perception of SME employees or more focus on certain business fields).
- This study uses self-reported data. This may have an impact on the general method variance. Further research should make a better contribution to the achievement independently and use workforce transformation measurements on more objective SMEs
- Respondents in this study were owners/leaders/managers of SMEs in Indonesia and Malaysia, with a minimum workforce of ten people and implemented ICT in running their business. For further research, it can be more specific to the SME's business sector (e.g., creative industries, culinary, fashion, tourism, etc.).

# Literature

Adhiatma, A., Fachrunnisa, O., Nurhidayati, & Rahayu, T. (2022). Creating digital ecosystem for small and medium enterprises: the role of dynamic capability, agile leadership and change readiness. *Journal of Science and Technology Policy Management, 15*(5). doi: 10.1108/JSTPM-12-2020-0171

Adhiatma, A., Fachrunnisa, O., & Sudarti, K. (2022). Individual Dexterity and Psychological Empowering Leadership for Digital Workplace. *International Journal of Technology and Human Interaction*, *18*(1), 1-21. doi: 10.4018/IJTHI.299354

Adler, P., & Heckscher, C. (2013). The Collaborative, Ambidextrous Enterprise/La Empresa colaborativa y ambidiestra. *Universia Business Review*, *40*, 34.

Ali, N., & Karimah, V. (2020). The Fourth Industrial Revolution, Pandemics, and The Future of Work. *The ASEAN Magazine*, *04*.

Azam, M. K., Hasan, S. M., & Qureshi, S. M. (2023). Exploring the critical success factors of a resilient supply chain. *Engineering Management in Production and Services*, *15*(1), 41-56. doi: 10.2478/emj-2023-0004

Badan Ekonomi Kreatif Indonesia. (2017). *Rekomendasi Strategi Kebijakan Pengembangan Promosi Produk Kreatif*.

Bertola, P., & Teunissen, J. (2018). Fashion 4.0. Innovating fashion industry through digital transformation. *Research Journal of Textile and Apparel*, *22*(4), 352-369. doi: 10.1108/rjta-03-2018-0023

BPS (Badan Pusat Statistik). (2017). *Survei Industri dan Kecil Tahunan: Profil Industri Mikro dan Kecil.*

Brislin, R. W. (1980). Translation and content analysis of oral and written material. In H. C. Triandis & J. W. Berry (Eds.), *Handbook of cross-cultural psychology*. Allyn & Bacon.

Buhler, P. (2010). The agile manager. *Supervision: The Journal of Industrial Relation and Operating Management*, *71*(12), 18-21.

Chin, Y.-W., & Lim, E.-S. (2018). SME policies and performance in Malaysia. *ISEAS Yusof Ishak Institute*, *3*(2018), 41.

Chua, S. G., & Dobberstein, N. (2017). The ASEAN Digital Revolution. *KEARNEY*.

Chuen, P. W., Mohammad, O., & Yusoff, W. F. W. (2018). The impact of behavioral complexity on exploitative and explorative behavior among owner-managers of SMEs in Malaysia. *Academy of Strategic Management Journal*, *17*(1), 1-13.

Costa Melo, D. I., Queiroz, G. A., Alves Junior, P. N., Sousa, T. B. de, Yushimito, W. F., & Pereira, J. (2023). Sustainable digital transformation in small and medium enterprises (SMEs): A review on performance. *Heliyon*, *9*(3), e13908. doi: 10.1016/j.heliyon.2023.e13908

Departement of Culture Media and Sport (DCMS). (1998). *Creative industries mapping document*. Departement of Culture, Media and Sport.

Ejdys, J. (2015). Innovativeness of Residential Care Services in Poland in the Context of Strategic Orientation. *Procedia - Social and Behavioral Sciences*, *213*, 746-752. doi: 10.1016/j.sbspro.2015.11.461

Fachrunnisa, O., Adhiatma, A., Lukman, N., & Majid, N. A. (2020). Towards SMEs ' digital transformation: The role of agile leadership and strategic flexibility an empirical study from Indonesia and Malaysia. *Journal of Small Business Strategy*, *30*(3).

Faisal, M. N., Banwet, D. K., & Shankar, R. (2007). Supply chain agility: Analysing the enablers. *International Journal of Agile Systems and Management*, *2*(1), 76-91. doi: 10.1504/IJASM.2007.015682

Ghee, W. Y., Ibrahim, M. D., & Abdul-Halim, H. (2015). Family business succession planning: Unleashing the key factors of business performance. *Asian Academy of Management Journal*, *20*(2), 103-126.

Grzesik, K., & Piwowar-Sulej, K. (2018). Project Managers' Competencies and Leadership Styles from the Perspective of Organizations Functioning in Poland. *Journal of Entrepreneurship, Management and Innovation*, *14*(3), 35-60.

Gunto, M., & Alias, M. H. (2013). SMEs Development in Malaysia: Lessons For Libya. *Persidangan Kebangsaan Ekonomi Malaysia Ke VIII (PERKEM VIII) "Dasar Awam Dalam Era Transformasi Ekonomi: Cabaran Dan Halatuju" Johor Bahru. 7-9 Juni 2013*, *3*, 1521-1530.

Halim, M. A. S. B. A., & Mat, A. B. C. (2010). The contribution of heritage product toward Malaysian Tourism Industry: A case of eastern coastal of Malaysia. *International Journal of Human Sciences*, *7*(January), 346-357.

Hamdan, J. B. (2020). Theory and Evidence on the Relationship between Leadership Style and Organizational Performance: A Case in Small Medium Enterprises in East Malaysia. *International Business Research*, *13*(7), 265. doi: 10.5539/ibr.v13n7p265

Hamdani, J., & Wirawan, C. (2012). Open Innovation Implementation to Sustain Indonesian SMEs. *Procedia Economics and Finance*, *4*(Icsmed), 223-233. doi: 10.1016/s2212-5671(12)00337-1

Hashim, F. (2015). SMEs' impediments and developments in the internationalization process. *World Journal of Entrepreneurship, Management and Sustainable Development*, *11*(2), 100-119. doi: 10.1108/wjemsd-11-2013-0055

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence-Based Nursing*, *18*(3), 66-67. doi: 10.1136/eb-2015-102129

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, *15*(2), 103-119.

Hussain, I., Si, S., Xie, X. M., & Wang, L. (2010). Comparative Study on Impact of Internal and External CFFs on SMEs. *Journal of Small Business and Entrepreneurship*, *23*(4), 637-648. doi: 10.1080/08276331.2010.10593506

Ikhsan, K., Almahendra, R., & Budiarto, T. (2017). Contextual ambidexterity in SMEs in Indonesia: A study on how it mediates organizational culture and firm performance and how market dynamism influences its role on firm performance. *International Journal of Business and Society*, *18*(S2), 369-390.

Islam, R. (2010). Critical success factors of the nine challenges in Malaysia's vision 2020. *Socio-Economic Planning Sciences*, *44*(4), 199-211. doi: 10.1016/j.seps.2010.07.002

Karmaker, C. L., Aziz, R. Al, Palit, T., & Bari, A. B. M. M. (2023). Analyzing supply chain risk factors in the small and medium enterprises under fuzzy environment: Implications towards sustainability for emerging economies. *Sustainable Technology and Entrepreneurship*, *2*(1), 100032. doi: 10.1016/j.stae.2022.100032

Khan, M. W. J., & Khalique, M. (2014). An Overview of Small and Medium Enterprises in Malaysia and Pakistan: Past, Present and Future Scenario. *Business and Management Horizons*, *2*(2), 38-49. doi: 10.5296/bmh.v2i2.5792

Kot, S., Onyusheva, I., & Grondys, K. (2018). Supply Chain Management in SMEs: Evidence from Poland and Kazakhstan. *Engineering Management in Production and Services*, *10*(3), 23-36. doi: 10.2478/emj-2018-0014

Laureiro-Martínez, D., Brusoni, S., Canessa, N., & Zollo, M. (2015). Understanding the exploration-exploitation dilemma: An fMRI study of attention control and decision-making performance. *Strategic Management Journal*, *36*(3), 319-338. doi: 10.1002/smj.2221

Li, F. (2018). The digital transformation of business models in the creative industries: A holistic framework and emerging trends. *Technovation*, *December*, 1-10. doi: 10.1016/j.technovation.2017.12.004

Madanchian, M., & Taherdoost, H. (2019). Assessment of Leadership Effectiveness Dimensions in Small and Medium Enterprises (SMEs). *Procedia Manufacturing*, *32*, 1035-1042. doi: 10.1016/j.promfg.2019.02.318

Marquest, J. (2018). What's new in leadership? *Human Resource Management International Digest*, *26*(4), 15-18.

National Creative Industry Policy (DIKN). (2018). *The Official Definition of 'The Creative Industry"*.

Nuryakin, Fatmawati, I., & Siriyota, K. (2022). Why does environmental uncertainty have a moderating effect on marketing performance? A comparative analysis of Indonesian and Thai service industries. *Engineering Management in Production and Services*, *14*(3), 57-67. doi: 10.2478/emj-2022-0026

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *Academy of Management Perspective*, *27*(4), 324-338.

Pan, G., Seow, P.-S., & Koh, G. (2019). Examining learning transformation in project-based learning process. *Journal of International Education in Business*, JIEB-06-2018-0022. doi: 10.1108/JIEB-06-2018-0022

Perker, D. W., Holesgrove, M., & Pathak, R. (2015). Improving productivity with self-organised teams and agile leadership. *International Journal of Productivity and Performance Management*, *64*(1), 112-128.

PWC. (2016). *PWC Malaysia*.

Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. (2009). Organizational ambidexterity: Balancing exploitation and exploration for sustained performance. *Organization Science*, *20*(4), 685-695. doi: 10.1287/orsc.1090.0428

Rosing, K., & Zacher, H. (2017). Individual ambidexterity: the duality of exploration and exploitation and its relationship with innovative performance. *European Journal of Work and Organizational Psychology*, *26*(5), 694-709. doi: 10.1080/1359432X.2016.1238358

Sam, M. F. M., Tahir, M. N. H., & Bakar, K. A. (2012). Owner-Managers of Smes in it Sector: Leadership and Company Performance. *International Journal of Business and Social Science*, *3*(14), 195-205.

Sanatigar, H., Peikani, M. H., & Gholamzadeh, D. (2017). Identifying organizational agility and leadership dimensions using Delphi technique and factor analysis: an investigating among public sector pension funds (PSPFs) in Iran. *International Journal of Public Leadership*, *13*(4), 276-294. doi: 10.1108/ijpl-01-2017-0005

Schaper, M. T. (2014). A brief history of small business in Australia, 1970-2010. *Journal of Entrepreneurship and Public Policy*, *3*(2), 222-236. doi: 10.1108/JEPP-08-2012-0044

Shaughnessy, H. (2018). Creating digital transformation: Strategies and steps. *Strategy and Leadership*, *46*(2), 19-25. doi: 10.1108/SL-12-2017-0126

Skare, M., de las Mercedes de Obesso, M., & Ribeiro-Navarrete, S. (2023). Digital transformation and European small and medium enterprises (SMEs): A comparative study using digital economy and society index data. *International Journal of Information Management*, *68*(July 2022), 102594. doi: 10.1016/j.ijinfomgt.2022.102594

SME Corporation Malaysia. (2018). SME Corporation Malaysia. In *SME Annual Report 2017/2018* (Issue August). doi: 10.1016/B978-0-408-70676-6.50020-6

SMEinfo. (2017). *SME Annual Report 2017/18*.

Solís-Molina, M., Hernández-Espallardo, M., & Rodríguez-Orejuela, A. (2018). Performance implications of organizational ambidexterity versus specialization in exploitation or exploration: The role of absorptive capacity. *Journal of Business Research*, *91*(June), 181-194. doi: 10.1016/j.jbusres.2018.06.001

Stevens, M. (2018). Commentary on "workforce development: perspectives from people with learning disabilities." *Tizard Learning Disability Review*, *23*(4), 173-177. doi: 10.1108/TLDR-08-2018-0024

Sudarti, K., Fachrunnisa, O., Nurhidayati, N., & Adhiatma, A. (2019). The role of organizational ambidexterity to increase innovation speed and marketing performance of SMEs. *Fokus Ekonomi: Jurnal Ilmiah Ekonomi*, *14*(2), 250-268. doi: 10.34152/fe.14.2.250-268

Suminar, T., Yusuf, A., & Utsman (2020). The Influence of Entrepreneurship Training on the Productivity of Smes in Semarang City, Indonesia. *PEOPLE: International Journal of Social Sciences*, *6*(1), 169-178. doi: 10.20319/pijss.2020.61.169178

Tai, C. F., Wang, E. T. G., & Yeh, H. (2019). Information & Management A study of IS assets , IS ambidexterity , and IS alignment : the dynamic managerial capability perspective. *Information and Management*, *56*(June 2018), 55-69. doi: 10.1016/j.im.2018.07.001

Tambunan, T. T. H. (2008). Development of SME in ASEAN with Reference to Indonesia and Thailand. *Chulalongkorn Journal of Economics*, *20*(1), 53-83.

Tuan, L. T. (2016). Organizational Ambidexterity, Entrepreneurial Orientation, and I-Deals: The Moderating Role of CSR. *Journal of Business Ethics*, *135*(1), 145-159. doi: 10.1007/s10551-014-2476-1

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2019). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *July 2018*. doi: 10.1016/j.jbusres.2019.09.022

Wahyono, & Hutahayan, B. (2020). The relationships between market orientation, learning orientation, financial literacy, on the knowledge competence, innovation, and performance of small and medium textile industries in Java and Bali. *Asia Pacific Management Review*. doi: 10.1016/j.apmrv.2020.07.001

Wignaraja, G. (2013). Can SMEs participate in global production networks? Evidence from ASEAN Firms. In D. Elms & P. Low (Eds.), *Global Value Chains in a Changing World, WTO, Geneva/TFCTN* (pp. 279-312). doi: 10.30875/d18b619c-en

World Bank Group. (2018). *World Bank Group Support for Small and Medium Enterprises A Synthesis of Evaluative Findings*.

Volume 15 • Issue 4 • 2023

sciendo

ISMSME International Society for Manufacturing, Service and Management Engineering

received: 9 January 2023
accepted: 30 September 2023

pages: 12-24



# Impact of human energy expenditure on order picking productivity: a Monte Carlo simulation study in a zone picking system

Nader A. Al Theeb
Omar Al-Araidah
Malik M. Al-Ali
Adnan I. Khudair

**Nader A. Al Theeb**

Jordan University of Science and Technology, Jordan
ORCID 0000-0003-1916-8076

Corresponding author:
naaltheeb@just.edu.jo

**Omar Al-Araidah**

Jordan University of Science and Technology, Jordan
ORCID 0000-0002-6871-139X

**Malik M. Al-Ali**

Jordan University of Science and Technology, Jordan

**Adnan I. Khudair**

Jordan University of Science and Technology, Jordan

ABSTRACT
This article aims to investigate the impact of allowable human energy expenditure (HEE) of order pickers on the throughput of workers in manual order zone picking systems MOP. The method used in this research is the Monte Carlo simulation, used while considering many human and job factors. The results showed that a worker's gender and an item's weight have little effect on the HEE. On the other hand, body weight, walking speed, distance travelled, and the targeted zone significantly impacted the HEE, rest allowance, and throughput. For example, male pickers at a weight of 75 kg can move up to speed to 1 m/s and pick up items weighing up to 5 kg without reaching the allowable HEE rate, equal to 4.3 kcal/min, and, thus, no rest is needed. Female pickers at a weight of 75 kg reach the allowable HEE rate, equal to 2.6 kcal/min, at a very low speed of approximately 0.1 m/s when picking up items up to 5 kg, and, thus, frequent rest is needed, which leads to low throughput. To increase the throughput of female pickers, they can be assigned to pick up lighter items. Utilising Monte Carlo simulation to evaluate the HEE in MOP while considering many factors.

KEY WORDS
**human energy expenditure, manual order picking, Monte Carlo simulation, warehouse management**

**10.2478/emj-2023-0025**

## Introduction

Warehouses form a vital link in the supply chain, where all types of products can be temporarily stored until ordered. Upon receipt of an order, the picking system is required to retrieve the requested items from the storage areas manually or automatically. The main objective of the picking process is to fulfil customer orders, which is an expensive, labour-based process that sometimes consumes around 55 % of the whole warehouse operations. Thus, efficiently managing this process will lead to shorter times for fulfil-

Al Theeb, N. A., Al-Araidah, O., Al-Ali, M. M., & Khudair, A. I. (2023). Impact of human energy expenditure on order picking productivity: a Monte Carlo simulation study in a zone picking system. *Engineering Management in Production and Services, 15*(4), 12-24. doi: 10.2478/emj-2023-0025

ment, less cost, and better customer satisfaction. The process should be efficiently managed to achieve the best picking process efficiency. Management of the picking process includes the selection picker speed and the corresponding rest, the number of items per trip, the number of orders per trip, and the picking strategy selection.

There are different picking strategies. First, the zone-picking strategy has similar items stored in one section of the warehouse called a zone, and each picker is assigned to a zone to pick all ordered items from that zone. Second, discrete picking applies more to small warehouses. In this strategy, a picker is assigned to pick up all items in the same order from the whole warehouse. Third, batch picking has pickers assigned to pick the same item or a group of items in their vicinity for many orders. Fourth, wave picking lets pickers pick up only one item per trip. Lastly, two or more strategies can be applied together as a new strategy, such as assigning multiple orders to a picker in the batch strategy and storing the items in zones in the zone-picking strategy.

As explained, the picking process is labour-based and mostly manually performed utilising picking equipment. The Manual Order-Picking process (MOP) is a crucial sub-process within warehouses, logistics, and supply chain processes (Al-Araidah et al., 2021). Therefore, it is important for the MOP to be managed efficiently to enhance the system's performance (Petersen, 2002; Marmidis et al., 2008). According to Tompkins et al. (2010), the time taken for a picking trip is divided into five components: setup, travel, searching, picking, and others, with percentages of 10 %, 50 %, 20 %, 15 %, and 5 %, respectively. In addition to time, MOP consumes the physical energy of the picking workers. It is important to study the combined effect of time and energy expenditure on the MOP process and the order picker to maximise efficiency. Another important term related to the MOP process is throughput, which is a key performance indicator of the picking process and is influenced by the picking workers' time and human energy consumption. During the MOP, pickers are using one of the routing policies to move between the locations. Selecting a suitable policy plays a significant role in minimising the total distance travelled. Three of the most common policies are the strict order, first-come-first-served combined orders, and zone-picking orders (Petersen & Aase, 2004); the latter is the topic of this research.

The picking consumes pickers' energy, denoted as human energy expenditure (HEE). Many human and environmental factors affect the HEE, such as body mass, speed, item mass, warehouse temperature, etc. Many studies have investigated the HEE with respect to other factors, e.g., Ocobock (2016) studied the effect of temperature on the students' energy expenditure in different schools. Similarly, Westerterp (2017) studied the effect of body size and food intake on the HEE and rest requirements during some physical activities. The effect of obesity on the HEE has been studied by Pontzer et al. (2016) with respect to different physical activities. Picking operations have limited studies. For example, Grosse et al. (2015) have developed a framework based on a literature review to discover the opportunities for MOP improvements.

Different research techniques can be utilised to study the relationships between time and human energy consumption with respect to different human factors. One of these techniques is the Monte Carlo simulation (MCS). According to Harrison (2010), American scientists developed and used the MCS method for the nuclear field during World War II. This method was then used in various scientific fields, particularly intractable problems or experiments which are extremely expensive or time-consuming. MCS is used to predict output-based different inputs in uncertain situations by repeating the calculations many times.

This study investigates the effects of human and job factors on the well-being of order pickers and on the throughput of the MOP system. Studying these factors helps to better understand the MOP problem, which leads to the improvement of the process performance by increasing the throughput and minimising the fatigue level. This work considers many factors, such as the gender of the pickers, their body weights, picked item weights, and the speed of the pickers. The study uses metabolic energy expenditure equations from the literature to estimate the energy needs for every single task and uses Predetermined Time Standards System equations (PTSS) to estimate the time needed to achieve the work. Consequently, the HEE and throughput are found, and the moment when the pickers reach the maximum allowable HEE is determined. Based on this, rest requirements are determined for both male and female pickers.

As demonstrated in the next section, gaps in this field of research can be summarised as little consideration given by most studies to factors, such as environmental, worker body or picked items, to study the HEE. Additionally, they mainly use a few calculated scenarios to evaluate the results. This research will consider many worker-related factors and picked items to evaluate the HEE and throughput. Furthermore, MCS will be used to find the results, covering most of the possible picking-up scenarios.

The remainder of this article is arranged as follows. Section 2 represents the research related to this work. Section 3 fully describes the methodology, including the model used in this research to generate the results, the warehouse design, calculations of different factors and outputs, and methodology steps. Section 4 shows and discusses the obtained results. Finally, the major outcomes from this research are given in the Conclusions section.

# 1. Literature review

A close literature review showed several studies on the MOP, zone picking, and human energy expenditure (HEE). The following review concerns some articles that addressed the subjects separately or jointly.

Several researchers investigated the impact of various warehouse design factors on the performance of the MOP system. Such factors include the warehouse layout, the routing policy, the picking strategy, and the storage assignment (Saderova et al., 2020). Among others, Petersen et al. (2005) evaluated storage assignment strategies in terms of the time and distance that pickers need to accomplish orders. The authors studied the effect of the golden zone concept on time and distance (i.e., in item storage, the golden zone is the level between a picker's waist and shoulders). The results showed that the storage assignment strategies considering the golden zone significantly improve the time to fulfil the orders compared to strategies that ignore this concept. However, the use of the golden zone concept significantly increases the distance for the picker to travel. The study used the Monte Carlo simulation method to get these results. Ho and Liu (2005) studied the impact of converting a regular warehouse into a zone-picking warehouse on the total order-picking travel distance (TTD). The study used a group of algorithms and route planning to find the TTD improvements after converting into the zone-picking method. Roodbergen et al. (2008) developed an optimisation model to minimise the distance travelled inside a warehouse with the goal of providing a suitable layout structure; as found, the layout that resulted from the model was similar to the layout that resulted from the simulation packages, but with a better travel distance by utilising the S-shape routing. Parikh and Meller (2008) studied the problem of selecting between the batch-picking strategy and the zone-picking strategy. The authors developed a cost-estimation model to compare between these two strategies from the cost viewpoint. The proposed model considered several factors and their effect on the cost. The factors included the pick rate, picker blocking, workload imbalance, and sorting system requirements. Moreover, the authors presented a case study to show the effect of system throughput, order size, and item distribution in orders on selecting the picking strategy. Elbert and Müller (2017) studied the effect of the dimensions scale of warehouses on the time needed for MOP at a constant speed and body weight. The authors also considered the curves/turn manoeuvres in time and energy calculations. The study concluded that the time and energy costs could not be positively affected, particularly in small-scale warehouses.

Several researchers studied human energy for a wide range of household, personal, and work activities. An early study by Garg et al. (1978) proposed a new approach to estimating the metabolic energy for manual handling of materials. The authors assumed that each job, regardless of its complexity, can be divided into a set of simpler tasks. The study yielded a set of equations to calculate the estimated metabolic energy. Price (1990) investigated a number of methods for calculating RA for different types of jobs. The author developed a model to calculate RA for construction work, which can be used for other types of physical work. Since human energy is among the constraints that may impact the MOP system's performance, several authors took the HEE into account. Battini et al. (2016) developed a multi-objective model to accommodate ergonomics into the line balancing problem considering the human energy expenditure and consumed time. The study provided a predetermined motion energy system based on Garg et al. (1978) to predict the human energy expenditure considered as a level indicator of ergonomics. The authors validated the results with numerical examples. Çakıt (2016) used an energy expenditure prediction software to estimate the energy cost of manual waste collection works. The software used was built based on the equation by Garg et al. (1978). The study results showed a minuscule difference between energy costs predicted by the software and estimated by the equations from the literature. Calzavara et al. (2019a) considered different store layouts and then developed equations to determine the cost of picking and the HEE. Calzavara et al. (2019b) presented an optimisation model to optimise the time of working and time of resting for manual order-picking workers. The model is limited to activities involving the whole body. In the proposed model, the authors aimed to improve worker productivity by better scheduling their work and recovery time. Moreover, the model considers the rate and duration of activities in addition to the worker's physiological factors affecting fatigue accumulation and recovery time. Sgarbossa and Vijayakumar (2020) developed an optimisation model for the RA based on the RA equation developed by Calzavara et al. (2019a). The model accounted for the ageing factor of pickers, tasks, and rest combinations in the picking schedule, aiming to minimise the workers' fatigue level, reducing the total work, and accordingly increasing productivity. Al-Araidah et al. (2021) studied a manual order-picking system in a high-demand rate warehouse. The study investigated the energy expenditure rate of female pickers and their fatigue allowance, considering some affecting factors, such as walking speed, body weight, and throughput rate.

To the best of the authors' knowledge, no study accounted for MOP and HEE zone picking, which is the research gap that will be investigated in this research, as explained in detail in the introduction section. Therefore, this work expands the work by Al-Araidah et al. (2021) to account for additional warehouse and human factors and picking scenarios. The methodology and details of the model are presented in the next section.

## 2. Research methods

In this section, the proposed model will be described beside the description of store layout, routing and picking. Then, the calculations used in this research will be presented. At the end of this section, the methodology steps are summarised.

### 2.1. Model description

This study utilises Monte Carlo simulation to generate picking routes and computes associated HEE and throughput of the picking system. The model relies on multiple sources of data from the literature, including HEE equations, predetermined time standards (PTS), human statistics, and job standards. The model was coded using Excel spreadsheets.

For the purpose of this study, a traditional warehouse design with a predefined layout and pre-fixed dimensions was created. In this design, all storage cells were identified by their (x, y, z) coordinates, and hence, the distances between any two cells could be calculated. The assumed total number of available locations inside the warehouse zone is 1620 locations/cells, and each generated location is reserved for one item only. Statistics on body weights were obtained from the National Health Statistical Report (Fryar et al., 2018).

The Monte Carlo simulation method randomly generates coordinates of items' locations inside the warehouse for a given number of items per order. Utilising input data and the time and energy equations from the literature, the model computes the time and HEE for each movement of each randomly generated picking tour. Many orders (replicates) are simulated to obtain the required statistics on throughput and HEE. For the purpose of this study, the number of replicates is fixed at 2000 replicates. Computed statistics include the average and standard deviation of the travel distance, travel time, travel energy, picking time, and picking energy. Moreover, time results are accumulated to estimate the number of orders fulfilled per work shift. Furthermore, results are manipulated to test the impact of RA on throughput.

The below sections detail design components and equations utilised in the proposed model.

### 2.2. Warehouse design

Warehouse layout configuration and routing policy are essential and have a marked effect on order picking. It affects the duration of the picking tour and the time needed to achieve the tasks. Accordingly, it affects the workers' HEE and throughput. A typical warehouse design usually starts with identifying the required area, selecting the suitable racking method, determining the layout configuration, and finally, identifying the operating policies (Roodbergen et al., 2008). Fig. 1 shows the layout configuration of the warehouse used in this study. The warehouse consists of four zones, and each zone includes 15 double racks, as shown in Zone 1. The used layout is compact in space and assumes less travel (Caron et al., 2000). The compartments in each rack are given a number to facilitate the assignment of products to compart-

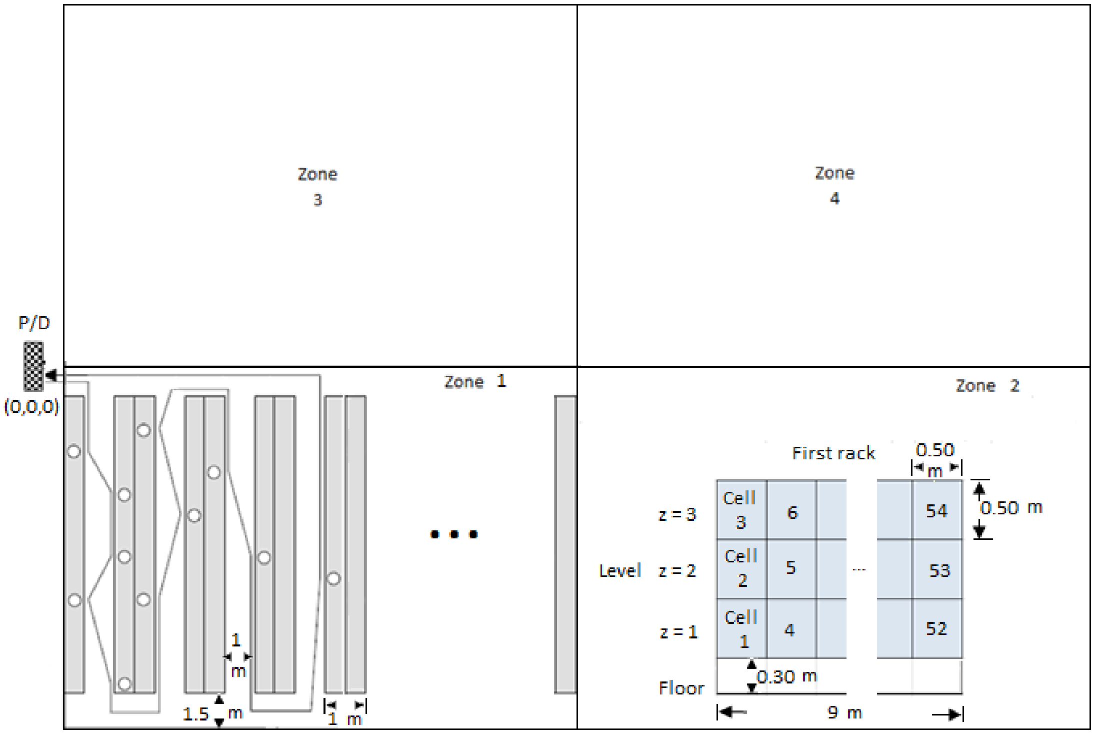



Fig. 1. Layout of the warehouse; zones, racks with a sample path of a picking tour and the numbering of cells/compartments in the first rack

ments. A sample numbering is shown in Zone 2 of Fig. 1 for the compartments of the first rack. Items are assumed to be located at the centre of the compartment and close to the opening of the compartment. Moreover, items are packaged to facilitate one-hand picking.

### 2.3. Routing and picking

All picking tours are assumed to start from and end at the pick-up/drop-off station (P/D), which is assigned a (0, 0, 0) coordinate. The picking tour starts when the order picker collects the order invoice from the P/D station. The invoice has n items assumed to be preordered to expedite picking. The picker travels to the items' locations based on the order in the invoice. To travel from the location of item i to that of i+1, the picker is assumed to walk in the middle of the aisle at a constant speed and to choose the shorter path to the target location. Moreover, the picker is assumed to use a shopping cart to move the picked items during the picking tour. The total travel distance/time is computed as the algebraic sum of the distances/times between visited locations, including that from and to the P/D station.

To collect an item from a compartment, the picker arrives at the position, rotates to face the rack, searches for the item, performs the pick, rotates back, stoops to place the item in the cart, and then continues to the next location. To perform a pick, the picker is assumed to position oneself at a convenient distance in front of the compartment. Based on the item's height, the picker is assumed to stand to pick items from upper and middle compartments (z=3 and z=2) or squat to pick items from lower compartments (z=1) to facilitate safe reach for the item. Following this, the picker reaches for, grasps, moves the item towards their body, reassumes the standing posture as needed, and then places the picked item in the cart. By the end of the tour, the picker empties the items from the cart at the P/D station. The time required to assume the needed posture (rotate, stand, stoop, or squat), the time to pick (reach for, grasp, move, and release) an item, and the time to lower the item into the cart are estimated using PTS systems, Tompkins et al. (2010) and Meyers and Stewart (2002). Times for eye travel and eye fixation are included for locating the item. It is worth mentioning that the item's weight may only impact the time required to move the item and that gender has no effect on the travel or the picking times. For convenience, these times are pre-estimated and are used as fixed inputs in the model, as shown in Table 1. The total picking time is computed as the algebraic sum of the time required to

Tab. 1. PTS picking time calculations

| Activity | Description | Z = 1 | Z = 2 | Z = 3 | Pick Invoice | Drop Items |
|---|---|---|---|---|---|---|
| Turn | To face the rack | 0.020 | 0.020 | 0.020 | 0.02 | 0.02 once for all items |
| Eye Travel | Search for the item | 0.010 | 0.010 | 0.010 | 0.01 | 0.01 |
| Eye fixation | Locate the item | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| Squat (sit) | For safe picking from a lower shelf | 0.020 | | | | |
| Reach 16 inches | Reach for the item | 0.011 | 0.011 | 0.011 | 0.011 | 0.011 |
| Grasp | Grasp a large item | 0.003 | 0.003 | 0.003 | 0.009 | 0.003 |
| Move 16 inches | Move the item toward the body or to the P/D station | 0.011 + 25 % for every 10 lb over 5 lb | | | | |
| Arise from squat (stand) | Stand tall | 0.020 | | | | |
| Move 16 inches | To place the item in the cart | 0.011 + 25 % for every 10 lb over 5 lb | | | | |
| Release | Release the item into the cart or at the P/D station | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Reach (16, 25.6, 45.3 inches for z= 1, 2, 3) | Reach back toward the body | 0.011 | 0.0158 | 0.02565 | | |
| Turn | To align with the cart | 0.020 | 0.020 | 0.020 | 0.02 | 0.02 once for all items |
| Total | Item weight ≤5 lb | 0.142 | 0.1116 | 0.1313 | 0.076 | 0.04 + number of items × 0.03 |
| | 5< item weight ≤15 lb | 0.1475 | 0.1183 | 0.140463 | | 0.04 + number of items × 0.04275 |
| | 15< item weight ≤25 lb | 0.153 | 0.125 | 0.149625 | | 0.04 + number of items × 0.0455 |

collect the invoice at the beginning of the tour, the picking times of items, and the time required to empty the items at the P/D station. The total time of the picking tour is computed as the algebraic sum of

## 2.4. Energy calculations

To estimate the rate of energy expenditure during a picking tour, the tour is decomposed into travel and picking activities. This study predicts the rate of HEE for each activity using the following equations from Garg et al. (1978). Other than standing activities, all computed HEE must be adjusted by adding an HEE for standing during the activity to account for holding the body in position (Garg et al., 1978).

Walking on a flat surface (kcal/min):

$$E = 10^{-2}\,(51 + 2.54\,BW \times V^2) \tag{1}$$

Standing (kcal/min):

$$E = 0.024\,BW \tag{2}$$

Standing in a bent position (kcal/min):

$$E = 0.028\,BW \tag{3}$$

Arm lowering (kcal/lower):

$$\Delta E = 10^{-2}\,(0.093\,BW\,(h_2 - 0.81) + +(1.02\,L + 0.37\,S \times L)\,(h_2 - h_1)) \tag{4}$$

Forward movement of the arm while standing (kcal/movement):

$$\Delta E = 10^{-2}\,(3.75 + 1.23\,L)\,X \tag{5}$$

Forward movement of the arm while sitting (kcal/movement):

$$\Delta E = 10^{-2}\,(6.3 + 2.71\,L)\,X \tag{6}$$

Squat lowering (kcal/lower):

$$\Delta E = 10^{-2}\,(0.511\,BW\,(0.81 - h_1) + +0701\,L\,(h_2 - h_1)) \tag{7}$$

Squat lifting (kcal/lift):

$$\Delta E = 10^{-2}\,(0.514\,BW\,(0.81 - h_1) + (2.19\,L + +0.62\,S \times L)\,(h_2 - h_1)) \tag{8}$$

Stoop lowering (kcal/lower):

$$\Delta E = 10^{-2} (0.268\ BW (0.81\text{-}h_1) + +0.675\ L (h_2\text{-}h_1) + 5.22\ S (0.81\text{-}h_1)) \tag{9}$$

Stoop lifting
(kcal/lift):

$$\Delta E = 10^{-2} (0.325\ BW (0.81\text{-}h_1) + +(1.41\ L + 0.76\ S \times L) (h_2 - h_1)) \tag{10}$$

Where:
$E$: human energy expenditure per time (kcal/min)
$\Delta E$: human energy expenditure per task (kcal)
$BW$: body weight of the worker (kg)
$h_1$: vertical height, in metres, from the floor; the starting (ending) point for the lift (lower)
$h_2$: vertical height, in metres, from the floor; the ending (starting) point for the lift (lower), $0.81<h_1<h_2$
$L$: item's weight (kg)
$S$: gender (0 female, 1 male)
$V$: walking speed of the worker (m/sec)
$X$: horizontal movement (m)

$$\Delta E = 2.4 \text{ x } 10^{-4} \times \mu \times G \times L_T \times D \tag{11}$$

Where:
$\mu$: the coefficient of friction between the cart's wheels and the floor
$L_T$: the total weight of the load (kg), including the weight of the cart
$D$: distance (metres)
$G$: gravitational acceleration (9.8 m/sec$^2$)

To estimate the HEE during the pushing of the shopping cart to move the picked items, the model assumes that the handle of the cart is 1.2 metres in height and that the worker's arms make a 30o angle with the horizontal while pushing the cart. For the purpose of the study, the weight of the cart is assumed to be 35 kg (Dc Graves, 2023). The energy consumed to overcome the friction between the wheels of a cart and a floor can be computed as follows (Garg et al., 1978):
Pushing (kcal):

$$\Delta E = 2.4 \text{ x } 10^{-4} \times \mu \times G \times L_T \times D \tag{11}$$

Where:
$\mu$: the coefficient of friction between the cart's wheels and the floor
$L_T$: the total weight of the load (kg), including the weight of the cart
$D$: distance (metres)
$G$: gravitational acceleration (9.8 m/sec$^2$)

The value of $\mu$ depends on the type of surfaces in contact. For the purpose of this study, the cart is assumed to have nylon or polyurethane mounted on steel wheels and the floor is assumed to be concrete; $\mu = 0.06$ (Al-Eisawi et al., 1999).

Compared to Zone 1 (Fig. 1), the difference in the HEE for the different zones can be estimated by the added HEE due to the travel between the P/D station and the first item while the cart is empty plus the HEE due to the travel between the last item and the P/D station while the cart is full. On the other hand, the HEE required to travel between items and to pick items is independent of the zone.

Equation 12 estimates the percentage of RA for pickers in the case that the rate of the HEE for the job exceeds the allowable HEE rate based on Price (1990). This study assumes that the allowable rate of the HEE is 4.3kcal/min for males and 2.6kcal/min for females (Price, 1990) and that the picker will spend their rest time standing.

Rest
Allowance:

$$\%RA = \frac{HEE_{work} - HEE_{allowable}}{HEE_{allowable} - HEE_{relaxation}} \times 100\ \% \tag{12}$$

Where:
$\%RA$: percentage of the required rest allowance
$HEE_{work}$: rate of energy consumption in a certain job (kcal/min)
$HEE_{allowable}$: allowable rate of energy consumption (kcal/min)
$HEE_{relaxation}$: rate of energy expenditure during rest time (kcal/min)

For high values of %RA, the inclusion of RA in the picking tour may significantly reduce the throughput of the picker because the total productive time of the picker will be reduced by an average of %RA. This is especially true for picking tours with high travel distances, pickers with high body weights, pickers walking at high speeds, and for combinations of previous factors. Specific findings of this study are presented in the next section.

### 2.5. Methodology steps

The next steps were followed by applying the methodology. First, items with their mass, location, and availabilities were stored in an Excel file. Second, datasets were randomly generated, containing the number of items per order and the locations of items based on stored data. Third, routings were generated as described in Section 3.3, and then, the time needed to complete the route was calculated as described in Table 1. Fourth, energy consumed by pickers was calculated as explained in Eq. 1–10. Fifth, this procedure was repeated many times (replicates = 2000); different measures were reported and evaluated, such as travel distance, travel time, travel energy, picking time, and picking energy.

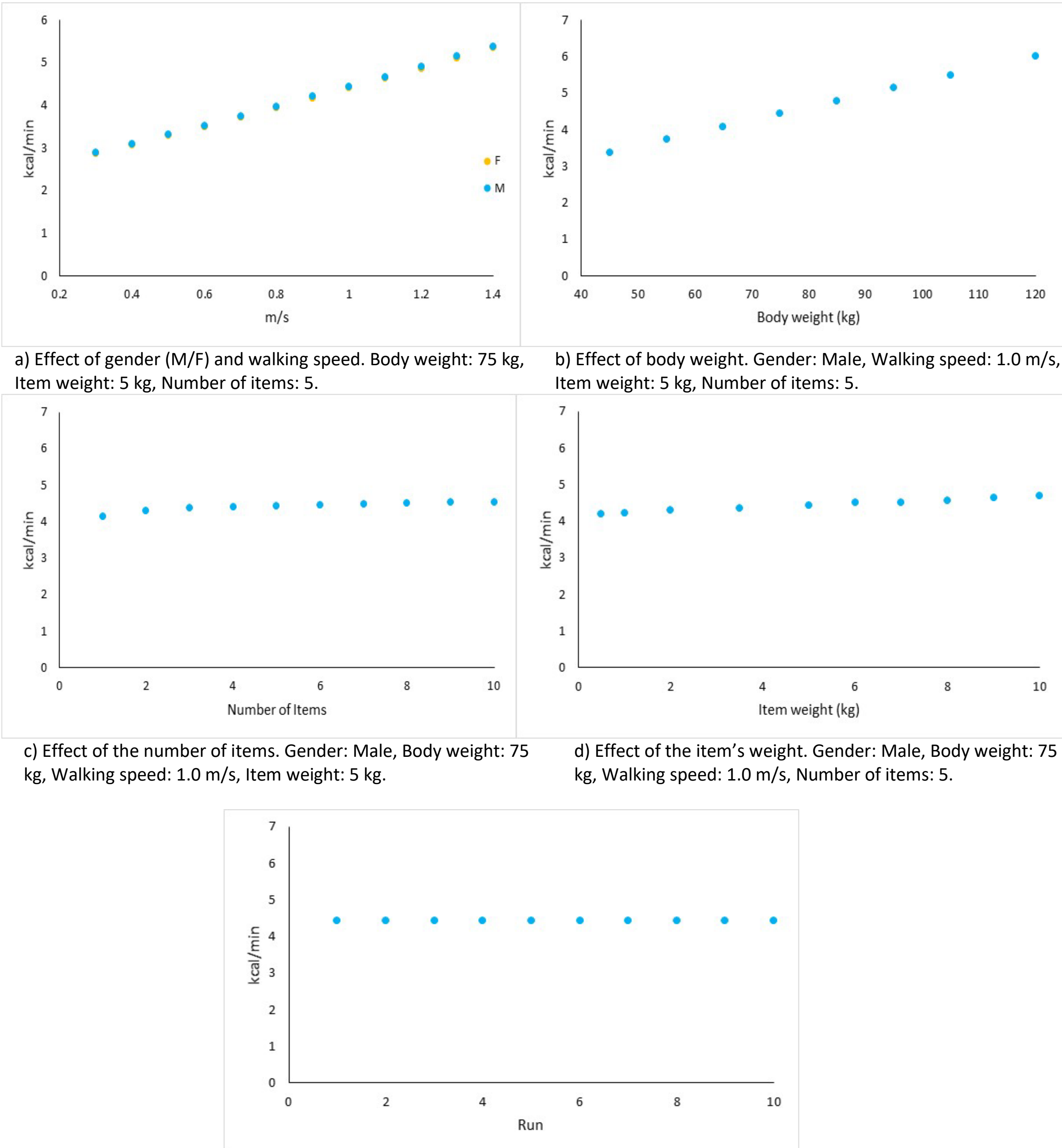
## 3. Research results

In this study, the Monte Carlo simulation was set to pick 2000 orders of the same number of items from different locations within Zone 1 (Fig. 1). Replicates of the simulation were executed to study the impacts of various warehouse, human, and trip factors on the rate of the HEE (kcal/min) and the throughput of the order picker (orders/shift). The work shift was assumed to be 480 minutes, excluding rest breaks. Allowable kcal/min were set at 2.6 and 4.3 for females and males, respectively. Input parameters are shown in Table 2. Note that body weights were selected to ensure that HEErelaxation was less than HEEallowable. The model was run for the two extremes to estimate the range of kcal/min and throughput for the assumed order-picking system. Extreme one (male picker, 120 kg body weight, 1.4 m/s, 10 kg items, and 10 items per tour) yielded an average HEE rate of about 7.48 kcal/min and a throughput of 141 orders per tour (1412 items). Extreme two (female picker, 45 kg body weight, 0.3 m/s, 0.5 kg item, and 1 item per tour) yielded an average HEE rate of about 1.89 kcal/min and a throughput of 187 orders per tour (187 items). The results showed significant differences in kcal/min and throughput. Moreover, the difference between the allowable kcal/min and the work kcal/min should be closely observed when assigning orders to workers.

Tab. 2. Input parameters

| Parameter name | Values / Range of values |
|---|---|
| Gender of a worker | 1 for male, 0 for female |
| Worker's body weight | 45 to 105 kg for female<br>45 to 120 kg for male |
| Walking speed | 0.3 to 1.4 m/sec |
| Weight of the item | 0.5 to 10 kg |
| Number of items per order | 1 to 10 |

Fig. 2 shows the impact of each studied factor on the HEE rate and the throughput of the picker without RA. Fig. 2a shows the impact of the picker's gender (F/M) and the walking speed (m/s) on the HEE rate (kcal/min). No significant effect of gender could be observed, <0.75 % and the significant impact of walking speed was highly recognisable. Therefore, the picker could significantly decrease their HEE rate by assuming a slower pace. Accordingly, warehouse management should keep their workers safe and not encourage rapidity. Since no significant impact of gender was observed, the rest of the experiments were performed assuming a male picker. Fig. 2b illustrates the significant impact of the picker's body weight on the HEE rate. It is obvious that body weight is not totally controllable; even if management insisted on hiring workers with lower body weights, they could not guarantee that weight would not build up over time. The picker is expected to drain their energy early in the shift when combined with faster walking speed. Therefore, management may encourage workers with higher body weights to assume a slower pace to avoid negative consequences. Figs. 2c and 2d show the impact of the number of items and the item weight on the kcal/min. Combining these impacts with those of other factors may add up and make the total kcal/min far above the allowable. In the traced scenario in Fig. 2c, e.g., the average kcal/min for picking one item at a time is about 4.15, less than the allowable kcal/min, while it equals 4.53, greater than the allowable kcal/min, for picking ten items. Moreover, Fig. 2d shows that picking five items of 0.5 kg each consumes around 4.2 kcal/min compared to about 4.7 kcal/min when the item weight is 10 kg. Fig. 2e shows no significant change in the output when the simulation is repeated. In summary, Fig. 2 shows that body weight and walking speed have the most significant impacts on the HEE rate. The rate is further increased by increasing the number of items picked per tour and by the increase in the item weight.




a) Effect of gender (M/F) and walking speed. Body weight: 75 kg, Item weight: 5 kg, Number of items: 5.

b) Effect of body weight. Gender: Male, Walking speed: 1.0 m/s, Item weight: 5 kg, Number of items: 5.

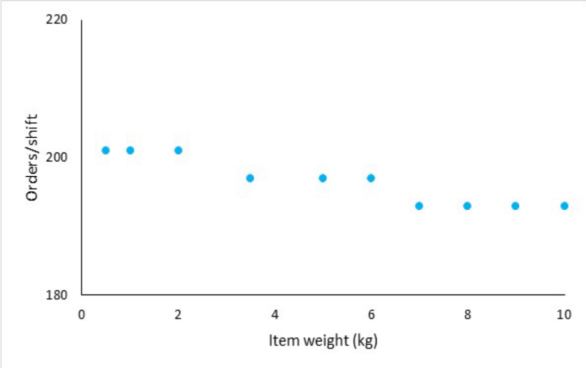
c) Effect of the number of items. Gender: Male, Body weight: 75 kg, Walking speed: 1.0 m/s, Item weight: 5 kg.

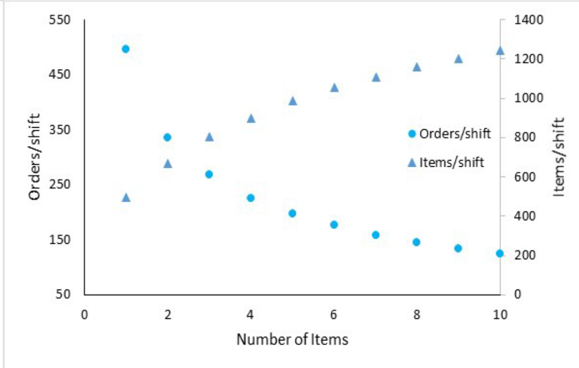
d) Effect of the item's weight. Gender: Male, Body weight: 75 kg, Walking speed: 1.0 m/s, Number of items: 5.

e) Effect of experiment replications. Gender: Male, Body weight: 75 kg, Walking speed: 1.0 m/s, Item weight: 5 kg, Number of items: 5.

Fig. 2. Effects of human and picking factors on the HEE (kcal/min) of order pickers with no rest allowance

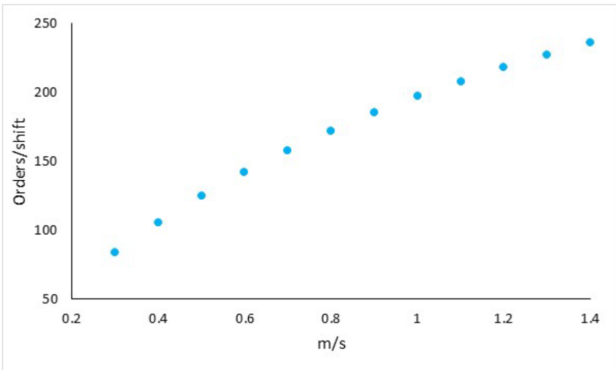
Fig. 3 shows the impact of the factors that contribute to increasing the tour time, which in turn impacts the system's throughput. Fig. 3a shows a slight decrease in the number of orders fulfilled per work shift. The slight drop, about four orders per weight group, in the number of orders is due to the increase in picking times: 25 % for every 10 lb above 5 lb of item weight, contributing to a few added seconds per pick. On the other hand, Fig. 3b shows a significant decrease in the number of orders fulfilled per work shift due to the added travel time. Although the number of orders decreases, the total number of items picked per tour increases as the order size increases. Therefore, management may consider the number of picked items instead of the number of orders fulfilled per work shift as a key performance indicator to balance work among pickers. Fig. 3c illustrates the significant impact of the walking speed of the picker on the number of orders fulfilled per work shift. Although faster pace means less travel




a) Effect of the item's weight. Gender: Male, Body weight: 75 kg, Walking speed: 1.0 m/s, Number of items: 5.

b) Effect of the number of items. Gender: Male, Body weight: 75 kg, Walking speed: 1.0 m/s, Item weight: 5 kg.



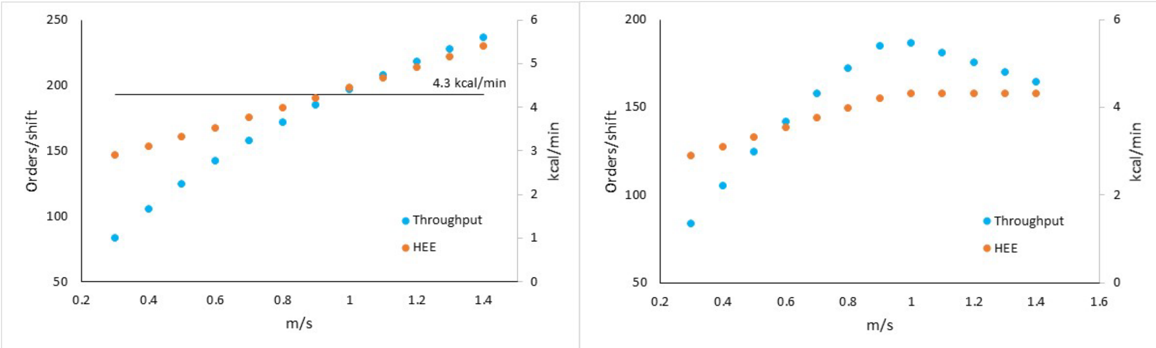

c) Effect of the walking speed. Gender: Male, Body weight: 75 kg, Item weight: 5 kg, Number of items: 5.

Fig. 3. Effects of human and picking factors on the throughput (orders/shift) of the order picking system with no rest allowance

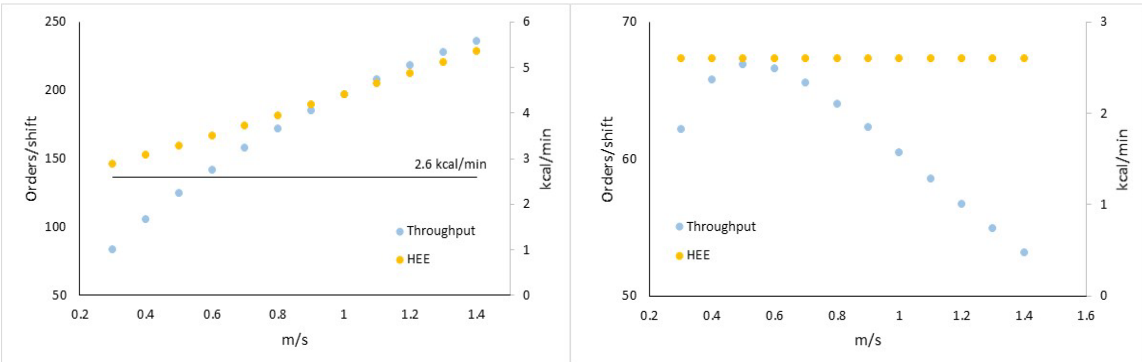
time and more output, it also means higher HEE rates, as seen in Fig. 2a. This calls for a balance between the two contradicting goals: to maximise throughput while keeping the HEE rate below the allowable.

Mini breaks, Eq. 12, can be introduced to reduce the kcal/min for a worker. This study assumed that the worker spends the break standing. Fig. 4 shows the impacts of introducing the mini-break on the kcal/min and the throughput of the picker for the given scenarios. Figs. 4a and 4b illustrate the impact for a male picker and Figs. 4c and 4d illustrate the impacts for a female picker. The figures provide the optimal walking speed for the picker that maximises their throughput while preserving energy. It can be clearly seen that walking speed is significantly lower for female pickers since they have lower allowable kcal/min. It is worth reminding that the allowable kcal/min for individuals may vary with age and health conditions. Therefore, management has to encourage workers not to force themselves beyond their capabilities to avoid injuries in the short and long term.

By layout symmetry (Fig. 1), the HEE rate and the throughput of the picker are similar for Zones 1 and 3 and are similar for Zones 2 and 4. Given the same sequence of items used before, a male picker of 75 kg body weight is walking at 1.0 m/s to pick five items each of 5 kg per the tour. The results obtained for picking from Zone 1 yielded an average travel distance of 85.23 metres, a HEE rate of about 4.43 kcal/min, and a throughput of 196.86 orders/shift. To estimate the effect of the zone on the HEE rate and the throughput of the picker, the model was executed for picking the locations; only the y-coordinate of the items was adjusted so that all items would be located in Zone 2. The obtained results yielded an average travel distance of 145.23 metres, a HEE rate of about 4.47kcal/min, and a throughput of 139.60 orders/




Gender: Male, Body weight: 75 kg, Allowable HEE: 4.3 kcal/min, Item weight: 5 kg, Number of items: 5. (left) with no rest, (right) with rest




Gender: Female, Body weight: 75 kg, Allowable HEE: 2.6 kcal/min, Item weight: 5 kg, Number of items: 5. (left) with no rest, (right) with rest

Fig. 4. Estimate of optimal average walking speed for a given combination of human and picking factors

shift. Although the travelled distance and the throughput were significantly different between the two zones, the kcal/min did not change significantly. This can be explained by the added time, a total of one minute, due to travel, which in turn prevented a significant increase in the average HEE rate.

# Conclusions

In this work, the effects of five factors on the human energy expenditure (HEE) and, consequently, the throughput of the picker are investigated for male and female pickers by utilising the Monte Carlo simulation. These factors are the worker's gender, body weight, walking speed, item weight, and the number of items picked per tour.

The results show that with no allowable rest, the HEE rate can be independent of the picker's gender for selected scenarios of low-weight items. Moreover, increasing the speed of a picker will significantly increase the HEE for both male and female pickers. Fixing all other factors, the HEE rate increased approx. from 2.9 to 5.3 kcal/min for the speed of 0.25 to 1.4 m/s. The male picker's body weight significantly affects the HEE, while the number of items and the weight of items have an insignificant effect on the male picker's HEE. To test the robustness of the Monte Carlo simulation, the output of each run was recorded, and a consistency was obtained in the results. Similarly, for the throughput, it is found that increasing the item's weight will slightly decrease the number of orders that are executed during the shift for male pickers. Additionally, for male pickers, increasing the number of items per order will significantly decrease the number of orders per shift, and increasing the speed of pickers will significantly increase the number of orders per shift. To reduce the HEE and keep it below the allowable rate, mini-breaks are allowed, and pickers are assumed to spend them standing. As results show, a speed of around 1.0 m/s for a given scenario will keep the HEE below the allowable rate for male pickers. So, considering the speed greater than this value should be incorporated with rests, leading to less throughput. The allowable

HEE rate is notably less for female pickers than the males' rate. Thus, rest allowances should be considered at low picking speeds to avoid injuries. Consequently, the throughput of female pickers will be low compared with the throughput of male pickers for the given scenario. Female pickers might be assigned to pick up lighter items to avoid such low throughputs.

Implications of this research were theoretical, which is the lack of equations that can be used in the calculation step. For example, it was found that all research depended on an equation published in 1978 to calculate the cart pushing energy. The following limitations of this work can be indicated. First, the model is limited to the zone-picking type, which makes the results invalid for other types, such as discrete and batch picking. Second, mass ranges are used to cover most of the common items, but rare items can be out of this considered range. Third, some factors were not considered in this research, although they can be significant, i.e., the picker's age.

This work can be extended in the future by applying the same concept for different store layouts, considering picking items with different weights in the same tour and investigating other factors, such as the picker's age.

## Literature

Al-Araidah, O., Okudan-Kremer, G., Gunay, E. E., & Chu, C.-Y. (2021). A Monte Carlo simulation to estimate fatigue allowance for female order pickers in high traffic manual picking systems. *International Journal of Production Research*, *59*, 4711-4722.

Al-Eisawi, K. W., Kerk, C. J., Congleton, J. J., Amendola, A. A., Jenkins, O. C., & Gaines, W. (1999). Factors affecting minimum push and pull forces of manual carts. *Applied Ergonomics*, *30*(3), 235-245.

Baležentis, T., & Streimikiene, D. (2017). Multi-criteria ranking of energy generation scenarios with Monte Carlo simulation. *Applied Energy*, *185*, 862-871.

Battini, D., Glock, C. H., Grosse, E. H., Persona, A., & Sgarbossa, F. (2016). Human energy expenditure in order picking storage assignment: A bi-objective method. *Computers & Industrial Engineering*, *94*, 147-157.

Çakıt, E. (2016). Estimation of energy expenditure based on divided manual material handling task: Waste collection example. *Celal Bayar University Journal of Science*, *13*, 51-54.

Calzavara, M., Glock, C. H., Grosse, E. H., Persona, A., & Sgarbossa, F. (2016). Models for an ergonomic evaluation of order picking from different rack layouts. *IFAC-PapersOnLine*, *49*, 1715-1720.

Calzavara, M., Glock, C. H., Grosse, E. H., Persona, A., & Sgarbossa, F. (2017). Analysis of economic and ergonomic performance measures of different rack layouts in an order picking warehouse. *Computers & Industrial Engineering*, *111*, 527-536.

Calzavara, M., Glock, C. H., Grosse, E. H. & Sgarbossa, F. (2019a). An integrated storage assignment method for manual order picking warehouses considering cost, workload and posture. *International Journal of Production Research*, *57*, 2392-2408.

Calzavara, M., Persona, A., Sgarbossa, F., & Visentin, V. (2019b). A model for rest allowance estimation to improve tasks assignment to operators. *International Journal of Production Research*, *57,* 948-962.

Caron, F., Marchet, G., & Perego, A. (2000). Optimal layout in low-level picker-to-part systems. *International Journal of Production Research*, *38*, 101-117.

De Vries, J., De Koster, R., & Stam, D. (2016). Exploring the role of picker personality in predicting picking performance with pick by voice, pick to light and RF-terminal picking. *International Journal of Production Research*, *54,* 2260-2274.

Dc Graves Industrial Steel Cart Index. Retrieved from https://www.dcgraves.com/Welded-Industrial-Steel-Carts-s/1818.htm

Elbert, R., & Müller, J. P. (2017). Manoeuvres in manual person-to-parts order picking systems: Is there a significant influence on travel time and metabolic rates? *IFAC-PapersOnLine*, *50*, 6894-6899.

Finco, S., Battini, D., Delorme, X., Persona, A., & Sgarbossa, F. (2020). Workers' rest allowance and smoothing of the workload in assembly lines. *International Journal of Production Research*, *58*, 1255-1270.

Fryar, C. D., Kruszan-Moran, D., Gu, Q., & Ogden, C. L. (2018). Mean body weight, weight, waist circumference, and body mass index among adults: United States, 1999–2000 through 2015–2016.

Garg, A., Chaffin, D. B., & Herrin, G. D. (1978). Prediction of metabolic rates for manual materials handling jobs. *American Industrial Hygiene Association Journal*, *39*, 661-674.

Gibbs, B. B., Kowalsky, R. J., Perdomo, S. J., Grier, M., & Jakicic, J. (2017). Energy expenditure of deskwork when sitting, standing or alternating positions. *Occupational Medicine*, *67*, 121-127.

Grosse, E. H., Glock, C. H., Jaber, M. Y., & Neumann, W. P. (2015). Incorporating human factors in order picking planning models: framework and research opportunities. *International Journal of Production Research*, *53*(3), 695-717.

Harrison, R. L. (2010). Introduction to Monte Carlo simulation. AIP conference proceedings. *American Institute of Physics*, 17-21.

Ho, Y.-C., & Liu, C.-F. (2005). A design methodology for converting a regular warehouse into a zone-picking warehouse. *Journal of the Chinese Institute of Industrial Engineers*, *22,* 332-345.

Horiuchi, M., Muraki, S., Horiuchi, Y., Inada, N., & Abe, D. (2014). Energy cost of pushing a wheelchair on various gradients in young men. *International Journal of Industrial Ergonomics*, *44*, 442-447.

Liftingsafety (2023). Retrieved from https://www.liftingsafety.co.uk/product/order-picking-trolley-1112.html

Marmidis, G., Lazarou, S., & Pyrgioti, E. (2008). Optimal placement of wind turbines in a wind park using Monte Carlo simulation. *Renewable Energy*, *33*, 1455-1460.

Meyers, F. E., & Stewart, J. R. (2002). *Motion and time study for lean manufacturing*. Pearson College Division.

Ocobock, C. (2016). Human energy expenditure, allocation, and interactions in natural temperate, hot, and cold environments. *American Journal of Physical Anthropology*, *161*(4), 667-675.

Papadopoulos, C. E., & Yeung, H. (2001). Uncertainty estimation and Monte Carlo simulation method. *Flow Measurement and Instrumentation*, *12*, 291-298.

Parikh, P. J., & Meller, R. D. (2008). Selecting between batch and zone order picking strategies in a distribution center. *Transportation Research Part E: Logistics and Transportation Review*, *44*, 696-719.

Petersen, C. G. (1997). An evaluation of order picking routeing policies. I*nternational Journal of Operations & Production Management*.

Petersen, C. G. (2002). Considerations in order picking zone configuration. *International Journal of Operations & Production Management.*

Petersen, C. G. & Aase, G. (2004). A comparison of picking, storage, and routing policies in manual order picking. *International Journal of Production Economics*, *92*, 11-19.

Petersen, C. G., Siu, C., & Heiser, D. R. (2005). Improving order picking performance utilizing slotting and golden zone storage. *International Journal of Operations & Production Management, 25*(10), 997-1012.

Pontzer, H., Durazo-Arvizu, R., Dugas, L. R., Plange-Rhule, J., Bovet, P., Forrester, T. E., ... & Luke, A. (2016). Constrained total energy expenditure and metabolic adaptation to physical activity in adult humans. *Current Biology*, *26*(3), 410-417.

Poulianiti, K. P., Havenith, G., & Flouris, A. D. (2018). Metabolic energy cost of workers in agriculture, construction, manufacturing, tourism, and transportation industries. *Industrial Health*.

Price, A. (1990). Calculating relaxation allowances for construction operatives—Part 1: Metabolic cost. *Applied Ergonomics*, *21*, 311-317.

Raychaudhuri, S. (2008). Introduction to monte carlo simulation. Winter simulation conference. *IEEE*, 91-100.

Roodbergen, K. J., Sharp, G. P., & Vis, I. F. (2008). Designing the layout structure of manual order picking areas in warehouses. *IIE Transactions*, *40*, 1032-1045.

Saderova, J., Poplawski, L., Balog Jr, M., Michalkova, S., & Cvoliga, M. (2020). Layout design options for warehouse management. *Polish Journal of Management Studies*, *22*(2), 443-455.

Sgarbossa, F., & Vijayakumar, V. (2020). *Reducing fatigue level through tasks and breaks assignment in order picking system*. 21st IFAC World Congress (Virtual) Berlin, Germany, July 12-17, 2020.

Tompkins, J. A., White, J. A., Bozer, Y. A., & Tanchoco, J. M. A. (2010). *Facilities planning*. John Wiley & Sons.

Vanheusden, S., Van Gils, T., Caris, A., Ramaekers, K., & Braekers, K. 2020. Operational workload balancing in manual order picking. *Computers & Industrial Engineering*, *141*, 106269.

Weisner, K., & Deuse, J. (2014). Assessment methodology to design an ergonomic and sustainable order picking system using motion capturing systems. *Procedia CIRP*, *17*, 422-427.

Westerterp, K. R. (2017). Control of energy expenditure in humans. *European Journal of Clinical Nutrition*, *71*(3), 340-344.

received: 9 March 2023
accepted: 15 October 2023

pages: 25-33



# Reshoring and friendshoring as factors in changing the geography of international supply chains

Piotr Banaszyk

ABSTRACT
The text covers the projection of the potential impact of the currently observed processes in the world economy on the international supply chains' geography. The economic effects of the pandemic, the modern trade war and Russia's aggression towards Ukraine are considered key factors in changing this geography. When examining the importance of these factors, the matrix of three components of global supply chains is adopted: production centres, transport corridors and consumption centres. The reasoning allowed for rejecting both the scenario of maintaining the so-called hyper-globalisation and forming a bilateral system of two isolated and hostile economic systems. The presented arguments lead to the expectation of a mixed solution in the form of the simultaneous existence of a system of high globalisation and concentrated regional systems. The primary objective of this study is to identify and assess emerging trends in the configuration of international supply chains. On this basis, it is also intended to identify the most likely scenario for the future formation of the geography of international supply chains. The research used the literature study methodology and deductive inference of the consequences of the identified processes taken as premises for reasoning. The above-presented arguments lead to the assumption that the so-called hyper-globalisation is probably unsustainable. Various economic, political, technological and social factors make it impossible to sustain, let alone further develop, the current logic of shaping the global economic system. A world economy system with a hybrid structure is expected to emerge. The model of full globalisation will coexist with the model of a multilateral structure with a regional character centred around the main consumption and production centres. The factors determining the evolution of economic globalisation have been systematised. Their potential impact is described, and a likely scenario for change is presented. The achieved results can contribute to the design of economic policy at the level of individual countries and their groupings.

KEY WORDS
**international supply chains, supply chains geography, globalization**

**10.2478/emj-2023-0026**

**Piotr Banaszyk**

Poznań University of Economics and Business, Poland
ORCID 0000-0002-9457-3613

Corresponding author:
piotr.banaszyk@ue.poznan.pl

## Introduction

Globalisation was and is a constitutive feature of the world economic system. Although the globalisation concept has multidimensional characteristics (Walas-Trębacz, 2007, p. 51–80), its economic aspect is particularly important. This is because globalisation has resulted in a process of interdependence between the economies of individual states through industrial cooperation, the provision of services across national borders, the liberalisation of national labour markets favouring population migration and

Banaszyk, P. (2023). Reshoring and friendshoring as factors in changing the geography of international supply chains. *Engineering Management in Production and Services, 15*(4), 25-33. doi: 10.2478/emj-2023-0026

relatively free financial flows. These phenomena have developed a rationale for increasing the enterprises' economic and financial efficiency, which is geared towards maximising the basic measures that assess their management efficiency (Banaszyk, 2022, 26–42). In these conditions, the management method known as outsourcing, meaning the relocation of production or service links from the point of view of potential economic and financial benefits, was of key importance (Rybinski, 2007). The end result of these efforts was the created global business system, i.e., geographically dispersed economic entities linked by logistical processes (Mańkowski, 2020, p. 31–45). Indeed, business dynamics require the movement and storage (transport of things, mobility of people and warehousing) of resources that constitute the so-called factors of production and their outputs. Economic globalisation based on the geographical dispersion of interdependent economic actors has thus become a determinant of the need for practice and knowledge about the efficiency (effectiveness and economisation) of logistics processes, which is sometimes referred to as the logistics of the world economy (Gołembska, 2022, p. 17–30).

In particular, Nathalie Fabbe-Costes and Aurélien Rouquet have tried to prove that logistics is becoming one of the most important drivers of mainly economic and, of course, political and socio-cultural globalisation. The publication prepared by these luminaries of French logistics thought was published relatively recently, in 2019. Then, the world economy experienced a pandemic crisis, and now (2022), a crisis is triggered by the aggression of the Russian Federation against Ukraine; in addition, a trade war was initiated mainly between the USA and China. The pandemic crisis highlighted the extent to which European economies depend on supplies from China, particularly in such key industrial sectors as automobiles, textiles, electronics and even pharmaceuticals (Fulconis & Paché, 2021). The pandemic showed in a few weeks how fragile global supply chains are and clarified that economic globalisation has rational limits. In turn, the war crisis demonstrated the dependence of the European economy on supplies from Belarus, Russia and Ukraine. The latter two countries supply 26 % of world exports of wheat, 16 % of maize, 30 % of barley and about 80 % of sunflower oil and sunflower meal. Ukraine supplies the world with about half of the neonics used to etch microchips. Russia is the world's third-largest oil producer, the second-largest gas producer and a leading exporter of nickel used in car batteries and palladium used in car exhaust systems (The Economist, 2022). The trade war has intensified protectionist practices, particularly raising tariffs on international trade[1].

The question on the agenda is whether the mechanism for building material wealth in European societies should continue to be the result of the increasing value and volume of international trade, which correlates with the increasing people's spatial mobility as a result of business travel and tourism. Pandemics and wars may be viewed as the exception rather than the rule. However, the global economy's dependence on the reliability of the transport of goods along international supply chains is a constant factor that lifts economic risk probably now beyond acceptable levels. It did not take a pandemic or a war for the large container ship "Ever Given" to block shipping in the Suez Canal for one week in spring 2021. According to Lloyd Insurance estimates, each day of the Suez Canal blockade resulted in a loss of USD 6–10 billion. It is not out of the question that the likelihood of such blockades will increase, as the "Ever Given" is a 20 000 TEU-equivalent container ship, and the shipyards of the Asian triangle (China, South Korea and Japan) are planning to build 30 000 TEU container ships (Berkovich, 2021).

Leaving aside sensitive goods, e.g., products of the pharmaceutical industry, a smaller or longer delay in the acquisition and consumption of the final product by the final customers is not of major importance. However, economic globalisation in its contemporary form is more complex, as about half of all internationally traded goods are intermediate, i.e., necessary to sustain the continuity of production in the downstream links of international supply chains. Henri Regnault argued that the peculiarity of the globalisation process depends on the horizontal or vertical strategy pushed by leading multinational corporations. The former involves locating dependent (proprietary or technological) plants as close as possible to promising markets. The vertical strategy is related to the location of dependent plants in search of cost reductions in supply, energy or labour (international outsourcing) (Regnault, 2021, p. 10–11). Consequently, it is possible to evoke three potential scenarios for the future of economic globalisation (Regnault, 2021, p. 11–12):

Scenario 1: Maintenance of a large globalisation evolving in line with changes in the comparative advantages of different countries.

1 E.g., average import tariffs from China to the US increased from 3 % to 21 % and from the US to China from 8 % to 21 % (Ambroziak, 2020).

Scenario 2: Marginal adaptation through limited regionalisation and variable geometry in the logic of sovereignty (immediate availability of medical goods, control of sensitive technologies such as 5G or artificial intelligence).

Scenario 3: Permanent fragmentation into rigid regional zones based on increased trade barriers (tariffs and different taxes, uniform standards of different zones but differentiation of zones). This would be the end of trade multilateralism in favour of bilateralism between regions and between countries, negotiated on a case-by-case basis.

The future is, of course, unknown, and its forecasting first requires establishing the current state.

The primary objective of this study is to identify and assess emerging trends in the configuration of international supply chains. On this basis, it is also intended to identify the most likely scenario for the future formation of the geography of international supply chains.

The key research questions focus on the reasons prompting the reconfiguration of international supply chains, the importance of economic, political and cultural conditions during this change, and the likely future of economic globalisation.

The research used the literature study methodology and deductive inference of the consequences of the identified processes taken as premises for reasoning.

# 1. Current state of logistics in international supply chains — literature review

Based on a report compiled by the United Nations UNCTAT (Global Trade…, 2022), international trade has seen steady growth in 2021. This is true for the exchange of goods and services. The value of world trade reached a record high in 2021 at USD 28.5 trillion, an increase of 25 % from the previous year. Admittedly, this was due to a slightly understated base due to the pandemic crisis, but in relation to 2019, the increase was 13 %. It is also noteworthy that international merchandise trade reached nearly USD 5.8 trillion in Q4 2021, a historical record. These figures seem to prove that the economic globalisation dynamics have remained high, which naturally results in the need for logistics services within international supply chains. According to UNCTAD, factors behind these dynamics are primarily rising commodity prices, a post-pandemic rebound in manufacturing and deferred demand transforming the financial resources accumulated as a result of the support channelled to businesses and households by many governments into an effective demand stream (Global Trade…, 2022). In the years to come, the impact of these factors will no longer be significant, i.e., sustaining robust international trade growth in the future is problematic. In the European Union, similar trends have emerged. Imports of goods increased by 27 % in Q4 2021 compared to a similar period in 2019, while exports increased by 10 % in that period (Global Trade…, 2022).

UNCTAD's calculated measures of export efficiency (a composite indicator with a receptive field including growth rate, relationship to competitors and the level of competitiveness) and export volatility (fluctuations over the last six months) show for the European Union an efficiency of 0.51 at a stable level with little volatility — a measure of 0.01 (Global Trade…, 2022).

In the case of the Polish economy, the most important international trade partners for imports were Germany (a share in total imports of 21.9 % in 2020 and 2019) and China (12.3 % in 2019 and 14.4 % in 2020), and for exports, Germany (27.7 % in 2019 and 29.0 % in 2020) and the Czech Republic (6.1 % in 2019 and 5.9 % in 2020) (Statistical Yearbook…, 2021). Overall, Polish imports reached USD 265.8 trillion in 2019 and USD 260.6 trillion at current prices and exports USD 267.1 trillion in 2019 and USD 272.7 trillion in 2020.

According to the European Commission, changes in international trade in goods from the European Union's point of view have become apparent over the last decade. For imports, the highest dynamics of these changes concerned the growing share of China and India (China has the largest share, followed by the USA), and for exports, the shares of China and South Korea were growing (however, the USA is the EU's largest partner, China taking the second place) (European Commission, 2022).

According to the CSO, the structure of gross value added of manufacturing in 2020 was as follows: North America produced 17 % of this value, Europe 19.2 %, Asia and the Pacific 41.9 % (including China 31.3 %). These figures demonstrate that international trade in goods must primarily use transport corridors in the Europe, Asia and North America triangle.

A very useful tool for diagnosing the state of international supply chains is the concept reported by Jean-Paul Rodrigue (Rodrigue, 2012, p. 15–23).

Characterising these chains requires a combination of three geographical locations: the concentration of production, the concentration of consumption and the distribution of transport corridors between them.

Irina Rodionova's (Rodionova, 2021) research examined production volumes in six geographical regions: North America, Central and South America, Europe, Asia, Africa and Oceania. They covered the period from 2005 to 2019. The share by volume in the world industrial production of the leading countries is presented in Table 1.

Tab. 1. Countries' share of global production in % by volume

| Country | 2005 | 2019 |
|---|---|---|
| China | 13.69 | 29.67 |
| USA | 22.80 | 15.99 |
| Japan | 9.47 | 7.01 |
| Germany | 6.60 | 5.42 |
| South Korea | 2.64 | 3.05 |

Source: (European Commission, 2022).

Table 2 presents the data in a similar arrangement for different world regions.

Tab. 2. Regions' share of global production in % by volume

| Country | 2003 | 2016 |
|---|---|---|
| North America | 30.3 | 22.5 |
| Central and South America | 3.4 | 4.0 |
| Europe | 32.4 | 22.5 |
| Africa | 1.0 | 1.1 |
| Asia | 31.7 | 49.0 |
| Oceania | 1.2 | 0.9 |

Source: (European Commission, 2022).

The figures show that Asia is of key importance in the geography of global industrial production, with China, Japan and South Korea leading the way. This region is the origin of the most important international supply chains.

Taking the opposite perspective, focused on the level of consumer expenditure[2] realised in each region, it is possible to infer the most important destinations of goods moved along international supply chains. This is illustrated in Table 3.

Tab. 3. Regions' share of global consumption in USD bn

| Country | 2020 |
|---|---|
| North America | 941.79 |
| Central and South America | 216.4 |
| Europe | 280.67 |
| Africa | 35.56 |
| Asia | 389.73 |
| Oceania | 207.27 |

Source: (The Global Economy, 2023).

The figures in Table 3 show that North America is the main destination for goods, followed by Asia and Europe.

The spatial gap between producers and consumers requires the creation of international transport corridors and, within them, the provision of logistics services. Transport services are of key importance. These, in turn, require efficient transport terminals, i.e., seaports, road and rail hubs and airports from which various transport modes can depart and enter. These terminals are recognised as nodes that significantly determine the efficiency of the movement of goods.

According to Kavin O'Connor (O'Connor, 2010, p. 354–362), only 44 regions of global logistics importance are responsible for handling nearly half of land freight and about two-thirds of sea freight. Key logistics hubs with an intermediary function in global freight transport are New York and Tokyo, as well as Hong Kong–Shenzhen, Singapore and Amsterdam–Rotterdam. Other locations with strong logistics functions are, in particular, Los Angeles–Long Beach, Tokyo–Yokohama, Shanghai–Ningbo and Dubai–Gulf. On the one hand, this results in high congestion in these regions and, on the other hand, in the desire of owners and managers of logistics companies to compete for land that allows the expansion of logistics infrastructure. Arguably, the development potential of these locations is close to being fully exploited.

The issue of logistical risk is also an important research perspective. Following Andrzej Szymonik, it refers to "conditions in which the logistician knows the probable size of the probability of obtaining business by a purposefully organised and interconnected set of such elements (subsystems) as, e.g., procurement, production, distribution together with the relations between them and their properties, conditioning the flow of material and information streams" (Szymonik, 2014, p. 128). These conditions and, therefore, the assessment of the efficiency of interna-

2 Household final consumption expenditure (formerly private consumption) is the market value of all goods and services, including durable goods (such as cars, washing machines and household computers), purchased by households. It does not include the purchase of housing but includes imputed rent for owner-occupied housing. It also includes payments and fees to governments for permits and licenses. Here, household consumption expenditure includes expenditure by non-profit institutions serving households, even if reported separately by the country. It also includes any statistical discrepancy in the use of resources relative to the supply of resources.

tional supply chains are currently undergoing change. Crucial in this regard is the trade war between the US and China (resulting, e.g., in obstacles to maritime transport through the Straits of Malacca (Paszak, 2021)), the pro-environmental socio-economic policies of the European Union and, more recently, the Russian war aggression against Ukraine, as well as the ongoing COVID epidemic. "At the same time, it is predicted that the likely outcome of these factors could be a division of the world economy into two blocs — one oriented around China, the other around the United States, with the European Union mainly but not entirely in the latter camp. Attempts to isolate each of these blocs and then reduce the influence of the other are possible. The economic consequences for the world and for the geography of international supply chains could be enormous" (Banaszyk & Gorynia, 2022, p. 154).

The geography of global supply chains is thus approaching a tipping point, the crossing of which marks a major modification. As indicated, this is not due to a single, isolated factor but the simultaneous impact of many, including political, ecological, sanitary and economic reasons, arising due to the current Industry 4.0 revolution, which means the use of contemporary information and communication technology, the Internet of Things, cloud computing, augmented reality, industrial robots, etc., in a coherent cyber-physical system that significantly improves customer service and reduces operating costs. Industry 4.0 makes it possible to use these innovations to build a completely transformed value chain and redefine the product life cycle within a self-organised manufacturing system (Kumar, Bawge & Kumar, 2021, p. 67).

Leaving aside political and formal-legal factors, the economic globalisation determining the need for international supply chains can be explained from an economic point of view. This is being addressed by the developers of economic activity location theory (Piętak, 2014, p. 5–28). Bearing in mind the widespread assessment that no universal and universally accepted theory has been developed to date, the following can be concluded from the efforts to date. Initially, many theorists were inclined to the view that the most important factors of industrial location are the characteristics of the sales market, factor markets and transport costs — the optimal location of an enterprise allows the highest profit to be achieved. Next was the recognition of the importance of industrial districts, also called clusters, due to their ability to reduce costs, i.e., increase profits (Banaszyk, 2022, p. 57–60). Slowly, there was also a realisation of the impact of the increasing size of these clusters in creating negative economic externalities, raising private and public costs. Over time, the benefits of expanding international trade complemented this one-sided approach of seeking ways to maximise profits. The importance of comparative advantages and the availability of economic resources was first pointed out, and later, the impact of economies of scale was added. The latter factor makes it most possible to reduce costs, i.e., increase profits. A further evolution of location theory resulted from synthesising the achievements of location theory and regional development theory. This emphasised the combined influence of endogenous economic resources, the size of effective demand, trade costs (including transport) and economies of scale, the pursuit of which usually leads to the emergence of imperfect competition. The above concepts can be classified as part of the so-called mainstream in economic science. Alongside it, a heterodox current is also developing, including behavioural economics (Polowczyk, 2004, p. 3–7). It emphasises the socio-psychic aspects of economic decision-making, i.e., sentiments, worldview and political beliefs and the imperfections of human reasoning as being just as important as objective economic factors, allowing for strictly logical decisions optimising economic criteria.

## 2. Rationale for changing the geography of international supply chains — the research assumptions

The reconfiguration of international supply chains is likely to be driven by the impact of several causal factors. The first is a welcome change in the decision criteria for managing these chains. In line with the dominant guidelines of the neo-liberal school of thought in economic sciences since the 1980s, the main criterion was to maximise profit in the long term. From an operational point of view, it was recommended to maximise shareholder value added (EVA), i.e., the difference between the profitability of net assets and the cost of capital employed in the business (Banaszyk, 2022, p. 28–29). This approach is now being increasingly criticised. The drive towards resilient supply chains is coming to the fore. Resilience can be defined as the fundamental competence to respond efficiently to significant changes that disrupt the achievement of established plans without falling into long periods of crisis. Resilience should include three main components: productivity, security and agility. Productivity refers to the relationship between the volume of production sold and the amount of resources consumed to produce that production. On the other hand, safety refers to sanitary protection and stable working conditions. Finally, agility is the flexibility to adapt to changing demand requirements. Agility and safety are constrained by productivity, ensuring at least a break-even point in supply chain management outcomes. There is, therefore, no way to be positive about a business activity that results in losses (Banaszyk, 2022, p. 34–36). Consequently, this means abandoning the ruthless pursuit of profit.

Another causal factor is politics. Its impact can be explained from the perspective of behavioral economics achievements to some extent. After all, politics is an activity subordinated to professed axiological values. The trade war between the USA and China and the hot war between Ukraine and Russia, as well as many other unrests in the world, are the result of the political aspirations of various states, their groupings or accidental alliances. The above-mentioned export specialisations of Belarus, Russia and Ukraine are a source of supply shock in the markets for the products indicated, forcing the search for alternative suppliers and substitute products. Even if it is possible to unlock the export opportunities of these countries, the residualisation criterion will require the creation of redundant producers and supply chains. According to an April 2022 White House report on supply chains, China currently refines 60 % of the world's lithium and 80 % of its cobalt, two key minerals critical to producing high-capacity batteries (Hayashi, 2022). Undoubtedly, resilience will also force Western countries (North America and Western and Central Europe) to minimise their dependence on China. Investments in creating new production facilities in closer and politically friendly countries can be expected. Profit-maximising outsourcing is likely to be replaced by residency-enhancing nearsourcing and friendsourcing. Nearsourcing is "the manufacture or acquisition of products and services from foreign suppliers located in geographical areas close to the buyers' facilities while being able to offer low prices" (Cagliano, De Marco & Rafele, 2013, p. 490). Its economic benefits mainly arise from shorter transport corridors, impacting costs. In addition, delivery times are also shorter, increasing flexibility, i.e., reacting more efficiently to fluctuations in demand. The idea of friendsourcing was popularised by Janet Yellen, the US Secretary of the Treasury, who described it as "deepening relationships and diversifying US supply chains with more trusted partners" (GEP, 2022). A survey of US business executives showed that bottlenecks in transportation and logistics top the list (46 %) of key drivers of supply chain disruption, followed by labour costs (45 %) and raw material costs (43 %) (GEP, 2022). Guided by the principle of friendsourcing, global supply chains can be rebuilt to reduce their dependence on countries with autocratic governments and non-market economies, namely China and Russia. It is a compromise between full globalisation and isolationism and between offshoring and domestic production (Hayashi, 2022).

Some foreign direct investment has been made because of the desire to avoid legally enforced, costly environmental and climate protection installations. Of course, certain environmental rules exist in every country receiving these investments, but they are not equally strict everywhere. Besides, even if, out of concern for their business reputation, investors are willing to take care of the environment voluntarily, the intensification of economic activities tends to worsen its condition. This is according to the so-called Kuznets curve, according to which a country's economic level must exceed a certain threshold beyond which the state of the environment begins to improve (although recent studies suggest that after a period of improvement, further economic development worsens the state again) (Genstwa, 2020, p. 39-50). However, currently recommended nearsourcing and friendsourcing take place in a changed legal and cultural environment. It is worth citing the European Green Deal (European Commission, 2020) or the Glasgow COP26 Climate Package (Consilium, 2022). For ecological and other reasons, it can, therefore, be expected that the pursuit of profit maximisation will recede into the background in favour of sustainability and corporate social responsibility (before profit (Tepper, 2020)).

Health security is the next factor prompting the reorganisation of international supply chains. However, it is not a question of guaranteeing a continuous and reliable supply of pharmaceuticals, medical infrastructure or components for the final production of the former two. Indeed, the experience of the COVID pandemic demonstrated the threat of microbial proliferation, which also has a serious impact on economic life. According to expert studies, the crisis caused by the pandemic in some way affected 93 % of employees worldwide. According to the International Labour Organisation, this meant a loss of 8.8 % of working time, or 255 million jobs (Global economic, 2021). A decline in GDP per capita affected 90 % of countries worldwide (Yeyati & Filippini, 2021). The perturbations of the real economy were reflected in the financial markets. Governments in many countries launched unprecedented bailouts of businesses and households. The result of these policies was budget deficits, which were particularly large in the economies of developed countries (Yeyati & Filippini, 2021).

Unsurprisingly, inflation has emerged globally and in Poland, and states usually adopted monetary policy targets (beyond 1.5–2.5 %). It is not excluded that the above phenomena signal the danger of an emerging or already beginning stagflation because of coexisting elevated inflation and a supply shock manifested in a change in the consumption structure. It is worth remembering the behaviour of many government representatives who abandoned the previously dominant policy of austerity and favoured QE (quantitative easing). Thus, there is no income rationale for the demand weakening. The causes of supply shocks, on the other hand, relate to the so-called breaking of international supply chains. The pandemic exposed the weaknesses of concentrating production facilities in the poor South and Far East and countries with not particularly demanding labour law or nature conservation from a cost viewpoint (Banaszyk & Gorynia, 2022).

## 3. Prospect of relocating international supply chains — the research results

Given the phenomena presented above, the macro-risk assessment of the use of international supply chains is undoubtedly changing. The popular systematisation of supply chain risks into micro, i.e., with sources inside companies, and macro, i.e., with sources external to companies and of a natural or human-induced nature, is adopted here. Natural risks arise from natural events (e.g., earthquakes, volcanic eruptions, etc.). Human-induced risks are caused by human actions (e.g., terrorism, war, legal or political obstacles) (Johnson & Haug, 2021, p. 704). Managers of companies involved in international supply chains are, of course, not directly influenced by macro-risks but are obliged to implement responses to counteract these growing risks, which can take place over a longer or shorter time horizon.

Short-term countering of macro-risks probably has no effect on changing the geography of international supply chains. It consists primarily of "waiting out" problems. The basic practice is to increase stocks, which can apply to materials, raw materials and finished goods. Attention is drawn, e.g., to the "exceptional inventory cycle" implemented by companies in Poland. The turn of 2021 and 2022 was a time of stockpiling inventory for fear of supply discontinuity and the prospect of rising prices (Morawski, 2022).

Long-term macro-risks can already significantly modify the geography of international supply chains. If one applies the systematisation of supply chain components outlined above, i.e., production centres, transport corridors (with point and line infrastructure), and consumption centres, new insights into potential changes are revealed. An additional factor influencing such modifications is arguably the nature of the supply chain. One proposal for classifying supply chains is to divide them according to the volume of goods moved, their variety and the uncertainty of demand for them (Chopra & Sodhi, 2014, p. 75).

With regard to production centres producing mass and undifferentiated goods with predictable demand, changes in production locations are probably not to be expected. Consequently, traditional transport corridors will move goods to existing consumption centres. A change in principals in inventory management may mitigate various obstacles to the continuity and reliability of transport. This involves a more rational approach to the concept of just-in-time (JIT) delivery[3].

However, if these goods are diversified assortments and produced on a small scale, regardless of the ability to forecast demand, priorities are likely to change. A key determinant of this change is the technical and technological advances most generally referred to as Industry 4.0. They will require investment in production capacity and the necessary logistics infrastructure. It is worth noting that the business's financial performance will be affected by two contradictory pressures. On the one hand, investments require capital, which will undoubtedly increase the cost of production activities[4]. On the

3 The rationalisation of JIT is supposed to mean abandoning just-in-time delivery within global supply chains while applying it even more within regional supply chains (Pisch, 2020).

4 If the threat of stagflation is real, overcoming supply shocks should take place through capacity-enhancing investments. It would, therefore, be logical for these to be supported by the state's economic authorities.

other hand, however, Industry 4.0 technology will reduce these costs through computerisation, robotisation and automation. The transport costs raised by the dynamics of fuel and insurance prices will also have an impact. The severity of these costs decreases when the length of transport routes is significantly reduced. On balance, especially for production where it will not be possible to discount economies of scale, relocating production centres closer to consumption centres may prove financially attractive. One may think that the paradigm of economic science is also evolving in this direction. Indeed, Dani Rodrik predicts that the hitherto core values of economic theory and practice of seeking to enhance globalisation, promote consumerism and take advantage of the opportunities of financial markets are beginning to be displaced by an appreciation of work and production in regional areas. Rodrik calls this new paradigm productivism, the essence of which is the spread of productive economic opportunities across all regions and all segments of the labour force (Rodrik, 2022).

## Conclusions

The arguments presented above lead to the assumption that the so-called hyper-globalisation is probably unsustainable. Various economic, political, technological and social factors make it impossible to sustain, let alone further develop, the current logic of shaping the global economic system. This probably does not mean a complete abandonment of the so-called sunk costs of infrastructure and institutionalisation of the global business model pursued to date. However, the economic and financial calculations are evolving. There are many commodities for which mass demand will persist, and their production, using the economies of scale, including in transport, will provide the opportunity to utilise the existing transport potential and, to some extent, the production potential built up under the hyper-globalisation model. At most, production centres will shift from China to other Far Eastern countries (India, Vietnam, Indonesia, Malaysia, etc.) over time.

However, many commodities will be subject to a reduction in the production volume, if only due to a reduction in the consumption scale (abandoning over-consumptionism), and new technologies for their production will allow profitable production in the countries of the rich North. In addition to the economic rationale, a change may be important in economic policy in these countries towards the recommendations of the so-called supply-side economics, i.e., the creation of valuable jobs without the need to expand social assistance for the poorer population segments.

As a result, a world economy system with a hybrid structure is expected to emerge. The model of full globalisation will coexist with the model of a multilateral structure with a regional character centred around the main consumption and production centres.

## Literature

Ambroziak, Ł. (2020). *Skutki amerykańsko-chińskiej wojny handlowych dla międzynarodowych łańcuchów dostaw* [*The effects of the US-China trade war on international supply chains*]. Warszawa, Poland: Polish Economic Institute. Retrieved from https://pie.net.pl/wp-content/uploads/2018/07/PIE-Raport_Wojna_handlowa.pdf

Banaszyk, P. (2022). Economic resilience and the business model of a logistics company. In S. Konecka & A. Łupicka (Eds.), *Logistykacja gospodarki światowej* [*Global ekonomy logistication*], (pp. 26-43). Poznań, Poland: Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu. doi: 10.18559/978-83-8211-106-4/2

Banaszyk, P. (2022). Istota klastra logistycznego [The essence of a logistics cluster]. In W. Budner (Ed.), *Klastry logistyczne. Podstawy teoretyczne i praktyka w Polsce* [*Logistics clusters. Theoretical basis and practice in Poland*], (pp. 57-60). Poznań, Poland: Bogucki Wydawnictwo Naukowe. doi: 10.12657/978-83-7986-418-8

Banaszyk, P., & Gorynia, M. (2022). Uwarunkowania polskiej polityki gospodarczej po 2022 [Conditions of Polish economic policy after 2022]. *Ruch Prawniczy, Ekonomiczny i Socjologiczny*, *2*, 149-161. doi: 10.14746/rpeis.2022.84.2.10

Berkovich, L. (2021). L'Ever Given, "le bateau ivre" de la mondialisation. *Le Echos*. Retrieved from https://www.lesechos.fr/idees-debats/cercle/opinion-lever-given-le-bateau-ivre-de-la-mondialisation-1309914

Cagliano, A., De Marco, A., & Rafele, C. (2013). The Impact of Near Sourcing on Global Dynamic Supply Chains: A Case Study. In H. Kreowski, B. Scholz-Reiter, & K. Thoben (Eds.). *Dynamics in Logistics. Lecture Notes in Logistics* (pp. 489-498). Berlin-Heidelberg: Springer. doi: 10.1007/978-3-642-35966-8_41

Chopra, S., & Sodhi, M. (2014) Reducing the risk of supply chain disruption. *MIT Sloan Management Review*, *55*(3), 73-81.

Consilium. (2022).Retrieved from https://www.consilium.europa.eu/pl/policies/climate-change/paris-agreement/cop26/

European Commission. (2020). *European Green Deal.* Retrieved from https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_pl

European Commission. (2022). Retrieved from https://policy.trade.ec.europa.eu/eu-trade-relationships-country-and-region/countries-and-regions/china_en

Fabbe-Costes, N. & Rouquet, A. (2019). *La logistisation du monde, Chronique sur de révolution en cours.* Presses Universitaires de Provence. Aix en Provence. doi: 10.4000/books.pup.31905

Fulconis, F. & Paché, G. (2021). Halte à la " logistisation " du monde ? *Revue Politique et Parlementaire.* Retrieved from https://www.revuepolitique.fr/halte-a-la-logistisation-du-monde/ (accessed 29.03.2022).

Genstwa, N. (2020). The environmental Kuznets curve: a theoretical and methodological review, *Regional Development and Policy* No. 49. doi: 10.14746/rrpr.2020.49.04

GEP. (2022). Janet Yellen has called for 'friend-shoring' supply chains. What does it mean? Retrieved from https://www.gep.com/blog/strategy/yellen-friend-shoring-supply-chains-what-it-means

*Global economic effects of COVID-19.* (2021). Jackson J. (Ed.). Retrieved from https://li.proquest.com/elhpdf/histcontext/CRS-2021-CRS-213724.pdf

*Global Trade Update.* (2022). Retrieved from https://unctad.org/system/files/official-document/ditcinf2022d1_en.pdf

Gołembska, E. (2022). *Important premises of logistics in international business.* In: Logistykacja gospodarki światowej. [Global ekonomy logistication]. Konecka, S. & Łupicka, A. (Eds.). Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu, Poznań. doi: 10.18559/978-83-8211-106-4/1

Hayashi, Y. (2022). Nations Aim to Secure Supply Chains by Turning Offshoring Into Friend-Shoring. *The Wall Street Journal*, Retrieved from https://www.wsj.com/articles/nations-aim-to-secure-supply-chains-by-turning-offshoring-into-friend-shoring-11652612580

*International Trade Statistics Yearbook.* (2021). Retrieved from https://stat.gov.pl/files/gfx/portalinformacyjny/pl/defaultaktualnosci/5515/9/15/1/rocznik_statystyczny_handlu_zagranicznego_2021_04_11.pdf

Johnson, J. & Haug, P. (2021). Modifications to global supply chain management strategies resulting from recent trade disruptions: an exploratory study, *Journal of Global Operations and Strategic Sourcing* 14(4).

Kumar, A., Bawge, G., & Kumar, V. (2021). An Overview of Industrial Revolution and Technology of Industrial 4.0. *International Journal of Research in Engineering and Science, 9*(1), 64-71.

Mańkowski, C. (2020). *Modelling of logistic processes.* Gdańsk, Poland: University of Gdańsk Publishing House.

Morawski, I. (2022). GDP is unnaturally swinging. *Puls Biznesu.* Retrieved from https://www.pb.pl/pkb-jest-nienaturalnie-rozhustany-1158772

O'Connor, K. (2010). Global city regions and the location of logistics activity. *Journal of Transport Geography*, *18*(3), 354-362.

Paszak, P. (2021). *China and the dilemma of the Malacca Straits.* Retrieved from https://warsawinstitute.org/pl/chiny-dylemat-ciesniny-malakka/

Piętak, Ł. (2014). Review of theoretical concepts of regional development. *Acta Universitatis Lodziensis: Folia Oeconomica, 306*(5), 45-60.

Pisch, F. (2020). Just-in-time supply chains after the COVID-19 crisis. *Obserwator Finansowy*. Retrieved from https://www.obserwatorfinansowy.pl/tematyka/makroekonomia/trendy-gospodarcze/lancuchy-dostaw-just-in-time-po-kryzysie-covid-19/

Polowczyk, J. (2004). Fundamentals of behavioural economics. *Organisation Review, 12*(839), 3-7. doi: 10.33141/po.2009.12.01

Regnault, H. (2021). L'avenir de la mondialisation: entre temporalités et stratégies. *Revue Interventions économiques*. doi: 10.4000/interventionseconomiques.14790

Rodionova, I. A. (2021). *Global industrial development trends: dynamics and regional aspects*. Retrieved from https://elibrary.kaznu.kz/wp-content/uploads/2021/06/vestnik-kaznu.-seriya-geograficheskaya_2021-60-1.pdf#page=17

Rodrigue, J-P. (2012). The Geography of Global Supply Chains: Evidence from Third-Party Logistics. *Journal of Supply Chain Management, 48*(3), 15-23. doi: 10.1111/j.1745-493X.2012.03268.x

Rodrik, D. (2022). *The new producvivisme paradigm?* Retrieved from https://www.project-syndicate.org/commentary/new-productivism-economic-policy-paradigm-by-dani-rodrik-2022-07

Rybinski, K. (2007). *Globalisation in Three Sides.* Retrieved from http://www.rybinski.eu/wp-content/uploads/offshoring_061027.pdf

Szymonik, A. (2014). Ryzyko w systemach logistycznych [Risk in logistics systems]. *Zeszyty Naukowe Politechniki Łódzkie: Organizacja i Zarządzanie, 1193*(58), 127-137.

Tepper, T. (2020). Responsibility of Business, 50 Years Later. *Forbes.* Retrieved from https://www.forbes.com/advisor/investing/milton-friedman-social-responsibility-of-business/

The Economist. (2020). Russia's war is creating corporate winners and losers. Retrieved from https://www.economist.com/business/russias-war-is-creating-corporate-winners-and-losers/21808223?utm_content=article-link-3&etear=nl_today_3&utm_campaign=a.the-economist-today&utm_medium=email.internal-newsletter.np&utm_source=salesforce-marketing-cloud&utm_term=3/16/2022&utm_id=1083317

The Global Economy. (2023). Retrieved from https://www.theglobaleconomy.com/rankings/household_consumption_dollars/

Walas-Trębacz, J. (2007). Uwarunkowania i skutki globalizacji [Conditions and effects of globalization]. In D. Surówka-Marszałek (Ed.), *Marketing* (pp. 51-68). Kraków, Poland: Oficyna Wydawnicza AFM.

Yeyati, E., & Filippini, F. (2021). *Social and economic impact of COVID-19.* Retrieved from https://ycsg.yale.edu/sites/default/files/files/Social%20and%20Economic-impact%20of%20covid%2019.pdf

Volume 15 • Issue 4 • 2023

sciendo

received: 10 April 2023
accepted: 1 November 2023

pages: 34-52



# Towards integration of business process management and knowledge management. IT systems' perspective

Agnieszka Bitkowska
Beata Detyna
Jerzy Detyna

A B S T R A C T
The processes of globalisation, the ongoing threat of the COVID-19 epidemic, the continuing war in Ukraine, and constantly emerging new technological solutions require organisations to adapt to changes constantly. Meanwhile, implemented business process management (BPM) often fails to integrate processes and knowledge resources. The awareness of the IT systems' role in management processes is still lacking. These premises influenced the implementation of the main research goal to identify the approach of Polish private and public enterprises and various industries to the BPM integration with knowledge management (MK) in the context of using new information technologies. The presented research results justify the usefulness of building relationships between the process and knowledge resources under dynamically changing conditions using IT systems. The diagnostic survey results confirmed the key importance of developing such BPM and MK elements as evidence-based decisions, strategic goals, measurement systems, databases, digital innovations, and IT use for data processing. The presented material can support managers of various organisation types in decision-making processes by fully understanding the IT systems' role and potential in process and knowledge management. Also, the article's implications are a source of guidelines, helping organisations to implement management systems based on modern technologies. The value of the publication is a wide range of respondents: 107 large, medium, small, and micro-enterprises operating in Poland. The article's research results also concern economic activities such as production, logistics, transport, banking, insurance, IT, telecommunications/media, public administration, healthcare/pharmaceuticals, consulting, energy, and construction.

K E Y  W O R D S
**business process management, knowledge management, knowledge resources, digital innovations, information technologies**

**10.2478/emj-2023-0027**

**Agnieszka Bitkowska**

Warsaw University of Technology, Poland
ORCID 0000-0002-2817-8244
Corresponding author:
e-mail: agnieszka.bitkowska@pw.edu.pl

**Beata Detyna**

The Angelus Silesius University of Applied Sciences, Poland
ORCID 0000-0002-4854-8433

**Jerzy Detyna**

Wrocław University of Science and Technology, Poland
ORCID 0000-0001-5750-2085

## Introduction

The relationship between process management and knowledge resources in the context of emerging digital innovations is currently the subject of intense debate in academia and business (Langley, 2007; Christiansson & van Looy, 2017; Helbin & Van Looy, 2021). Meanwhile, according to many authors, this concept has recently focused primarily on the control and optimisation of processes rather than occurring and potential disruptions (Zakrzewska-Bielawska & Staniec, 2020; OMG, 2008; Lombarts et al., 2009;

Bitkowska, A., Detyna, B., & Detyna, J. (2023). Towards integration of business process management and knowledge management. IT systems' perspective. *Engineering Management in Production and Services, 15*(4), 34-52. doi: 10.2478/emj-2023-0027

Badakhshan et al., 2019; BPM, 2020; BPM, 2021b). Until 2020, relatively little attention was paid by researchers and practitioners to the IT systems' importance for the integration of process and knowledge management, including the integration with business stakeholders (the environment), which is key in building relational capital (Gupta, Iyer & Aronson, 2000; Pant et al., 2011; Sanchez et al., 2011; Hove, von Rosing & Storms, 2015; Brajer-Marczak, 2016; Pereira, Barbosa & Duarte, 2020; Sobolewska & Bitkowska, 2020; Szelagowski & Lupeikiene, 2020; Grisold et al., 2021; Gzik, 2020). A dynamic change in this context occurred with the outbreak of the COVID-19 pandemic, which re-evaluated many of the strategies and systems used so far. For two years, a significant increase has been observed in the interest in IT systems that could effectively support management processes and communication with customers (Adam, Hofbauer & Stehling, 2021; Mahdi & Nassar, 2021; Keser Aschenberger et al., 2022; Toralles et al., 2021). The technological area in management is increasingly seen as a source of potential competitive advantage in virtually every sector and industry (AlShathry, 2016; Muntean, 2018; Muntu et al., 2021; El Ghalbzouri & El Bouhdidi, 2022; Mohamad, Jayakrishnan & Yusof, 2022, Polančič, Orban, 2023; Zakrzewska-Bielawska & Staniec, 2020). The geopolitical and socio-economic situation was greatly complicated by the war in Ukraine, which had been going on for several months and became another strong impulse for enterprises to verify the used and implemented strategies and solutions, including those relating to new information technologies. Many companies were forced to quickly redesign their current practices, including those related to activities within broken supply chains (Anderson, Müllern, Danilovic, 2023; Mbah & Wasum, 2022).

A literature review shows that large companies are less able to respond to disruptions (including digital) and adapt their BPM practices or knowledge management to disruptive technologies due to inertia, lack of incentives, or lack of faith in the effectiveness of new technologies (Hill & Rothaermel, 2003). The exception is enterprises with robotic process automation, which, as part of process and knowledge management, use the latest digital technologies more exploratorily (Dumas et al., 2013, 2018; Gross et al., 2020; Mendling, Pentland & Recker, 2020; Grisold et al., 2021). These premises encourage the scientific community to advocate for the need to extend the scope of BPM from process and operation control to greater emphasis on exploration and radical innovation, including the implementation of information technologies (Benner & Tushman, 2002; Bitkowska, 2018; BPM, 2021b; BPM, 2021a; Helbin & Van Looy, 2021; Zuhaira & Ahmad, 2021; Sitnikov et al., 2022).

Based on these premises, while considering the contemporary, difficult-to-predict social and economic challenges, the main research goal was to identify the approach of Polish private and public enterprises and various industries to the BPM integration with knowledge management (MK) in the context of the new IT use. The empirical research conducted in 2020 concerned such economic activities as production, logistics, banking, insurance, IT, telecommunications, public administration, health care, consulting, energy, and construction. The diagnostic survey confirmed the key importance of such elements as decisions, strategic goals, measurement systems, databases, digital innovations, and the use of information technology for data processing for the development of process and knowledge management.

# 1. Theoretical background

## 1.1. Determinants of business process management

According to Harmon, the BPM aims to improve managers' thinking and management of their organisations. Its manifestations, in particular Six Sigma, business process reengineering or business process management, are the basic impulse to change the mindset of managers and employee attitudes towards the organisation's continuous development (Harmon, 2010; Harmon, 2020).

The research described in the literature presents numerous factors that determine the implementation and functioning effectiveness of business process management in organisations. The most frequently mentioned elements are:

- aware process owners — having the appropriate knowledge resources,
- involvement of top management,
- appropriate communication,
- linking process goals with personal goals,
- high level of innovation in the organisation,
- follow-up of reported corrective and improvement actions,
- friendly and accessible process documentation,
- the process complexity,
- linking process goals with strategic goals,

- tool support.

Among the many methods and systems supporting the development of organisations that implement the concepts of process-managed organisations, the most frequently mentioned are TQM, ERP, CRM, SCM, BPR, BPI, ABC, BSC, TBM, JiT, LO, PERT, CPM, the concept of Kaizen continuous improvement, card systems Kanban, Benchmarking, E-business and many more (Kaplan & Norton, 2001; Bitkowska, 2017a; Detyna & Detyna, 2017; Badakhshan et al., 2019; Battisti et al., 2020; Sobolewska & Bitkowska, 2020; Espírito Santo et al., 2022; Gómez, Salazar & Vargas, 2022).

All these methods and tools require using appropriately collected and processed knowledge resources — data and indicators, based on which decisions are made. Meanwhile, knowledge resources must be reliable and up-to-date to fulfil their role in the organisation's improvement processes.

Recognising that knowledge is the most important strategic resource of an organisation implies the contemporary development of systems supporting the creation and application of knowledge (Moreno, Cavazotte & Lapa, 2015; Bitkowska, 2020; Criado-García, Calvo-Mora & Martelo-Landroguez, 2020). Meanwhile, the identification, acquisition, presentation, and documentation of knowledge are not independent tasks but internal elements of the processes implemented. Therefore, the starting point for managing knowledge resources in an organisation is understanding and accurately defining them. Previous research shows that creating knowledge management process models in organisations has a positive effect on generating innovation, stimulating the creativity of employees, and supporting internal communication (Anna, 2014; Bitkowska, 2017b, 2020; Kulesza & Rakowska, 2018; Sobolewska & Bitkowska, 2020).

## 1.2. Integration determinants for business process and knowledge management

The primary objectives of process management include, inter alia, standardisation and integration of the organisation's activities, which should potentially facilitate the prediction of ongoing processes, e.g., production, service provision, environmental changeability, etc. (Team, 2010; Bitkowska, 2017a; Sobolewska & Bitkowska, 2020; Bracci, Gobbo & Papi, 2022; Harymawan et al., 2022; Ispas & Mironeasa, 2022; Lopes et al., 2022; Silvestre, Fonseca & Morioka, 2022). Meanwhile, integration within process management and knowledge management should be manifested, e.g., in the pursuit of:

- improving access to services or products,
- appropriate quality of services/products in line with customer expectations,
- efficient use of resources,
- improving the flow efficiency of material streams,
- elimination of unnecessary or ineffective processes,
- shortening the duration of selected processes,
- improving the efficiency and effectiveness of IT systems,
- high flexibility of processes according to the needs of customers and other stakeholder groups,
- cost rationalisation (Detyna, 2016; Pereira, Barbosa & Duarte, 2020; Harymawan et al., 2022).

However, the growing complexity of processes carried out in companies limits the possibilities of their control by individual employees. One way of solving emerging problems may be to use various forms of teamwork, which gives a greater possibility:

- to deal with a wider range of problems beyond the scope of individual employees,
- to use various experiences, skills, predispositions, and knowledge,
- to solve problems characterised by complexity and a wider range of impact, usually concerning many organisational structures at the same time,
- to positively impact the motivation and satisfaction of employees,
- to easier implement recommendations resulting from the team's work compared to the implementation of individual ideas (Detyna, Detyna & Dudek-Kajewska, 2016; Bilas & Adeeb, 2017; Detyna, 2018; Chromjakova, Trentesaux & Kwarteng, 2021; Kir & Erdogan, 2021; Marín-González & Pérez-González, 2021; Tubis & Werbińska-Wojciechowska, 2021).

In light of scientific research, teamwork features are a key element in improving processes (including management) and creating the basis for constructing methods supporting the increase in employee engagement. However, their adequate motivation, ensuring the suitable group work, requires the management's involvement. The manager's role is primarily to create conditions for team problem-solving, creating a sense of acceptance and responsibility for decisions made (Govender & Parumasur, 2010; Bilas & Adeeb, 2017; Riyanto, Endri & Herlisha, 2021). Business specialists believe that process management effectiveness depends on management support (Baumgartner, 2011; Muntean, 2018; Schwartz et al., 2020; Adam, Hofbauer & Stehling, 2021). The main problems include competition from other process groups (teams) within the organisation, conflicts and quarrels over process solutions, and the lack of focus on process management. It also indicates the need for an integrated approach, in which the IT department works closely not only with business analysts, Six Sigma or Lean groups but also with individual process groups (Harmon, 2020). The main obstacles to the implementation and functioning of BPM and KM practices include the use of several techniques to analyse business processes. In the "BPTrends State of Business Process Management — 2020 Report", the most frequently indicated challenges related to the exploration of enterprise processes were financial aspects, including budgeting (46 %), the lack of know-how (55 %) and the lack of management support (45 %). These findings revealed gaps to be filled for organisations to strengthen the efficiency of processes with the possibility of exploring them and implementing innovative solutions (Harmon, 2021).

In this context, it should be clearly emphasised that for process and knowledge management to be effective and perceptible by customers and employees, managers need to concentrate on the processes. It is necessary to integrate equipment, including IT tools, activities, knowledge, employees, cooperating companies, etc.

### 1.3. IT systems for the integration of business process management and knowledge management

In the context of the article's subject, interesting data has been published based on the BPM Pulse study, actively involving over 450 organisations in April–May 2021 (BPM, 2021a). The conclusions of the report are as follows:

- According to the organisations surveyed, BPM applications are very effective in automating routine tasks, i.e., budgeting, planning, and forecasting, consolidation, and reporting. Businesses need measurement, analysis, and visibility in a wide range of management tasks, and many non-finance users are ready to deploy BPM applications in their workplaces (BPM, 2017);
- Vendors of business process management software increasingly recognise the importance of Artificial Intelligence (AI) capabilities in their products. Most software vendors currently have some AI-based features or are in the process of developing them. At the same time, only a few respondents perceive artificial intelligence as a strategic, crucial element in the management system. Financial services companies seem most interested (BPM, 2018).

Researchers and business practitioners are inspired by the comparisons and summaries of survey results published in cyclical BPTrends reports. The BPTrends 2021 report summarises the results for 2006, 2010, 2012, 2014, 2016, 2018, and 2020. This review demonstrates how BPM practitioners have changed the perception of business process management and knowledge issues as an organisation's resource over the last 16 years (Harmon, 2020). One hundred twenty-nine respondents actively participated in the survey, with the largest group of companies from Europe (36 %), followed by North America (29 %), Central and South America (15 %), Africa and the Middle East (12 %), and Eastern South Asia (5 %). Organisations from China, Japan, Korea, Australia and New Zealand accounted for 4 %. Respondents mentioned tools, including IT software used by the organisation to manage knowledge resources and model processes. There are two types of BPM solutions: those used to build diagrams (e.g., Visio) and those used to define processes, i.e., store models in a database. According to Harmon, the use of process modelling tools has not changed practically over the last two years. In 2017, 58 % of respondents used BPM software for process modelling. In 2019, the percentage was higher (70 %). This increase is assessed as rather small, considering that IT solutions for BPM have been on the market for over 20 years, and in recent years, there has been a significant evolution with the addition of countless new technologies and modules. The study group saw increased use of formal BPM tools for process modelling, e.g., AuraPortal, Bizagi, IBM Blueworks Live, Signavio, Pega BPM, and Software AG ARIS. Meanwhile, a large number of users still rely on tools that simply perform the function of defining process diagrams (i.e., Microsoft Visio, Lucidchart, and even Microsoft PowerPoint), which do not support business process management in its broader scope, considering additional functionalities (in the field of design and modelling processes, implementation and execution). Currently, organisations still have difficulties understanding, evaluating, and choosing the right software for their business. The market offers intelligent applications for business process management (iBPMS), business software for process automation (BPA —

Business Process Automation), and a tool for the automation of robotic processes (Robotic Process Automation — RPA). This choice makes it increasingly difficult for organisations to adopt the best solution (Harmon, 2020).

## 2. Materials and methods

The data source published in this article is a survey conducted in 2020 among 107 organisations operating in Poland. They were territorial enterprises: international (48 %), national (39 %), regional (6 %) and local (6 %), Fig. 1. The dominant group of respondents was private companies with mixed Polish and foreign capital (36 %), then, private companies with Polish capital only (31 %), State Treasury companies (18 %), and private companies with foreign capital only (11 %), Fig. 2. The research sample is represented by large (55 %), medium-sized enterprises (22 %), small (19 %), and micro-enterprises employing up to nine employees (4 %), Fig. 3. The organisations surveyed included enterprises operating in various industries: production (18 %), logistics (11 %), banking (11 %), IT (8 %), telecommunications/media (7 %), public administration (7 %), insurance (6 %), healthcare/pharmaceuticals (6 %), transport (5 %), consultancy (4 %), energy (1 %), construction (1 %) and others (15 % in total). The structure of the industries represented by the surveyed organisations is presented in Fig. 4.

In statistical research, it is often necessary to establish the relationship between two features, X and Y, both of which (or at least one) are qualitative. In such a situation, multi-way tables (contingency tables) are built with a specified number of rows and columns, including numbers of individual variants of features. The chi-square test of independence was used to assess the dependence of the variables studied in this publication. The study of interdependence is justified only when there are stochastic or at least correlational relationships between the variables. The study of stochastic independence based on the equality of conditional means and conditional variances is possible only in the case of measurable features. However, in statistical research, the necessity is also encountered to assess the stochastic independence of immeasurable features. In such cases, the chi-square test of independence enables the verification of the variable independence (Rubin & Levin, 2013).

The nonparametric null hypothesis states that the n-element random sample comes from a general population with stochastic independence of the random variables X and Y. The wording of both hypotheses is as follows:

$H_0$: X and Y features are independent,

$H_1$: the features of X and Y are interdependent.

The chi-square statistic is used to verify H0 with stochastic independence of variables (Sobczyk, 2022). The value of this statistic depends on three factors:

- the strength of the relationship between the investigated features: the greater the differences between the empirical and theoretical numbers, the greater the value of the chi-square statistic, and thus, the greater the strength of the relationship,
- the sample size, which, according to the test requirements, should be large,
- the level of detail of data grouping; it is required that the empirical counts in each field of the independence table be at least eight and at least not below five.

The literature assumes that if the analysis of the multi-way table shows a relationship between the two considered features (verified by, e.g., the chi-square test of independence), then its strength should be determined. The literature on the subject provides many measures of the relationship strength between two features expressed on nominal scales (Rubin & Levin, 2013; Sobczyk, 2022). One of these is Pearson's contingency coefficient C, used in this publication. It can be used with multi-way tables of any size (the minimum number of fields is four) and any form (rectangular or square). Theoretically, Pearson's contingency coefficient can take values from 0 (features are independent) to 1 (when the number of fields in the table increases to infinity). Determining the maximum values of the $C_{max}$ contingency coefficient for square and rectangular tables has been described in detail in the statistical literature (Sobczyk, 2022). Considering this value, the adjusted value of the contingency coefficient is often determined as a relative measure based on the relationship:

$$C^* = \frac{C}{C_{\max}} \qquad (1)$$

In addition, for the purpose of this article, one of the modern statistical modelling methods — Partial Least Squares (PLS) — was used. Modelling in economics or management and quality sciences, or, more broadly, social sciences, refers to the creation, disclo-

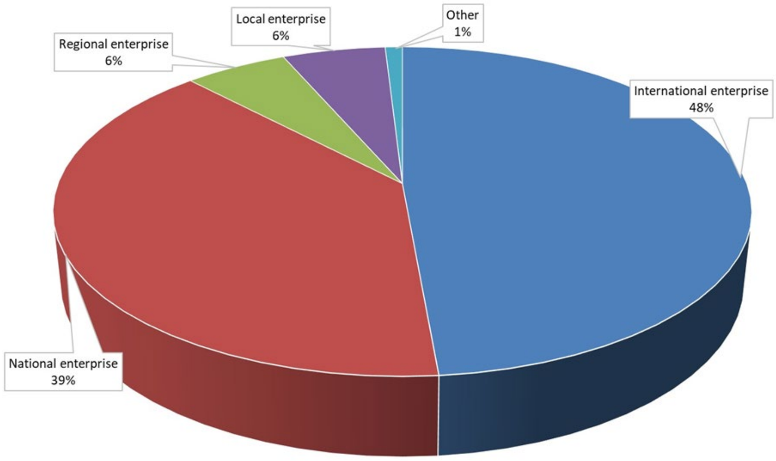



Fig. 1. Territorial scope of the activity conducted by the surveyed organisations

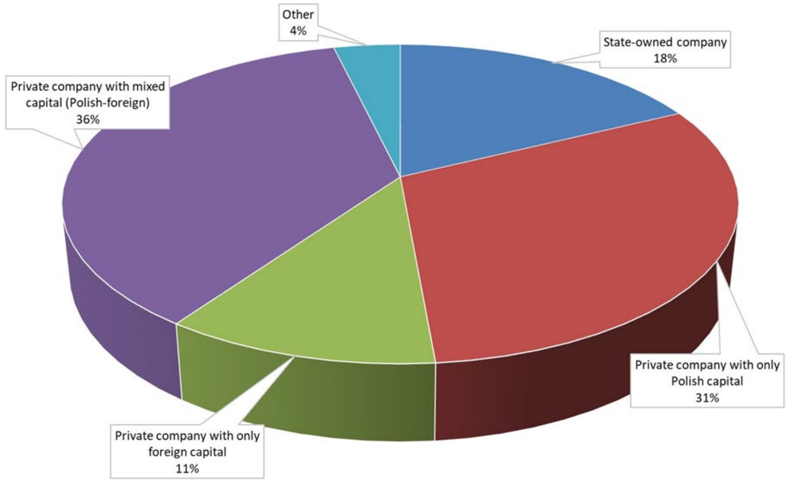



Fig. 2. Form of ownership of the surveyed organisations

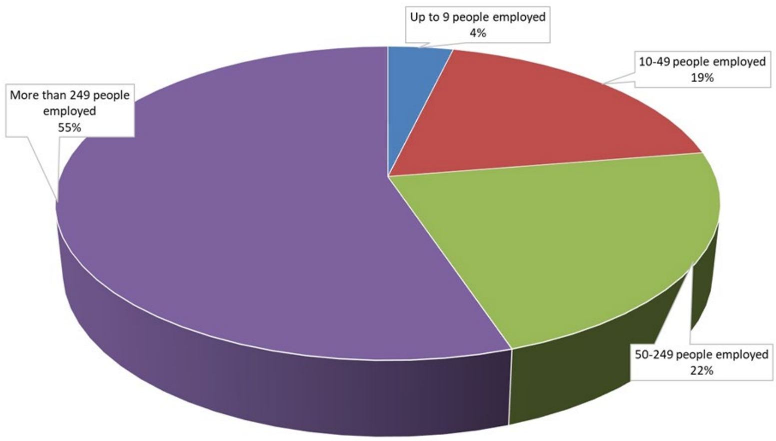



Fig. 3. Size of the surveyed organisations by the number of employees

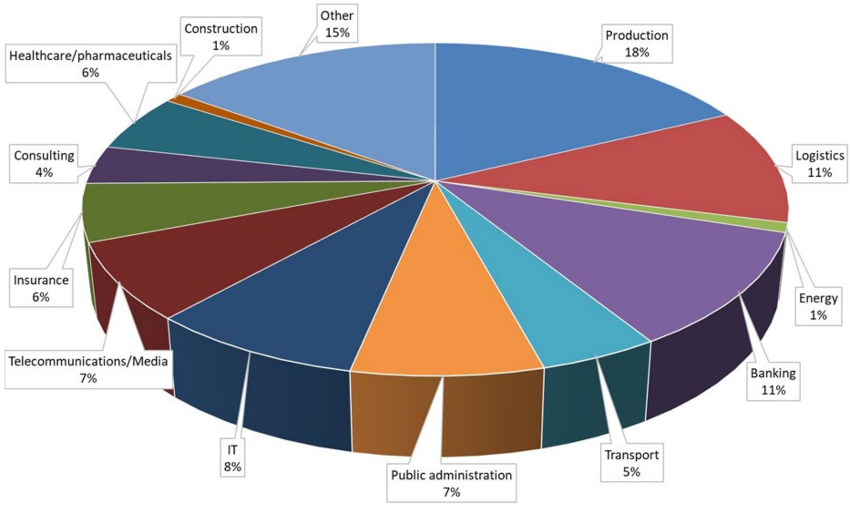



Fig. 4. Industries represented by the surveyed organisations

sure, and verification of relationship structures between the investigated elements. A given model illustrates the relational relationships, usually cause-and-effect relationships of the impact nature, occurring between the concepts or factors that are the research subject. Auch a relationship assumes that existing influencing factors (explanatory, independent, causal variables) impact the behaviour of some effect factors (dependent and effect variables). It is also possible for these factors to influence each other. In social sciences, these factors are often abstract and relate to concepts that are directly immeasurable (e.g., customer value, satisfaction, loyalty, experience, attractiveness, etc.).

The model simplifies the image of these relations: in essence, it assumes the omission of some reality's fragment, usually elements with a smaller scale of influence, less significant or unknowable. The model is a reflection of the theory, hypotheses or assumptions adopted by the researcher and is subject to empirical verification; therefore, it requires appropriate research and results analysis using appropriate methods (Biesok & Wyród-Wróbel, 2016).

The PLS-DA method was described for the first time in the late 1980s as a method aiming to find and visualise the maximum covariance between the input data and the predefined information related to belonging to a given class. This is the same as in the case of PCA. This is done by a linear transformation of the input data to a new orthogonal coordinate system, the so-called latent components (LC). The first LC reflects the maximum variability between classes (Sjöström, Wold & Söderström, 1986; Ståhle & Wold, 1987).

The quality of the PLS-DA model is determined by three parameters:

- the sum of squares of the data X, explained by the hidden components extracted,
- the sum of squares of data Y, explained by the hidden components extracted,
- the predictive ability of the model, defined by the sum of squares of the prediction error for all the extracted components.

As in the case of PCA, the number of identifiable hidden components depends on the order of the X matrix (bold – designation of a vector, matrix); however, this time, the selection of an appropriate number is crucial for ensuring the correct functioning of the model. The significance of the input variables in case factor loadings and weight plots is usually assessed visually: the further a given variable is from the centre of the action, the more significant it is. Such an assessment largely depends on the operator's experience and knowledge of the nature of the analysed data. In addition, the PLS-DA model allows the significance of input variables (variable importance — VIP) to be determined based on the absolute value of weights for a given variable, multiplied by the R2Y value for a given hidden component, which allows for the visual method's verification. It is assumed that the value of VIP> 1 allows for the recognition of a given variable as significant in the projection of the Y matrix. All the methods of statistical analysis presented above were performed using the TIBCO Statistica v. 13.3 statistical package.

# 3. Results

The methods used for the analyses — the chi-square test and Pearson's contingency coefficient C — also allowed linking the business process management activities in companies with their storage and use of knowledge resources. The statistical connection of business process management with the storage and use of knowledge resources in analysed organisations is presented in Table 1. The maximum value of the contingency coefficient for the investigated variables, in this case, is $C_{max}$ (2x2) = 0.707. Considering this value, it can be stated that in most cases, the strength of connections is moderate, and in some cases, it is relatively high (C*> 0.5).

The greatest strength of connections was noted between the process simulation areas in the surveyed organisations and the process risks registered by them (C* = 0.625) and the use of so-called other process documents (C* = 0.520). A relatively high degree of association was also noted between process modelling and the storage of knowledge resources in the form of process models and their subsequent versions (C* = 0.605). A comparatively high rate was obtained by examining the strength of the relationship between the risk assessment in processes and the recording of these risks (C* = 0.549).

Tab. 1. Statistical connection of process management with the storage and use of knowledge resources in the surveyed organisations ($C_{max}$ (2x2) = 0.707)

| Process activities | Knowledge resources | Significant dependencies, chi-square test, p<0.05 | |
|---|---|---|---|
| | | p-value | Contingency coefficient *C** |
| Identification of processes in the company | Process models and their successive versions | 0.00126 | 0.412 |
| | Results from process audits | 0.00213 | 0.400 |
| | KPI performance indicators assigned to appropriate processes | 0.02017 | 0.304 |
| | Procedures and instructions assigned to processes | 0.00028 | 0.464 |
| | Risk registers of process | 0.00013 | 0.472 |
| Modelling of processes in the company | Process models and their successive versions | 0.00000 | 0.605 |
| | Database of good trial practices | 0.02331 | 0.303 |
| | KPI performance indicators assigned to appropriate processes | 0.00008 | 0.499 |
| | Procedures and instructions assigned to processes | 0.00778 | 0.351 |
| Optimisation of processes in the company | KPI performance indicators assigned to appropriate processes | 0.00791 | 0.335 |
| Simulation of processes in the company | Process models and their successive versions | 0.03738 | 0.279 |
| | Results from process audits | 0.00992 | 0.337 |
| | Database of good trial practices | 0.03928 | 0.276 |
| | KPI performance indicators assigned to appropriate processes | 0.00064 | 0.443 |
| | Procedures and instructions assigned to processes | 0.00218 | 0.396 |
| | Other documents from the processes | 0.00004 | 0.520 |
| | Risk registers of process | 0.00000 | 0.625 |
| Improving processes in the company | Database of good trial practices | 0.01096 | 0.330 |
| | Other documents from the processes | 0.00426 | 0.373 |
| | Risk registers of process | 0.00021 | 0.454 |
| Controlling processes in the company | Process models and their successive versions | 0.02662 | 0.293 |
| | KPI performance indicators assigned to appropriate processes | 0.00041 | 0.443 |
| | Risk registers of process | 0.02021 | 0.304 |
| Risk assessment in processes | Other documents from the processes | 0.00643 | 0.362 |
| | Risk registers of process | 0.00001 | 0.549 |

One of the key tasks in modelling PLS relationships is the selection of variables (predictors). A dedicated module was used in the Statistica v. 13.3 program, i.e., Selection of Variables from the area of Data Mining Analyses. Of all the variables resulting from the respondents' answers, the selected were statistically related to the so-called effect factors, differently explained, or caused (significance level $p < 0.05$ for the chi-square test). The lower the p-value, the smaller the error of the first type made when rejecting the null hypothesis (H0) about the independence of the variables (the hypothesis was rejected more strongly). The analysis considers three effect factors:

- quality of process implementation,
- optimisation of key performance indicators (KPIs), costs and process time,
- customer satisfaction.

A specific ranking of the so-called influencing factors (explanatory, causal) that are statistically significantly related to the quality of process implementation is presented in Table 2 and Fig. 5. The most strongly related variables in this context are the use of IT systems for process modelling, the use of IT systems for process optimisation, and the use of IT systems for process identification.

Table 5 and Fig. 6 present the factor selection results for influencing the optimisation of KPIs, costs and process time. The most closely related variables in this context are KPI performance indicators assigned to the respective processes, the use of KPIs and the implementation of IT tools supporting business process management.

Tab. 2. Results of the selection of variables in the PLS analysis concerning the quality improvement of process implementation in the surveyed organisations

| Variable | Best predictors for categorical dependent var: Increasing the quality of process implementation | |
|---|---|---|
| | Chi-square | p-value |
| Use of IT systems for process modelling | 47.81 | 0.000003 |
| Use of IT systems for process optimisation | 36.86 | 0.000236 |
| Use of IT systems to identify processes | 33.56 | 0.000792 |
| Use of IT systems for process improvement | 28.47 | 0.004722 |
| Implementation of risk management in processes | 12.25 | 0.006580 |
| Process models and their successive versions | 11.43 | 0.009615 |
| Implementation of IT tools supporting process management | 8.25 | 0.041205 |
| Employee training in process management/process improvement | 7.95 | 0.047006 |

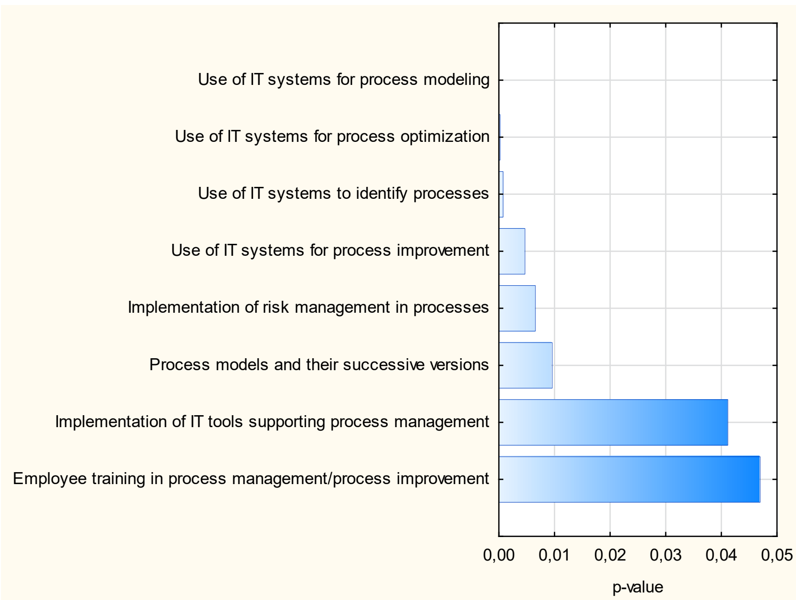



Fig. 5. Results of the selection of variables in the PLS analysis concerning the quality improvement of process implementation in the surveyed organisations

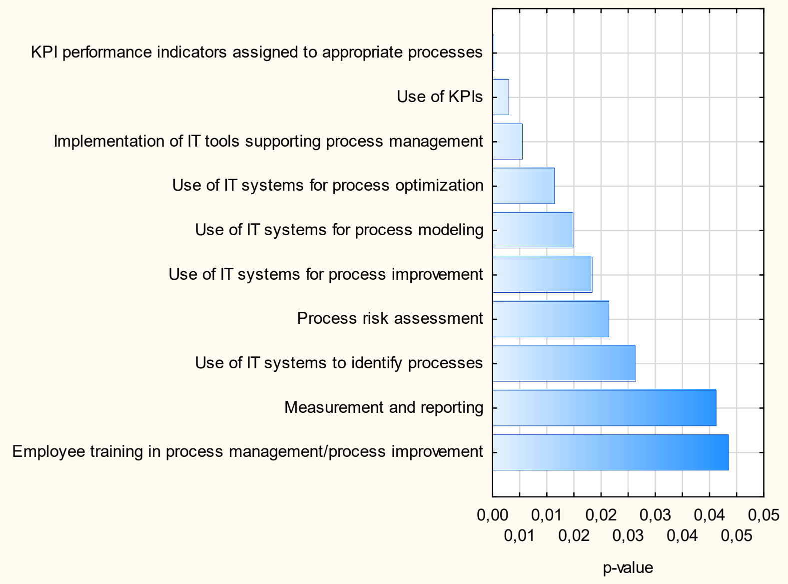



Fig. 6. Results of the variable selection in the PLS analysis regarding the optimisation of KPI, costs and time of processes in the analysed organisations

Tab. 3. Results of the variable selection in the PLS analysis regarding the optimisation of KPI, costs and time of processes in the analysed organisations

| Variable | Best predictors for categorical dependent var: Optimisation of KPIs, costs and processes time | |
|---|---|---|
| | Chi-square | p-value |
| KPI performance indicators assigned to appropriate processes | 21.32 | 0.000274 |
| Use of KPIs | 16.01 | 0.003005 |
| Implementation of IT tools supporting process management | 14.63 | 0.005530 |
| Use of IT systems for process optimisation | 31.55 | 0.011446 |
| Use of IT systems for process modelling | 30.66 | 0.014868 |
| Use of IT systems for process improvement | 29.93 | 0.018380 |
| Process risk assessment | 11.50 | 0.021474 |
| Use of IT systems to identify processes | 28.65 | 0.026416 |
| Measurement and reporting | 9.95 | 0.041249 |
| Employee training in process management/process improvement | 9.82 | 0.043531 |

Tab. 4. Results of the variable selection in the PLS analysis regarding the increase in customer satisfaction in the surveyed organisations

| Variable | Best predictors for categorical dependent var: Increase in customer satisfaction | |
|---|---|---|
| | Chi-square | p-value |
| Use of IT systems for process monitoring | 37.28 | 0.000201 |
| Implementation of IT tools supporting process management | 13.43 | 0.003796 |
| Use of IT systems for process modelling | 28.80 | 0.004213 |
| Use of IT systems to identify processes | 27.25 | 0.007116 |
| Simulation of processes in the company | 11.33 | 0.010058 |
| Use of Cloud Computing | 10.22 | 0.016788 |
| Implementation of risk management in processes | 9.33 | 0.025209 |
| Procedures and instructions assigned to processes | 9.20 | 0.026712 |
| Employee training in process management/process improvement | 8.69 | 0.033744 |

Tab. 5. Results of the PLS analysis for the dependent variable: improvement of the quality of the implemented processes

| Variable | Variable importance Number of components is 2 | |
|---|---|---|
| | VIP | Importance |
| Use of IT systems for process modelling {To a very large extent, for all processes} | 2.191 t1 | 1 |
| Use of IT systems to identify processes {To a very large extent, for all processes} | 1.392 t1 | 2 |
| Use of IT systems for process optimisation {To a very large extent, for all processes} | 1.352 t1 | 3 |
| Use of IT systems for process improvement {To a very large extent, for all processes} | 1.317 t1 | 4 |
| Process models and their successive versions {Yes} | 1.257 t1, t2 | 6 |
| Process models and their successive versions {No} | 1.257 t1, t2 | 6 |
| Use of IT systems to identify processes {To a small extent for single processes} | 1.242 t2 | 7 |
| Implementation of risk management in processes {Yes} | 1.217 t2 | 9 |
| Implementation of risk management in processes {No} | 1.217 t2 | 9 |
| Use of IT systems for process modelling {To a small extent for single processes} | 1.213 t1 | 10 |
| Use of IT systems for process improvement {To a small extent for single processes} | 1.019 t2 | 11 |

Tab. 6. Results of the PLS analysis for the dependent variable: optimisation of KPI, costs and process time

| Variable | Variable importance Number of components is 2 | |
|---|---|---|
| | VIP | Importance |
| Use of IT systems for process optimisation {To a very large extent, for all processes} | 1.512 t2 | 1 |
| KPI performance indicators assigned to appropriate processes {Yes} | 1.452 t1 | 3 |
| KPI performance indicators assigned to appropriate processes {No} | 1.452 t1 | 3 |
| Use of IT systems to identify processes {To a very large extent, for all processes} | 1.409 t2 | 4 |
| Use of KPIs {Yes} | 1.328 t1 | 6 |
| Use of KPIs {No} | 1.328 t1 | 6 |
| Use of IT systems for process modelling {To a very large extent, for all processes} | 1.302 t2 | 7 |
| Use of IT systems for process improvement {To a very large extent, for all processes} | 1.190 t2 | 8 |
| Process risk assessment {Yes} | 1.138 t1, t3 | 10 |
| Process risk assessment {No} | 1.138 t1, t3 | 10 |
| Implementation of IT tools supporting process management {Yes} | 1.103 t1 | 12 |
| Implementation of IT tools supporting process management {No} | 1.103 t1 | 12 |
| Measurement and reporting {Yes} | 1.042 t1, t3 | 14 |
| Measurement and reporting {No} | 1.042 t1, t3 | 14 |
| Use of IT systems for process improvement {To a large extent} | 1.006 t2 | 15 |

The variable selection results for the PLS analysis regarding the third effect factor — increasing customer satisfaction in the organisations surveyed — are shown in Table 6 and Fig. 7. The best predictors for this factor include the use of IT systems for process monitoring, the implementation of IT tools supporting business process management, the use of IT systems for modelling processes, and using them to identify processes.

The results of the PLS analysis concerning individual effect factors are presented in Tables 2–7 and Figs. 8–10. Tables 2–7 present only those variables for which the VIP coefficient (i.e., the importance of the variable) has values greater than 1. The higher the VIP value, the greater the importance of a given variable. Table 7 presents a list of variables according to their strength of influence on the quality of processes implemented in companies.

A cause-and-effect model was built in the computer package Statistica v. 13.3. (PCA Analysis module, PLS) only for previously selected variables (predictors), which, based on the chi-square independence test, showed a statistical relationship with the dependent variable under investigation (improve-

Tab. 7. Results of the PLS analysis for the dependent variable: increased customer satisfaction

| Variable | Variable importance Number of components is 2 | |
|---|---|---|
| | VIP | Importance |
| Use of IT systems for process monitoring {To a very large extent, for all processes} | 1.372 t1 | 1 |
| Use of IT systems to identify processes {In a medium range, the main processes} | 1.337 t2 | 2 |
| Use of IT systems for process modelling {To a small extent for single processes} | 1.277 t3 | 3 |
| Implementation of IT tools supporting process management {Yes} | 1.169 t1 | 5 |
| Implementation of IT tools supporting process management {No} | 1.169 t1 | 5 |
| Use of IT systems to identify processes {To a very large extent, for all processes} | 1.100 t2 | 6 |
| Simulation of processes in the company {Yes} | 1.073 t1 | 8 |
| Simulation of processes in the company {No} | 1.073 t1 | 8 |
| Procedures and instructions assigned to processes {Yes} | 1.058 t2 | 10 |
| Procedures and instructions assigned to processes {No} | 1.058 t2 | 10 |
| Cloud Computing Usage {Yes} | 1.038 t2, t3 | 12 |
| Cloud Computing Usage {No} | 1.038 t2, t3 | 12 |
| Implementation of risk management in processes {Yes} | 1.021 t2 | 14 |
| Implementation of risk management in processes {No} | 1.021 t2 | 14 |

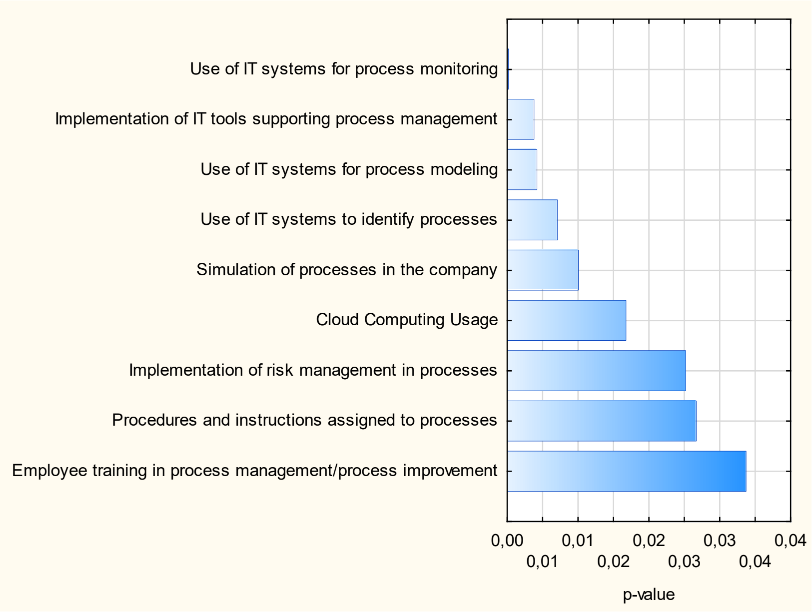



Fig. 7. Results of the variable selection in the PLS analysis regarding the increase in customer satisfaction in the surveyed organisations

ment of the quality of implementation processes). In this case, during the PLS analysis on the basis of the input variables, two principal components (t1, t2) were determined, which are related to the weight of the investigated explanatory variables (responses from the questionnaires in the left column of Table 5). The main first component (t1) plays a more important role as it is related to the use of IT systems in business process management. Such factors as the use of IT systems for process modelling, identification, optimisation, and improvement have the most substantial influence on process quality improvement.

An attractive graphical presentation of the studied factor dependence and the variable improving the quality of process implementation is a biplot (here, specifically a bagplot or in other words bag graph), which shows how the responses regarding the process quality correlate with answers to the questions concerning the selected variables (Fig. 8). It is visible that the improvement of the quality of process implemen-

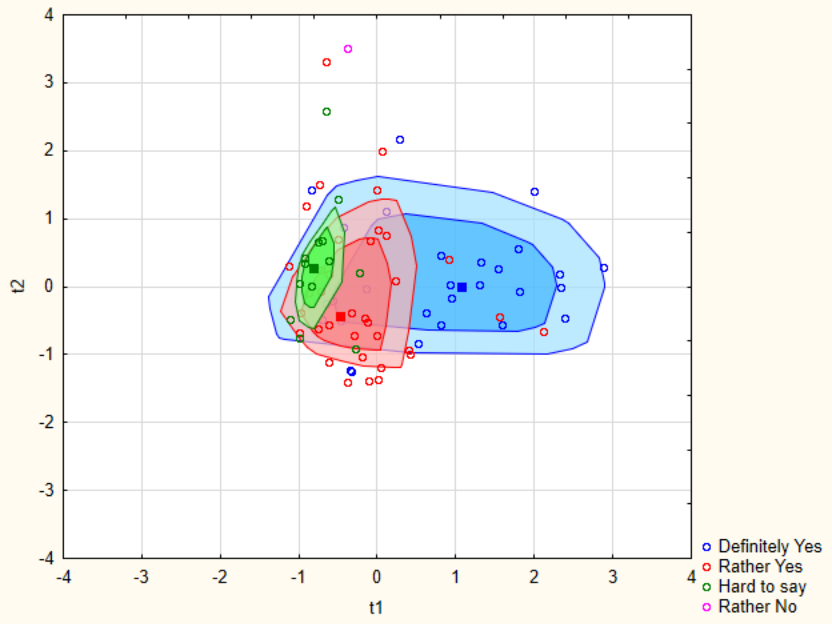



Fig. 8. Standardised biplot (t1 vs. t2): increasing the quality of process implementation

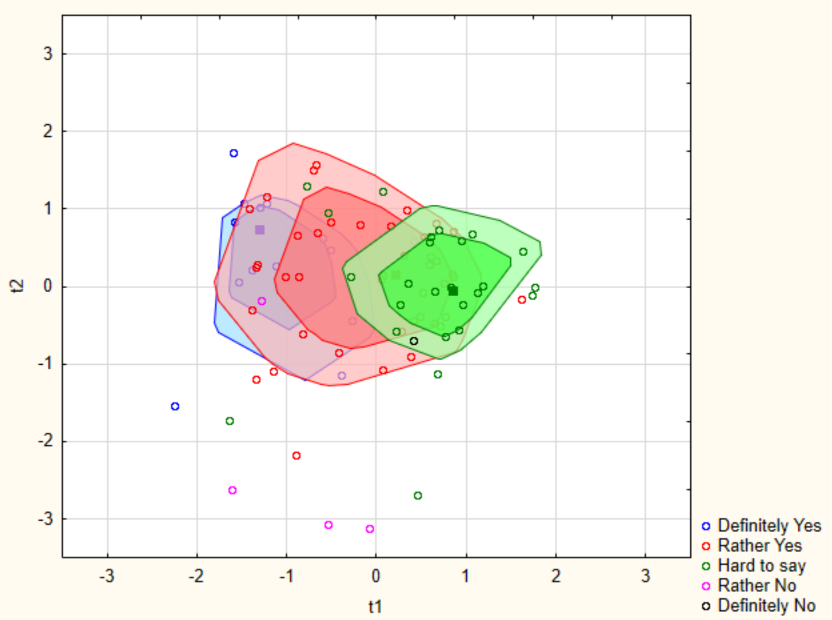



Fig. 9. Standardised biplot (t1 vs. t2): optimisation of KPIs, costs and processes time

tation (Definitely Yes) proceeds along the first principal component (t1, horizontal axis), which is related to the responses most strongly associated with this variable (Table 5), i.e., with very strong use of IT systems for modelling, identification, optimisation, and process improvement. This group of respondents is represented the strongest in the chart (Fig. 8) (blue bag). The answer of the respondents, "Hard to say", is visible in the green "bag", i.e., slightly to the right along the t1 component and slightly in the positive direction for the t2 part (the group of respondents is relatively small). This applies to companies that use IT systems to a lesser extent to identify processes (including individual), their modelling, and improvement. These companies can store knowledge resources about process models and their subsequent versions, and initiatives are planned for the implementation of risk management in processes (t2 component). Single points indicate the answer "Rather No", and the absence of the answer "Definitely No" is noticeable.

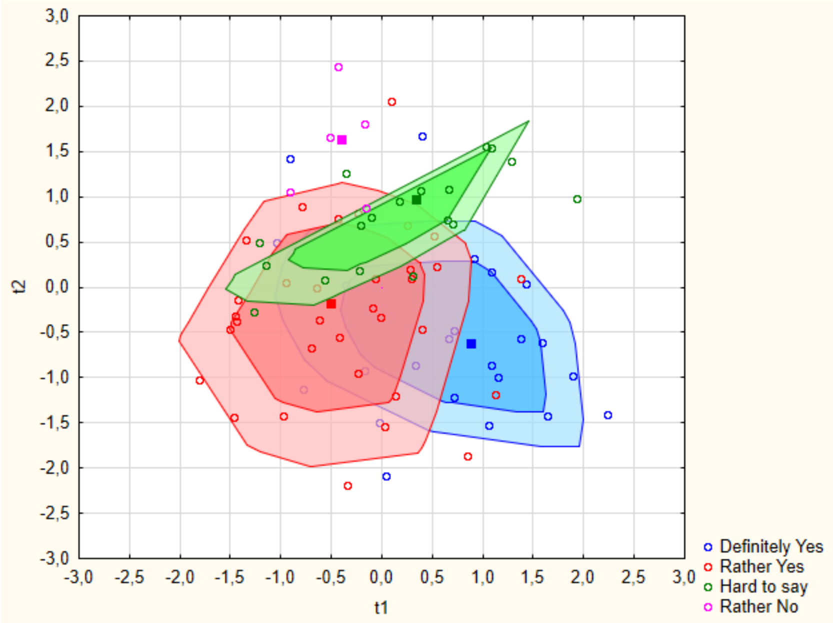



Fig. 10. Standardised biplot (t1 vs. t2): increasing the level of customer satisfaction

The results of the PLS analysis for the dependent variable KPI, cost and process time optimisation are presented in Table 6 and Fig. 9. The variables that have the strongest impact on the improvement of KPIs are use of IT systems to optimise processes, assigned KPIs to relevant processes and use of IT systems for process identification (very much for all processes). The bag graph (Fig. 9) does not show a clear correlation of observations with the main components. A large number of responses are concentrated in the central part of the graph, which may indicate a variation in the value of the predictors in relation to KPI optimisation, costs, and process execution time. Many predictors have a higher weight assigned to the principal component t2, even the most important value, "Use of IT systems for process optimisation {To a very large extent, for all processes}". However, two predictors directly related to KPI optimisation, namely, KPI performance indicators assigned to appropriate processes and use of KPIs, are assigned to the main component t1, which explains a much larger part of the dependent variable's variance. In addition, the chart shows that the largest part is taken up by "Rather Yes" responses and a relatively extensive set of "Hard to say" responses. This indicates that the respondents are less determined with regard to the optimisation of KPIs, costs and process time in relation to the previously described dependent variable.

PLS results for the dependent variable increasing the level of customer satisfaction are presented in Table 7 and Fig. 10. The causal variables that have the strongest impact on customer satisfaction are the use of IT systems for process monitoring, identification, modelling, and implementation of IT tools supporting business process management. A large proportion of respondents using IT tools indicate an increase in the level of customer satisfaction (Fig. 10, blue and red areas). It is not without significance, however, that there is quite a large group of undecided respondents who answered "Hard to say" (green area in Fig. 10), mainly those who use IT tools to a small or medium extent for individual processes. Single respondents (responding "Rather No") do not observe an increase in the level of customer satisfaction (although not definitely, because there were no such answers) using knowledge management methods and IT tools for business process management indicated here.

# 4. Discussion, implications and concluding remarks

## 4.1. Theory contributions

Comparing the research results with literature reports on the subject confirmed the significant connections between the use of IT systems, the level of business process management development and knowledge management, and the quality of processes implemented in companies, their effectiveness, and the level of customer satisfaction.

The research found that the knowledge resources stored by respondents most often include the results of process audits, databases of good process practices, KPI performance indicators assigned to appropriate processes, procedures and instructions assigned to processes, and other documents from processes or process risk registers. Statistically, the strongest links between the storage and use of knowledge resources by companies and a given industry concern the IT and banking sectors.

The greatest strength of connections between business process management practices and the methods of storing and using knowledge resources was noted between simulating processes in organisations and the process risks registered by them. A relatively high degree of association was noted between process modelling and storing knowledge resources in the form of process models and their subsequent versions. A comparatively high rate was obtained by examining the strength of the relationship between risk assessment in processes and recording these risks.

The research methodology allowed the authors to identify influencing (causal) factors statistically significantly related to the quality of processes, their effectiveness, and the level of customer satisfaction, which is the essence of the study. Thus, process implementation quality is most strongly influenced by such variables as the use of IT systems for modelling, optimisation, and identification of processes. In turn, the optimisation of KPIs, costs and process time is most influenced by variables in the form of KPI performance indicators assigned to appropriate processes, the use of these indicators, and the implementation of IT tools supporting business process management.

The strongest predictors influencing the increase of customer satisfaction in the surveyed organisations include the use of IT systems to identify, model, and monitor processes and the implementation of IT tools supporting business process management.

### 4.2. Implications for practice

The value of the presented research results has cognitive and utilitarian aspects. The presented material can support the decision-making processes of managers of various organisation types in fully understanding the IT systems' role and potential in process management. The implications shown in the article are also a source of guidelines that help organisations implement management systems based on modern technologies. The practical value of the publication is a wide range of respondents, i.e., 107 large, medium, small and micro-enterprises operating in Poland. In the literature on the subject, the dominant industries described in the context of using IT systems in BPM or knowledge management are finance, insurance, banking, trade, and logistics. The research results concern banking, insurance and logistics, production, IT, telecommunications/media, public administration, health care/pharmaceuticals, transport, consulting, energy, and construction.

The research results confirmed that IT systems and knowledge management processes are strongly integrated into enterprise management processes. Noticed by the management, these implications may result in appropriate and correct decisions regarding proper planning, organisation, monitoring, and improvement of management processes at every stage of the company's operations. It will be beneficial for companies to raise employee awareness of the IT systems' role and their personal commitment to the effectiveness and efficiency of the knowledge management system or BPM functioning in the organisation.

Proper identification of key knowledge management processes and the relationships between them, as well as the appropriate use of evidence-based information, experience, and competences of employees, are the conditions for the effective building (strengthening) of intellectual capital. This capital is unique for each organisation and is often not fully used as a source of competitive advantage. This publication may improve the awareness of the management staff and process owners responsible for specific tasks (projects).

### 4.3. Limitations and future research directions

The limitations of the presented research results refer to the adopted methodology, which was based on a diagnostic survey conducted using the proprietary questionnaire form. Despite its considerable diversity and relatively large number, the group of respondents is not a representative sample as it does not reflect the structure of enterprises operating in Poland. Manufacturing companies represented the largest group of respondents (18 %). Despite being broadly represented in the context of industries, not all sectors were represented.

Bearing in mind the specificity of each enterprise, it would be advisable to plan future research dedicated to specific sectors (industries), including the division into the private and public sectors. Contemporary geopolitical, socio-economic, and technological challenges do not only concern the private sphere. The rapidly changing expectations of customers also apply to public services that are often overlooked in research work (education, science, culture, local governments, etc.). Research dedicated to individual groups of organisations could significantly contribute to their development, including the acceleration of improvement activities with the use of new information technologies.

The literature review and the obtained empirical research results regarding the role of IT systems in integrating business process management and knowledge management indicate numerous directions of possible further research in this field. In this context, further research is particularly recommended by the authors:

- improvement of BPM systems and knowledge management,
- improvement of IT methods and tools used in process management and knowledge management,
- concepts, methods, and IT tools for the integration of knowledge management and BPM,
- models of integrated management systems in enterprises of various sectors and industries,
- research on the specificity of BPM and knowledge management in the public sector,
- new concepts and solutions in the field of sharing dedicated databases, as well as software for various types of organisations,
- tools for monitoring the effectiveness, efficiency and capacity of systems and processes in enterprises and within the created networks of enterprises,
- tools for monitoring management processes, main and auxiliary organisations,
- the role of IT systems in the development of process maturity of enterprises,
- creating new models of knowledge management maturity,
- research in the field of creating models of process maturity dedicated to cooperating organisations (networks, consortia, etc.),
- research on the effectiveness of IT systems used in companies,
- research on organisational structures, their flexibility and ability to achieve the set goals, including in the BMP context, knowledge management and the introduction of innovative management and organisational solutions,
- analyses and proposals regarding the usability of IT tools in the field of cooperation between enterprises and their clients,
- proposals for streamlining and increasing the efficiency of systems monitoring organisational and management processes.

# Literature


Adam, M., Hofbauer, M., & Stehling, M. (2021). Effectiveness of a lean simulation training: challenges, measures and recommendations. *Production Planning and Control*, *32*(6), 443-453. doi: 10.1080/09537287.2020.1742375

AlShathry, O. (2016). Business process management: a maturity assessment of Saudi Arabian organizations. *Business Process Management Journal*, *22*(3), 507-521. doi: 10.1108/BPMJ-072015-0101

Anderson, H., Müllern, T., & Danilovic, M. (2023). Exploring barriers to collaborative innovation in supply chains – a study of a supplier and two of its industrial customers. *Business Process Management Journal*, *29*(8), 25-47. doi: 10.1108/BPMJ-12-2021-0796

Anna, Č. (2014). Process management in modern organization. In *Vision 2020: Sustainable Growth, Economic Development, and Global Competitiveness - Proceedings of the 23rd International Business Information Management Association Conference, IBIMA 2014*. Retrieved from https://www.proceedings.com/54684

Avila, D. T., Santos, R. I. d., Mendling, J., & Thom, L. H. (2020). A systematic literature review of process modeling guidelines and their empirical support. *Business Process Management Journal*, *27*(1), 1-23. https://doi.org/10.1108/bpmj-10-2019-0407

Badakhshan, P., Conboy, K., Grisold, T., & vom Brocke, J. (2019). Agile business process management. *Business Process Management Journal*, *26*(6), 1505-1523. doi: 10.1108/BPMJ-12-2018-0347

Battisti, E., Shams, S. M. R., Sakka, G., & Miglietta, N. (2020). Big data and risk management in business processes: implications for corporate real estate. *Business Process Management Journal*, *26*(5), 1141-1155. doi: 10.1108/BPMJ-03-2019-0125

Baumgartner, R. J. (2011). Critical perspectives of sustainable development research and practice. *Journal of Cleaner Production*, *19*(8), 783-786. doi: 10.1016/j.jclepro.2011.01.005

Benner, M. J., & Tushman, M. (2002). Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly*, *47*(4), 676-707. doi: 10.2307/3094913

Biesok, G., & Wyród-Wróbel, J. (2016). *Modele satysfakcji klienta* [*Customer satisfaction models*]. Warszawa, Poland: Difin.

Bilas, L., & Adeeb, M. (2017). Innovation Management: The importance of Leadership and Teamwork in Business

Organisation. *Economica*, *2*(100), 51-61. Retrieved from https://ase.md/files/publicatii/economica/ec_2017_2.pdf

Bitkowska, A. (2017a). Business Processes Modelling in Knowledge Management Perspective. *Research on Enterprise in Modern Economy*, *21*(2), 7-16. Retrieved from https://zie.pg.edu.pl/documents/30328766/58054239/REME_21_(2-2017)-Art1.pdf

Bitkowska, A. (2017b). Knowledge management in production enterprises. *Production Engineering Archives*, *15*(15), 23-26. doi: 10.30657/pea.2017.15.06

Bitkowska, A. (2018). Business Process Management centre of excellence as a source of knowledge. *Business, Management and Education*, *16*, 121-132. doi: 10.3846/bme.2018.2190

Bitkowska, A. (2020). The relationship between Business Process Management and Knowledge Management - selected aspects from a study of companies in Poland. *Journal of Entrepreneurship, Management and Innovation*, *16*(1), 169-194. doi: 10.7341/20201616

BPM. (2017). *Extending Performance Management for Company-Wide Benefits* Retrieved from https://www.bpmpartners.com/2017/10/01/extending-performance-management-forcompany-wide-benefits

BPM. (2018). *The Importance of AI in Corporate Budgeting, Planning, and Forecasting*. Retrieved from https://www.bpmpartners.com/2018/12/06/ai-in-corporate-budgeting

BPM. (2020). *Managing Performance in a Tough Economy*. Retrieved from https://www.bpmpartners.com/2020/04/21/managing-performance-in-a-tough-economy

BPM. (2021a). BPM Pulse 2021 Survey. *Results: What's Next*. Retrieved from https://www.bpmpartners.com/2021/10/18/bpm-pulse-2021-whats-next

BPM. (2021b). *The Data Foundation Your CPM Initiative Needs to Succeed*. Retrieved from https://www.bpmpartners.com/2021/08/24/data-foundation-for-cpm

Bracci, E., Gobbo, G., & Papi, L. (2022). The integration of risk and performance management: the role of boundary objects. *Journal of Public Budgeting, Accounting and Financial Management*, *34*(1), 139-161. doi: 10.1108/JPBAFM-02-2020-0024

Brajer-Marczak, R. (2016). Elements of knowledge management in the improvement of business processes. *Management*, *20*(2), 242-260. doi: 10.1515/manment-2015-0063

Christiansson, M. T., & Van Looy, A. (2017), Elements for tailoring a BPM maturity model to simplify its use. In J. Carmona, G. Engels, & A. Kumar (Eds.), *Business Process Management Forum*, *Business Process Management Conference Business Process Management Forum,* Vol. 297. Cham: Springer International Publishing (Lecture Notes in Business Information Processing). doi: 10.1007/978-3-319-65015-9

Chromjakova, F., Trentesaux, D., & Kwarteng, M. A. (2021). Human and cobot cooperation ethics: The process management concept of the production workplace. *Journal of Competitiveness*, *13*(3), 21-38. doi: 10.7441/joc.2021.03.02

Criado-García, F., Calvo-Mora, A., & Martelo-Landroguez, S. (2020). Knowledge management issues in the EFQM excellence model framework. *International Journal of Quality and Reliability Management*, *37*(5), 781-800. doi: 10.1108/IJQRM-11-2018-0317

Detyna, B. (2016). Integrated management system of local administration against modern challenges of the economy. *Economic and Regional Studies/Studia Ekonomiczne i Regionalne*, *9*(1), 18-32. Retrieved from http://www.ers.edu.pl/Issue-1-2016,4134

Detyna, B. (2018). Implementation of lean management concept at the university. *Zeszyty Naukowe Wyższej Szkoły Humanitas* [*Scientific Journals of the Humanitas University*], *19*(2), 65-81. doi: 10.5604/01.3001.0012.2039

Detyna, B., & Detyna, J. (2017). Possibility of using control cards in the improvement of medical services quality. *International Journal of Current Advanced Research*, *6*(3), 2564-2570. doi: 10.24327/ijcar.2017.2570.0050

Detyna, B., Detyna, J., & Dudek-Kajewska, A. (2016). Evaluation of training programs by medical employees in a chosen hospital in Poland. *Managerial Economics*, *17*(2), 203-216. doi: 10.7494/manage.2016.17.2.203

Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2013). *Fundamentals of Business Process Management*. Berlin, Heidelberg: Springer Berlin Heidelberg. doi: 10.1007/978-3-642-33143-5

Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2018). Introduction to Business Process Management. *Fundamentals of Business Process Management*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1-33. doi: 10.1007/978-3-662-56509-4_1

El Ghalbzouri, H., & El Bouhdidi, J. (2022). Integrating Business Intelligence with Cloud Computing: State of the Art and Fundamental Concepts. In M. Ben Ahmed, H-N.L. Teodorescu, T. Mazri, P. Subashini, A.A. Boudhir (Eds.), *Networking, Intelligent Systems and Security. Smart Innovation, Systems and Technologies*, vol 237. Singapore: Springer. doi: 10.1007/978-981-16-3637-0_14

Espírito Santo, P. M., Cardoso, P. M. A., & Marques, A. M. A. (2022). Effects of E-Business Adoption on Organizational Agility in the COVID-19 Context. *International Journal of Marketing, Communication and New Media*, *11*, 45-61. doi: 10.54663/2182-9306.2022.sn11.45-61

Gabryelczyk, R., Kulesza, P., & Rakowska, E. (2018). Improving public sector performance by using business process modelling and measurement: a case study analysis. *Sinergie Italian Journal of Management*, *35*(102), 115-132. doi: 10.7433/s102.2017.09

Gómez, J., Salazar, I., & Vargas, P. (2022). Production outsourcing, technological cooperation and E-business adoption by Spanish manufacturing firms. *Journal of Engineering and Technology Management*, 63(Complete). doi: 10.1016/j.jengtecman.2022.101677

Govender, S., & Parumasur, S. B. (2010). The relationship between employee motivation and job involvement. *South African Journal of Economic and Management Sciences*, *13*(3), 237-253. doi: 10.4102/sajems.v13i3.102.

Grisold, T., Groß, S., Stelzl, K., Brocke, J., Mendling, J., Röglinger, M., & Rosemann, M. (2022). The Five Diamond Method for Explorative Business Process Management. *Business and Information Systems Engineering*, *64*(2), 149-166. doi: 10.1007/s12599-02100703-1

Groß, S., Stelzl, K., Grisold, T., Mendling, J., & Röglinger, M. (2021). The business process design space for exploring process redesign alternatives. *Business Process Management Journal*, *27*(8), 25-56. doi: 10.1108/bpmj-03-2020-0116

Gupta, B., Iyer, L. S., & Aronson, J. E. (2000). Knowledge management: practices and challenges. *Industrial Management & Data Systems*, *100*(1), 17-21. doi: 10.1108/02635570010273018.

Gzik, T. (2020). Business Process as a Service – A systematic literature review. In M. Hernes, A. Rot, D. Jelonek (Eds.), *Towards Industry 4.0 — Current Challenges in Information Systems*/Studies in Computational Intelligence, vol. 887 (pp. 163-181). Cham Switzerland: Springer. doi: 10.1007/978-3-030-40417-8_10

Harmon P. (2020). *BPTrends State of Business Process Management – 2020 Report*. Retrieved from https://www.bptrends.com/bptrends-state-of-business-process-management-2020-report

Harmon, P. (2010). The Scope and Evolution of Business Process Management. *Handbook on Business Process Management 1*. Berlin, Heidelberg: Springer Berlin Heidelberg. doi: 10.1007/978-3-642-45100-3_3

Harymawan, I., Nasih, M., Agustia, D., Putra, F. K. G., & Djajadikerta, H. G. (2022). Investment efficiency and environmental, social, and governance reporting: Perspective from corporate integration management. *Corporate Social Responsibility and Environmental Management*, *29*(5), 1186-1202. doi: 10.1002/csr.2263

Helbin, T., & Van Looy, A. (2021). Is business process management (BPM) ready for ambidexterity? Conceptualization, implementation guidelines and research agenda. *Sustainability (Switzerland)*, *13*(4), 1906. doi: 10.3390/su13041906

Hill, C. W. L., & Rothaermel, F. T. (2003). The performance of incumbent firms in the face of radical technological innovation. *Academy of Management Review*, *28*(2), 257-274. doi: 10.5465/AMR.2003.9416161

Hove, M., von Rosing, G., & Storms, B. (2015). Business Process Management Governance. In M.V. Rosing, A-W. Scheer, H. von Scheel (Eds.), *The Complete Business Process Handbook – Body of Knowledge from Process Model to BPM*. vol. 1 (pp. 603-616). Waltham: Elsevier. doi: 10.1016/B978-0-12-799959-3.00029-X

Ispas, L., & Mironeasa, C. (2022). The Identification of Common Models Applied for the Integration of Management Systems: A Review. *Sustainability (Switzerland)*, *14*(6), 3559. doi: 10.3390/su14063559

Kaplan, R. S., & Norton, D. P. (2001). The strategy-focused organization. *Strategy & Leadership*, *29*(3). doi: 10.1108/sl.2001.26129cab.002

Keser Aschenberger, F. K., Radinger, G., Brachtl, S., Ipser, Ch., & Oppl, S. (2023). Physical home learning environments for digitally supported learning in academic continuing education during COVID-19 pandemic. *Learning Environments Research*, *26*, 97-128. doi: 10.1007/s10984-022-09406-0

Kir, H., & Erdogan, N. (2021). A knowledge-intensive adaptive business process management framework. *Information Systems*, *95*. doi: 10.1016/j.is.2020.101639

Langley, A. (2007). Process thinking in strategic organization. *Strategic Organization*, *5*(3), 271–282. doi: 10.1177/1476127007079965

Lombarts, M. J. M. H., Rupp, I., Vallejo, P., Suñol, R., & Klazinga, N. S. (2009). Application of quality improvement strategies in 389 European hospitals: results of the MARQuIS project. *Quality and Safety in Health Care*, *18*(Suppl 1), i28–i37. doi: 10.1136/qshc.2008.029363

Lopes, A., Polónia, D., Gradim, A., & Cunha, J. (2022). Challenges in the Integration of Quality and Innovation Management Systems. *Standards*, *2*(1), 52-65. doi: 10.3390/standards2010005

Mahdi, O. R., & Nassar, I. A. (2021). The business model of sustainable competitive advantage through strategic leadership capabilities and knowledge management processes to overcome COVID-19 pandemic. *Sustainability (Switzerland)*, *13*(17), 9891. doi: 10.3390/su13179891

Marín-González, F., & Pérez-González, J. (2021). Process management in intersectoral cooperation networks. *Revista de Ciencias Sociales*, *27*(1), 162-179. Retrieved from https://dialnet.unirioja.es/servlet/articulo?codigo=7817689

Mbah, R. E., & Wasum, D. (2022). Russian-Ukraine 2022 War: A Review of the Economic Impact of Russian-Ukraine Crisis on the USA, UK, Canada, and Europe. *Advances in Social Sciences Research Journal*, *9*(3), 144-153. doi: 10.14738/assrj.93.12005

Mendling, J., Pentland, B. T., & Recker, J. (2020). Building a complementary agenda for business process management and digital innovation. *European Journal of Information Systems*, *29*(3), 208-219. doi: 10.1080/0960085X.2020.1755207

Mohamad, A. K., Jayakrishnan, M., & Yusof, M. M. (2022). Thriving information system through business intelligence knowledge management excellence framework. *International Journal of Electrical and Computer Engineering*, *12*(1), 506-514. doi: 10.11591/ijece.v12i1

Moreno, V., Cavazotte, F., & Lapa, E. (2015). Integrating Knowledge Management Practices and Business Processes: A Case Study. *Academy of Management Proceedings*, *2015*(1). doi: 10.5465/ambpp.2015.18915abstract

Muntean, M. (2018). Business intelligence issues for sustainability projects. *Sustainability (Switzerland)*, *10*(2), 335. doi: 10.3390/su10020335

Muntu, D., Setyawati, R., Riantini, L. S., & Ichsan, M. (2021). Effect of human resources management and advances to improve construction project performance. *Physics and Chemistry of the Earth*, *Parts A/B/C*, *122*, 103000. doi: 10.1016/j.pce.2021.103000

OMG. (2008). Business Process Maturity Model (BPMM), version 1.0. OMG Document Number: formal/2008-06-01, Object Management Group, Nedham, MA.

Pereira, F. C. M., Barbosa, R. R., & Duarte, L. da C. (2020). Integration between knowledge management and business process management: Perspectives of bpm professionals. *Perspectivas em Ciencia da Informacao*, *25*(4), 170-191. doi: 10.1590/19815344/4088

Polančič, G., & Orban, B. (2023). An experimental investigation of BPMN-based corporate communications modelling. B*usiness Process Management Journal*, *29*(8), 1-24. doi: 10.1108/BPMJ-08-2022-0362

Riyanto, S., Endri, E., & Herlisha, N. (2021). Effect of work motivation and job satisfaction on employee performance: Mediating role of employee engagement. *Problems and Perspectives in Management*, *19*(3), 162-174. doi: 10.21511/ppm.19(3).2021.14

Rubin, D., & Levin, R. (2013). *Statistics for Management*. 7th edn. London: Pearson Education.

Sanchez, L., Delgado, A., Ruiz, F., Garcia, F., & Piattini, M. (2009). Measurement and Maturity of Business Processes. In J. Cardoso & W. van der Aalst (Eds.), *Handbook of Research on Business Process Modeling* (pp. 532-556). IGI Global. doi: 10.4018/978-1-60566-288-6.ch024

Silvestre, W. J., Fonseca, A., & Morioka, S. N. (2022). Strategic sustainability integration: Merging management tools to support business model decisions. *Business Strategy and the Environment*, *31*(5), 2052-2067. doi: 10.1002/bse.3007

Sitnikov, P., Dodonova, E., Dokov, E., Ivaschenko, A., & Efanov, I. (2022). Digital Transformation of Public Service Delivery Processes in a Smart City. In K. Arai (Ed.), *Intelligent Systems and Applications. IntelliSys 2021. Lecture Notes in Networks and Systems*, vol 296. Cham: Springer. doi: 10.1007/978-3-030-82199-9_21

Sjöström, M., Wold, S., & Söderström, B. (1986). PLS discriminant plots. In E. S. Gelsema, & L. N. Kanal (Eds.), *Pattern Recognition in Practice* (pp. 461-470). Amsterdam: Elsevier. doi: 10.1016/b978-0-444-87877-9.50042-x

Sobczyk, M. (2022). *Statystyka* [*Statistics*]. Warszawa, Poland: Wydawnictwo Naukowe PWN.

Sobolewska, O., & Bitkowska, A. (2020). Selected aspects of evaluating knowledge management quality in contemporary enterprises. *Information (Switzerland)*, *11*(5), 244. doi: 10.3390/INFO11050244

Ståhle, L., & Wold, S. (1987). Partial least squares analysis with cross-validation for the two-class problem: A Monte Carlo study. *Journal of Chemometrics*, *1*(3), 185-196. doi: 10.1002/cem.1180010306

Steinke, G., & Nickolette, C. (2003). Business rules as the basis of an organization's information systems. *Industrial Management & Data Systems*, *103*(1), 52-63. doi: 10.1108/02635570310456904

Szelagowski, M., & Lupeikiene, A. (2020). Business Process Management Systems: Evolution and Development Trends. *Informatica (Netherlands)*, *31*(3), 579-595. doi: 10.15388/20-INFOR429

Team, CMMI Product. (2018). CMMI for Services, Version 1.3. Improving processes for providing better services. Carnegie Mellon University. Report. doi: 10.1184/R1/6572375.v1

Tubis, A. A., & Werbińska-Wojciechowska, S. (2021). Risk management maturity model for logistic processes. *Sustainability (Switzerland)*, *13*(2), 659. doi: 10.3390/su13020659

Zakrzewska-Bielawska, A., & Staniec, I. (2020). *Contemporary challenges in cooperation and coopetition in the age of industry 4.0. Springer Proceedings in Business and Economics*. Cham, Switzerland: Springer Nature Switzerland AG. doi: 10.1007/978-3-030-30549-9

Zapalska, A., Wroblewski, B., Imbriale, P., Kaleiwahea, P., & Schwartz, J. (2020). Strategy for development and assessment of critical thinking in undergraduate management and leadership education. *Obrazovanje za poduzetništvo - E4E*, *10*(1) 54-75. doi: 10.38190/ope.10.1.8

Zuhaira, B., & Ahmad, N. (2021). Business process modeling, implementation, analysis, and management: the case of business process management tools. *Business Process Management Journal*, *27*(1), 145-183. doi: 10.1108/BPMJ-06-2018-0168

sciendo

received: 1 May 2023
accepted: 10 November 2023

pages: 53-75



# Artificial intelligence in the smart city — a literature review

Danuta Szpilko
Felix Jimenez Naharro
George Lăzăroiu
Elvira Nica
Antonio de la Torre Gallegos

**Danuta Szpilko**

Bialystok University of Technology, Poland
ORCID 0000-0002-2866-8059

Corresponding author:
d.szpilko@pb.edu.pl

**Felix Jimenez Naharro**

University of Seville, Spain
ORCID 0000-0001-9217-2624

**George Lăzăroiu**

Curtin University, Australia
Toronto Metropolitan University/ICCL, Canada
ORCID 0000-0002-3422-6310

**Elvira Nica**

Bucharest University of Economic Studies, Romania
ORCID 0000-0002-7383-2161

**Antonio de la Torre Gallegos**

University of Seville, Spain
ORCID 0000-0001-7839-0385

ABSTRACT
The influence of artificial intelligence (AI) in smart cities has resulted in enhanced efficiency, accessibility, and improved quality of life. However, this integration has brought forth new challenges, particularly concerning data security and privacy due to the widespread use of Internet of Things (IoT) technologies. The article aims to provide a classification of scientific research relating to artificial intelligence in smart city issues and to identify emerging directions of future research. A systematic literature review based on bibliometric analysis of Scopus and Web of Science databases was conducted for the study. Research query included TITLE-ABS-KEY ("smart city" AND "artificial intelligence") in the case of Scopus and TS = ("smart city" AND "artificial intelligence") in the case of the Web of Sciences database. For the purpose of the analysis, 3101 publication records were qualified. Based on bibliometric analysis, seven research areas were identified: safety, living, energy, mobility, health, pollution, and industry. Urban mobility has seen significant innovations through AI applications, such as autonomous vehicles (AVs), electric vehicles (EVs), and unmanned aerial vehicles (UAVs), yet security concerns persist, necessitating further research in this area. AI's impact extends to energy management and sustainability practices, demanding standardised regulations to guide future research in renewable energy adoption and developing integrated local energy systems. Additionally, AI's applications in health, environmental management, and the industrial sector require further investigation to address data handling, privacy, security, and societal implications, ensuring responsible and sustainable digitisation in smart cities.

KEY WORDS
**smart city, artificial intelligence, energy, safety, living, pollution, mobility, transport, industry, health, Internet of Things, big data, blockchain, machine learning, European Green Deal, bibliometric analysis**

**10.2478/emj-2023-0028**

## Introduction

With increasing urbanisation worldwide, cities are turning to innovative, specialised technologies to address social, economic, environmental, and other challenges. Artificial intelligence (AI) has been increasingly recognised as a transformative tool, holding the potential to revolutionise city development. With its capabilities to learn, predict, and potentially operate autonomously, AI offers a wealth of opportunities for developing and managing smart cities. Its applications span various areas, from pre-

Szpilko, D., & Jimenez Naharro, F., Lăzăroiu, G., Nica, E., & de la Torre Gallegos, A. (2023). Artificial intelligence in the smart city — a literature review. *Engineering Management in Production and Services, 15*(4), 53-75. doi: 10.2478/emj-2023-0028

dictive maintenance and enhanced citizen services to improved sustainability initiatives. However, despite its growing prevalence, a comprehensive understanding of AI's role, its range of applications in smart cities, and the potential implications are currently lacking.

As a technological tool, AI can significantly contribute to integrating pivotal smart city dimensions, such as living, people, economy, mobility, environment, and government. AI and other advanced techniques have shown great promise in developing optimal policies to tackle complex issues intrinsic to the evolution of smart cities, ranging from intelligent transportation systems and cybersecurity to energy-efficient smart grids and smart healthcare systems.

However, the application of AI in smart cities has its risks. The same power that allows AI to drive urban transformations also presents a slew of challenges. Ensuring ethical AI application, maintaining data privacy, and mitigating the potential for AI misuse are among the top concerns in this emerging field. It is also critical to remember that the shift towards an AI-driven city can exacerbate social inequalities and create a digital divide among citizens if not managed thoughtfully.

Given the topic's relevance related to the application of artificial intelligence in a smart city, this article aims to classify scientific research relating to artificial intelligence in smart city issues and identify emerging directions for future research. The methodology used in this study combines a systematic literature review to identify the most relevant studies and new topics to be developed in the future. The research shows the scope and importance of AI in smart city development and the challenges it brings to cities and citizens.

# 1. Literature review

As the global urban population is projected to surge to 66 % or 70 % by 2050 (O'Dwyer et al., 2019), there are escalating concerns about the environmental, managerial, and security impacts. In response to this challenge, smart cities which heavily rely on information and communication technologies (ICTs) have been proposed and realised in various nations (Aguilera et al., 2017; Alifi & Supangkat, 2016; Al_Turjman & Baali, 2022; Galindo, 2014; Yamakami, 2017; Szpilko et al., 2020). Smart cities integrate different technologies, such as the Internet of Things, blockchain, artificial intelligence, machine learning (ML), and deep reinforcement learning (DRL), to provide comprehensive solutions (Alam et al., 2017; Ali et al., 2020; Allam et al., 2019; Allam & Dhunny, 2019; Chen et al., 2021; Liu et al., 2019; Bilan et al., 2022).

AI emerged in 1956 but developed slowly because of immature computational technologies. Now, it is deployed at a scale of cities (Yigitcanlar et al., 2020). Its diverse computational technologies range from rule-based systems to deep learning systems, and these technologies play increasingly critical roles in the delivery of public services (Ma et al., 2020; Wirtz et al., 2019). For instance, Robotic Process Automation (RPA) projects are automating mundane, repetitive, and costly tasks, freeing up valuable resources (Mendling et al., 2018; Siderska et al., 2023).

The AI role in managing the massive amounts of data generated by IoT, a crucial component of smart city applications, cannot be overstated (Al-Turjman et al., 2021; Ullah, Al-Turjman, Mostarda et al., 2020). By employing AI, ML, and DRL techniques, cities can harness and analyse this data to make optimal decisions (Allam et al., 2019; Allam & Dhunny, 2019; Liu et al., 2019). It is important to note that the accuracy and precision of these technologies can be further enhanced by increasing the amount of training data, thereby strengthening their learning capabilities and improving automated decision efficiencies (Ullah, Al-Turjman, Mostarda et al., 2020).

Significant strides have been made in such different sectors as intelligent transportation, cybersecurity, smart grids, and UAVs-assisted next-generation communication in smart cities (Allam & Newman, 2018). AI, ML, and DRL technologies play a transformative role in these sectors by enhancing their efficiency and scalability (Ferdowsi et al., 2019).

Intelligent transportation systems have integrated ML and DRL-based technologies in various applications, including self-driving vehicles, ensuring the security of connected vehicles, efficient passenger hunting, and safe travels (Ang et al., 2022; Ferdowsi et al., 2019; Wences et al., 2017). Similarly, the role of AI, ML, and DRL technologies in cybersecurity is outstanding, with significant impacts on almost all sectors of a smart city (Ullah, Al-Turjman, Mostarda et al., 2020). Furthermore, AI continues to revolutionise energy generation, management, and consumption within smart cities, underscoring its far-reaching implications for societal and economic development (Golinska-Dawson & Sethanan, 2023; Muhammad et al., 2019; Pramod et al., 2023).

Autonomous vehicles are also explored as a modernisation tool for public transport infrastructure

(Gaber et al., 2020; Toglaw et al., 2018). Furthermore, smart cities are venturing into using robotics for law enforcement to lower conflict incident rates and free up human resources (Galindo, 2014; Hu & Jiang, 2019; Ma et al., 2018). The utilisation of AI and ML in predicting and preventing incidents is also gaining traction. For example, an efficient crime detection system for smart cities has been proposed utilising DRL and neural networks to identify and analyse criminal activity (Castelli et al., 2017; Diro & Chilamkurti, 2018; David et al., 2023). Likewise, an ML-based architecture has been put forward to predict incidents and generate responses before their occurrence (Aqib et al., 2020). As AI and ML become increasingly integrated into urban governance, there is the potential for more sustainable, safe, inclusive, and resilient cities (Allam & Newman, 2018; Choudhary & Sarthy, 2022; Lourenco et al., 2018).

Through AI and associated technologies like ML and DRL, cities can harness and analyse big data, improve decision-making, enhance public services, and foster more sustainable and resilient urban environments. However, it is crucial to consider the societal implications of such technologies to avoid potential pitfalls and maximise the benefits. Ethical considerations surrounding the use of artificial intelligence in smart cities are also crucial, particularly regarding data privacy, bias, and potential impacts on citizen rights and autonomy. Balancing technological advancements with ethical guidelines is essential to ensure responsible and inclusive AI integration in urban environments.

## 2. Research methods

The literature on artificial intelligence in smart cities was examined using a bibliometric analysis approach. This method is frequently employed by researchers, especially when first exploring a specific research topic. With a vast number of publications available, it facilitates the identification, synthesis, analysis, and critical evaluation of their contents (Bornmann & Haunschild, 2017; Keathley-Herring et al., 2016). Utilising quantitative techniques allows for the identification of the current state and developmental trends in the research area under consideration. The results provide insights into the main research directions, trends, and changes in the number of publications over a specific period. Moreover, it enables the creation of rankings for the most productive authors, journals, research units, and countries within the field of research (Niñerola et al., 2019; Szum, 2021). Bibliometric analysis is applicable to well-established research areas in the literature (Winkowska et al., 2019; Gudanowska, 2017; Glińska & Siemieniako, 2018; Halicka, 2017), as well as emerging ones (Siderska & Jadaan, 2018; Szpilko, 2017).

Table 1 illustrates the operationalisation of the process employed in this article using the bibliometric analysis method.

The research process was conducted following a methodology comprising seven distinct phases. These phases encompassed the selection of bibliographic databases (I), the choice of keywords (II), and the criteria to narrow down the search for publications (III). Subsequently, data extraction and selection (IV) was performed, followed by the analysis of the selected publications (V). The last two phases involved identifying research areas (VI) and defining thematic clusters (VII) (Table 1).

In the initial phase of the study, the researchers opted for Scopus and Web of Science bibliographic databases, as they offered a comprehensive array of scientific publications. The selection of these databases was driven by their wide availability and thematic coverage across various scientific disciplines. The bibliometric analysis began by focusing on publications that contained the specific terms "smart city" and "artificial intelligence". In the first and second samples, the search encompassed publications with this phrase throughout the entire document, while the third sample included titles, abstracts, and keywords.

To refine the search, certain restriction criteria were applied. The search was limited to materials published between 2010 and 2023. For further analysis, articles, conference proceedings, books, book chapters, reviews, editorials, early access and short survey publications were considered eligible. On the other hand, publication types like retracted publications, conference reviews, notes, erratum, and letters were excluded. The outcomes of the search are presented in Table 2.

The initial search for the term "smart city AND artificial intelligence" across the entire set of papers in the first sample yielded 107475 records in Scopus and 3250 records in Web of Science. However, upon the initial analysis, it became evident that many of these publications were not directly relevant to the study area. The search in the second attempt, enclosing the keywords in quotation marks ("smart city" AND

Tab. 1. Methodology of bibliometric analysis

| No. | Task | Scope |
|---|---|---|
| 1. | Database selection | Scopus, Web of Science |
| 2. | Keywords selection | "smart city" AND "artificial intelligence" in topic |
| 3. | Criteria selection | Period: 2010–2023<br><br>Document types: articles, proceedings papers, conference papers, books, book chapters, editorial materials, reviews, early access, short survey |
| 4. | Data extraction, removal of duplicates | Criteria for deleting duplicates: DOI, title, authors |
| 5. | Quantitative analysis of the results | Scope: number of publications per year, document types, the most productive authors, institutions, countries, journals |
| 6. | Identification of research areas | Visualisation of the most frequent keywords |
| 7. | Creation of thematic clusters | Visualisation of thematic clusters |

Tab. 2. Search results

| Stage | Web of Science | Scopus |
|---|---|---|
| First search | | |
| Research query | ALL=smart city AND artificial intelligence | ALL (smart city AND artificial intelligence) |
| Number of articles before inclusion criteria | 3250 | 107475 |
| Number of articles after inclusion criteria | 3216 | 105672 |
| Second search | | |
| Research query | ALL= "smart city" AND "artificial intelligence" | ALL ("smart city" AND "artificial intelligence") |
| Number of articles before inclusion criteria | 1464 | 69049 |
| Number of articles after inclusion criteria | 1463 | 68660 |
| Third search | | |
| Research query | TS="smart city" AND "artificial intelligence" | TITLE-ABS-KEY ("smart city" AND "artificial intelligence") |
| Number of articles before inclusion criteria | 1237 | 3014 |
| Number of articles after inclusion criteria | 1237 | 2896 |

Source: elaborated by the authors based on the Scopus and Web of Science databases.

"artificial intelligence"), also did not yield satisfactory results. As a result, a third attempt was made, restricting the search only to publications containing the specified phrase in their titles, abstracts, and keywords. Subsequently, the refined search produced 3014 records in Scopus and 1237 in Web of Science. After applying the limiting criteria, 2896 records in Scopus and 1237 in Web of Science were obtained. The search results are detailed in Table 2.

Full records in *csv format were downloaded from each database, and these files were aggregated into one, resulting in a total of 4133 records. After eliminating duplicates, a subset of 3101 records was selected for further analysis.

Based on the acquired dataset, various analyses were conducted to examine the number of publications within specific periods and identify the most productive authors, organisations, countries, and journals. The research also focused on identifying the most notable articles with the highest frequency of citations.

Furthermore, a thorough investigation of commonly recurring keywords was conducted, leading to the creation of a map depicting the co-occurrence of keywords associated with the application of artificial intelligence in smart cities. The creation of the keyword co-occurrence map was accomplished using VOSviewer software (version 1.6.19).

To ensure accuracy and relevance, a thesaurus file was additionally prepared (van Eck & Waltman, 2018) to eliminate duplicate terms with similar meanings (e.g., Internet of Things and IoT) or terms not relevant to the study (e.g., article, research, analysis). This file was developed based on keyword analysis and a thorough review of the publication collection. The outcome of this analysis allowed for the identification of thematic clusters representing the main and emerging research directions.

# 3. Research results

In the initial phase of the study, an examination was carried out to assess the interest in the subject matter over the years. Additionally, the predominant types of publications were identified, along with their connections to the primary subject areas in the Scopus and Web of Science databases.

Between 2018 and 2023, a significant number of publications emerged in both databases (Fig. 1). Prior to this period, references to AI in smart cities were infrequent, representing an "emerging thematic". The total number of citations for publications indexed in the Scopus database was 31 783, while in Web of Science, it amounted to 15 665. There were 865 uncited publications in Scopus and 343 in Web of Science.

In the Web of Science and Scopus databases jointly, the majority of publications consisted of articles (63.5 % and 32.5 %, respectively) and conference papers (50.5 % and 25.1 %). Reviews, editorials, and book chapters made up a smaller portion. The distribution of publications by document type is depicted in Fig. 2.

The preponderance of literature in both databases is primarily allocated to the domains of Engineering,

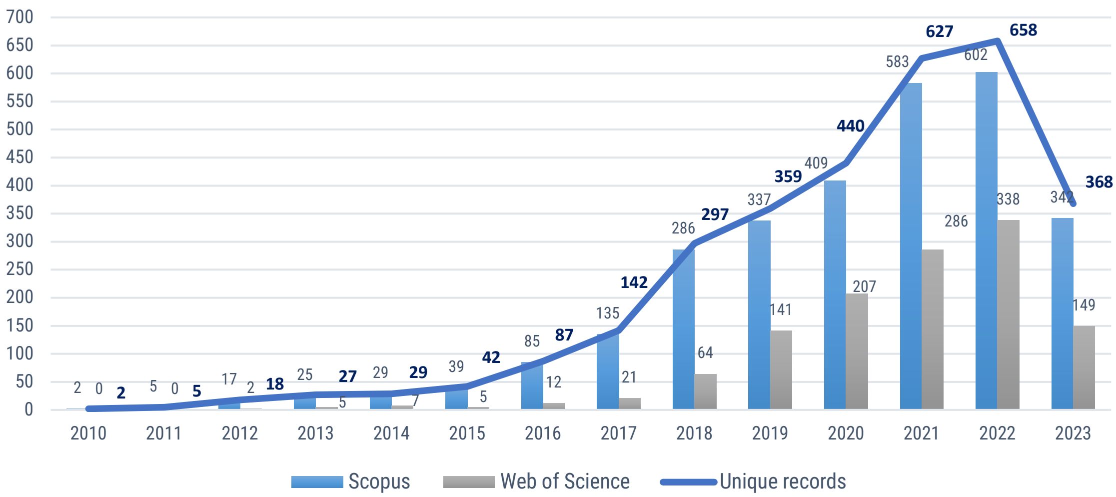



Fig. 1. Number of publications in the field of artificial intelligence in smart cities in the Scopus and Web of Science databases (indexed from January 2010 to July 2023)

Source: elaborated by the authors based on the Scopus and Web of Science databases.

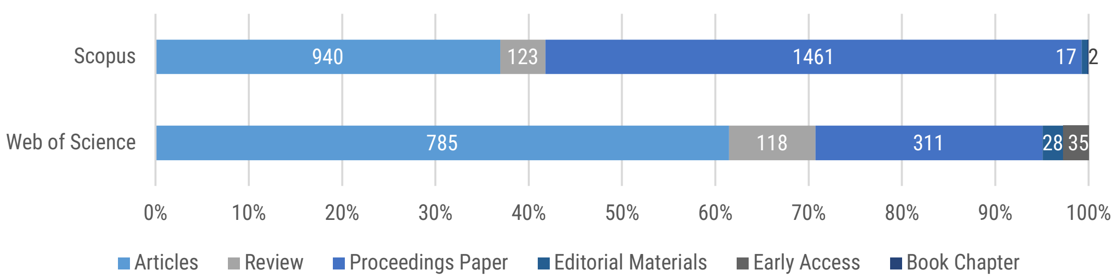



Fig. 2. Type of documents of publications in the field of artificial intelligence in smart cities in the Scopus and Web of Science databases (indexed from January 2010 to July 2023)

Source: elaborated by the authors based on the Scopus and Web of Science databases.

specifically Electrical and Electronic Engineering and Computer Science (Computer Science Information Systems). Specifically, these represent 77.5 % and 44.9 % of all entries in Scopus and 33.1 % and 29.4 % in the Web of Science. Furthermore, a considerable amount of literature in Scopus is also categorised under Social Sciences (17.8 %) and Mathematics (15.9 %), whereas in Web of Science, a significant percentage is attributed to Telecommunications (23.4 %).

The most productive author in this regard is Yigitcanlar, with 16 publications. The most referenced piece by Yigitcanlar et al. is "Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature" from 2020 and "Can building 'artificially intelligent cities' safeguard humanity from natural disasters, pandemics, and other catastrophes? An urban scholar's perspective" from the same year, amassing 161 and 140 citations in Scopus, respectively. Next is Mehmood, with 14 publications, who held the highest average citation count per publication in both databases. His most cited piece was "Data Fusion and IoT for Smart Ubiquitous Environments: A Survey", published in IEEE Access in 2017, with 254 citations in Scopus and 195 in Web of Science. Allams' (and Dhunny's) most referenced publication was "On big data, artificial intelligence and smart cities", published in Cities in 2019, amassing 456 citations in Web of Science and 305 in Scopus. Table 3 provides a comprehensive list of the most productive authors.

With regard to geographical distribution, the majority of the publications are from China (550), followed by India (495) and the United States (316). Considering author affiliation, King Abdulaziz University produced the highest number of publications (36), followed closely by the Egyptian Knowledge Bank EKB (32) and Universidad de Salamanca (25). Notably, publications from the Queensland University of Technology (Scopus: 36.4, WoS: 28.0), the Chinese Academy of Sciences (Scopus: 25.2, WoS: 45.3), and the King Abdulaziz University (Scopus: 26.9, WoS: 29.2) have been cited most frequently. Compared to other institutions in the ranking, they have a notably high average citation count in both Scopus and the Web of Science databases.

In the ranking of most productive journals, Lecture Notes in Computer Science Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes In Bioinformatics took the top spot (134 publications), followed by Advances in Intelligent Systems and Computing with 108 publications, and IEEE Access with 63 publications. However, the journals with the highest average citation count in each database were IEEE Access (Scopus: 38.8, WoS: 26.6) and Sensors (Scopus: 32.9, WoS: 11.3).

The cumulative citation count for publications focusing on artificial intelligence in the context of smart cities amounted to 15665 in the Web of Science and 31783 in Scopus. Among the eleven most cited works, two were published in IEEE Access and Future Generation Computer Systems, while SN Computer Science, Cities, Advanced Materials, Proceedings — 2015 IEEE International Conference on smart city, Healthcare, Computer Communications, and Sustainable Cities and Society each contributed one. Notably, six of these top-cited works originated from the year 2020.

The most cited publication, with 619 citations in Scopus and 392 in the Web of Science, was by Fuller et al. (2020), "Digital Twin: Enabling Technologies, Challenges and Open Research". Next was the article by Diro and Chilamkurti (2018), "Distributed Attack Detection Scheme using Deep Learning Approach for Internet of Things", and the article by Allam and Dhunny (2019), "On Big Data, Artificial Intelligence and Smart Cities". The total citation counts for these articles were somewhat lower than for the first, with Scopus counts of 537 and 456 and Web of Science counts of 402 and 305, respectively (Table 4).

In the context of the bibliometric analysis, keywords recurrently associated with the subject of artificial intelligence in smart cities were extracted. The analytical process employed the use of VOSviewer software. The resulting collection consisted of 380 words or phrases that occurred a minimum of five times in the keywords of the 3101 articles examined. This collection also included words synonymous with abbreviations or repetitions (i.e., "Internet of Things", "internet-of-things", "IoT", "neural-network", and "neural-networks") and terms not intrinsically related to the central theme of analysis (such as "article", "analysis", "model", "knowledge", "literature review"). A thesaurus file was curated and deployed to systematise the word set. Search keywords (e.g., "artificial intelligence", "AI", "smart city", "smart cities") were purposely excluded from this collection. The nomenclature of terms and abbreviations sharing similar meanings was standardised, and terms unrelated to the analysis were discarded. The refined collection included 166 keywords. The most prevalent terms and their interconnections are depicted in Fig. 3.

Tab. 3. Most productive authors, organisations, countries and journals

| No. | Item | NP | [%] | Average citation count | |
|---|---|---|---|---|---|
| | | | | Scopus | Web of Science |
| **Authors** | | | | | |
| 1. | Yigitcanlar, T. | 16 | 0.5 | 48.2 | 35.4 |
| 2. | Mehmood, R. | 14 | 0.5 | 51.9 | 143.5 |
| 3. | Allam, Z. | 12 | 0.4 | 113.3 | 63.2 |
| 4. | Al-Turjman, F. | 11 | 0.4 | 45.4 | 58.4 |
| 5. | Park, J.H. | 11 | 0.4 | 56.4 | 39.0 |
| 6. | Corchado, J.M. | 11 | 0.4 | 37.7 | 36.1 |
| 7. | Chui, K.T. | 9 | 0.3 | 28.9 | 38.5 |
| 8. | Lytras, M.D. | 9 | 0.3 | 26.3 | 36.0 |
| 9. | Lv, Z. | 8 | 0.3 | 25.5 | 19.4 |
| 10. | Aloqaily, M. | 8 | 0.3 | 25.6 | 17.8 |
| **Countries** | | | | | |
| 1. | China | 550 | 17.7 | 10.8 | 15.0 |
| 2. | India | 495 | 16.0 | 8.2 | 12.5 |
| 3. | United States | 316 | 10.2 | 17.0 | 17.5 |
| 4. | United Kingdom | 201 | 6.5 | 19.5 | 18.7 |
| 5. | Saudi Arabia | 163 | 5.3 | 16.2 | 15.5 |
| 6. | Italy | 162 | 5.2 | 10.8 | 13.0 |
| 7. | Spain | 148 | 4.8 | 10.4 | 12.6 |
| 8. | South Korea | 126 | 4.1 | 17.9 | 17.1 |
| 9. | Australia | 114 | 3.7 | 40.9 | 24.9 |
| 10. | Canada | 94 | 3.0 | 14.8 | 14.1 |
| **Organisations** | | | | | |
| 1. | King Abdulaziz University | 36 | 1.2 | 26.9 | 29.2 |
| 2. | Egyptian Knowledge Bank EKB | 32 | 1.0 | N/A | 6.6 |
| 3. | Universidad de Salamanca | 25 | 0.8 | 19.0 | 18.9 |
| 4. | King Saud University | 23 | 0.7 | 12.8 | 12.3 |
| 5. | Amity University | 22 | 0.7 | 5.7 | 12.3 |
| 6. | Chinese Academy of Sciences | 21 | 0.7 | 25.2 | 45.3 |
| 7. | Queensland University of Technology | 19 | 0.6 | 36.4 | 28.0 |
| 8. | University of Ottawa | 18 | 0.6 | 21.5 | 14.3 |
| 9. | Wuhan University | 18 | 0.6 | 8.1 | 4.5 |
| 10. | Vellore Institute of Technology | 17 | 0.5 | 16.7 | 12.6 |
| 11. | Universidade do Minho | 17 | 0.5 | 3.2 | 5.6 |
| 12. | N8 Research Partnership | 17 | 0.5 | N/A | 9.9 |
| **Journals** | | | | | |
| 1. | Lecture Notes in Computer Science, Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics | 134 | 4.3 | 6.5 | 1.8 |
| 2. | Advances in Intelligent Systems and Computing | 108 | 3.5 | 2.6 | 0.9 |
| 3. | IEEE Access | 63 | 2.0 | 38.8 | 26.6 |
| 4. | ACM International Conference Proceeding Series | 59 | 1.9 | 3.7 | 4.0 |
| 5. | Sensors (Switzerland) | 55 | 1.8 | 32.9 | 11.3 |
| 6. | Sustainability (Switzerland) | 53 | 1.7 | 18.6 | 13.7 |
| 7. | Lecture Notes in Networks and Systems | 50 | 1.6 | 1.0 | 0.1 |
| 8. | Communications in Computer and Information Science | 44 | 1.4 | 3.6 | 1.9 |
| 9. | MCCSIS 2018 Multi Conference on Computer Science and Information Systems Proceedings of the International Conferences on Big Data Analytics Data Mining and Computational Intelligence 2018 Theory and Practice in Modern Computing 2018 and Connected Smart Cities 2018 | 33 | 1.1 | 0.4 | N/A |
| 10. | Ceur Workshop Proceedings | 30 | 1.0 | 1.0 | 1.0 |
| 11. | Smart Cities | 30 | 1.0 | 24.0 | 12.2 |

Note: NP — number of publications, [%] — percentage of the total number of publications (3101), N/A — not applicable.

Source: elaborated by the authors based on the Scopus and Web of Science databases.

Tab. 4. Most cited articles on artificial intelligence in the smart city area

| No. | Authors | Article title | Journal | Number of citations | |
|---|---|---|---|---|---|
| | | | | Scopus | Web of Science |
| 1. | (Fuller et al., 2020) | Digital Twin: Enabling Technologies, Challenges and Open Research | IEEE Access | 619 | 392 |
| 2. | (Diro & Chilamkurti, 2018) | Distributed Attack Detection Scheme using Deep Learning Approach for Internet of Things | Future Generation Computer Systems | 537 | 402 |
| 3. | (Allam & Dhunny, 2019) | On Big Data, Artificial Intelligence and Smart Cities | Cities | 456 | 305 |
| 4. | (J. Shi et al., 2020) | Smart Textile-Integrated Microelectronic Systems for Wearable Applications | Advanced Materials | 332 | 356 |
| 5. | (Sarker, 2021) | Machine Learning: Algorithms, Real-World Applications and Research Directions | SN Computer Science | 710 | N/A |
| 6. | (Tian & Pan, 2015) | Predicting Short-Term Traffic Flow by long Short-Term Memory Recurrent Neural Network | Proceedings - 2015 IEEE International Conference on Smart City | 350 | 281 |
| 7. | (Allam & Jones, 2020) | On the Coronavirus (Covid-19) Outbreak and the Smart City Network: Universal Data Sharing Standards Coupled with Artificial Intelligence (AI) to Benefit Urban Health Monitoring and Management | Healthcare | 272 | 187 |
| 8. | (Alam et al., 2017) | Data Fusion and IoT for Smart Ubiquitous Environments: A Survey | IEEE Access | 254 | 195 |
| 9. | (Ullah et al., 2020) | Applications of Artificial Intelligence and Machine Learning in Smart Cities | Computer Communications | 271 | 176 |
| 10. | (S. K. Singh et al., 2020) | BlockIoTIntelligence: A Blockchain-enabled Intelligent IoT Architecture with Artificial Intelligence | Future Generation Computer Systems | 241 | 170 |
| 11. | (S. Singh et al., 2020) | Convergence of Blockchain and Artificial Intelligence in IoT Network for the Sustainable Smart City | Sustainable Cities and Society | 240 | 153 |

Note: N/A — not applicable.

Source: elaborated by the authors based on the Scopus and Web of Science databases.

To clearly present the obtained results, the co-occurrence map was reduced to 86 keywords strictly linked to the area under investigation. Among the most frequent keywords related to artificial intelligence in the context of a smart city are terms associated with technological aspects — Internet of Things (655), machine learning (408), big data (253), deep learning (207), cloud computing (121), blockchain (111). These are interconnected with artificial intelligence and are closely linked with keywords identified in seven clusters, encompassing issues related to the development of a smart city. Within these individual clusters, the most frequently appearing keywords were safety — security (91) and privacy (54); energy — energy (69), smart grid (52); mobility — Intelligent Transport Systems (61) and traffic management (52); health — healthcare (52) and digital twin (49); living — smart building (41) and smart home (35); industry — industry 4.0 (42); pollution — smart waste management (21). The larger the circle in Fig. 6, the more often a given keyword occurs. It should also be highlighted that these terms exhibit the most connections to other terms.

An in-depth analysis of the most frequently occurring keywords allowed for identifying seven thematic clusters and linking them to the eight transformative policies of the European Green Deal (EDG). In the context of smart city development, the European Green Deal strategy, implemented in 2020, plays a significant role. This strategy is the European Union's plan to make the EU climate-neutral by 2050 and to chart a course towards economic development

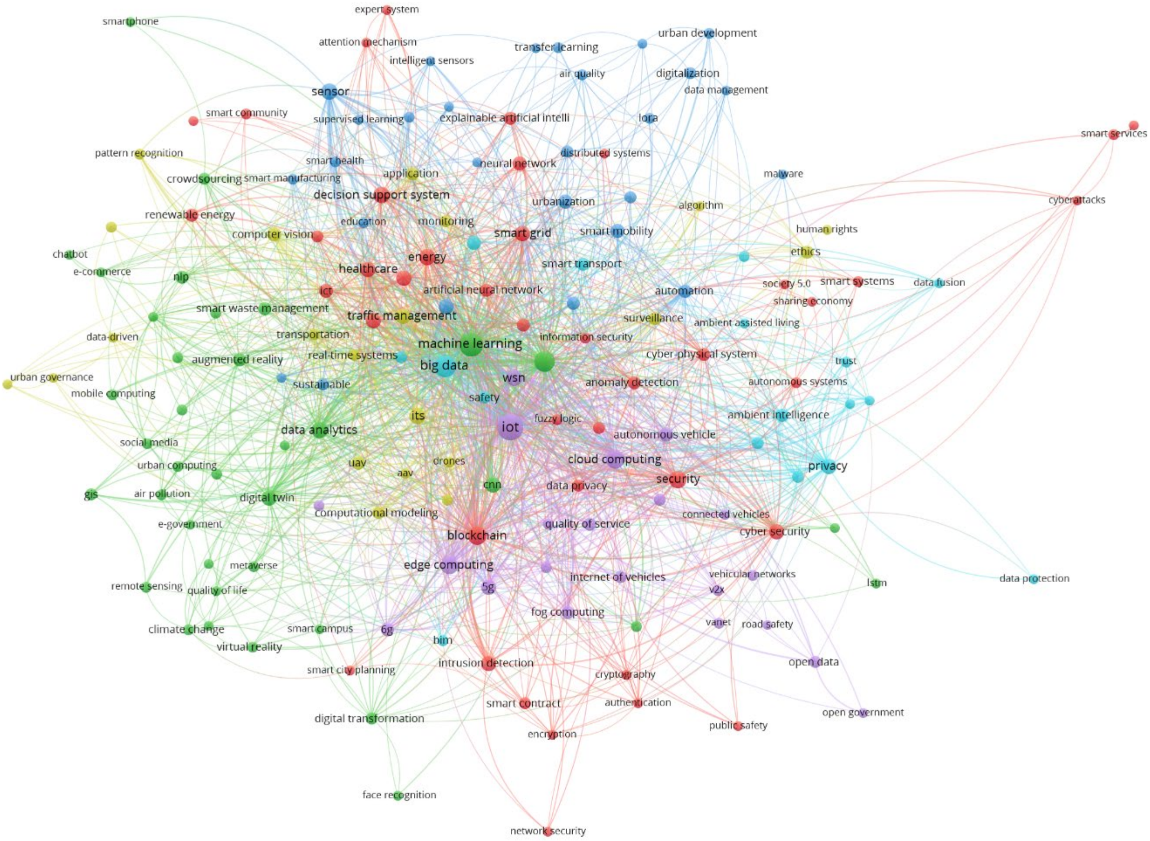



Fig. 3. Keyword co-occurrence map for artificial intelligence in smart cities
Source: elaborated by the authors using VOSviewer software.

that does not increase the consumption of natural resources. The EGD is a key component of the current European Commission's strategy for the fulfilment of the UN 2030 Agenda for Sustainable Development and the Sustainable Development Goals (United Nations, 2015). The European Green Deal serves as a blueprint, outlining the path towards a sustainable European economy. The primary target of the European Green Deal strategy is to achieve a minimum 55 % reduction in net greenhouse gas emissions by 2030, using 1990 levels as a benchmark, and to reach climate neutrality by 2050 (Communication …, 2019). The overarching aim of the European Green Deal strategy is to make sustainable development and human well-being the cornerstone of economic policy, positioning them as a crucial aspect of all policymaking decisions and ensuing actions (Amoroso et al., 2021; Szpilko & Ejdys, 2022). Due to the significant issue of implementing the European Green Deal in EU regions and cities, the identified subareas of artificial intelligence in smart cities were related to its policies (Table 5).

The first cluster, "Safety", primarily refers to areas in which the application of artificial intelligence can ensure safety in smart cities (e.g., privacy, public safety, security, cyber security, cyberattacks, data privacy, data protection, e-commerce, e-government, monitoring, open data, open government, smart environment, smart infrastructure, smart services, intrusion detection, anomaly detection, trust, ethics, human rights). This cluster is closely linked to the transformative policy of the European Green Deal, which involves, among other things, supplying clean, affordable and secure energy and mobilising industry for a clean and circular economy. It is also related to zero pollution and striving for a toxin-free environment.

The second cluster, "Living", focuses on ensuring the highest possible standard of living for residents in smart cities through the use of artificial intelligence. It includes keywords such as quality of life, sharing economy, smart city 5.0, smart community, smart education, smart government, smart home, air quality, smart building, disaster management, society 5.0,

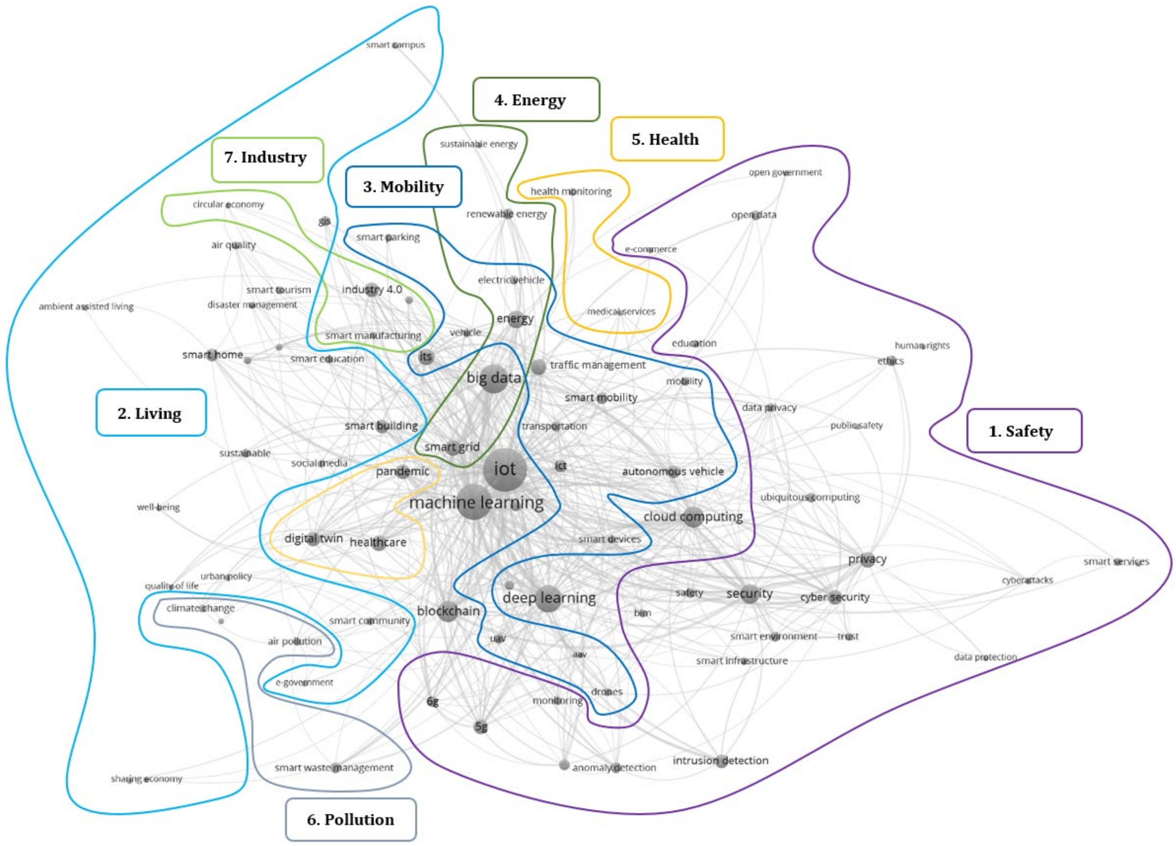



Fig. 4. Thematic clusters of artificial intelligence in smart cities
Source: elaborated by the authors using VOSviewer software.

sustainable, urban policy, and well-being. This cluster is linked to the EGD, which focuses on building and renovation in an energy and resource-efficient way. Striving to provide comfortable living conditions in smart cities also refers to the protection and restoration of ecosystems and biodiversity, which are also subject to EGD transformation policy.

The third cluster, "Mobility", relates to the development of innovative vehicles to enable the most efficient mobility while reducing CO2 emissions. It is associated with the following keywords: vehicle, autonomous vehicle, electric vehicle, ICT, intelligent transport system, smart mobility, smart parking, smart transport, traffic management, transportation, autonomous air vehicles, unmanned aerial vehicles, drones, and smart devices. This cluster is closely linked to the transformative policy of the European Green Deal in terms of transitioning to sustainable and smart mobility.

The fourth cluster, "Energy", primarily refers to technological solutions using AI that enable efficient and safe energy supply and storage, including from renewable sources (e.g., energy, renewable energy, smart energy, sustainable energy, smart grid). This cluster is closely linked to the transformative policy of the European Green Deal aimed at providing clean, affordable, and secure energy.

The fifth cluster, "Health", is oriented towards providing solutions that use artificial intelligence to support residents of smart cities in caring for their health. It is represented by keywords: smart health, healthcare, medical services, digital twin, health monitoring, pandemic. Within the EGD, these topics partially refer to the objective of designing a fair, healthy and environmentally friendly food system.

The sixth cluster, "Pollution", includes keywords related to various pollutants, especially air pollution and waste management (air pollution, climate change, smart waste management). This is closely linked to the goal of zero pollution and a toxin-free environment set out in the EGD.

The last cluster, "Industry", is represented by keywords such as circular economy, digital economy, industry 4.0, RFID, and smart manufacturing. It focuses on Industry 4.0 based on artificial intelligence and simultaneously environmentally friendly production. It appears to be an emerging research area hitherto poorly recognised in the literature. It is

Tab. 5. Sub-areas of artificial intelligence in smart city research in the context of European Green Deal policies

<table>
<tr><th>No.</th><th>Cluster name</th><th>General words</th><th>Words</th><th colspan="2">Transformative policies of the European Green Deal</th></tr>
<tr><td>1.</td><td>Safety</td><td rowspan="7">Internet of Things, machine learning, big data, deep learning, blockchain, cloud computing</td><td>privacy, public safety, quality of service, safety, security, cyber security, cyberattacks, data privacy, data protection, e-commerce, e-government, monitoring, open data, open government, smart environment, smart infrastructure, smart services, intrusion detection, anomaly detection, ubiquitous computing, 5G, 6G, BIM, education, trust, ethics, human rights</td><td>2. Supplying clean, affordable and secure energy<br>3. Mobilising industry for a clean and circular economy<br>8. A zero pollution ambition for a toxic-free environment</td><td rowspan="7">1. Increasing the EU's climate ambition for 2030 and 2050</td></tr>
<tr><td>2.</td><td>Living</td><td>quality of life, sharing economy, smart campus, smart city 5.0, smart community, smart education, smart government, smart home, smart tourism, air quality, ambient assisted living, smart building, disaster management, GIS, social media, society 5.0, sustainable, urban policy, well-being</td><td>2. Supplying clean, affordable and secure energy<br>4. Building and renovating in an energy and resource-efficient way</td></tr>
<tr><td>3.</td><td>Mobility</td><td>mobility, vehicle, autonomous vehicle, electric vehicle, ICT, intelligent transport system, smart mobility, smart parking, smart transport, traffic management, transportation, autonomous air vehicles, unmanned aerial vehicle, drones, smart devices</td><td>5. Accelerating the shift to sustainable and smart mobility</td></tr>
<tr><td>4.</td><td>Energy</td><td>energy, renewable energy, smart energy, sustainable energy, smart grid</td><td>4. Building and renovating in an energy and resource-efficient way</td></tr>
<tr><td>5.</td><td>Health</td><td>smart health, healthcare, medical services, digital twin, health monitoring, pandemic</td><td>6. From 'Farm to Fork': designing a fair, healthy and environmentally-friendly food system</td></tr>
<tr><td>6.</td><td>Pollution</td><td>air pollution, climate change, smart waste management</td><td>8. A zero pollution ambition for a toxic-free environment<br>7. Preserving and restoring ecosystems and biodiversity</td></tr>
<tr><td>7.</td><td>Industry</td><td>circular economy, digital economy, industry 4.0, RFID, smart manufacturing</td><td>3. Mobilising industry for a clean and circular economy</td></tr>
</table>

closely linked to the EGD goal of mobilising industry for a clean and circular economy. It should also be noted that all the mentioned clusters directly or indirectly also refer to achieving the EU's climate goals for 2030 and 2050.

The application of solutions using artificial intelligence technologies can significantly improve the issue of implementing the European Green Deal assumptions in smart cities.

# 4. Discussion of results

The bibliometric analysis facilitated the identification of seven thematic domains within international research in connection with artificial intelligence in smart cities. These span a diverse range of subjects, including primarily computer science, engineering and social sciences.

## 4.1. Safety

Artificial intelligence has emerged as a transformative tool, reshaping the concept and construction of smart cities by enhancing efficiency, accessibility, and quality of life in urban areas (Braun et al., 2018). It is recognised as a crucial instrument in redefining the realms of safety, security, and privacy within these complex urban ecosystems (Allam & Dhunny, 2019; Ullah et al., 2020).

Within the spheres of safety and security, AI has found a range of applications, from traffic management to healthcare and city-wide surveillance (Allam & Jones, 2020; Shi et al., 2020; Ullah et al., 2020; Badura, 2017). Technologies, such as Smart Textile-Integrated Microelectronic Systems (STIMES) and Intelligent Transportation Systems (ITSs), have utilised AI to optimise safety protocols and enhance service quality (Shi et al., 2020; Ullah et al., 2020). AI and machine learning strategies have been employed to enhance health service delivery in the healthcare sector, proving advantageous for urban inhabitants and city management (Ullah et al., 2020).

Despite these advancements, the considerable influx of data facilitated by the Internet of Things introduces significant security and privacy challenges. Issues of centralisation and resource constraints present notable hurdles for AI-driven systems (Singh et al., 2020). With its decentralised architecture, the deployment of blockchain has been proposed as a solution to mitigate these problems (K. Singh et al., 2020; S. Singh et al., 2020; Łasak & Wyciślak, 2023).

Furthermore, federated learning, a distributed collaborative AI approach, enables AI training on distributed IoT devices without data sharing, thereby enhancing data security and privacy (Nguyen et al., 2021; Lv et al., 2021).

Additionally, the convergence of AI and blockchain in smart cities introduces new security challenges, necessitating further investigation (S. Singh et al., 2020). For example, the widespread implementation of IoT, coupled with evolving cyber threats, demands more dynamic and adaptive security measures (Sarker et al., 2022). Innovative approaches such as Holistic Big Data Integrated Artificial Intelligence Modelling (HBDIAIM) aim to address these issues by optimising the scalability and privacy of smart city data management interfaces (Chen et al., 2021).

Preserving privacy, particularly in high-dimensional data collected by IoT devices, poses a significant challenge (Braun et al., 2018). Encrypted data storage on cloud platforms (Anuradha et al., 2021) has been suggested as a solution to this issue, offering secure, remote access to data such as healthcare records. Federated learning approaches can also alleviate these privacy concerns by enabling model training on locally stored data (Liu, Huang et al., 2020).

AI applications also need to consider cultural, metabolic, and governance aspects, necessitating a delicate balance between technological utilisation for economic growth and the maintenance of urban livability (Allam & Dhunny, 2019). Global approaches to AI application control have varied, ranging from a human-centric approach in Western democracies to a techno-centric approach in places like China (Kummitha, 2020).

## 4.2. Living

The growing trend of urbanisation worldwide has put a tremendous strain on the daily lives of citizens, necessitating solutions to issues such as environmental pollution, public security, and congestion. Smart cities, utilising novel technologies and concepts, aim to create more efficient, technologically advanced, and socially inclusive urban environments, which could potentially alleviate these burdens (Atitallah et al., 2020; Ghazal et al., 2021). The integration of artificial intelligence and the Internet of Things into these urban environments plays a pivotal role in this process.

These technologies generate substantial data, which, upon analysis, provide invaluable insights to enhance the quality of urban life (Atitallah et al., 2020; Ghazal et al., 2021; Skouby & Lynggaard, 2014; Rahman et al., 2023; Gams et al., 2019). The revolutionary progress of AI, driven by advancements in 5G technology, cloud computing, and ICT, forms the foundation for seamless service delivery and the management of interconnected infrastructures, including smart homes (Skouby & Lynggaard, 2014; Gams et al., 2019).

The smart home concept, a vital element of smart cities, has significantly enhanced urban living through the integration of various technological advancements, such as AI, big data, mobile networks, and cloud computing (Li et al., 2022; Shi et al., 2022; Khoa et al., 2020). Such advancements serve as prime examples of the pivotal role AI-powered IoT plays in addressing contemporary societal challenges, like the COVID-19 pandemic, where SDL-based smart health diagnosis systems have been effectively utilised (Shankar et al., 2021). Similarly, AIoT systems have substantially improved safety and air quality monitoring in smart homes, offering potential advancements in hazard detection (Chang et al., 2020).

AI applications in smart cities have also expanded to include emotion-guided interaction architectures, enabling enhanced human–machine interaction while addressing issues such as handling information redundancy in the collected spatiotemporal environment data (Jiang et al., 2020). Nevertheless, despite the promises, concerns about security and privacy remain paramount, necessitating robust security measures and cautious information handling (Khoa et al., 2020; Wu et al., 2023; Braun et al., 2018).

The impact of AI extends beyond smart homes, influencing broader domains, including mobility, logistics, energy, healthcare, and environmental management (Frey et al., 2022; Chang et al., 2020; López-Blanco et al., 2023; Zhi-Xian & Zhang, 2022; Hu et al., 2021; Alsamhi et al., 2019). A prime example of AI integration in urban development is the living lab concept, like the Bauhaus.MobilityLab, which facilitates data processing, analytics, and forecasting for innovative service development (Frey et al., 2022). Moreover, environmental forecasting and urban planning reap significant benefits from AI and IoT combined with big data, enabling the development of future environmental scenarios (López-Blanco et al., 2023).

However, despite these significant advancements, challenges persist. Concerns regarding privacy preservation, network security, and trustworthy data-sharing practices are of utmost importance (Braun et al., 2018). Additionally, social and juristic challenges emerge when individual interests conflict with others, highlighting the necessity for constructive guidelines (Perc et al., 2019).

### 4.3. Mobility

Artificial intelligence and other digital technologies have been instrumental in shaping mobility within the landscape of smart cities, leading to significant advancements in transportation and sustainability (Ortega-Fernández et al., 2020; Kuźmicz et al., 2022). Implementing AI into various mobility applications has transformed conventional transportation paradigms, prompting further research into this domain.

A pivotal component of this transformation is the utilisation of autonomous vehicles. Enabled by AI and big data analytics, AVs have revolutionised urban mobility, reducing travel times and increasing efficiency. Network calculus (NC) has been proposed to further optimise the Avs' performance by modelling queueing networks, thereby improving the user experience (Cui et al., 2019). Simultaneously, cybersecurity measures, such as blockchain technology and intelligent sensing, are vital for ensuring the safety and reliability of these systems (Reebadiya et al., 2021). Furthermore, AI-driven sensor information fusion systems have enhanced understanding of citizens' mobility patterns, contributing to the development of improved transportation models (Leung et al., 2019; Ejdys & Gulc, 2020; Szpilko et al., 2023).

Electric vehicles also represent a significant commitment to eco-friendly initiatives and the smart city concept, with AI facilitating the management of power within vehicles to optimise energy usage (Aymen & Mahmoudi, 2019). This approach includes collecting and processing data on road conditions and vehicle status.

Moreover, unmanned aerial vehicles have shown promise in various applications, such as wireless coverage and aerial surveillance, with AI and machine learning techniques contributing to their efficiency (Ullah et al., 2020). The growth of the Internet of Things, in conjunction with AI, has been significant in promoting sustainable transitions towards more efficient paradigms in smart city mobility (Nikitas et al., 2020). This integration involves addressing several security challenges (Kim et al., 2021).

An interesting development within this context is the proposition of Autonomous Shuttles (AS) for efficient delivery of goods and last-mile mobility services. The Autonomous Shuttles-as-a-Service (ASaaS) concept, coupled with machine learning techniques for mobility planning and journey tracking certification via AI and blockchain, offers a comprehensive solution for enhancing proximity mobility (Bucchiarone et al., 2021).

Beyond this, Fully Autonomous Ground Vehicles (FAGVs) present an exciting future for smart city development, with real-time data analytics enabling these vehicles to integrate seamlessly with other smart city components, thereby optimising urban environments and promoting sustainable development (Kuru, 2021).

These developments in mobility have been influenced by various factors, including social attitudes, technological innovation, urban politics, and even significant global events such as the COVID-19 pandemic, which has prompted a transformation towards sustainability and smart growth (Kakderi et al., 2021). The introduction of concepts like Mobility-as-a-Service (MaaS), traffic flow optimisation, and reduction in traffic congestion, all underpinned by technologies such as AI, blockchain, and big data, are set to further revolutionise urban environments (Tian & Pan, 2015; Paiva et al., 2021; Wu, 2021).

## 4.4. Energy

Artificial intelligence continues to exert a transformative influence on smart city development. A major challenge for these cities is energy management, which necessitates the employment of modern technologies for optimal efficiency (Abbas et al., 2020; Kozłowska et al., 2023). Given the complexity and vital role of energy systems, AI and machine learning, in conjunction with the Internet of Things, have emerged as indispensable tools.

AI models, especially those based on artificial neural networks (ANNs) and meta-heuristic algorithms, have been introduced for forecasting and optimising the heating load of buildings' energy efficiency (Le et al., 2019). These innovative approaches contribute significantly to managing and optimising energy usage in buildings, accounting for a considerable proportion of global final energy demand (Vázquez-Canteli et al., 2019; Wu & Chu, 2021). Machine learning algorithms, particularly deep reinforcement learning, are central to this process, fostering adaptive and automated energy controllers for energy savings and demand response (Le et al., 2019).

AI's role extends to promoting energy sustainability, a pivotal aspect of urban development. AI-enabled solutions, such as smart metering and non-intrusive load monitoring (NILM), along with hybrid algorithms like GA-SVM-MKL, are reshaping energy management, enhancing sustainability, and adding a novel dimension to the discourse on energy utilisation (Chui et al., 2018). AI, along with IoT and big data analytics, has been recognised as a potential tool for intelligently prioritising data, thereby fostering more energy-efficient and greener smart cities (Muhammad et al., 2019).

AI also assists in renewable energy adoption within the context of smart cities. AI tools like ANN and statistical analysis have accurately predicted electrical energy consumption while promoting renewable energy generation (Ghadami et al., 2021; Serban & Lytras, 2020).

Moreover, AI contributes to energy consumption prediction and integrated local energy systems (ILES). For instance, the implementation of hybrid networks, such as the "DB-Net", which integrates a dilated convolutional neural network (DCNN) with bidirectional long short-term memory (BiLSTM), has enhanced predictive performance for long- and short-term energy consumption prediction (Khan et al., 2021). Additionally, AI's integration with emerging technologies like electric vehicles optimises energy use in smart cities (Aymen & Mahmoudi, 2019).

Finally, AI is instrumental in short-term photovoltaic (PV) energy generation forecasting (Zhou et al., 2021), optimising energy consumption in infrastructures like Automated Vacuum Waste Collection (AVWC) systems (Fernández et al., 2014), supporting intelligent building energy management systems (BEMSs) (Park et al., 2020), and enhancing the efficiency of critical urban infrastructure sectors, such as sewage treatment and waste management systems (Gaska & Generowicz, 2020).

In conclusion, AI is profoundly influencing the energy sector within smart cities, transforming energy use, improving energy forecasts, and enhancing urban infrastructure operations. As AI and big data technologies continue to evolve, the need for standardised regulations regarding their energy efficiency becomes increasingly important (Anthopoulos & Kazantzi, 2022). Future research and development should address this challenge, ensuring the sustainable growth of these promising technologies.

## 4.5. Health

The convergence of healthcare and AI within the context of smart cities marks a pivotal juncture in the evolution of health services delivery. This marriage of disciplines holds transformative potential for enhancing well-being, refining healthcare management processes, and strengthening disease control mechanisms (Laamarti et al., 2020; Kamel Boulos et al., 2019; Dong & Yao, 2021).

One of the prime developments within this context is the advent of Digital Twin technology (Fuller et al., 2020), which involves creating digital replicas of living entities. The use of the ISO/IEEE 11073 standardised framework in this regard allows for the collection, analysis, and feedback generation from personal health data accrued from both compliant and non-compliant devices (Laamarti et al., 2020). Additionally, the confluence of GeoAI, the integration of geographic information systems and AI, underscores the significance of location-specific factors in both population and individual health, thus expanding the scope of AI application within healthcare (Kamel Boulos et al., 2019).

The recent COVID-19 pandemic has further magnified the transformative potential of digital solutions within healthcare, paving the way for data-driven smart city models (Hantrais et al., 2021; Dong & Yao, 2021; Allam & Jones, 2020). The effectiveness of AI in managing health emergencies is evident from the different approaches adopted by governments during the COVID-19 pandemic. While Chinese cities and the government used a techno-driven approach, Western governments adopted a human-driven approach to control the transmission of the virus. The analysis suggests that while the techno-driven approach may be more efficient in identifying and isolating infected individuals, it may also suppress and censor citizens' views. Therefore, understanding the human–technology relationship is critical in managing virus transmissions during pandemics (Kummitha, 2020).

One of the technologies that have received attention in the healthcare sector is blockchain, which offers solutions for securing patient and provider identities, managing pharmaceutical and medical device supply chains, clinical research and data monetisation, medical fraud detection, and public health surveillance (Boulos et al., 2018). Coupling blockchain technologies with AI may enhance their power and robustness, leading to more effective healthcare solutions in smart cities.

Healthcare delivery has further been enriched through the integration of telemedicine, telecare, and AI within smart home systems, thereby improving the quality and efficiency of care (Khatoon et al., 2019). Alongside these advancements, the incorporation of cloud computing and deep learning technologies has enabled accurate prediction of diseases based on data collected from IoT sensors embedded within human bodies (Anuradha et al., 2021).

Despite the numerous benefits, several challenges, including privacy and security issues, data handling, and algorithm optimisation, remain and must be addressed to harness the full potential of AI within the healthcare sector (Laamarti et al., 2020; Kamel Boulos et al., 2019; Gad, 2022; Hantrais et al., 2021; Dong & Yao, 2021; Zheng et al., 2022).

The AI technologies, such as deep learning, machine learning, Internet of Things, mobile computing, big data, blockchain, and advanced network systems, are predicted to play a significant role in future smart cities (Javed et al., 2022; Ullah et al., 2020). The amalgamation of AI with big data analytics further enhances the precision of future action plans and improves decision-making strategies (Hariri et al., 2019). Despite the wide array of applications of AI in healthcare, the black-box nature of AI inhibits its widespread acceptance, which necessitates the development of explainable artificial intelligence (XAI) techniques (Loh et al., 2022).

### 4.6. Pollution

Environmental pollution is one of the major challenges of urban growth, manifesting in multiple forms, such as air, noise, and waste pollution. This pollution, arising from industrial and transportation activities, exacerbates the stress experienced by urban inhabitants (Kaginalkar et al., 2021; Liu et al., 2020; Navarro-Espinoza et al., 2022). AI, IoT, big data, smartphones, and cloud computing offer promising solutions to manage and mitigate these pollution types, thus enhancing urban mobility and quality of life (Kaginalkar et al., 2021; Liu et al., 2020; Bucchiarone et al., 2021; Garcia-Retuerta et al., 2021).

The introduction of predictive and preventative measures has introduced a novel approach to combat pollution. Specifically, deep learning models have demonstrated efficacy in predicting traffic flow at intersections, enabling adaptive traffic control and, consequently, reducing pollution resulting from traffic congestion (Tian & Pan, 2015; Navarro-Espinoza et al., 2022; Yuan et al., 2022). Likewise, IoT devices like drones have been deployed for environmental surveillance, contributing to pollution monitoring and management (Gohari et al., 2022).

Regarding waste management, AI and IoT technologies hold immense potential. They can optimise waste collection, mitigate overflows, and enhance recycling processes, leading to a cleaner urban environment (Ghazal et al., 2021). For instance, smart bins providing real-time data about their status can significantly improve waste collection efficiency (Abuga & Raghava, 2021). Furthermore, AI's implementation in waste management allows for predictive analysis, enabling cities to anticipate and effectively plan for waste accumulation and disposal (Gaska & Generowicz, 2020).

Nonetheless, the adoption of these advanced technologies faces challenges, including inadequate infrastructure, insufficient funding, cybersecurity risks, and a general lack of trust in these technologies (Wang et al., 2021). Understanding and addressing these challenges are crucial to realising the full potential of AI and IoT in developing sustainable smart cities (Rani et al., 2021).

### 4.7. Industry

Artificial intelligence, in conjunction with other modern technologies, is undoubtedly reshaping various sectors in smart cities. However, the transition to Industry 4.0 is not without its challenges, particularly concerning cloud-based data storage, computation, and communication. Concerns have arisen due to problems such as transmission delay, single points of failure, and privacy disclosure. As a potential solution, blockchain technology has been suggested with its decentralised, tamper-proof, and transparent nature, and it is expected to work alongside AI and 5G to overcome these challenges (Chen et al., 2022).

In the manufacturing sector, AI has played a pivotal role in the development of intelligent systems, enhancing decision-making and increasing flexibility in physical processes to meet the dynamic global market demands (Espina-Romero et al., 2023).

During the era of Industry 4.0 and smart city paradigms, the synergistic application of AI and IoT has proven to be highly effective in monitoring and tracking water consumption, achieving an impressive recognition rate of approx. 98 % (Ktari et al., 2022). Additionally, in the hospitality sector, AI-enabled robots are being deployed to provide personalised services and facilitate seamless guest experiences (Gupta et al., 2022). Notably, these technologies have had a significant impact on the hotel industry by improving service quality and minimising operational costs (Khan et al., 2017; Nam et al., 2021).

Digital Twin technology, recognised as one of the top ten strategic technology trends by Gartner Inc. in 2017, has been integrated into manufacturing and the Industrial Internet of Things. The combination of AI, machine learning, deep learning, and big data within the Industry 4.0 paradigm has facilitated this integration, enabling predictive analysis of potential issues, thus preventing downtime and fostering new opportunities (Augustine, 2020).

Furthermore, the transition from Industry 4.0 to Industry 5.0 has witnessed an increased adoption of metaverse technology, promoting responsible digital transformation. However, this transition is not without challenges, including potential job losses due to automation, increased energy consumption, and the ongoing financial commitments required by AI systems. Therefore, sustainable practices and responsible digitisation must play a central role in managing these challenges (De Giovanni, 2023).

Industry 5.0 signifies a paradigm shift, emphasising collaboration between humans and machines to enhance customer satisfaction. This shift involves the utilisation of advanced technologies, such as big data analytics, IoT, collaborative robots, blockchain, digital twins, and future 6G systems (Adel, 2022). In the transition to a circular economy (CE), the construction industry is notably leveraging these digital technologies for asset tracking, performance optimisation, and increased salvage value, ultimately contributing to a more sustainable industry (Elghaish et al., 2022).

Finally, it is crucial to acknowledge that this increased reliance on AI demands a better understanding and management of potential environmental, social, and economic impacts. Combining tools such as Life Cycle Assessment (LCA) with AI and machine learning can help anticipate uncertainties in the early stages of design, thereby contributing to the comprehensive performance assessment of smart cities (Ragab et al., 2023).

## Conclusions

The transformative influence of artificial intelligence within the context of smart cities is undeniable. AI has permeated various sectors, catalysed by complementary technologies, such as the Internet of Things, blockchain, machine learning, deep learning, and federated learning. These benefits include enhanced efficiency, accessibility, and an improved quality of life in urban areas. However, the amalgamation of these advancements brings forth a plethora of new challenges that warrant further research and investigation.

Foremost among these challenges is the issue of data security and privacy. The ubiquitous integration of IoT technologies amplifies the volume of generated data, leading to significant security and privacy concerns (S. K. Singh et al., 2020). These concerns often stem from centralisation and resource constraints, necessitating innovative solutions such as deploying blockchain and federated learning.

Within urban mobility, AI and digital technologies have revolutionised the landscape, bringing forward innovations such as AVs, EVs, and UAVs. Specifically, the application of AI for mobility planning and journey tracking certification via AI and blockchain, along with concepts like Mobility-as-a-Service, form promising areas of exploration. However, these advancements are not devoid of security challenges, highlighting the need for further research in this domain (Kim et al., 2021).

AI's transformative impact extends into the energy sector, where intelligent solutions reshape energy management and sustainability practices. The role of AI in promoting renewable energy adoption, forecasting energy consumption, and developing Integrated Local Energy Systems is increasingly pronounced (Ghadami et al., 2021; Le et al., 2019; Khan et al., 2021). This evolution necessitates standardised regulations regarding energy efficiency as AI and big data technologies advance, signifying another area ripe for future research (Anthopoulos & Kazantzi, 2022).

In the health sector, advancements such as Digital Twin technology and the integration of GeoAI provide opportunities for location-specific health interventions (Laamarti et al., 2020; Kamel Boulos et al., 2019). However, optimising data handling, addressing privacy and security concerns, and improving data sharing protocols require further research. The ethical and societal implications of these applications should also be studied to understand their potential impacts on citizens' rights and trust (Kummitha, 2020).

With regard to environmental management, AI can contribute to mitigating urban growth challenges such as pollution through applications like traffic flow prediction and optimised waste management systems. However, the adoption of these technologies is not without its challenges, including infrastructure development, funding, and cybersecurity risks, pointing towards the need for further research (Wang et al., 2021; Rani et al., 2021).

Finally, the industrial sector, transitioning towards Industry 4.0 and 5.0, heavily depends on AI and blockchain technologies. The potential for job losses due to automation, increased energy consumption, and the financial commitments required by AI systems are challenges that need to be addressed, advocating for further research into sustainable practices and responsible digitisation (De Giovanni, 2023).

In conclusion, while the integration of AI in smart cities holds promising potential for transforming urban life, it is also accompanied by a series of challenges related to data security, privacy, and regulatory compliance. Future research needs to grapple with these issues to unlock the full potential of AI and facilitate sustainable growth and advancement of these technologies.

# Acknowledgements

This research was funded under the International Academic Partnership Programme no. BPI/PST/2021/1/00011/U/00001 with the Polish National Agency for Academic Exchange.

# Literature

Abbas, S., Khan, M. A., Falcon-Morales, L. E., Rehman, A., Saeed, Y., Zareei, M., Zeb, A., & Mohamed, E. M. (2020). Modeling, Simulation and Optimization of Power Plant Energy Sustainability for IoT Enabled Smart Cities Empowered with Deep Extreme Learning Machine. *IEEE Access*, *8*, 39982-39997. doi: 10.1109/ACCESS.2020.2976452

Abuga, D., & Raghava, N. S. (2021). Real-time smart garbage bin mechanism for solid waste management in smart cities. *Sustainable Cities and Society*, *75*. doi: 10.1016/j.scs.2021.103347

Adel, A. (2022). Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing-Advances Systems and Applications*, *11*(1). doi: 10.1186/s13677-022-00314-5

Aguilera, U., Peña, O., Belmonte, O., & López-de-Ipiña, D. (2017). Citizen-centric data services for smarter cities. *Future Generation Computer Systems*, *76*, 234-247. doi: 10.1016/j.future.2016.10.031

Alam, F., Mehmood, R., Katib, I., Albogami, N. N., & Albeshri, A. (2017). Data Fusion and IoT for Smart Ubiquitous Environments: A Survey. *IEEE Access*, *5*, 9533-9554. doi: 10.1109/ACCESS.2017.2697839

Alifi, M. R., & Supangkat, S. H. (2016). Information extraction for traffic congestion in social network: Case study: Bekasi city. *2016 International Conference on ICT for Smart Society, ICISS 2016*, 53-58. doi: 10.1109/ICTSS.2016.7792848

Ali, R., Zikria, Y. B., Kim, B.-S., & Kim, S. W. (2020). Deep reinforcement learning paradigm for dense wireless networks in smart cities. In *EAI/Springer Innova-*

*tions in Communication and Computing* (pp. 43-70). Springer Science and Business Media Deutschland GmbH. doi: 10.1007/978-3-030-14718-1_3

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities*, *89*, 80-91. doi: 10.1016/j.cities.2019.01.032

Allam, Z., & Jones, D. S. (2020). On the coronavirus (Covid-19) outbreak and the smart city network: Universal data sharing standards coupled with artificial intelligence (ai) to benefit urban health monitoring and management. *Healthcare, 8*(1). doi: 10.3390/healthcare8010046

Allam, Z., & Newman, P. (2018). Redefining the Smart City: Culture, Metabolism and Governance. *Smart Cities*, *1*(1), 4-25. doi: 10.3390/smartcities1010002

Allam, Z., Tegally, H., & Thondoo, M. (2019). Redefining the use of big data in urban health for increased liveability in smart cities. *Smart Cities*, *2*(2), 259-268. doi: 10.3390/smartcities2020017

Alsamhi, S. H., Ma, O., Ansari, M. S., & Almalki, F. A. (2019). Survey on collaborative smart drones and internet of things for improving smartness of smart cities. *IEEE Access*, *7*, 128125-128152. doi: 10.1109/ACCESS.2019.2934998

Al-Turjman, F., & Baali, I. (2022). Machine learning for wearable IoT-based applications: A survey. *Transactions on Emerging Telecommunications Technologies*, *33*(8). doi: 10.1002/ett.3635

Al-Turjman, F., Nayyar, A., Devi, A., & Shukla, P. K. (2021). Intelligence of things: AI-IoT based critical-applications and innovations. In *Intelligence of Things: AI-IoT Based Critical-Applications and Innovations*. Springer International Publishing. doi: 10.1007/978-3-030-82800-4

Amoroso, S., Aristodemou, L., Criscuolo, C., Dechezleprete, A., Dernis, H., Grassano, N., Moussiegt, L., Napolitano, L., Nawa, D., Squicciarini, M., & Tuebke, A. (2021). World Corporate Top R&D investors: Paving the way for climate neutrality. *Publications Office of the European Union, Luxembourg, JRC126788, EUR 30884 EN*.

Ang, K. L.-M., Seng, J. K. P., Ngharamike, E., & Ijemaru, G. K. (2022). Emerging Technologies for Smart Cities' Transportation: Geo-Information, Data Analytics and Machine Learning Approaches. *ISPRS International Journal of Geo-Information*, *11*(2). doi: 10.3390/ijgi11020085

Anthopoulos, L., & Kazantzi, V. (2022). Urban energy efficiency assessment models from an AI and big data perspective: Tools for policy makers. *Sustainable Cities and Society*, *76*. doi: 10.1016/j.scs.2021.103492

Anuradha, M., Jayasankar, T., Prakash, N. B., Sikkandar, M. Y., Hemalakshmi, G. R., Bharatiraja, C., & Britto, A. S. F. (2021). IoT enabled cancer prediction system to enhance the authentication and security using cloud computing. *Microprocessors and Microsystems*, *80*. doi: 10.1016/j.micpro.2020.103301

Aqib, M., Mehmood, R., Alzahrani, A., & Katib, I. (2020). In-memory deep learning computations on gpus for prediction of road traffic incidents using big data fusion. In *EAI/Springer Innovations in Communication and Computing* (pp. 79-114). Springer Science and Business Media Deutschland GmbH. doi: 10.1007/978-3-030-13705-2_4

Atitallah, S. B., Driss, M., Boulila, W., & Ghezala, H. B. (2020). Leveraging Deep Learning and IoT big data analytics to support the smart cities development: Review and future directions. *Computer Science Review*, *38*. doi: 10.1016/j.cosrev.2020.100303

Augustine, P. (2020). The industry use cases for the Digital Twin idea. In P. Raj & P. Evangeline (Eds.), *Advances in Computers* (pp. 79-105). Academic Press Inc. doi: 10.1016/bs.adcom.2019.10.008

Aymen, F., & Mahmoudi, C. (2019). A novel energy optimization approach for electrical vehicles in a smart city. *Energies*, *12*(5). doi: 10.3390/en12050929

Badura, D. (2017). Urban traffic modeling and simulation. *Forum Scientiae Oeconomia*, *5*(4), 85-97. doi: 10.23762/FSO_VOL5NO4_17_7

Bilan, S., Šuleř, P., Skrynnyk, O., Krajňáková, E., & Vasilyeva, T. (2022). Systematic bibliometric review of artificial intelligence technology in organizational management, development, change and culture. *Business: Theory and Practice*, *23*(1), 1-13. doi: 10.3846/btp.2022.13204

Bornmann, L., & Haunschild, R. (2017). Quality and impact considerations in bibliometrics: a reply to Ricker. *Scientometrics*, *111*(3), 1857-1859. doi: 10.1007/s11192-017-2373-3

Boulos, M. N. K., Wilson, J. T., & Clauson, K. A. (2018). Geospatial blockchain: promises, challenges, and scenarios in health and healthcare. *International Journal of Health Geographics*, *17*. doi: 10.1186/s12942-018-0144-x

Braun, T., Fung, B. C. M., Iqbal, F., & Shah, B. (2018). Security and privacy challenges in smart cities. *Sustainable Cities and Society*, *39*, 499-507. doi: 10.1016/j.scs.2018.02.039

Bucchiarone, A., Battisti, S., Marconi, A., Maldacea, R., & Ponce, D. C. (2021). Autonomous Shuttle-as-a-Service (ASaaS): Challenges, Opportunities, and Social Implications. *IEEE Transactions on Intelligent Transportation Systems*, *22*(6), 3790-3799. doi: 10.1109/TITS.2020.3025670

Castelli, M., Sormani, R., Trujillo, L., & Popovič, A. (2017). Predicting per capita violent crimes in urban areas: an artificial intelligence approach. *Journal of Ambient Intelligence and Humanized Computing*, *8*(1), 29-36. doi: 10.1007/s12652-015-0334-3

Chang, C.-Y., Ko, K.-S., Guo, S.-J., Hung, S.-S., & Lin, Y.-T. (2020). CO multi-forecasting model for indoor health and safety management in smart home. *Journal of Internet Technology*, *21*(1), 273-284. doi: 10.3966/160792642020012101023

Chen, J., Ramanathan, L., & Alazab, M. (2021). Holistic big data integrated artificial intelligent modeling to improve privacy and security in data management of smart cities. *Microprocessors and Microsystems*, *81*. doi: 10.1016/j.micpro.2020.103722

Chen, M., Liu, W., Wang, T., Liu, A., & Zeng, Z. (2021). Edge intelligence computing for mobile augmented reality with deep reinforcement learning approach. *Computer Networks*, *195*. doi: 10.1016/j.comnet.2021.108186

Chen, Y., Lu, Y., Bulysheva, L., & Kataev, M. Y. (2022). Applications of Blockchain in Industry 4.0: a Review. *Information Systems Frontiers*. doi: 10.1007/s10796-022-10248-7

Choudhary, P., & Sarthy, P. (2022). Transforming Cities for Sustainability: Role of Standards on Smart City. *2022 2nd International Conference on Power Electronics and IoT Applications in Renewable Energy and Its Control, PARC 2022*. doi: 10.1109/PARC52418.2022.9726674

Chui, K. T., Lytras, M. D., & Visvizi, A. (2018). Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. *Energies*, *11*(11). doi: 10.3390/en11112869

Communication from The Commission to The European Parliament, The European Council, The Council, The European Economic and Social Committee and The Committee of the regions. The European Green Deal. COM (2019) 640 Final. (2019).

Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society*, *62*. doi: 10.1016/j.techsoc.2020.101257

Cui, Q., Wang, Y., Chen, K.-C., Ni, W., Lin, I.-C., Tao, X., & Zhang, P. (2019). Big data analytics and network calculus enabling intelligent management of autonomous vehicles in a smart city. *IEEE Internet of Things Journal*, *6*(2), 2021-2034. doi: 10.1109/JIOT.2018.2872442

David, M., Mbabazi, E. S., Nakatumba-Nabende, J., & Marvin, G. (2023). Crime Forecasting using Interpretable Regression Techniques. *7th International Conference on Trends in Electronics and Informatics, ICOEI 2023 - Proceedings*, 1405-1411. doi: 10.1109/ICOEI56765.2023.10126071

De Giovanni, P. (2023). Sustainability of the Metaverse: A Transition to Industry 5.0. *Sustainability*, *15*(7). doi: 10.3390/su15076079

Diro, A. A., & Chilamkurti, N. (2018). Distributed attack detection scheme using deep learning approach for Internet of Things. *Future Generation Computer Systems*, *82*, 761-768. doi: 10.1016/j.future.2017.08.043

Dong, Y., & Yao, Y.-D. (2021). IoT platform for covid-19 prevention and control: A survey. *IEEE Access*, *9*, 49929-49941. doi: 10.1109/ACCESS.2021.3068276

Ejdys, J., & Gulc, A. (2020). Trust in Courier Services and Its Antecedents as a Determinant of Perceived Service Quality and Future Intention to Use Courier Service. *Sustainability*, *12*, 1-18. doi: 10.3390/su12219088

Elghaish, F., Matarneh, S. T., Edwards, D. J., Pour Rahimian, F., El-Gohary, H., & Ejohwomu, O. (2022). Applications of Industry 4.0 digital technologies towards a construction circular economy: gap analysis and conceptual framework. *Construction Innovation*, *22*(3), 647-670. doi: 10.1108/CI-03-2022-0062

Espina-Romero, L., Guerrero-Alcedo, J., Goñi Avila, N., Noroño Sánchez, J. G., Gutiérrez Hurtado, H., & Quiñones Li, A. (2023). Industry 5.0: Tracking Scientific Activity on the Most Influential Industries, Associated Topics, and Future Research Agenda. *Sustainability*, *15*(6). doi: 10.3390/su15065554

Ferdowsi, A., Challita, U., & Saad, W. (2019). Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems: An Overview. *IEEE Vehicular Technology Magazine*, *14*(1), 62-70. doi: 10.1109/MVT.2018.2883777

Fernández, C., Manyà, F., Mateu, C., & Sole-Mauri, F. (2014). Modeling energy consumption in automated vacuum waste collection systems. *Environmental Modelling and Software*, *56*, 63-73. doi: 10.1016/j.envsoft.2013.11.013

Frey, C., Hertweck, P., Richter, L., & Warweg, O. (2022). Bauhaus.MobilityLab: A Living Lab for the Development and Evaluation of AI-Assisted Services. *Smart Cities*, *5*(1), 133-145. doi: 10.3390/smartcities5010009

Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access*, *8*, 108952-108971. doi: 10.1109/ACCESS.2020.2998358

Gaber, H., Othman, A. M., & Fahad, A. H. (2020). Future of connected autonomous vehicles in smart cities. In *Solving Urban Infrastructure Problems Using Smart City Technologies: Handbook on Planning, Design, Development, and Regulation* (pp. 599-611). Elsevier. doi: 10.1016/B978-0-12-816816-5.00027-9

Gad, A. G. (2022). Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review. *Archives of Computational Methods in Engineering*, *29*(5), 2531-2561. doi: 10.1007/s11831-021-09694-4

Galindo, F. (2014). Methods for law and ICT: An approach for the development of smart cities. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8929*, 26-40. doi: 10.1007/978-3-662-45960-7

Gams, M., Gu, I. Y.-H., Härmä, A., Muñoz, A., & Tam, V. (2019). Artificial intelligence and ambient intelligence. *Journal of Ambient Intelligence and Smart Environments*, *11*(1), 71-86. doi: 10.3233/AIS-180508

Garcia-Retuerta, D., Chamoso, P., Hernández, G., Guzmán, A. S. R., Yigitcanlar, T., & Corchado, J. M. (2021). An efficient management platform for developing smart cities: Solution for real-time and future crowd detection. *Electronics*, *10*(7). doi: 10.3390/electronics10070765

Gaska, K., & Generowicz, A. (2020). SMART Computational Solutions for the Optimization of Selected Technology Processes as an Innovation and Progress in Improving Energy Efficiency of Smart Cities—A Case Study. *Energies*, *13*(13). doi: 10.3390/en13133338

Ghadami, N., Gheibi, M., Kian, Z., Faramarz, M. G., Naghedi, R., Eftekhari, M., Fathollahi-Fard, A. M., Dulebenets, M. A., & Tian, G. (2021). Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods. *Sustainable Cities and Society*, *74*. doi: 10.1016/j.scs.2021.103149

Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., Alzoubi, H. M., Ahmad, M., Akbar, S. S., Al Kurdi, B., & Akour, I. A. (2021). IoT for smart cities: Machine learning approaches in smart healthcare—A review. *Future Internet*, *13*(8). doi: 10.3390/fi13080218

Glińska, E., & Siemieniako, D. (2018). Binge drinking in relation to services - Bibliometric analysis of scientific research directions. *Engineering Management in Production and Services*, *10*(1), 45-54. doi: 10.1515/emj-2018-0004

Gohari, A., Ahmad, A. B., Rahim, R. B. A., Supa'at, A. S. M., Razak, S. A., & Gismalla, M. S. M. (2022). Involvement of Surveillance Drones in Smart Cities: A Systematic Review. *IEEE Access*, *10*, 56611-56628. doi: 10.1109/ACCESS.2022.3177904

Golinska-Dawson, P., & Sethanan, K. (2023). Sustainable Urban Freight for Energy-Efficient Smart Cities—Systematic Literature Review. *Energies*, *16*(6). doi: 10.3390/en16062617

Gudanowska, A. E. (2017). A Map of Current Research Trends within Technology Management in the Light of Selected Literature. *Management and Production Engineering Review*, *8*(1), 78-88. doi: 10.1515/mper-2017-0009

Gupta, S., Modgil, S., Lee, C.-K., Cho, M., & Park, Y. (2022). Artificial intelligence enabled robots for stay experience in the hospitality industry in a smart city. *Industrial Management and Data Systems*, *122*(10), 2331-2350. doi: 10.1108/IMDS-10-2021-0621

Halicka, K. (2017). Main Concepts of Technology Analysis in the Light of the Literature on the Subject. *Procedia Engineering, 182*, 291-298. doi: 10.1016/j.proeng.2017.03.196

Hantrais, L., Allin, P., Kritikos, M., Sogomonjan, M., Anand, P. B., Livingstone, S., Williams, M., & Innes, M. (2021). Covid-19 and the digital revolution. *Contemporary Social Science*, *16*(2), 256-270. doi: 10.1080/21582041.2020.1833234

Hariri, R. H., Fredericks, E. M., & Bowers, K. M. (2019). Uncertainty in big data analytics: survey, opportunities, and challenges. *Journal of Big Data*, *6*(1). doi: 10.1186/s40537-019-0206-3

Hu, S., & Jiang, T. (2019). Artificial Intelligence Technology Challenges Patent Laws. *Proceedings - 2019 International Conference on Intelligent Transportation, Big Data and Smart City, ICITBS 2019*, 241-244. doi: 10.1109/ICITBS.2019.00064

Hu, Y.-C., Lin, Y.-H., & Gururaj, H. L. (2021). Partitional clustering-hybridized neuro-fuzzy classification evolved through parallel evolutionary computing and applied to energy decomposition for demand-side management in a smart home. *Processes*, *9*(9). doi: 10.3390/pr9091539

Javed, A. R., Shahzad, F., Rehman, S. U., Bin Zikria, Y., Razzak, I., Jalil, Z., & Xu, G. D. (2022). Future smart cities requirements, emerging technologies, applications, challenges, and future aspects. *Cities*, *129*. doi: 10.1016/j.cities.2022.103794

Jiang, Y., Xiao, W., Wang, R., & Barnawi, A. (2020). Smart Urban Living: Enabling Emotion-Guided Interaction with Next Generation Sensing Fabric. *IEEE Access*, *8*, 28395-28402. doi: 10.1109/ACCESS.2019.2961957

Kaginalkar, A., Kumar, S., Gargava, P., & Niyogi, D. (2021). Review of urban computing in air quality management as smart city service: An integrated IoT, AI, and cloud technology perspective. *Urban Climate*, *39*. doi: 10.1016/j.uclim.2021.100972

Kakderi, C., Oikonomaki, E., & Papadaki, I. (2021). Smart and Resilient Urban Futures for Sustainability in the Post COVID-19 Era: A Review of Policy Responses on Urban Mobility. *Sustainability*, *13*(11). doi: 10.3390/su13116486

Kamel Boulos, M. N., Peng, G., & Vopham, T. (2019). An overview of GeoAI applications in health and healthcare. *International Journal of Health Geographics*, *18*(1). doi: 10.1186/s12942-019-0171-2

Keathley-Herring, H., Van Aken, E., Gonzalez-Aleu, F., Deschamps, F., Letens, G., & Orlandini, P. C. (2016). Assessing the maturity of a research area: bibliometric review and proposed framework. *Scientometrics*, *109*(2), 927-951. doi: 10.1007/s11192-016-2096-x

Khan, N., Haq, I. U., Khan, S. U., Rho, S., Lee, M. Y., & Baik, S. W. (2021). DB-Net: A novel dilated CNN based multi-step forecasting model for power consumption in integrated local energy systems. *International Journal of Electrical Power and Energy Systems*, *133*. doi: 10.1016/j.ijepes.2021.107023

Khatoon, S., Rahman, S. M. M., Alrubaian, M., & Alamri, A. (2019). Privacy-Preserved, Provable Secure, Mutually Authenticated Key Agreement Protocol for Healthcare in a Smart City Environment. *IEEE Access*, *7*, 47962-47971. doi: 10.1109/ACCESS.2019.2909556

Khoa, T. A., Nhu, L. M. B., Son, H. H., Trong, N. M., Phuc, C. H., Phuong, N. T. H., Van Dung, N., Nam, N. H., Chau, D. S. T., & Duc, D. N. M. (2020). Designing Efficient Smart Home Management with IoT Smart Lighting: A Case Study. *Wireless Communications and Mobile Computing*, *2020*. doi: 10.1155/2020/8896637

Kim, K., Kim, J. S., Jeong, S., Park, J.-H., & Kim, H. K. (2021). Cybersecurity for autonomous vehicles: Review of attacks and defense. *Computers and Security*, *103*. doi: 10.1016/j.cose.2020.102150

Kozłowska, J., Benvenga, M. A., & de Alencar Nääs, I. (2023). Investment Risk and Energy Security Assessment of European Union Countries Using Multicriteria Analysis. *Energies*, *16*, 1-28. doi: 10.3390/en16010330

Ktari, J., Frikha, T., Hamdi, M., Elmannai, H., & Hmam, H. (2022). Lightweight AI Framework for Industry 4.0 Case Study: Water Meter Recognition. *Big Data and Cognitive Computing*, *6*(3). doi: 10.3390/bdcc6030072

Kummitha, R. K. R. (2020). Smart technologies for fighting pandemics: The techno-and human-driven approaches in controlling the virus transmission. *Government Information Quarterly*, *37*(3). doi: 10.1016/j.giq.2020.101481

Kuru, K. (2021). Planning the Future of Smart Cities with Swarms of Fully Autonomous Unmanned Aerial Vehicles Using a Novel Framework. *IEEE Access*, *9*, 6571-6595. doi: 10.1109/ACCESS.2020.3049094

Kuźmicz, K., Ryciuk, U., Glińska, E., Kiryluk, H., & Rollnik-Sadowska, E. (2022). Perspectives of mobility development in remote areas attractive to tourists. *Ekonomia i Środowisko*, *80*, 150-188. doi: 10.34659/eis.2022.80.1.440

Laamarti, F., Badawi, H. F., Ding, Y., Arafsha, F., Hafidh, B., & Saddik, A. E. (2020). An ISO/IEEE 11073 Standardized Digital Twin Framework for Health and Well-Being in Smart Cities. *IEEE Access*, *8*, 105950-105961. doi: 10.1109/ACCESS.2020.2999871

Le, L. T., Nguyen, H., Dou, J., & Zhou, J. (2019). A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning. *Applied Sciences*, *9*(13). doi: 10.3390/app9132630

Leung, C. K., Braun, P., & Cuzzocrea, A. (2019). AI-Based Sensor Information Fusion for Supporting Deep Supervised Learning. *Sensors*, *19*(6). doi: 10.3390/s19061345

Liu, Y., Huang, A., Luo, Y., Huang, H., Liu, Y., Chen, Y., Feng, L., Chen, T., Yu, H., & Yang, Q. (2020). FedVision: An online visual object detection platform powered by federated learning. In R. Puri & N.

Yorke-Smith (Eds.), *Proceedings of the 32nd Innovative Applications of Artificial Intelligence Conference, IAAI 2020* (pp. 13172-13179). The AAAI Press.

Liu, Y., Ma, X., Shu, L., Yang, Q., Zhang, Y., Huo, Z., & Zhou, Z. (2020). Internet of things for noise mapping in smart cities: State of the art and future directions. *IEEE Network*, *34*(4), 112-118. doi: 10.1109/MNET.011.1900634

Liu, Y., Yang, C., Jiang, L., Xie, S., & Zhang, Y. (2019). Intelligent Edge Computing for IoT-Based Energy Management in Smart Cities. *IEEE Network*, *33*(2), 111-117. doi: 10.1109/MNET.2019.1800254

Li, W., Yigitcanlar, T., Liu, A., & Erol, I. (2022). Mapping two decades of smart home research: A systematic scientometric analysis. *Technological Forecasting and Social Change*, *179*. doi: 10.1016/j.techfore.2022.121676

Loh, H. W., Ooi, C. P., Seoni, S., Barua, P. D., Molinari, F., & Acharya, U. R. (2022). Application of explainable artificial intelligence for healthcare: A systematic review of the last decade (2011-2022). *Computer Methods and Programs in Biomedicine*, *226*. doi: 10.1016/j.cmpb.2022.107161

López-Blanco, R., Martín, J. H., Alonso, R. S., & Prieto, J. (2023). Time Series Forecasting for Improving Quality of Life and Ecosystem Services in Smart Cities. In V. Julián, J. Carneiro, R. S. Alonso, P. Chamoso, & P. Novais (Eds.), *Lecture Notes in Networks and Systems: Vol. 603 LNNS* (pp. 74-85). Springer Science and Business Media Deutschland GmbH. doi: 10.1007/978-3-031-22356-3_8

Lourenco, V., Mann, P., Guimaraes, A., Paes, A., & De Oliveira, D. (2018). Towards Safer (Smart) Cities: Discovering Urban Crime Patterns Using Logic-based Relational Machine Learning. *Proceedings of the International Joint Conference on Neural Networks*, *2018-July*. doi: 10.1109/IJCNN.2018.8489374

Lv, Z., Qiao, L., Singh, A. K., & Wang, Q. (2021). AI-empowered IoT Security for Smart Cities. *ACM Transactions on Internet Technology*, *21*(4), 99. doi: 10.1145/3406115

Łasak, P., & Wyciślak, S. (2023). Blockchain and cloud platforms in banking services: A paradox perspective. *Journal of Entrepreneurship, Management, and Innovation*, *19*(4), 12-47. doi: 10.7341/20231941

Ma, M., Stankovic, J. A., & Feng, L. (2018). CityResolver: A Decision Support System for Conflict Resolution in Smart Cities. *Proceedings - 9th ACM/IEEE International Conference on Cyber-Physical Systems, ICCPS 2018*, 55-64. doi: 10.1109/ICCPS.2018.00014

Ma, Y., Ping, K., Wu, C., Chen, L., Shi, H., & Chong, D. (2020). Artificial Intelligence powered Internet of Things and smart public service. *Library Hi Tech*, *38*(1), 165-179. doi: 10.1108/LHT-12-2017-0274

Mendling, J., Decker, G., Hull, R., Reijers, H. A., & Weber, I. (2018). How do Machine Learning, Robotic Process Automation, and Blockchains Affect the Human Factor in Business Process Management? *Communications of the Association for Information Systems*, 297-320. doi: 10.17705/1CAIS.04319

Muhammad, K., Lloret, J., & Baik, S. W. (2019). Intelligent and energy-efficient data prioritization in green smart cities: Current challenges and future directions. *IEEE Communications Magazine*, *57*(2), 60-65. doi: 10.1109/MCOM.2018.1800371

Nam, K., Dutt, C. S., Chathoth, P., Daghfous, A., & Khan, M. S. (2021). The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges. *Electronic Markets*, *31*(3), 553-574. doi: 10.1007/s12525-020-00442-3

Navarro-Espinoza, A., López-Bonilla, O. R., García-Guerrero, E. E., Tlelo-Cuautle, E., López-Mancilla, D., Hernández-Mejía, C., & Inzunza-González, E. (2022). Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms. *Technologies*, *10*(1). doi: 10.3390/technologies10010005

Nguyen, D. C., Ding, M., Pathirana, P. N., Seneviratne, A., Li, J., & Vincent Poor, H. (2021). Federated Learning for Internet of Things: A Comprehensive Survey. *IEEE Communications Surveys and Tutorials*, *23*(3), 1622-1658. doi: 10.1109/COMST.2021.3075439

Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability (Switzerland)*, *12*(7), 1-19. doi: 10.3390/su12072789

Niñerola, A., Sánchez-Rebull, M.-V., & Hernández-Lara, A.-B. (2019). Tourism research on sustainability: A bibliometric analysis. *Sustainability (Switzerland)*, *11*(5). doi: 10.3390/su11051377

O'Dwyer, E., Pan, I., Acha, S., & Shah, N. (2019). Smart energy systems for sustainable smart cities: Current developments, trends and future directions. *Applied Energy*, *237*, 581-597. doi: 10.1016/j.apenergy.2019.01.024

Ortega-Fernández, A., Martín-Rojas, R., & García-Morales, V. J. (2020). Artificial intelligence in the urban environment: Smart cities as models for developing innovation and sustainability. *Sustainability (Switzerland)*, *12*(19). doi: 10.3390/SU12197860

Paiva, S., Ahad, M. A., Tripathi, G., Feroz, N., & Casalino, G. (2021). Enabling technologies for urban smart mobility: Recent trends, opportunities and challenges. *Sensors*, *21*(6), 1-45. doi: 10.3390/s21062143

Park, S., Park, S., Choi, M. I., Lee, S., Lee, T., Kim, S., Cho, K., & Park, S. (2020). Reinforcement Learning-Based BEMS Architecture for Energy Usage Optimization. *Sensors*, *20*(17). doi: 10.3390/s20174918

Perc, M., Ozer, M., & Hojnik, J. (2019). Social and juristic challenges of artificial intelligence. *Palgrave Communications*, *5*(1). doi: 10.1057/s41599-019-0278-x

Pramod, M. S., Balodi, A., Pratik, A., Satya Sankalp, G., Varshita, B., & Amrit, R. (2023). Energy-Effcient Reinforcement Learning in Wireless Sensor Networks Using 5G for Smart Cities. In *Applications of 5G and Beyond in Smart Cities* (pp. 63-86). CRC Press. doi: 10.1201/9781003227861-4

Ragab, A., Osama, A., & Ramzy, A. (2023). Simulation of the Environmental Impact of Industries in Smart Cities. *Ain Shams Engineering Journal*, *14*(6). doi: 10.1016/j.asej.2022.102103

Rani, S., Mishra, R. K., Usman, M., Kataria, A., Kumar, P., Bhambri, P., & Mishra, A. K. (2021). Amalgamation of advanced technologies for sustainable development of smart city environment: A review. *IEEE Access*, *9*, 150060-150087. doi: 10.1109/ACCESS.2021.3125527

Reebadiya, D., Rathod, T., Gupta, R., Tanwar, S., & Kumar, N. (2021). Blockchain-based Secure and Intelligent Sensing Scheme for Autonomous Vehicles Activity Tracking Beyond 5G Networks. *Peer-to-Peer Networking and Applications*, *14*(5), 2757-2774. doi: 10.1007/s12083-021-01073-x

Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science*, *2*(3). doi: 10.1007/s42979-021-00592-x

Sarker, I. H., Khan, A. I., Abushark, Y. B., & Alsolami, F. (2022). Internet of Things (IoT) Security Intelligence: A Comprehensive Overview, Machine Learning Solutions and Research Directions. *Mobile Networks and Applications*. doi: 10.1007/s11036-022-01937-3

Serban, A. C., & Lytras, M. D. (2020). Artificial intelligence for smart renewable energy sector in Europe - Smart energy infrastructures for next generation smart cities. *IEEE Access*, *8*, 77364-77377. doi: 10.1109/ACCESS.2020.2990123

Shankar, K., Perumal, E., Elhoseny, M., Taher, F., Gupta, B. B., & El-Latif, A. A. A. (2021). Synergic Deep Learning for Smart Health Diagnosis of COVID-19 for Connected Living and Smart Cities. *ACM Transactions on Internet Technology*, *22*(3). doi: 10.1145/3453168

Shi, J., Liu, S., Zhang, L., Yang, B., Shu, L., Yang, Y., Ren, M., Wang, Y., Chen, J., Chen, W., Chai, Y., & Tao, X. (2020). Smart Textile-Integrated Microelectronic Systems for Wearable Applications. *Advanced Materials*, *32*(5). doi: 10.1002/adma.201901958

Shi, X., Luo, J., Luo, J., Li, X., Han, K., Li, D., Cao, X., & Wang, Z. L. (2022). Flexible Wood-Based Triboelectric Self-Powered Smart Home System. *ACS Nano*, *16*(2), 3341-3350. doi: 10.1021/acsnano.1c11587

Siderska, J., Alsqour, M., & Alsaqoor, S. (2023). Employees' attitudes towards implementing robotic process automation technology at service companies. *Human Technology*, *19*(1), 23-40. doi: 10.14254/1795-6889.2023.19-1.3

Siderska, J., & Jadaan, K. S. (2018). Cloud manufacturing: A service-oriented manufacturing paradigm. A review paper. *Engineering Management in Production and Services*, *10*(1), 22-31. doi: 10.1515/emj-2018-0002

Singh, S. K., Rathore, S., & Park, J. H. (2020). BlockIoTIntelligence: A Blockchain-enabled Intelligent IoT Architecture with Artificial Intelligence. *Future Generation Computer Systems*, *110*, 721-743. doi: 10.1016/j.future.2019.09.002

Singh, S., Sharma, P. K., Yoon, B., Shojafar, M., Cho, G. H., & Ra, I.-H. (2020). Convergence of blockchain and artificial intelligence in IoT network for the sustainable smart city. *Sustainable Cities and Society*, *63*. doi: 10.1016/j.scs.2020.102364

Skouby, K. E., & Lynggaard, P. (2014). Smart home and smart city solutions enabled by 5G, IoT, AAI and CoT services. *Proceedings of 2014 International Conference on Contemporary Computing and Informatics, IC3I 2014*, 874-878. doi: 10.1109/IC3I.2014.7019822

Szpilko, D. (2017). *Tourism Supply Chain – Overview of Selected Literature. Procedia Engineering*, *182*, 687-693. doi: 10.1016/j.proeng.2017.03.180

Szpilko, D., & Ejdys, J. (2022). European Green Deal — research directions. A systematic literature review. *Ekonomia i Środowisko - Economics and Environment*, *81*(2), 8-38. doi: 10.34659/eis.2022.81.2.455

Szpilko, D., Budna, K., Drmeyan, H., & Remiszewska, A. (2023). Sustainable and smart mobility — research directions. A systematic literature review. *Ekonomia i Środowisko - Economics and Environment*, *86*(3). doi: 10.34659/eis.2023.86.3.584

Szpilko, D., Szydło, J., & Winkowska, J. (2020). Social Participation of City Inhabitants Versus Their Future Orientation. Evidence From Poland. *WSEAS Transactions on Business and Economics*, *17*, 692-702. doi: 10.37394/23207.2020.17.67

Szum, K. (2021). IoT-based smart cities: A bibliometric analysis and literature review. *Engineering Management in Production and Services*, *13*(2), 115-136. doi: 10.2478/emj-2021-0017

Tian, Y., & Pan, L. (2015). Predicting Short-Term Traffic Flow by Long Short-Term Memory Recurrent Neural Network. *2015 IEEE International Conference on Smart City/SocialCom/SustainCom (SmartCity)*, 153-158. doi: 10.1109/SmartCity.2015.63

Toglaw, S., Aloqaily, M., & Alkheir, A. A. (2018). Connected, autonomous and electric vehicles: The optimum value for a successful business model. *2018 5th International Conference on Internet of Things: Systems, Management and Security, IoTSMS 2018*, 303-308. doi: 10.1109/IoTSMS.2018.8554391

Tomaszewska, E. J., & Florea, A. (2018). Urban smart mobility in the scientific literature - Bibliometric analysis. *Engineering Management in Production and Services*, *10*(2), 41-56. doi: 10.2478/emj-2018-0010

Ullah, Z., Al-Turjman, F., Moatasim, U., Mostarda, L., & Gagliardi, R. (2020). UAVs joint optimization problems and machine learning to improve the 5G and Beyond communication. *Computer Networks*, *182*. doi: 10.1016/j.comnet.2020.107478

Ullah, Z., Al-Turjman, F., Mostarda, L., & Gagliardi, R. (2020). Applications of Artificial Intelligence and Machine learning in smart cities. *Computer Communications*, *154*, 313-323. doi: 10.1016/j.comcom.2020.02.069

United Nation. (2015). Transforming our world: the 2030 Agenda for Sustainable Development. In *United Nation: Vol. A/RES/70/1*.

van Eck, N. J., & Waltman, L. (2018). *VOSviewer Manual. Manual for VOSviewer version 1.6.11 software documentation.*

Vázquez-Canteli, J. R., Ulyanin, S., Kämpf, J., & Nagy, Z. (2019). Fusing TensorFlow with building energy simulation for intelligent energy management in smart cities. *Sustainable Cities and Society*, *45*, 243-257. doi: 10.1016/j.scs.2018.11.021

Wang, K., Zhao, Y. F., Gangadhari, R. K., & Li, Z. X. (2021). Analyzing the Adoption Challenges of the Internet of Things (IoT) and Artificial Intelligence (AI) for Smart Cities in China. *Sustainability*, *13*(19). doi: 10.3390/su131910983

Wences, P., Martinez, A., Estrada, H., & Gonzalez, M. (2017). Decision-making intelligent system for passenger of urban transports. In P. Singh, J. Bravo, & S. F. Ochoa (Eds.), *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) LNCS* (pp. 128-139). Springer Verlag. doi: 10.1007/978-3-319-67585-5_14

Winkowska, J., Szpilko, D., & Pejić, S. (2019). Smart city concept in the light of the literature review. *Engineering Management in Production and Services*, *11*(2), 70-86. doi: 10.2478/emj-2019-0012

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial Intelligence and the Public Sector—Applications and Challenges. *International Journal of Public Administration*, *42*(7), 596-615. doi: 10.1080/01900692.2018.1498103

Wu, T.-Y., Meng, Q., Chen, Y.-C., Kumari, S., & Chen, C.-M. (2023). Toward a Secure Smart-Home IoT Access Control Scheme Based on Home Registration Approach. *Mathematics*, *11*(9). doi: 10.3390/math11092123

Wu, Y. (2021). Cloud-Edge Orchestration for the Internet of Things: Architecture and AI-Powered Data Processing. *IEEE Internet of Things Journal*, *8*(16), 12792-12805. doi: 10.1109/JIOT.2020.3014845

Wu, Z., & Chu, W. (2021). Sampling Strategy Analysis of Machine Learning Models for Energy Consumption Prediction. *2021 9th IEEE International Conference on Smart Energy Grid Engineering, SEGE 2021*, 77-81. doi: 10.1109/SEGE52446.2021.9534987

Yamakami, T. (2017). An organizational coordination model for IoT: A case study of requirement engineering of city-government in Tokyo in city platform as a service. *International Conference on Information and Communication Technology Convergence: ICT Convergence Technologies Leading the Fourth Industrial Revolution, ICTC 2017*, *2017-December*, 259-263. doi: 10.1109/ICTC.2017.8190982

Yigitcanlar, T., Desouza, K. C., Butler, L., & Roozkhosh, F. (2020). Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies*, *13*(6). doi: 10.3390/en13061473

Yuan, T. T., Da RochaNeto, W., Rothenberg, C. E., Obraczka, K., Barakat, C., & Turletti, T. (2022). Machine learning for next-generation intelligent transportation systems: A survey. *Transactions on Emerging Telecommunications Technologies*, *33*(4). doi: 10.1002/ett.4427

Zheng, Z., Zhou, Y., Sun, Y., Wang, Z., Liu, B., & Li, K. (2022). Applications of federated learning in smart cities: recent advances, taxonomy, and open challenges. *Connection Science*, *34*(1), 1-28. doi: 10.1080/09540091.2021.1936455

Zhi-Xian, Z., & Zhang, F. (2022). Image Real-Time Detection Using LSE-Yolo Neural Network in Artificial Intelligence-Based Internet of Things for Smart Cities and Smart Homes. *Wireless Communications and Mobile Computing*, *2022*. doi: 10.1155/2022/2608798

Zhou, H., Liu, Q., Yan, K., & Du, Y. (2021). Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT. *Wireless Communications and Mobile Computing*, *2021*. doi: 10.1155/2021/9249387

Volume 15 • Issue 4 • 2023

received: 15 March 2023
accepted: 20 September 2023

pages: 76-89



# Generative AI in the manufacturing process: theoretical considerations

Duong Cong Doanh
Zdenek Dufek
Joanna Ejdys
Romualdas Ginevičius
Pawel Korzynski
Grzegorz Mazurek
Joanna Paliszkiewicz
Krzysztof Wach
Ewa Ziemba

**Joanna Ejdys**
Bialystok University of Technology, Poland
ORCID 0000-0002-5132-166X
Corresponding author:
e-mail: j.ejdys@pb.edu.pl

**Dunog Cong Doanh**
National Economics University, Hanoi, Vietnam
ORCID 0000-0003-4431-9761

**Zdenek Dufek**
Brno University of Technology, Czechia
ORCID 0000-0003-4616-4142

**Romualdas Ginevičius**
Mykolas Romeris University, Lithuania
ORCID 0000-0003-2067-4398

**Pawel Korzynski**
Kozminski University, Poland
ORCID 0000-0002-6457-4965

**Grzegorz Mazurek**
Kozminski University, Poland
ORCID 0000-0002-0047-6944

**Joanna Paliszkiewicz**
Warsaw University of Life Sciences, Poland
ORCID 0000-0002-6250-0583

**Krzysztof Wach**
Krakow University of Economics, Poland
ORCID 0000-0001-7542-2863

**Ewa Ziemba**
University of Economics in Katowice, Poland
ORCID 0000-0002-1084-7497

ABSTRACT
The paper aims to identify how digital transformation and Generative Artificial Intelligence (GAI), in particular, affect the manufacturing processes. Several dimensions of the Industry 4.0 field have been considered, such as the design of new products, workforce and skill optimisation, enhancing quality control, predictive maintenance, demand forecasting, and marketing strategy. The paper adopts qualitative research based on a critical review approach. It provides evidence of the GAI technology support in the mentioned areas. Appropriate use of emerging technology allows managers to transform manufacturing by optimising processes, improving product design, enhancing quality control, and contributing to overall efficiency and innovation in the industry. Simultaneously, GAI technologies facilitate predictive analytics to forecast and anticipate future demand, quality issues, and potential risks, improve a marketing strategy and identify market trends.

KEY WORDS
**Generative AI, ChatGPT, Industry 4.0, technology, manufacturing processes**

**10.2478/emj-2023-0029**

## Introduction

The advent of digital transformation has significantly impacted the landscape of modern entrepreneurship and current business. Undoubtedly, digital transformation, defined as the integration and adoption of digital technologies, processes, and strategies across various aspects of an organisation, is the primary challenge of the third decade of the twenty-first century, particularly in the post-pandemic era (Głodowska et al., 2023), multidimensionally impacting the manufacturing industry defined nowadays as

Doanh, D. C., Dufek, Z., Ejdys, J., Ginevičius, R., Korzyński, P., Mazurek, G., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative AI in the manufacturing process: theoretical considerations. *Engineering Management in Production and Services, 15*(4), 76-89. doi: 10.2478/emj-2023-0029

Industry 4.0 (Nosalska et al., 2018). The ongoing changes in modern business management are caused by the use of several disruptive technologies, including blockchain, AR, VR, social media, mobile, and IoT (Mazurek, 2018). In recent months, it has gained importance because of the Generative Artificial Intelligence (GAI) concept in various managerial aspects and dimensions with its business and manufacturing advantages (Korzynski et al., 2023) and dark sides (Wach et al., 2023).

This article presents the results of a literature review approach based on the analysis of publications. The critical review primarily aimed to methodically assess, analyse, and integrate the existing body of literature on applying GAI in the manufacturing process to foster the development of innovative theoretical frameworks and perspectives within the field. Different areas of manufacturing processes have been considered, such as new product design, innovation management, human resources, quality control, predictive maintenance, forecasting and marketing strategy creation and implementation. The uniqueness of this publication lies in the review execution and literature description on the field of retrofitting and its classification. Additionally, it involves the extraction of the primary trends presented in the literature.

This publication answers the following questions: What is the current development stage of theory linked with the GAI application in the manufacturing process? What are the most important managerial insights concerning the application of AI to manufacturing processes? What AI implications can be found in the literature on several manufacturing and product engineering dimensions?

The article consists of four parts. The introduction includes a description of the techniques and technologies connected to AI in manufacturing processes. The second part presents the research methods. The third part describes the research results, focusing on such dimensions as new product design, innovation management, human resources, quality control, predictive maintenance, forecasting and marketing strategy. The fourth part summarises the article.

# 1. Methodology

An integrative or critical review approach was employed to achieve the research objective. The applied method provided a framework for understanding and appreciating the complexities of narrative literature. Many integrative literature reviews are designed to tackle subjects that have matured or are in the early stages of emergence. In the case of emerging topics, the primary aim is to establish initial or preliminary concepts and theoretical frameworks rather than simply revisiting existing models (Snyder, 2019).

The main aim of this critical review was to systematically evaluate, critique, and synthesise the body of literature relevant to GAI application in the manufacturing process. This comprehensive analysis was conducted in a manner designed to facilitate the emergence of novel theoretical frameworks and perspectives within the field.

The integrative review method led to the advancement of knowledge and the development of theoretical frameworks rather than merely providing an overview or description of previous research (Snyder, 2019).

The authors' intention was to provide an integrated, synthesised overview of the current state of knowledge and research insights, existing gaps, and future research directions in the field of AI application in manufacturing processes (Palmatier et al., 2018). Alongside the normative recommendations, this review provides summaries and suggestions that could provide valuable managerial insights (Mazumdar et al., 2005) into the future application of AI to manufacturing processes.

Authors adopted domain-based review papers, which allowed for reviewing, synthesising, and extending a body of literature in the substantive domain, i.e., AI application in the manufacturing process. The manufacturing process structure refers to the organisation and sequence of activities involved in the production of goods or products. It outlines the steps and stages required to transform raw materials or components into finished products. The specific structure of a manufacturing process can vary widely depending on the industry, product complexity, and technology used. Considering the complexity and comprehensiveness of manufacturing processes, the conducted literature studies were focused on the following processes supporting the manufacturing process: the design of new products, workforce and skill optimisation, enhancement of quality control, predictive maintenance, demand forecasting, and marketing strategy.

The application of the critical literature review method aimed to answer the following research questions:

- How can AI adaptation help manufacturers to create products that are more efficient, effective, and safe?
- How can AI adaptation help analyse and predict the necessary skills required for manufacturing processes?
- How can GAI be used to identify defects in products and processes?
- How can GAI be used as a proactive approach to maintenance to predict when equipment and machinery are likely to fail or require maintenance?
- How can AI be used to analyse market trends, consumer behaviour, and sales data to predict demand for manufactured goods?
- How can AI be used to optimise marketing strategies and improve the timing of product releases, promotional campaigns, or sales events?

## 2. Literature review and theory development

### 2.1. Application of Generative AI in the design of new products

This research study investigates the GAI's possible transformative effects within the product design domain. GAI can be harnessed for designing new products because it can explore vast design spaces, generate diverse and innovative solutions, and optimise designs based on predefined parameters (Kwong et al., 2016). GAI is applied to explore innovative design possibilities and generate optimum product designs, considering user-defined parameters (Cappa et al., 2021). This novel GAI methodology has the potential to transform manufacturing procedures by facilitating the development of goods that possess enhanced efficiency, effectiveness, and safety, especially in the post-pandemic world (Villar et al., 2023).

In recent years, the emergence of GAI has presented novel opportunities for innovation across several industries (Cappa et al., 2021), such as the automotive industry (e.g., Tesla). Another example could be bioengineering. In recent times, additive manufacturing (AM) has been widely used to create things specifically designed for human use, including orthoses, prostheses, therapeutic helmets, finger splints, and other customised devices (Liu et al., 2022). Product design is a domain that shows significant potential for application, where GAI might serve as a crucial tool for exploring and optimising design spaces (Di Vaio et al., 2020). This study focuses on the possible advantages of utilising GAI to design novel goods, with a particular emphasis on developing solutions characterised by enhanced efficiency, effectiveness, and safety. GAI can explore new design possibilities and generate optimised designs based on user-defined parameters. Designers can input user-defined parameters into GAI systems, guiding the AI to generate designs that meet specific criteria. This user-centric approach ensures the final product's alignment with the intended goals and requirements. This can help manufacturers to create more efficient, effective, and safe products.

GAI can evaluate extensive datasets of preexisting designs, acquiring knowledge of patterns and correlations among different design components. This allows it to investigate vast design possibilities that may be inconvenient or time-consuming for human designers to navigate. GAI functions by leveraging machine learning concepts, allowing the system to acquire knowledge from extensive datasets and produce novel outputs according to predetermined criteria (Plantec et al., 2023). Within the realm of product design, this technology allows designers and manufacturers to swiftly and effectively explore a wide range of design possibilities (Iansiti & Lakhani, 2020). GAI algorithms can develop designs that meet or surpass specified requirements by incorporating user-defined characteristics such as material qualities, weight limitations, and performance standards (Plantec et al., 2023). Through an iterative process, these algorithms may generate designs that follow the given specifications (Lei et al., 2022).

In conclusion, GAI presents a groundbreaking opportunity for revolutionising product design processes (Hu et al., 2023). The utilisation of GAI holds immense potential for transforming the processes involved in product design. GAI, due to its capacity to navigate extensive design spaces and swiftly produce optimum solutions, is positioned as a pivotal facilitator for innovation in the manufacturing sector (Lei et al., 2022). The utilisation of this technology serves as a demonstration of its capacity to generate products with enhanced efficiency, efficacy, and safety. The ongoing progress of technology has led to the potential incorporation of GAI in the field of product design, which can revolutionise several industries and facilitate the creation of innovative products that surpass existing limitations (Wang & Wu, 2024). As technology continues to advance, the integration of GAI in product design holds the promise of reshaping industries and driving the development of products that push the boundaries of what is currently achievable.

### 2.2. GAI as a facilitator of the HRM process in manufacturing

In the era of Industry 4.0, the fusion of advanced manufacturing processes and cutting-edge digital technologies, such as general artificial intelligence, heralds unparalleled innovations in human resource management (HRM) (Sigov et al., 2022; Rymarczyk, 2021). Looking ahead to Industry 5.0, where human collaboration with machines is expected to be more harmonious and optimised (Leng et al., 2022), the role of GAI becomes even more pivotal. Industry 5.0 focuses on the coalescence of human touch with technological autonomy, aiming to create a balanced ecosystem where human creativity and machine efficiency coexist and complement each other (Adel, 2022).

In its current form, GAI, such as ChatGPT, can be incorporated into work settings as an element of a custom network of applications (OpenAI, 2023). Therefore, the potential utility of GAI, exemplified by technologies like ChatGPT, extends beyond just text generation (Korzynski, Kozminski, & Baczynska, 2023). Its diverse functionalities can seamlessly integrate with various HRM systems, working collaboratively to enhance and streamline numerous HR-related processes in the manufacturing sector. The integration of GAI with HRM systems can facilitate the comprehensive analysis and synchronisation of various elements, such as workforce planning (Koole & Li, 2023), scheduling shifts (Dworski, 2023), position description analysis (Chang & Ke, 2023) and performance management (Budhwar et al., 2023).

In reference to workforce planning and scheduling, constant manufacturing operations demand accurate planning (Heuser, Letmathe, & Schinner, 2022), and GAI can synchronise various elements, such as production demands, employee availability, and skill sets, to formulate optimised shift schedules. This application ensures that every shift is adequately staffed with individuals possessing the right skills, enhancing the alignment with production targets while maintaining compliance with labour regulations.

Furthermore, GAI holds the key to revolutionising position description analysis and task standardisation. Considering the advancements brought about by smart factories, a precise understanding and delineation of tasks and roles become increasingly vital. Automated and semi-automated systems in manufacturing lines coexist with manual processes, highlighting the significance of clear and well-defined position descriptions (Cha et al., 2023). By harnessing GAI to analyse and standardise position descriptions and tasks, organisations ensure clarity and uniformity in role expectations and responsibilities, synchronising manual and automated processes effectively.

Additionally, in performance management within the manufacturing milieu, adherence to specific production norms is pivotal. GAI may play a fundamental role here by continually analysing employee activities and outputs. By monitoring adherence to production norms and standards, GAI provides critical insights and data that enable both managers and employees to refine and optimise performance (Khang et al., 2023). This continuous oversight and analysis ensure that any deviations from the established norms are rapidly identified and rectified, contributing to the streamlined and effective functioning of the manufacturing operations.

In the sphere of smart factories, the deployment of GAI furthers the enhancement of performance management. The centralised data hubs in smart factories, which streamline the rapid exchange of information, are leveraged by GAI to meticulously monitor and analyse employee performance and operations (Haponik, 2022). This integration facilitates instantaneous feedback and insights, enabling immediate corrective actions and ensuring the consistent alignment of operations with established production norms and standards.

### 2.3. Enhance quality control process by AI

Quality control, defined as a systematic process involving checks, testing, verification, and response, ensures that product features and process conditions align with design standards and internal and external specifications (Hull, 2011). It entails examining products at various stages of the production process to guarantee they meet specific criteria, such as size, weight, colour, or other requirements (Nadira, 2023). Despite being a critical aspect of modern manufacturing, it presents significant challenges and demands substantial time. As production enterprises expand and the demand for higher product quality rises, industrial processes have become increasingly intricate. Consequently, the likelihood of production system failures and the associated hazards related to product quality have escalated. When faults occur in the production process, specific product quality indicators can fluctuate, leading to subpar quality (Xu et al., 2024).

The rapid advancement of information technologies makes it crucial to utilise them for monitoring and achieving stable, precise control over industrial processes and product quality (Xu et al., 2024). To address challenges in industrial process monitoring, fault diagnosis, and product quality control, experts and scholars have proposed the application of AI (Hartung et al., 2022; Zeng et al., 2022; Xu et al., 2024), including GAI as evidenced in recent studies (Narasimhan, 2023; Raja, 2023; Wang et al., 2019). The utilisation of GAI holds the potential to enhance quality control processes by effectively detecting and identifying defects and anomalies in various products. GAI can create virtual models of products, enabling simulation of the manufacturing process. This aids in the early detection and prevention of potential defects and anomalies in actual products (Raja, 2023).

GAI can revolutionise manufacturing quality control in several ways, such as (Raja, 2023):

- Defect identification. GAI can rapidly identify product defects by analysing images or data from manufacturing processes. This capability enables manufacturers to detect defects in real-time during the manufacturing process, ensuring that products meet quality standards before they are delivered to customers.
- Defect prediction. GAI can anticipate and identify potential product defects by leveraging historical defect data. With this capability, manufacturers can then pinpoint vulnerable areas and take proactive measures to prevent these issues.
- Automated quality control. GAI can automate quality control tasks by analysing more data about each production process and product, especially in defect inspection. It enhances accuracy and efficiency in quality control processes and boosts worker productivity, allowing them to concentrate on other essential tasks.
- Personalised quality control. GAI facilitates the personalisation of quality control processes by developing tailored inspection plans for different product types. It guarantees that each product undergoes scrutiny at a suitable level, ensuring compliance with the necessary quality standards.

In the conventional quality control process, humans are responsible for tasks such as understanding requirements, preparing and conducting tests, and reporting defects. However, this approach is prone to human errors, is time-consuming, and encounters challenges related to scalability in complex systems. GAI revolutionises quality control by automating these tasks and ensuring comprehensive test coverage, overcoming these challenges. Using machine learning algorithms trained on extensive datasets and continuous learning from previous errors, thus eliminating the need for human supervision and ensuring significant time and resource savings, GAI (Nadira, 2023; Vaddi & Khan, 2023):

- comprehends requirements and autonomously generates test cases;
- autonomously generates test data;
- automates test execution, minimising errors and time consumption;
- enhances test generation and execution, leading to quicker testing cycles, improved precision, and elevated product quality;
- generates clear, concise, and actionable reports after executing the test cases and
- predicts potential issues and forecasts and likely points to failures before they occur, enabling proactive and real-time addressing of problems.

The overall comparison between the traditional quality control process and the GAI-based quality control process is presented in Table 1.

Some examples of how GAI is being used in the manufacturing quality control process include (Raja, 2023; Srivastava, 2023; Wlodarczyk, 2023):

- Intel: GAI is used to detect imperfections in computer chips. By analysing images of computer chips, GAI identifies defects that are too minuscule for human observation, significantly enhancing Intel's chip quality.
- Bosch: GAI is used to forecast defects in automotive components. The company uses GAI to examine historical defect data, predicting which parts are more likely to be faulty. This predictive approach has significantly reduced the number of defective automotive parts shipped to customers.
- BMW: GAI is used to predict defects in car parts. AI employs computer vision to analyse images or videos of components and undergoes training to differentiate between defective and non-defective car parts. Once trained, AI can inspect new car parts in real-time, promptly identifying any defects and detecting deviations from the standard, ensuring all required parts are without defects and correctly mounted in their designated places.

Tab. 1. Traditional and GAI-based quality control process

| Aspects | Traditional Quality Control Process | Generative AI-Based Quality Control Process |
|---|---|---|
| **Tasks of the quality control process** | | |
| Test case generation | Manual creation of test cases based on various manufacturing documents and human experiences. Limited by human capacity and understanding, time-consuming | Automatic generation of diverse test cases based on provided scenarios and AI algorithms. Saving time, improving the breadth, depth, and scalability of testing |
| Test data generation | Manual creation of test data or generation of test data using predefined templates. May lack diversity and volume, time-consuming, and overlook certain real-world scenarios | Automatic generation of diverse, high-volume, and realistic test data. Saving time, improving the breadth, depth and scalability of testing |
| Test execution | Manual testing by human testers. Requirement of human intervention to interpret results and generate summary reports. Time-consuming, limited by human capacity and understanding | Automatic testing. Automatically generating clear, concise, and actionable reports after executing the test cases. Reducing human involvement, speeding up the test process by quickly generating test cases and data |
| Defect identification | Spotting patterns and anomalies depends largely on the skill and experience of human testers. Some defects might be missed. Reactive approach with errors being detected post-production | Spotting patterns and anomalies more consistently, possibly finding defects that human testers might miss. Proactive identification of errors and prevention |
| Defect prediction | Manually leveraging and analysing historical defect data. Some defects might be missed and lacking proactive measures to prevent these issues | Automatic leveraging and analysing historical defect data. Pinpointing vulnerable areas and implementing proactive measures to prevent these issues |
| **Features of quality control process** | | |
| Realism | Human bias may result in overlooking certain real-world scenarios | AI models can more accurately mimic real-world scenarios, leading to more effective testing |
| Scalability | Limited scalability, challenging for complex systems. Scaling up requires additional human resources and time | Scalable and capable of handling intricate processes. AI models can easily handle large data volumes and more complex scenarios, making them highly scalable |
| Time and resource efficiency | Time-consuming and resource-intensive. Manual creation of test case and data, the test execution and analysis of defects | Efficient use of time and resources. AI models efficiently generate test cases and data, automating the execution of tests and analysis of defects |
| Learning from past errors | Limited ability to learn from historical data. Limited by human capacity and understanding, time-consuming | Continuous learning, improving over time |
| Human oversight | High dependency on human supervision. Requirement of regular manual updates and adjustments based on changes in requirements | Reduced need for human interventions. AI models can be retrained and adapted to new or updated requirements |

Source: elaborated by the authors based on Narasimhan (2023), Raja (2023) and Vaddi and Khan (2023).

- Siemens: GAI is used to automate wind turbine quality control. This technology is used by Siemens to customise inspection plans for various wind turbines, streamlining the quality control process and enhancing efficiency in wind turbine production.
- Georgia-Pacific: GAI is used to enhance the quality of paper production. AI prevents paper tearing during production by predicting the optimal speed for converting lines.

Overall, the integration of GAI into the quality control process opens new possibilities for innovative transformation and efficiency enhancement of the quality control process. GAI promises to reshape manufacturing quality control, making it swifter, more effective, and exceptionally precise. Using the analysis of production data and the application of machine learning algorithms, it can pinpoint potential quality problems and defects.

This proactive approach empowers manufacturers to address issues in real time before they escalate, ensuring smoother production processes. Nevertheless, the effectiveness of AI in quality control directly depends on the quality and diversity of data it is trained on, as well as test algorithms. Test data and algorithms are important in delivering accurate and consistent results and deriving edge-case scenarios or exceptions.

### 2.4. Application of artificial intelligence in the context of predictive maintenance in production processes

Predictive Maintenance (PdM) is a proactive maintenance strategy that uses data, analytics, and machine learning to predict when equipment or machinery will likely fail, allowing for timely maintenance interventions. The main goal of PdM is to anticipate potential issues and perform maintenance activities just before they are needed, avoiding unexpected breakdowns and minimising downtime. There is strong evidence that using AI-based solutions improves the maintenance process in companies. AI can be applied to various stages of PdM, encompassing Data Collection, Data Preprocessing, Feature Selection, Model Training, Model Evaluation, Deployment, Monitoring, Alerts and Notifications, Maintenance Intervention and Feedback Loop. Artificial intelligence in the context of improving maintenance processes is applicable when maintenance processes are carried out by humans (in the form of inspections) (Shin et al., 2021) and when they are automated.

Cost savings are among the primary benefits of PdM (Shin et al., 2021), resulting from improving productivity (e.g., downtime reduction) (Arena et al., 2022); reducing environmental negative impact (e.g., waste reduction) (Allahloh et al., 2023), improving safety conditions (Katreddi et al., 2022) and reliability (Achouch et al., 2022).

The literature provides numerous examples of studies indicating the application of AI for maintenance operations in various industries and sectors: the renewable energy industry (Shin et al., 2021), manufacturing and processing of wood products (Rossini et al., 2021), the power generation industry (Allahloh et al., 2023), the automotive sector (Theissler et al., 2021; Arena et al., 2022; Katreddi et al., 2022) and particular industrial infrastructure (machinery) (Pandey et al., 2023).

Based on the experiment being conducted by Bahrudin Hrnjica and Selver Softic (2020), the integration of explainable AI, embodied in a dependable prediction model and visual representations, can effectively assist in mitigating avoidable costs linked to unscheduled downtime resulting from machine errors or tool failures. This means that by having an AI system that predicts potential issues and provides understandable explanations and visual insights into those predictions, businesses can make informed decisions to address issues pre-emptively (Bahrudin Hrnjica, Selver Softic, 2020).

To overcome the limitations of relying solely on human inspection, Shin et al. (2021) employed machine vision approaches to create AI-based solutions (AI-assisted approach) for image-based fault diagnoses. The authors examined the impact of AI based on deep learning algorithm assistance on the performance and perception of human inspectors, considering their task proficiency. The conducted studies confirmed that implementing AI to support inspectors significantly improved results (specificity, sensitivity, and time efficiency), particularly when inspectors were not experts in their field.

The results demonstrated that AI can yield significant benefits in scenarios with limited human resources and time-consuming expert training. The authors have posited the hypothesis that, even in the long-term perspective, it is improbable to fully automate the stage of reading and diagnosing images. This limitation stems from the inherent nature of artificial intelligence algorithms, which can only recognise faults they have thoroughly mastered based on training data. In situations involving novel issues, human involvement remains imperative for the early detection of potentially catastrophic cases (Shin et al., 2021).

The Digital Twin, which can deliver additional services by leveraging physical simulation and AI algorithms, is another example of applying AI in maintenance process improvement. These services include such functions as fault diagnosis, troubleshooting, predicting the remaining useful life, and facilitating maintenance activities (Rossini et al., 2021). Application of DT solutions enabled the real-time creation and modification of workflows essential for fault diagnosis and predictive maintenance. This involves the dynamic addition, removal, or replacement of entities to accurately represent the status of components within the system.

Allahloh et al. (2023) showcased the viability of markedly improving fuel efficiency and anticipating maintenance needs. Our discoveries indicate that deploying IIoT and AI solutions opens avenues for substantial fuel preservation, heightened performance through predictive maintenance, and practical strategies for industries to optimise processes and enhance efficiency in internal combustion genset operations. The IoT platform application allows for identifying potential issues before they become critical problems, significantly reducing downtime and maintenance costs (Allahloh et al., 2023).

The application of artificial intelligence in the maintenance field can predict potential system failures based on specific characteristics or system settings (input variables) and may prevent future failures and minimise downtime.

### 2.5. Artificial intelligence application for demand forecasting

Forecasting demand plays a vital role in contemporary business operations, allowing manufacturers to optimise their production processes, effectively manage inventory levels, and efficiently fulfil customer requirements (Ghosh, 2022; Tadayonrad & Ndiaye, 2023; Viverit et al., 2023). The emergence of artificial intelligence (AI) has provided businesses with a potent tool for examining intricate datasets and making more precise prognoses regarding future demand (Kumar et al., 2023). This part elucidates the utilisation of AI for analysing market trends, consumer behaviours, and sales information, ultimately heightening the accuracy of demand forecasting and contributing to improved decision-making within manufacturing workflows.

In the rapidly changing and dynamic landscape of contemporary business, grasping market trends is imperative to maintain a competitive edge (Li et al., 2022; Mathur et al., 2023). AI algorithms can analyse extensive quantities of information from diverse origins, including social media, online forums, news articles, and industry reports. This enables them to detect emerging trends and changes in consumer preferences (Liyanage et al., 2022). AI can extract valuable understandings regarding customer conversations, the rising popularity of specific products, and the influential trends steering purchasing choices by evaluating sentiment analysis, keyword frequency, and topic modelling. These insights equip manufacturers with the information needed to adapt their production strategies and harmonise their offerings with present and forthcoming market requirements (Li et al., 2022). Specifically, AI algorithms can sift through vast volumes of data sourced from social media platforms, pinpointing nascent trends, sentiments, and dialogues about particular products or sectors. Applying natural language processing (NLP) techniques facilitates sentiment analysis, topic modelling, and keyword extraction, thereby facilitating an understanding of consumer viewpoints and inclinations. For example, a fashion retailer uses AI to analyse social media conversations and identifies that a particular clothing style is gaining popularity among influencers and consumers. This insight prompts the retailer to adjust their production plans to meet the anticipated demand for that style. Moreover, AI can scan news articles, blog posts, and industry reports to identify shifts in consumer behaviour, economic indicators, and technological advancements that could impact market trends. AI can provide insights into upcoming trends by analysing the frequency and context of certain keywords and phrases. AI-powered web scraping tools can also extract data from e-commerce platforms, competitor websites, and marketplaces to track product prices, availability, and customer reviews (Dwivedi et al., 2023). This data can be analysed to detect pricing trends, product popularity, and consumer feedback. An online retailer, for instance, uses AI-driven web scraping to track competitors' pricing strategies and identifies that a certain product is consistently priced higher than similar offerings. This insight helps the retailer adjust their pricing strategy to remain competitive.

The utilisation of AI-driven analysis of consumer behaviour grants manufacturers an unparalleled comprehension of their intended audience (Sohrabpour et al., 2021; Yaiprasert & Hidayanto, 2023). AI can create detailed customer profiles by collecting and interpreting data from e-commerce platforms, loyalty programmes, and even IoT devices (Zhu et al., 2022). Machine learning algorithms can detect patterns within purchasing habits, preferences, and factors that prompt buying decisions. AI can potentially augment the precision of demand forecasting by identifying connections between external variables like seasonality, economic indicators, cultural occurrences, and consumer purchasing trends. This, in turn, empowers manufacturers to customise their production and marketing approaches to synchronise with these discernments, guaranteeing that the appropriate products are accessible at the right moment and in suitable quantities (Vaid et al., 2023). AI-powered sentiment analysis can analyse customer reviews, social media interactions, and online conversations to gauge consumer sentiment towards products and brands (Hyun Baek & Kim, 2023). This insight provides businesses with valuable feedback and helps them address customer concerns. For instance, restaurant chains utilise AI to analyse social media posts and reviews. It is discovered that customers consistently praise their food quality but express dissatisfaction with long wait times. The restaurant management addresses this issue by optimising their service speed, leading to improved customer satisfaction.

Sales data serves as a goldmine of information for demand forecasting (Ma et al., 2016). AI-driven analytics can construct predictive models by analysing historical sales data, considering such elements as product life cycle, promotional endeavours, and geographical discrepancies (Abolghasemi et al., 2020). These models can forecast demand with remarkable precision, aiding manufacturers in making informed decisions about production volumes and inventory management. Machine learning algorithms, such as time-series analysis, regression, and neural networks, can be trained on historical sales data to identify patterns and trends, enabling accurate predictions for future demand (Liu et al., 2023). AI can continually learn from prior forecasting inaccuracies and modify its models accordingly, resulting in progressively enhanced accuracy over time. These adaptable models aid businesses in honing their demand forecasts as fresh sales data becomes accessible. For example, an automobile manufacturer uses AI to forecast demand for different car models. Over time, the AI system learns that demand for SUVs is influenced by fluctuating fuel prices and economic indicators. The manufacturer can make more accurate predictions and optimise production plans. Consequently, incorporating AI into harnessing sales data for demand prediction allows businesses to make data-driven decisions, optimise production, and minimise the risk of overstocking or stockouts. By analysing historical sales patterns and their relationships with external factors, AI empowers businesses to anticipate and meet consumer demand more effectively.

While AI offers immense potential for revolutionising demand forecasting, it is important to acknowledge its benefits and challenges. AI-driven demand forecasting can lead to reduced inventory costs, minimised stockouts, optimised production schedules, and improved customer satisfaction (Njomane & Telukdarie, 2022; Soori et al., 2023). However, implementing AI systems requires substantial initial investment, data infrastructure, and skilled personnel. Additionally, the AI prediction accuracy relies on the quality and relevance of the input data. The dynamic nature of markets and consumer behaviour also challenges maintaining accurate forecasts over extended periods. As AI continues to evolve, demand forecasting techniques will likely become even more sophisticated. Predictive analytics, machine learning, and data-driven insights will drive manufacturers to embrace AI-driven forecasting models. Moreover, advancements in AI will facilitate real-time analysis, enabling businesses to respond swiftly to market changes and consumer behaviours. However, ethical considerations, data privacy concerns, and the need for transparent AI decision-making processes will remain important considerations in integrating AI into demand forecasting practices.

Integrating AI into demand forecasting processes offers manufacturers a competitive edge by providing insights into market trends, consumer behaviour, and sales data. Manufacturers can make informed decisions, optimise production, and enhance customer satisfaction by leveraging AI algorithms to analyse these key factors. As AI technology continues to advance, its role in demand forecasting is poised to become increasingly vital for businesses seeking to thrive in a rapidly changing marketplace.

## 2.6. Leveraging artificial intelligence for enhanced marketing strategies

The adoption of GAI for marketing is rapidly growing (Kshetri et al., 2023; De Mauro, Sestino, & Bacconi, 2022). By March 2023, 73 % of US businesses had already incorporated GAI tools, such as chatbots, into their marketing efforts (Dencheva, 2023).

Optimising marketing strategies in the ever-evolving manufacturing landscape is a crucial success facet. With the integration of GAI in manufacturing, companies gain a powerful tool for achieving more efficient and data-driven marketing approaches. The application of GAI in this context goes far beyond traditional methods, enabling manufacturers to make smarter decisions regarding the timing of product releases, promotional campaigns, and sales events.

One of the most remarkable aspects of utilising AI in marketing strategy is the capacity to harness predictive analytics. This technology allows manufacturers to forecast market trends and consumer behaviour with a high degree of accuracy. By analysing historical data, market conditions, and consumer preferences, GAI systems can identify potential spikes in demand for particular products or services. Managers can achieve significant value and a competitive edge by making effective data-based decisions (Conboy et al., 2020; Sivarajah et al., 2017). Furthermore, high-performing companies tend to be more inclined to use analytics compared to their less successful competitors (LaValle et al., 2011). Companies have utilised AI and machine learning to analyse historical sales data, market trends, and external factors such as weather conditions, which helps them predict consumer demand for their products more accurately.

The company's AI-driven demand forecasting can lead to better inventory management and optimised marketing campaigns, ensuring products are available when and where consumers need them. Utilising predictive and behavioural analytics models enables the customisation of new product offerings in response to evolving customer requirements and the precise targeting of marketing initiatives towards specific audiences.

When manufacturers can foresee increased demand accurately, they can adjust their marketing strategies and production schedules accordingly. This ability to predict demand patterns enables companies to allocate resources more effectively (Tadayonrad & Ndiaye, 2023), ensuring that products are available when and where they are most needed. As a result, manufacturers can maximise revenue by capitalising on market trends and customer preferences on time.

GAI also enables manufacturers to tailor their marketing campaigns to specific customer segments. AI systems can identify consumer preferences and behaviours by analysing vast datasets, allowing for highly targeted advertising and promotional efforts. Today, marketers can emphasise the customer and address their immediate needs as they arise (Haleem et al., 2022). GAI plays a crucial role in achieving extreme personalisation of content by analysing a potential customer's Internet browsing history, previous purchases, and other digital traces. This approach leads to the creation of dynamic offers, which, in turn, can significantly boost the conversion rate of promotional offers (Ooi et al., 2023). This level of personalisation can significantly enhance the effectiveness of marketing campaigns, ultimately leading to higher interactive experiences and increased customer satisfaction. By analysing the behaviour of similar customers, AI can suggest products more likely to resonate with each individual (Haleem et al., 2022). This approach enhances the customer experience and increases cross-selling and upselling opportunities.

Moreover, GAI aids in efficient resource allocation, ensuring that marketing budgets are spent in the most cost-effective way. Manufacturers can optimise their marketing investments and avoid wasteful spending by identifying which marketing channels and strategies yield the best results. This approach enhances a more sustainable and environmentally friendly manufacturing process.

GAI can be set to streamline data analysis and enhance marketing and customer service interactions. Companies like Nestlé, General Mills, and AB InBev have embraced GPT-4 to assist in deciphering data for their business intelligence needs. Meanwhile, Coca-Cola is leveraging ChatGPT and DALL-E 2 to craft their marketing campaigns (Global Data, 2023).

# Conclusions

Integrating AI in manufacturing offers a multifaceted approach to enhancing product efficiency, effectiveness, and safety. Manufacturers can significantly improve their overall operational outcomes by streamlining processes, optimising resource utilisation, and implementing advanced quality control measures. In the realm of skills analysis for manufacturing processes, AI adaptation plays a pivotal role. This technology facilitates a proactive approach to workforce development by evaluating historical data, identifying patterns, and forecasting evolving skill requirements, ensuring the necessary competencies are identified and cultivated.

GAI contributes to product quality by identifying defects in products and processes. Manufacturers can swiftly address issues, improving the overall quality of their products by analysing data patterns, anomaly detection, and real-time insights.

In the maintenance domain, GAI emerges as a proactive solution. This technology enables timely interventions by predicting equipment failures or maintenance needs through comprehensive data analysis. This approach helps prevent downtime, optimise operational efficiency, and extend the lifespan of machinery and equipment.

AI's capabilities extend to market dynamics by analysing trends, consumer behaviour, and sales data to predict demand for manufactured goods. This empowers manufacturers to align their production with market needs, facilitating efficient inventory management and resource allocation.

Furthermore, AI optimises marketing strategies by leveraging data analysis. AI enhances overall marketing effectiveness and customer engagement by improving the timing of product releases, promotional campaigns, and sales events. This holistic integration of AI technologies underscores their transformative impact on various facets of the manufacturing industry.

AI can be leveraged to analyse and predict the necessary skills required for manufacturing. It can also assist in mapping current employee skills and identifying gaps, allowing HR to proactively train or hire to meet future workforce demand. For instance, machine learning algorithms can identify patterns in worker skills and suggest appropriate training modules or process adjustments to increase overall manufacturing efficiency.

AI can analyse market trends, consumer behaviour, and sales data to predict demand for manufactured goods. Integrating GAI in manufacturing empowers companies to revolutionise their marketing strategies. With predictive analytics, data-driven insights, and highly targeted campaigns, manufacturers can respond to shifting market dynamics with precision. By maximising revenue and making more efficient use of resources, AI is an invaluable tool for manufacturers seeking a competitive edge in the global marketplace, allowing companies to be flexible and adaptable to new trends and staying relevant as consumer tastes change.

The future research directions regarding the application of artificial intelligence to enhance manufacturing processes are expected to be characterised by interdisciplinary studies that integrate teams of researchers and practitioners from technical, social, economic, and ethical disciplines. Undoubtedly, a long-term challenge will be the assessment of the consequences (positive and negative) of AI applications in various areas of human life and activity.

## Literature

Abolghasemi, M., Hurley, J., Eshragh, A., & Fahimnia, B. (2020). Demand forecasting in the presence of systematic events: Cases in capturing sales promotions. *International Journal of Production Economics*, *230*. doi: 10.1016/j.ijpe.2020.107892

Achouch, M., Dimitrova, & M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Applied* Sciences, *12*(16), 8081. doi: 10.3390/app12168081

Adel, A. (2022). Future of industry 5.0 in society: Human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing, 11,* 1-15. doi: 10.1186/s13677-022-00314-5

Allahloh, A. S., Sarfraz, M., Ghaleb, A. M., Al-Shamma'a, A. A., Hussein Farh, H. M., & Al-Shaalan, A. M. (2023). Revolutionizing IC Genset Operations with IIoT and AI: A Study on Fuel Savings and Predictive Maintenance. *Sustainability 15*(11), 8808. doi: 10.3390/su15118808

Arena, F., Collotta, M., Luca L., Ruggieri, M., & Termine, F. G. (2022). Predictive Maintenance in the Automotive Sector: A Literature Review. *Mathematical and Computational Applications 27*(1), 2. doi: 10.3390/mca27010002

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., & Denisi, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal, 33,* 606-659. doi: 10.1111/1748-8583.12524

Cappa, F., Oriani, R., Peruffo, E., & McCarthy, I. (2021). Big data for creating and capturing value in the digitalized environment: unpacking the effects of volume, variety, and veracity on firm performance. *Journal of Production and Innovation Management*, 38, 49-67. doi: 10.1111/jpim.12545

Cha, J.-H., Jeong, H.-G., Han, S.-W., Kim, D.-C., Oh, J.-H., Hwang, S.-H., & Park, B.-J. (2023). *Development of MLOps Platform Based on Power Source Analysis for Considering Manufacturing Environment Changes in Real-Time Processes*. In International Conference on Human-Computer Interaction (pp. 224–236). Springer.

Chang, Y.-L., & Ke, J. (2023). Socially Responsible Artificial Intelligence Empowered People Analytics: A Novel Framework Towards Sustainability. *Human Resource Development Review,* 15344843231200930.

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research, 281*(3), 656-672. doi: 10.1016/j.ejor.2019.06.051

De Mauro, A., Sestino, A., & Bacconi, A. (2022). Machine learning and artificial intelligence use in marketing: a general taxonomy. *Italian Journal of Marketing*, 439-457. doi: 10.1007/s43039-022-00057-w

Dencheva, V. (2023). Share of marketers using generative artificial intelligence (AI) in their companies in the United States as of March 2023. Retrieved from https://www.statista.com/statistics/1388390/generative-ai-usage-marketing/

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: a systematic literature review. *Journal of Business Research*, *121*, 283-314. doi: 10.1016/j.jbusres.2020.08.019

Dwivedi, Y. K., Sharma, A., Rana, N. P., Giannakis, M., Goel, P., & Dutot, V. (2023). Evolution of artificial intelligence research in Technological Forecasting and Social Change: Research topics, trends, and future directions. *Technological Forecasting and Social Change*, *192*. doi: 10.1016/j.techfore.2023.122579

Dworski, B. (2023). C-store retailers weigh in on automation, AI and data challenges. Retrieved from https://www.cstoredive.com/news/c-store-retailers-weigh-in-on-automation-ai-and-data-challenges/650008/

Ghosh, S. (2022). COVID-19, clean energy stock market, interest rate, oil prices, volatility index, geopolitical risk nexus: evidence from quantile regression. *Journal of Economics and Development*. doi: 10.1108/jed-04-2022-0073

Global Data. (2023). The impact of artificial intelligence in the consumer goods sector. Retrieved from https://just-drinks.nridigital.com/just_drinks_magazine_aug23/artificial-intelligence-impact-consumer-goods-industry

Głodowska, A., Maciejewski, M., & Wach, K. (2023). Navigating the digital landscape: A conceptual framework for understanding digital entrepreneurship and business transformation. *International Entrepreneurship Review, 9*(4), 7-20. doi: 10.15678/IER.2023.0904.01

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks, 3*, 119-132. doi: 10.1016/j.ijin.2022.08.005

Haponik, A. (2022). How AI improves productivity in manufacturing companies? Retrieved from https://addepto.com/blog/how-ai-improves-productivity-in-manufacturing-companies/

Hartung, J., Dold, P. M., Jahn, A., & Heizmann, M. (2022). Analysis of AI-Based Single-View 3D Reconstruction Methods for an Industrial Application. *Sensors, 22*, 6425. doi: 10.3390/s22176425

Heuser, P., Letmathe, P., & Schinner, M. (2022). Workforce planning in production with flexible or budgeted employee training and volatile demand. *Journal of Business Economics, 92,* 1093-1124. doi: 10.1007/s11573-022-01090-z

Hrnjica, B., & Softic, S. (2020). *Explainable AI in Manufacturing: A Predictive Maintenance Case Study*. In IFIP International Conference on Advances in Production Management Systems (APMS), (pp. 66–73). Novi Sad, Serbia.

Hu, X., Liu, A., Li, X., Dai, Y., & Nakao, M. (2023). Explainable AI for customer segmentation in product development. *CIRP Annals*, *72*(1), 89-92. doi: 10.1016/j.cirp.2023.03.004

Hull, B. (2011). *Manufacturing Best Practices: Optimizing Productivity and Product Quality*. Hoboken, New Jersey, USA: John Wiley & Sons.

Hyun Baek, T., & Kim, M. (2023). Ai robo-advisor anthropomorphism: The impact of anthropomorphic appeals and regulatory focus on investment behaviors. *Journal of Business Research, 164*. doi: 10.1016/j.jbusres.2023.114039

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the Age of AI*. Boston, MA.

Katreddi, S., Kasani, S., & Thiruvengadam, A. (2022). A Review of Applications of Artificial Intelligence in Heavy Duty Trucks. *Energies, 15*(20), 7457. doi: 10.3390/en15207457

Khang, A., Rani, S., Gujrati, R., Uygun, H., & Gupta, S. K. (2023). *Designing Workforce Management Systems for Industry 4.0: Data-Centric and AI-Enabled Approaches (1st ed.)*. CRC Press. doi: 10.1201/9781003357070

Koole, G. M., & Li, S. (2023). A practice-oriented overview of call center workforce planning. *Stochastic Systems*. doi: 10.1287/stsy.2021.0008

Korzynski, P., Kozminski, A. K., & Baczynska, A. (2023). Navigating leadership challenges with technology: Uncovering the potential of ChatGPT, virtual reality, human capital management systems, robotic process automation, and social media. *International Entrepreneurship Review, 9*(2), 7-18. doi: 10.15678/IER.2023.0902.01

Korzynski, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaite, R., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: analysis of ChatGPT. *Central European Management Journal*, *31*(1). doi: 10.1108/CEMJ-02-2023-0091

Kshetri, N., Dwivedi, Y. K., Davenport, T. H., & Panteli, N. (2023). Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda. *International Journal of Information Management,* 102716. doi: 10.1016/j.ijinfomgt.2023.102716

Kumar, A., Gupta, N., & Bapat, G. (2023). Who is making the decisions? How retail managers can use the power of ChatGPT. *Journal of Business Strategy.* doi:10.1108/jbs-04-2023-0067

Kwong, C. K., Jiang, H., & Luo, X. G. (2016). AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products. *Engineering Applications of Artificial Intelligence*, *47*(10), 49-60. doi: 10.1016/j.engappai.2015.04.001

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21-32.

Lei, Y., Vyas, S., Gupta, S., & Shabaz, M. (2022). AI based study on product development and process design. *International Journal of System Assuring Engineering Management*, *13*(1), 305-311. doi: 10.1007/s13198-021-01404-4

Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D., & Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, *65*, 279-295. doi: 10.1016/j.jmsy.2022.09.017

Li, X., Pan, L., Zhou, Y., Wu, Z., & Luo, S. (2022). A Temporal–Spatial network embedding model for ICT supply chain market trend forecasting. *Applied Soft Computing, 125*. doi: 10.1016/j.asoc.2022.109118

Liu, B., Song, C., Liang, X., Lai, M., Yu, Z., & Ji, J. (2023). Regional differences in China's electric vehicle sales forecasting: Under supply-demand policy scenarios. *Energy Policy, 177*. doi: 10.1016/j.enpol.2023.113554

Liu, C., Tian, W., & Kan, Ch., (2022). When AI meets additive manufacturing: Challenges and emerging opportunities for human-centered products development. *Journal of Manufacturing Systems*, *64*, 648-656. doi: 10.1016/j.jmsy.2022.04.010

Liyanage, S., Abduljabbar, R., Dia, H., & Tsai, P.-W. (2022). AI-based neural network models for bus passenger demand forecasting using smart card data. *Journal of Urban Management, 11*(3), 365-380. doi: 10.1016/j.jum.2022.05.002

Ma, S., Fildes, R., & Huang, T. (2016). Demand forecasting with high dimensional data: The case of SKU retail sales forecasting with intra- and inter-category promotional information. *European Journal of Operational Research, 249*(1), 245-257. doi: 10.1016/j.ejor.2015.08.029

Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, *122*, 102623. doi: 10.1016/j.technovation.2022.102623

Mathur, S., Kumar, D., Kumar, V., Dantas, A., Verma, R., & Kuca, K. (2023). Xylitol: Production strategies with emphasis on biotechnological approach, scale up, and market trends. *Sustainable Chemistry and Pharmacy, 35*. doi: 10.1016/j.scp.2023.101203

Mazumdar, T., Raj, S. P., & Sinha, I. (2005). Reference price research: Review and propositions. *Journal of Marketing, 69*, 84-102. doi: 10.1509/jmkg.2005.69.4.84.

Mazurek, G. (2018). Internet Rzeczy a cyfrowa transformacja – implikacje dla marketingu B2C [The Internet of Things and digital transformation - implications for B2C marketing]. In L. Sułkowski, & D. Kaczorowska-Spychalska (Eds.). *Nowy paradygmat rynku [A new market paradigm]*, (pp. 33–57), Warsaw, Poland: Difin.

Nadira, K. (2023). Implementing AI-Automation in Manufacturing for Product Quality Assurance. Retrieved from https://gleematic.com/implementing-ai-automation-in-manufacturing-for-product-quality-assurance/

Narasimhan, S. (2023). How AI & ML are Revolutionizing Product Quality Control. Retrieved from https://www.hurix.com/how-ai-ml-are-revolutionizing-product-quality-control/

Njomane, L., & Telukdarie, A. (2022). Impact of COVID-19 food supply chain: Comparing the use of IoT in three South African supermarkets. *Technology in Society, 71*, 102051. doi: 10.1016/j.techsoc.2022.102051

Nosalska, K., Piatek, Z. M., Mazurek, G., & Rzadca, R. (2018). Industry 4.0: coherent definition framework with technological and organizational interdependencies. *Journal of Manufacturing Technology Management*, *31*(5), 837-862. doi: 10.1108/JMTM-08-2018-0238

Ooi, K. B., Wei-Han Tan, G., Al-Emran, M., Al-Sharafi, M., Capatina, A., Chakraborty, A., Dwivedi, Y. K., Huang, T.-L., Kumar Kar, A., Lee, V. H., Loh, X.-M., Micu, A., Mikalef, P., Mogaji, E., Pandey, N., Raman, R., Rana, N. P., Sarker, P., Sharma, A., Teng, Ch., Wamba F. S., & Wong, L.-W. (2023). The Potential of Generative Artificial Intelligence Across Disciplines: Perspectives and Future Directions. *Journal of Computer Information Systems*. doi: 10.1080/08874417.2023.2261010

Open AI. (2023). Introducing ChatGPT and Whisper APIs. Retrieved from https://openai.com/blog/introducing-chatgpt-and-whisper-apis

Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: Purpose, process, and structure. *Journal of the Academy of Marketing Science*, *46*, 1-5. doi: 10.1007/s11747-017-0563-4

Pandey, R., Uziel, S., Hutschenreuther, T., & Krug, S. (2023) Towards Deploying DNN Models on Edge for Predictive Maintenance Applications. *Electronics*, *12*(3), 639. doi. 10.3390/electronics12030639

Plantec, Q., Deval, M.-A., Hooge, S., & Weil, B. (2023). Big data as an exploration trigger or problem-solving patch: Design and integration of AI-embedded systems in the automotive industry. *Technovation*, *124*, 102763. doi: 10.1016/j.technovation.2023.102763

Raja, A. (2023). How Generative AI can enhance the Manufacturing Industries? Retrieved from https://www.linkedin.com/pulse/how-generative-ai-can-enhance-manufacturing-industries-raja/

Rossini, R., Prato, G., Conzon, D., Pastrone, C., Pereira, E., Reis, J., Gonçalves, G., Henriques, D., Santiago, A. R., & Ferreira, A. (2021). AI environment for predictive maintenance in a manufacturing scenario. In*2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, (pp. 1-8). Vasteras, Sweden. doi: 10.1109/ETFA45728.2021.9613359

Rymarczyk, J. (2021). The impact of Industrial Revolution 4.0 on international trade. *Entrepreneurial Business and Economics Review*, *9*(1), 105-117. doi: 10.15678/EBER.2021.090107

Shin, W., Han, J., & Rhee, W. (2021). AI-assistance for predictive maintenance of renewable energy systems. *Energy, 221,* 119775. doi: 10.1016/j.energy.2021.119775.

Sigov, A., Ratkin, L., Ivanov, L. A., & Xu, L. D. (2022). Emerging Enabling Technologies for Industry 4.0 and Beyond. *Information Systems Frontiers.* doi: 10.1007/s10796-021-10213-w

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263-286. doi: 10.1016/j.jbusres.2016.08.001

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, Elsevier, 104*(C), 333-339. doi: 10.1016/j.jbusres.2019.07.039

Sohrabpour, V., Oghazi, P., Toorajipour, R., & Nazarpour, A. (2021). Export sales forecasting using artificial intelligence. *Technological Forecasting and Social Change, 163*. doi: 10.1016/j.techfore.2020.120480

Soori, M., Arezoo, B., & Dastres, R. (2023). Internet of things for smart factories in industry 4.0, a review. *Internet of Things and Cyber-Physical Systems, 3*, 192-204. doi: 10.1016/j.iotcps.2023.04.006

Srivastava, S. (2023). How AI is Proving as a Game Changer in Manufacturing – Use Cases and Examples. Retrieved from https://appinventiv.com/blog/ai-in-manufacturing/

Tadayonrad, Y., & Ndiaye, A. B. (2023). A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. *Supply Chain Analytics, 3*. doi: 10.1016/j.sca.2023.100026

Tadayonrad, Y., & Ndiaye, A. B. (2023). A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. *Supply Chain Analytics*, *3*. doi: 10.1016/j.sca.2023.100026

Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability Engineering & System Safety, 215*, 107864. doi: 10.1016/j.ress.2021.107864

Vaddi, K., & Khan, M. (2023). A New Era of Quality Assurance – Role of Generative AI in Reshaping Software Testing. Retrieved from https://www.encora.com/insights/a-new-era-of-qa-role-of-generative-ai-in-reshaping-software-testing

Vaid, S., Puntoni, S., & Khodr, A. (2023). Artificial intelligence and empirical consumer research: A topic modeling analysis. *Journal of Business Research, 166*. doi: 10.1016/j.jbusres.2023.114110

Villar, A., Paladini, S., & Buckley, O. (2023). Towards Supply Chain 5.0: Redesigning Supply Chains as Resilient, Sustainable, and Human-Centric Systems in a Post-pandemic World. *Operational Research Forum*, *4*, 60. doi: 10.1007/s43069-023-00234-3

Viverit, L., Heo, C. Y., Pereira, L. N., & Tiana, G. (2023). Application of machine learning to cluster hotel booking curves for hotel demand forecasting. *International Journal of Hospitality Management, 111*. doi: 10.1016/j.ijhm.2023.103455

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J., & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(2), 7-30. doi: 10.15678/EBER.2023.110201

Wang, G., Ledwoch, A., Hasani, R. M., Grosu, R., & Brintrup, A. (2019). A generative neural network model for the quality prediction of work in progress products. *Applied Soft Computing, 85*, 105683. doi: 10.1016/j.asoc.2019.105683

Wang, T., & Wu, D. (2024). Computer-Aided Traditional Art Design Based on Artificial Intelligence and Human-Computer Interaction. *Computer-Aided Design and Applications*, *21*(S7), 59-73. doi: 10.14733/cadaps.2024.S7.59-73

Wlodarczyk, S. (2023). How Generative AI will transform manufacturing. Retrieved from https://aws.amazon.com/blogs/industries/generative-ai-in-manufacturing/

Xu, Q., Dong, J., Peng, K., & Yang, X. (2024). A novel method of neural network model predictive control integrated process monitoring and applications to hot rolling process. *Expert Systems With Applications, 237*, 121682. doi: 10.1016/j.eswa.2023.121682

Yaiprasert, C., & Hidayanto, A. N. (2023). AI-driven ensemble three machine learning to enhance digital marketing strategies in the food delivery business. *Intelligent Systems with Applications, 18*. doi: 10.1016/j.iswa.2023.200235

Zeng, W., Wang, J., Zhang, Y., Han, Y., & Zhao, Q. (2022). DDPG-based continuous thickness and tension coupling control for the unsteady cold rolling process. *The International Journal of Advanced Manufacturing Technology, 120*(11-12), 7277-7292. doi: 10.1007/s00170-022-09239-4

Zhu, Y., Zhang, J., Wu, J., & Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. *Journal of Business Research, 150*, 642-652. doi: 10.1016/j.jbusres.2022.06.044

Volume 15 • Issue 4 • 2023

sciendo

received: 10 May 2023
accepted: 20 November 2023

pages: 90-103



# Towards Intelligent Automation (IA): literature review on the evolution of Robotic Process Automation (RPA), its challenges, and future trends

Julia Siderska
Lili Aunimo
Thomas Süße
John von Stamm
Damian Kedziora
Suraya Nabilah Binti Mohd Aini

**Julia Siderska**
Bialystok University of Technology, Poland
ORCID 0000-0001-5717-8043
Corresponding author:
e-mail: j.siderska@pb.edu.pl

**Lili Aunimo**
Haaga-Helia University of Applied Sciences, Finland
ORCID 0000-0002-3336-0948

**Thomas Süße**
Bielefeld University of Applied Sciences, Germany
ORCID 0000-0001-6832-7753

**John von Stamm**
RWTH Aachen University, Germany
ORCID 0009-0001-5410-7204

**Damian Kedziora**
Lappeenranta-Lahti University of Technology, Finland
Kozminski University, Poland
ORCID 0000-0003-2021-6661

**Suraya Nabilah Binti Mohd Aini**
International Islamic University Malaysia, Malaysia
ORCID 0009-0001-9558-0292

A B S T R A C T
Robotic Process Automation (RPA) and Artificial Intelligence (AI) integration offer great potential for the future of corporate automation and increased productivity. RPA rapidly evolves into Intelligent Process Automation (IPA) by incorporating advanced technologies and capabilities beyond simple task automation. The paper aims to identify the organisational, technological, and human-centred challenges that companies face in transitioning from RPA to IPA. The research process involved conducting the scientific literature search using the ResearchRabbit AI tool, which provided a set of reference papers relevant to the formulated research questions. As a result of the conducted literature review, the authors identified key challenges and possible countermeasures for companies transitioning from RPA to IPA. The resulting collection of reference scientific articles formed the basis for this study's content and substantive analysis. Furthermore, this study contributes by identifying artificial intelligence techniques and algorithms, such as Natural Language Processing (NLP), Machine Learning (ML), Deep Learning (DL), predictive analytics, and others, that can be integrated with RPA to facilitate the transition to IPA. The paper also offers insights into potential future research areas.

K E Y W O R D S
**Robotic Process Automation, RPA, Intelligent Process Automation, IPA, AI, Intelligent Automation, challenges**

**10.2478/emj-2023-0030**

## Introduction

Artificial intelligence has witnessed rapid expansion in recent years, and its applications are gaining widespread popularity (Wach et al., 2023). There is a growing interest across all sectors in AI-driven automation software, driven by the near-complete automation of administrative operations and significant operational efficiency gains enabled by these technologies. Nowadays, organisations are leveraging cutting-edge automation solutions to optimise their

Siderska, J., Aunimo, L., Süße, T., von Stamm, J., Kedziora, D., & Aini, S. N. B. M. (2023). Towards Intelligent Automation (IA): literature review on the evolution of Robotic Process Automation (RPA), its challenges, and future trends. *Engineering Management in Production and Services, 15*(4), 90-103. doi: 10.2478/emj-2023-0030

informational operations, with Robotic Process Automation technology emerging as particularly important and useful (Götzen et al., 2022). This technology combines software, artificial intelligence, and machine learning to automate manual operations traditionally performed by humans. It involves programming autonomous software robots to replicate fundamental administrative procedures. With its cognitive capabilities, AI can simulate human behaviour and handle unstructured data through machine learning, natural language processing, and image processing. RPA enables intelligent agents to eliminate operational errors and replicate routine manual decisions, including rule-based, well-structured, and repetitive decisions that involve substantial amounts of data within a digital system (Ng et al., 2021). RPA should be considered one of the digital transformation technologies that assist businesses in automating repetitive and regular processes (Kudlak, 2019; Siderska, 2020). In addition to these advantages, the complementary application of artificial intelligence methods and methodologies enhances RPA process accuracy and execution in information extraction, recognition, classification, forecasting, and process optimisation (Ribeiro et al., 2021).

Robotic Process Automation and AI integration hold significant promise for the future of corporate automation and increased productivity. RPA is growing into Intelligent Process Automation (IPA) by incorporating advanced technologies and capabilities beyond simple task automation. The transition towards IPA is fuelled by the synergy of AI technologies and automation tools. IPA seamlessly integrates automation, machine learning, and artificial intelligence to enhance and streamline corporate processes.

RPA can harness AI's decision-making capabilities to enhance technical proficiency, readiness for new technologies, and process automation potential across various application domains, ultimately leading to Intelligent Automation. According to the authors, enterprises can undergo digital transformation through hyper-automation and potentially overcome some challenges associated with RPA deployment by leveraging artificial intelligence (Moreira et al., 2023). Pairing RPA with AI skills enhances their capabilities, offering an effective solution for addressing complex issues and providing the means to overcome obstacles that RPA alone faces. RPA tools extend AI's capabilities, aiding organisations in enhancing their operational and business processes. By leveraging artificial neural network algorithms, text mining techniques, and natural language processing for information extraction, optimisation, and scenario forecasting, RPA tools extend AI's capabilities, ultimately helping organisations improve their operational and business processes (Lievano-Martínez et al., 2022).

The existing literature offers limited sources on the drivers and prerequisites, challenges in implementation, and future research directions for intelligent automation (Ng et al., 2021; Siderska et al., 2023). Therefore, this article aims to identify and understand the key organisational, technological, and human-centred challenges and propose possible countermeasures for companies transitioning from RPA to IPA. Considering this background, the following three research questions were formulated to build upon existing research advances:

RQ1. What are the key advantages of integrating AI with RPA?

RQ2. What are the common AI technologies used for IPA transitioning?

RQ3. What are the key challenges of organisations transitioning from RPA to IPA?

# 1. Research method

As previously mentioned, there is a growing demand to investigate the research and development of intelligent automation. Therefore, this review article outlines the challenges in IPA implementation and research directions. Based on a literature review, the study aims to provide and discuss the challenges companies face when transitioning from RPA to IPA. Three main approaches were considered to achieve this: organisational, technological, and individual human-centred levels, following the socio-technical framework proposed by Goetzen et al. (2023). The authors elaborated and followed the research methodology presented in Fig. 1 to achieve the planned goals and address the research questions.

The research began with identifying key concepts and definitions within the scope of the review, including Robotic Process Automation, Intelligent Process Automation, artificial intelligence technologies, cognitive automation, etc. The adopted perspective considered RPA and IPA from both business and human-centred viewpoints.

The next step in the research process involved conducting literature screening and searches using the ResearchRabbit AI tool. ResearchRabbit is an innovative, freely accessible online tool for citation-

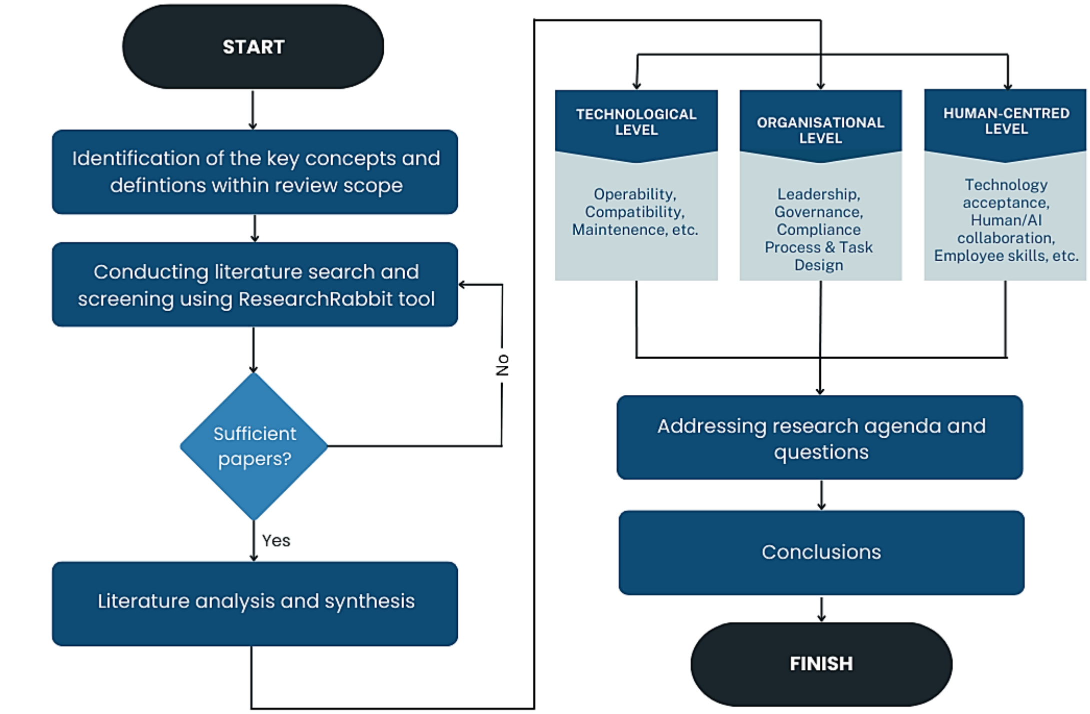



Fig. 1 Research methodology
Source: elaborated by the authors based on Goetzen et al. (2023).

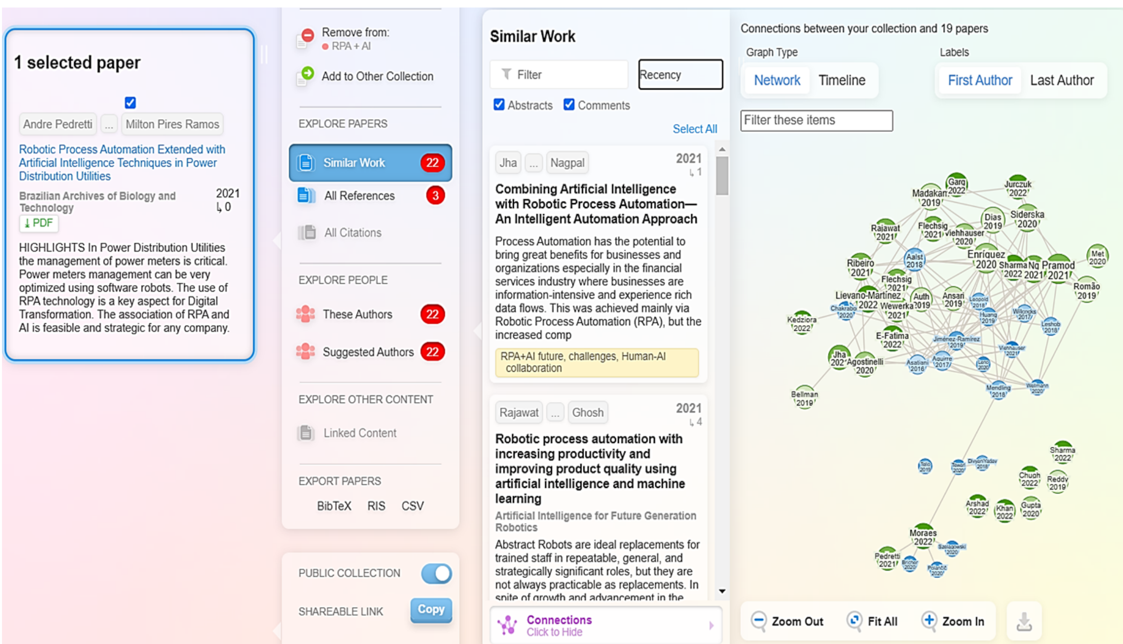



Fig. 2. Example of using the ResearchRabbit AI tool

based literature mapping. This program scours the Internet for publicly available sources and selects scientific publications based on similarities. This web-based platform offers interactive conceptual maps and streamlines the research process. The platform provides a user-friendly interface that simplifies mapping out a literature review. Its interactive visualisation allows researchers to connect their interests with related articles and authors. Users can easily link their research interests to relevant papers and authors, and

ResearchRabbit also includes features like note-taking and highlighting, making it convenient to summarise and extract essential information.

The initial step of using the ResearchRabbit tool involved providing reference papers relevant to the formulated research questions. After adding key papers to the collection, the software used AI algorithms to select 150 scientific publications based on similarities. An example of finding similar articles to the indicated work and related connections is shown in Fig. 2.

ResearchRabbit utilises natural language processing, machine learning, and semantic understanding to offer highly accurate and contextually meaningful results. It serves as compelling evidence of how artificial intelligence has the power to revolutionise information access. Key features of the tool include personalised recommendations, where it learns from users' search history and preferences; semantic understanding, which enables it to grasp the semantic context of queries, enhancing the depth and accuracy of search results; trend analysis, by which it can identify emerging trends and topics within specific research fields by analysing patterns in research publications, enabling researchers to anticipate breakthroughs or pivot their research directions; and visual summarisation, where ResearchRabbit AI utilises data visualisation techniques to condense complex information into easily digestible visual summaries.

The next step in the research process involved conducting a literature review, content analysis, and synthesis. The primary goal was to describe the theoretical or empirical nature of publications chosen by AI algorithms, highlighting major directions for future research in these fields and revealing the foundational knowledge pillars. Challenges and potential countermeasures were considered at the organisational, technological, and human-centred levels.

## 2. Theory development within RPA, AI, and IPA

Throughout history, innovative efforts have never ceased influencing, improving, and revolutionising human life. Recent technological advancements have proven to provide an array of solutions and opportunities for various complex problems. More specifically, the increasingly dominant role of technologies like AI has overhauled the common activities related to business processes and functions. This trend can only be expected to grow rapidly, as Furman and Seamans (2019) highlighted how AI-related activity in the workforce significantly impacted multiple industries, the labour market, and the general economy.

It is important to note that the definitions of AI prove to be contingent on its boundaries and limits, which have mostly become prevalent recently as technological developments have made it more difficult to define AI's scope (Wang, 2019) specifically. Nevertheless, AI is generally viewed as a conglomerate of different techniques, including subjects like natural language processing (NLP), machine learning (ML), neural networks, and computer vision (Sarker, 2022). Regarding the subjects of this paper, some studies show that the relevant AI techniques can be segmented into two (2) categories: classical AI and constructed AI (Richardson, 2020). Where classical AI refers to the application of pre-defined instructions towards the machine's decision-making, the latter is defined as the machine's advanced use of ML algorithms to discover patterns from data.

This notion feeds into the topic of RPA, a software solution ostensibly designed to limit the repetitive, non-value-added tasks humans perform (Baranauskas, 2018; Costa et al., 2022). Low-complexity business tasks are overtaken and concurrently pave the way for human workers to embark on more meaningful work. Furthermore, powered by low-code and clearly defined definitions, companies began to leverage RPA solutions to achieve increased productivity with ease and employee satisfaction (Kortesalmi et al., 2023). The future of RPA highlights how it serves as a powerful gateway technology towards advanced AI applications (Siderska, 2020). Eventually, as intelligent solutions rapidly evolve, industries are beginning to make headway towards an even smarter and more advanced model of RPA, coined Intelligent Process Automation (IPA). Richardson (2020) describes that the distinction between RPA and IPA lies in integrating intelligent features and algorithms (AI) that can exceed human capabilities. IPA is generally recognised as more advanced. Essentially, incorporating cognitive functions allows IPA to recognise patterns in decision-making, adapt to new data, and self-improve through experience (Berruti et al., 2017). Concerning the categorisation of AI, as RPA performs under logic-based rules for repetitive processes, it fundamentally fits within the definitions of classical AI, while IPA falls under constructed AI since it includes ML and AI technologies. Ultimately, a company's desire to meet its business challenges and increase competitiveness can be achieved through RPA and IPA integration. Despite the developmental differences between the two technologies, both can be utilised to support different business departments.

As mentioned, advanced AI technologies can be used to facilitate essential business management tasks. The features of RPA and IPAs are capable of equipping businesses with strategic opportunities and consequently aiding different stakeholders involved through their applications. More specifically, this can ostensibly be achieved through the evolution and application of IPA, with its functions overshadowing RPA's relatively limited capabilities. Advanced IPA integration can uplift processes' strategic (business) and human-centred aspects, enforcing strategic plans and business improvement. On the one hand, since IPAs can improve themselves through reinforcement learning, these machines can outperform humans in various business tasks.

Asadov (2023) highlights that streamlining IPA into the workforce effectively enables end-to-end automation that shortens lead time and eliminates process bottlenecks. Furthermore, on top of efficient resource allocation, deep learning algorithms and cognitive capabilities promise companies real-time monitoring and performance analytics (Berrutti et al., 2017). In effect, data-driven insights develop decision-making to enhance process performance and overcome organisational shortcomings, which will guide industry leaders towards green practices and subsequently create spillover effects towards achieving sustainability. On the other hand, IPA deployment reaps many beneficial impacts on the human stakeholders involved in the business. According to Berruti et al. (2017), human workers can be granted improved internal work opportunities and roles that exceed their preceding job scope. The additional responsibilities can cover more meaningful and innovative tasks, increasing their agency and allowing employees to forge their career paths. Touching on another human-centred perspective, technologically simplifying interactions through IPA can positively enhance the customer journey. Additionally, possessing comprehensive target clientele information leads companies to accurate decision-making, further enhancing customer relationships. Thus, advanced AI inclusion in IPA can unlock significant values, drive productivity gains for a business and achieve strong customer experience and retention.

With more companies transitioning towards automation, solutions like IPA emerged to meet the flourishing demands of outperforming technology. Studies show that incorporating technological resources and systems into business administration will benefit the sectors' operational and industrial growth (Ahmad et al., 2022). In the prospects of achieving increased productivity and performance, implementing advanced robotic AI solutions has impacted various business activities related to different departments and stakeholders. Incorporating automation of relevant processes through IPA is primarily needed to progress towards innovative movements like the Industrial Revolution 5.0 (IR5.0). However, even though businesses know their need to implement digital innovation and automation, they may face challenges in including such advanced technologies.

# 3. Challenges for organisations with IPA transitions

The relentless pursuit of operational excellence and efficiency has driven the evolving landscape of business automation. With increasing technological opportunities in AI, digital pioneers grow increasingly aware of the potential benefits IPA offers. Compared to the rudimentary predecessor RPA, which focused primarily on rule-based, repetitive tasks, IPA leverages the capabilities of AI, machine learning, and data analytics to automate routine tasks and complex cognitive functions. As a result, IPA has great potential to empower organisations to realise multifaceted advantages that resonate throughout their operations.

However, implementing IPA or transitioning from RPA to IPA presents significant challenges for companies. These challenges go beyond technical considerations and are primarily associated with organisational adjustments and the changing role of the human workforce. Organisations are challenged with redefining job roles, addressing data security concerns, and providing training and upskilling opportunities for employees. Following the socio-technical framework proposed by Goetzen et al. (2023), these challenges are classified into three distinct categories: organisational, technical, and human-centred, as shown in Table 1. A comprehen-

Tab. 1. Challenges for organisations transitioning from RPA to IPA

| Challenge category/ perspective | Key challenges | Possible countermeasures | References |
|---|---|---|---|
| organisational | • leadership-related challenges, e.g., missing alignment across business areas, workforce management, and change management;<br>• governance-related challenges, e.g., allocation of roles and responsibilities, missing rule-based frameworks and implementation guidelines;<br>• process and task design-related challenges, e.g., routine organisation and task aspects and deficiencies;<br>• compliance and IT security, e.g., missing policies, guidelines, and audit processes | • transparent communication protocols and knowledge transfer need to be considered within the organisational design;<br>• clear allocation of responsibilities and incentives;<br>• collaborative task design considering human aspects and AI limitations;<br>• definition of clear IT security guidelines detailing access rights and data use restrictions for humans and IPA bots | Brás et al. (2023); Lievano-Martínez et al. (2022); Feio & dos Santos (2022); Chakraborti et al. (2020); Flechsig (2021); Agostinelli et al. (2020); Kedziora & Hyrynsalmi (2023); Brás et al. (2023) |
| technological | • lack of good quality data for ML;<br>• wrong ML model chosen for a task;<br>• challenges in software integration | • data curation;<br>• trained ML engineers and better documentation of the algorithms with practical use cases and open-source reference implementations;<br>• better standardisation and compliance with standards; | Kedziora & Hyrynsalmi (2023) |
| human-centred | • transformation of job roles;<br>• novel skills and competence demands;<br>• fear of job loss, identify void & less-abled;<br>• mutual learning between heterogeneous actors | • clarification and implementation of new job roles;<br>• identification of required skills and competence;<br>• AI-related learning at the workplace with support from new HR practices | Moulaï et al. (2022); Schulte et al. (2022); Süße et al. (2023) |

sive analysis of these challenges is provided in subchapters 3.1–3.3, as presented in Table 1.

### 3.1. Organisational challenges

Various organisational tasks arise in the transformation from RPA to IPA. The organisational tasks can be classified into four main categories: Leadership, Governance, Process and Task Design, and Compliance (Goetzen et al., 2023). The most important aspects of each category are discussed in more detail below. Afterwards, the question is addressed of whether and to what extent the emerging challenges depend on the technological maturity of IPA and the maturity levels suggested for the transformation to be classified. However, further research is needed on which challenge can be assigned to which maturity level.

Leaders are at the forefront of guiding their organisations through the complexities of IPA implementation. Their ability to provide strategic direction, promote alignment, nurture the workforce, and effectively manage change and communication is fundamental to the success of IPA initiatives. Within the literature, several leadership challenges have been identified, encompassing strategic planning and flexibility, alignment across business areas, workforce management, change management, and communication, explained in the following paragraph.

A paramount challenge in leadership involves the formulation of a roadmap and strategy for IPA implementation, which necessitates careful planning to ensure the successful integration of IPA into organisational processes (Feio & dos Santos, 2022; Kedziora & Hyrynsalmi, 2023). Notably, the strategy must be adaptable, given the dynamic nature of processes that are in constant flux (Brás et al., 2023). Organisations must adopt a comprehensive approach to harness the full advantages of automation and effectively mitigate risks, failures, or potential threats. It should involve ensuring alignment between the business and IT, business continuity, and the implementation of new controls specifically tailored to address the unique risks associated with IPA (Brás et al., 2023). Brás et al. (2023) and Lievano-Martínez et al. (2022) recommended a holistic approach to addressing this challenge. Organising and managing the workforce effectively is a multifaceted challenge. Ensuring the organisation possesses the requisite human resource capabilities is imperative for successful IPA implementation (Feio & dos Santos, 2022). Thus, employees must receive training to develop new skills related to

IPA. Additionally, it is essential to prevent deskilling, whereby employees do not lose their creative and judgmental abilities during the automation process (Flechsig, 2021; Kholiya et al., 2021; Zeltyn et al., 2022; Feio & dos Santos, 2022). Furthermore, a challenge arises from the scarcity of qualified experts in this field (Flechsig, 2021; Kholiya et al., 2021). Change management is an integral part of IPA implementation. It involves orchestrating the transformation and ensuring the changes are seamlessly integrated into the organisational culture and practices. Effective communication is paramount in achieving internal organisational synergies, managing expectations, and mitigating user resistance (Flechsig, 2021; Mohanty & Vyas, 2018; Kedziora & Hyrynsalmi, 2023), also encompassing the readiness of the organisational culture and technology (Feio & dos Santos, 2022).

Governance is the guiding framework that ensures IPA initiatives are executed precisely and in alignment with the organisation's strategic objectives. It establishes the rules of engagement, resolves conflicts, defines the scope and provides the necessary support to make IPA adoption a success. The literature review identified three major governance-related challenge areas: allocation of responsibilities, rule-based framework, and adoption and implementation guidelines. Responsibilities and rules must be clearly defined during implementation (Flechsig, 2021). Lievano-Martínez et al. (2022) stated that responsibilities must be separated, and a review of mechanisms must ensure that conflicts are resolved quickly, e.g., via a decision matrix framework, programmed meetings, and reporting rules. According to Chakraborti et al. (2020), new frameworks and approaches are required to enable the composition and collaboration of multiple IPA-bots. In addition, the scope of autonomy and decision-making of the bot needs to be determined (Flechsig, 2021). Herm et al. (2021) claimed that critical success factors need to be identified so that methodological support for adoption and implementation can be developed. Brás et al. (2023) supported this by stating that adopting new processes entails evaluating and understanding the impact on business continuity.

The imperative for process and task (re-)design emerges as a requisite for restructuring operations, with the primary objective of optimising the synergistic collaboration between IPA bots and the human workforce. This restructuring aims to enhance operational efficiency and effectiveness by harmonising the capabilities of IPA bots with human skills and expertise. Challenges within the process and task design could be assigned to the following categories: data challenges, process and routine organisation and task aspects and deficiencies. The crucial data issue lies at the heart of process and task design. Initially, it is imperative to identify, clean, and transform the pertinent data to make it amenable to automation (Chakraborti et al., 2020). However, within the context of IPA, a heightened demand for data quality arises, accompanied by the risk of potential data gaps essential for model building (Kaarnijoki, 2019). Kaarnijoki (2019) further highlighted the data dimension by underscoring the challenge of avoiding or accounting for data bias within training data. This bias may stem from certain features present in the dataset. When an automated model is trained on biased data, it consequently inherits the same biases, potentially impacting its accuracy and fairness. A parallel challenge emerges in managing the processes and routines vital to the success of an IPA implementation. In this context, adopting new procedures unfolds rapidly, often potentially disrupting existing workflows (Brás et al., 2023). The effectiveness of automation hinges on the identification of suitable routines and processes that can be automated (Agostinelli et al., 2020, p. 4). As Godbolde et al. (2022) articulated, determining the utility of automating specific IPA opportunities requires comprehensively assessing the process complexity level and the necessary intelligence degree.

The final identified challenge category pertains to deficiencies in various task-related aspects. These include the potential absence of standardised and up-to-date process documentation, which could impede the smooth automation of processes (Kedziora & Hyrynsalmi, 2023). Additionally, challenges may arise concerning task selection and scalability management techniques. If effective strategies in these areas are missing, this could pose significant obstacles to the automation journey (Feio & dos Santos, 2022). Furthermore, robust testing and penetration testing are of paramount importance. The absence of such measures may expose vulnerabilities within the automation system, potentially rendering it susceptible to security breaches (Al-Slais & Ali, 2023).

The final major challenge category covers organisational challenges related to compliance. These challenges mainly relate to IT security concerns (Kedziora & Hyrynsalmi, 2023) and the integration with legacy systems (Feio & dos Santos, 2022). Regarding IT security, it should be added that robust cybersecurity is required to ensure safe IPA implementation and scaling (Kholiya et al., 2021). In addition, policies and guidelines must be updated to reflect audit capabilities for secure monitoring of changes (Brás et al., 2023).

### 3.2. Technological challenges

The evolution of intelligent automation software has been affected by technical limitations. The type of technical challenge the organisation faces depends on the intelligent automation technology in question. Therefore, the software was classified into six categories reflecting the most common types of intelligent automation. The classes were created based on the review papers on IPA by Ng et al. (2021) and Devarajan (2019) and on the literature review described in this paper. The classes, their explanations, and some use cases are given in Table 2.

The technical challenges related to conversational AI are often related to hallucinations, which refer to unreliable information generated by large language models (Ji et al., 2023) and a bias and lack of data for training. Security and compliance are also common technical challenges in many IPA types, including conversational AI (Herm et al., 2021). Overall, according to Herm et al. (2021), the four latter technical challenges are very common in IPA. All ML-based techniques may suffer from the lack of good-quality data, which is a very stringent challenge, as most IPA techniques rely on ML techniques.

Business process mining suffers from the inherent challenge of relying on past data, and thus, it is unable to account for changes in the business processes or the environment. The same applies to all ML techniques except those employing the human-in-the-loop approach, such as reinforcement learning (Sutton & Barto, 2018). De la Oliva (2020) pointed out the integratory elements of cognitive automation related to embedding automation toolsets at enterprise platforms. This challenge has also been addressed by Ng et al. (2021). Another challenge indicated by Pramod (2021) was the manual or human-driven identification of automation potential, favourably substituted by technical solutions of the

Tab. 2. Common AI techniques used in IPA

| AI technique | Short explanation | Common use cases |
|---|---|---|
| Conversational AI, including generative AI | Techniques for the automated generation and interpretation of natural language and for keeping up a conversation. They may address several modalities, such as text, speech, sign language and gestures | Build conversational interfaces that enable communication between a computer and a human, such as an interface for filling in forms and other structured data. The agent may work, e.g., as a customer service agent or a bot, helping the expert use financial software (Moiseva, 2020; Shidaganti et al., 2023; Zeltyn et al., 2022) |
| Business Process or Task Mining | Using data mining and ML techniques to extract business rules from data | Automate the manual work of writing executable RPA scripts. Rules may be mined from user interface log data or history data annotated by humans (Agostinelli et al., 2020) |
| Intelligent OCR | Intelligent OCR is an advancement to the traditional OCR as it uses extratextual and textual information to scrape business information from scanned documents. It may contain such features as key information extraction (IE) and ML-based adaptive decision-making in unclear OCR cases. Multimodal IE incorporates extratextual information, such as layout or other visual information | Scanning damaged or unclear hand-written documents. Extracting structured data directly from physical documents, such as paper bills. (Cho et al., 2023; Kedziora & Hyrynsalmi, 2023; Hong et al., 2023) |
| Information extraction (IE) | Extract relevant information from natural language input, such as text documents and speech, thus creating structured data from unstructured data | Extracting software requirements from business documentation, extracting patient information from a medical doctor's speech and saving it to a database |
| Machine Learning (ML) | Using ML techniques, including deep learning and reinforcement learning, to create classifiers and clusters from data. Also, human-in-the-loop approaches are included | Create a classifier using ML and history data on customers and their loan payments to automate bank loan decision-making. Create an anomaly detector for monitoring fraudulent transactions using ML techniques |
| Data Science (incl. Predictive Analytics) | Based on past data, create a model that predicts the future | Predictive maintenance for elevators and other machines, planning of transaction volumes (Vajgel et al., 2021) |

task of process mining origin (Geyer-Klingeberg, 2018), where the software controls and analyses the flow of processes based on specific rules (Huang [MOU5] & Vasarhelyi 2019). Stople et al. (2017) pointed out that challenges with infrastructural scalability negatively impact the entire ecosystem and need to be systematically updated (Lacity et al., 2015). From the perspective of the strategy for data storage and acquisition, Bhatnagar (2020) identified issues with multi-source inputs with no standardisation. Aspects of regulatory challenges for technical setups and security handling have been discussed by Priya et al. (2019). Regulatory challenges are prevalent when ML models are built using personal data, as regulations, such as GDPR, restrict the collection and use of data often required to build the models. The upcoming AI Act (Veale & Borgesius, 2021) will classify software employing AI into categories with different risk levels and limit AI application in high- or medium-risk sectors, such as healthcare or education.

IPA that relies on ML may suffer from poorly trained or immature models that might lead to unsupported or even wrong decisions and an increase in errors (Wojciechowska-Filipek, 2019). Poorly trained models may result from a lack of expertise of the ML engineers if they do not know which model to select for the task at hand. Poor-quality data is another common source of poor models (Geiger et al., 2020).

### 3.3. Human-centred challenges

From a human-centred perspective, AI implementation and extended use, particularly IPA, create novel employee challenges. Herm et al. (2021) pointed out a lack of training data, human bias in data, compliance issues with transfer learning, poor explainability of robot decisions, and job-security-induced fear of AI-based robots. In addition, implementing AI robots in professional work contexts can lead to a human perception of an identity void and a feeling of being less able (Moulaï et al., 2022). Kassekert et al. (2022) argued that the rather human-centred process of finding and having appropriate training data for ML models is rather challenging while the demands for harmonised regulatory guidance, e.g., for providing orientation for human decision-making processes, increase.

Based on several interviews and empirical analysis, Lamberti et al. (2019) emphasised that the most significant challenges during AI implementation include the skills of staff (55 %), data structure (52 %), and budgets (49 %). In addition, the authors showed that 60 % of their respondents during interviews referred to a planned increase in staff within the next 1–2 years. This increase is required to support AI use or implementation within the organisation. These results are in line with other field research results that show how the implementation of AI into the value-creation process contributes to the emergence of new job roles and profiles in the industry. While these developments also create new opportunities for the workforce, there are challenges as well, like additional time and effort human actors have to spend on learning and training initiatives (Schulte et al., 2022). Another study (Süße et al., 2023) investigated a shift in human behavioural patterns of technology interaction during the implementation and product use of an AI robot within a remanufacturing company. The authors emphasised a new set of cognitive, social and emotional competencies required for human actors to interact more collaboratively and cooperatively with AI robots.

However, while the above-mentioned literature focused rather on the human side of these newly emerging IPA-related human-AI systems, Chakraborti et al. (2020) highlighted a technological perspective with a human-centred standpoint in mind, i.e., that novel conversational systems may be required for a productive and sustainable collaboration among IPAs and users (p. 220 ff.). As such, the emergence of a mutual and rather iterative learning process between human actors and AI robots has to be enabled and supported to implement IPA-related human-AI systems successfully. It is related to another key challenge from the human-centred perspective discussed by Martínez-Rojas et al. (2021), who pointed out that a success critical factor for the implementation of AI robots and IPA is the involvement of heterogeneous experts and professionals from different disciplines with diverse skills, competences and backgrounds as the added value of transdisciplinary solutions will be required to make IPA work appropriately in organisations.

In their literature review, Jha et al. (2021) concluded that the shift in human tasks is another key challenge of IPA implementation in organisations. They argued that middle-skilled employees might migrate to high-skilled jobs with the help of extensive learning and development initiatives. Furthermore, they highlight the emergence of a new management position, which they call Chief Data Supply Chain Officer. One key component of this role is the capabilities and responsibility of creating end-to-end data supply chains across all levels of the organisation and within a value network of organisations, which could help fully leverage the extensive benefits of available data in AI (p. 261).

In summary, the authors argue that research so far points out four key IPA challenges from a human-centred perspective. First, the transformation of traditional job roles has to be addressed adequately at all hierarchical levels within the organisation. Second, employees and management require novel skill sets and competencies as both groups will interact with the new technology more collaboratively in a human-AI system. Third, trust and explainability of AI and regulatory guidance play a critical role in reducing job-security-induced fear of AI-based robots, which also relates to identity void and feeling less able among employees. Fourth, mutual and iterative learning processes between heterogeneous experts and managers from different disciplines and backgrounds and between humans and AI must be enabled and supported to contribute to the emergence of highly collaborative and sustainable IPA-related human-AI systems.

## 4. Future research trends

Empirical-based field research is scarce on specific skills and competence demands and more context-related specifications of job role changes. Furthermore, the human-centred perspective so far focused more on the psychological perspective of humans, e.g., the collaborative concept human actors have in mind when interacting with AI robots (Süße et al., 2023). Furthermore, research should more explicitly focus on the human–AI system as a whole and not address the human or AI, which is very often the case in most research approaches (Waefler et al., 2021).

Future research aims to address the organisational challenges arising from adopting IPA or the transition from RPA to IPA, prioritising specific essential areas, including exploring task designs and routine definitions that enable effective collaboration between humans and IPA bots. Further research efforts should also focus on comprehensive change management and communication strategies, allowing for a smoother transition to IPA (Flechsig, 2021). Ethical and legal concerns are relevant in considering the data-driven nature of IPA and potential biases in AI algorithms. Furthermore, IT security and risk management are critical areas where further investigation can help develop robust strategies to safeguard information when using IPA. As a descriptive framework, IPA maturity models could offer organisations valuable orientation for assessing their readiness and progress on their automation journey. Finally, exploring scientific approaches to seamlessly integrate IPA with legacy systems, ensure regulatory compliance, and enhance scalability and adaptability could provide essential support for organisations to overcome challenges and mitigate risks associated with IPA implementation.

Methodology and practices for data curation are needed to overcome the technical challenges of adopting IPA, which is essential to ensure access to good quality data critical for ML. Another major challenge in IPA is that the selection process for the used ML model is not optimal. This results in low-quality output in IPA. Research on reference models and ML model implementations is needed to overcome this shortcoming. The reference models should be published as open-source implementations, and the documentation should contain practical examples of use cases illustrating their optimal application. The third technological challenge is related to integration and may be overcome with standardisation work where good-quality interface and data standards are created, and the widespread uptake of the standards is facilitated.

Emerging Low-Code Development Platforms (LCDPs) are a significant phenomenon that requires further exploration as they will impact building process automation solutions. RPA and IPA were targeted and focused on the automation of particular business processes, whereas LCDPs go beyond simple process automation by aiming at building entire business applications, enabling persons with introductory software skills to develop fully functioning apps. In this context, integrating more technologies across the entire value chain shall enable further simplification and effectiveness of available tools. Hence, the relationship and opportunities resulting from integrating RPA and LCDPs will certainly become an important trend, as according to Gartner (2023), by 2027, low-code application development will be responsible for more than 70 per cent of application development activity globally.

These research trends reflect the diverse and evolving nature of intelligent automation. Researchers in this field will play a crucial role in advancing automation technologies and ensuring their responsible and effective use, as well as shaping the future of IPA across a wide range of industries, fostering innovation, and addressing the practical, technical, and ethical challenges that arise along the way. Additionally, addressing the potential impact on the workforce and engaging in collaborative efforts with experts and stakeholders is essential to navigating the challenges of human-centred design in the context of intelligent automation.

# Conclusions

Integrating AI with RPA significantly enhances automation capabilities, empowering organisations to increase efficiency, reduce errors, enhance customer service, and remain competitive in a rapidly evolving business landscape. This combination provides a robust solution for organisations looking to streamline their processes and deliver added value. AI-powered RPA excels at handling unstructured data, utilising natural language processing (NLP) and applying machine learning to execute tasks that demand cognitive abilities, including understanding text, images, and speech. These developments expand the range of tasks that RPA can automate. AI's ability to identify patterns, predict outcomes, and suggest process improvements further enhances and refines operations. When seamlessly integrated with RPA, it streamlines workflows, ensuring heightened efficiency. AI's capacity to continually learn and adapt from new data and experiences makes RPA processes more agile and adaptable in dynamic environments.

Organisations encounter numerous challenges when adopting IPA or transitioning from RPA to IPA. These challenges are predominantly associated with organisational adjustments and the changing role of the human workforce, extending beyond technological concerns. The primary areas of organisational focus encompass (Geotzen et al., 2023) leaders as they are critical in navigating organisations through the complexity of IPA implementation. The ability of IPA leaders to provide strategic direction, foster cohesion, nurture the workforce, and effectively manage change and communication is essential for the success of IPA initiatives. Governance is the guiding structure for ensuring that IPA projects are carried out precisely and following the organisation's strategic objectives. It establishes engagement norms, dispute resolution processes, and scope definition and provides the required support for effective IPA implementation. Restructuring of operations and (re-)design of processes and tasks are necessary to maximise the cooperation between IPA bots and human labour. Challenges in this domain encompass several categories: data challenges, process and routine organisation, and task aspects and deficiencies. Notably, a significant challenge category pertains to corporate compliance hurdles, specifically focusing on legacy system integration and IT security issues. Robust cybersecurity measures are imperative to ensure secure IPA deployment and scaling. Furthermore, policies and guidelines should be updated to include audit capabilities for secure change monitoring.

The research highlights four key human-centred challenges in IPA implementation: the transformation of traditional job roles, the need for novel skill sets and competencies, the importance of trust and explainability of AI, and the necessity of mutual and iterative learning processes among diverse experts and managers from different backgrounds. These challenges must be addressed to facilitate collaborative and sustainable IPA-related human–AI systems. Many organisations plan to increase their workforce to support AI implementation, reflecting the emergence of new job roles and profiles in the industry. These advancements, however, are not without hurdles, such as the increased time and effort necessary for staff learning and training efforts.

The evolution of intelligent automation software has been influenced by technical limitations. The specific technical challenges encountered by organisations vary depending on the type of intelligent automation technology in use. The software was categorised into six common types of intelligent automation to provide a structured perspective: conversational AI (including generative AI), business process (task mining), intelligent OCR, information extraction, Machine Learning, and data science (including predictive analytics). Issues were underlined, e.g., hallucinations, where unreliable information is generated by large language models and concerns regarding bias and insufficient training data. Security and compliance challenges were identified as widespread issues in IPA, including conversational AI applications. The overarching importance of data quality in machine learning techniques employed in IPA is highlighted, given that many IPA approaches rely on ML. Business process mining and its reliance on historical data are recognised as a challenge, as changes in business processes or the environment may not be adequately considered. Infrastructure scalability challenges, which can negatively impact the entire IPA ecosystem, are discussed, emphasising the need for systematic updates.

# Literature

Agostinelli, S., & Marrella, A. (2022). Intelligent Robotic Process Automation: Generating Executable RPA Scripts from Unsegmented UI Logs, Retrieved from https://ceur-ws.org/Vol-3310/paper13.pdf

Agostinelli, S., Lupia, M., Marrella, A., & Mecella, M. (2020). Automated generation of executable RPA scripts from user interface logs. In *Business Process Management: Blockchain and Robotic Process Automation Forum*, BPM 2020 Blockchain and RPA Forum (pp. 116-131). Springer International Publishing. doi: 10.1007/978-3-030-58779-6_8

Agostinelli, S., Marrella, A., & Mecella, M. (2020). Towards Intelligent Robotic Process Automation for BPMers. Retrieved from https://arxiv.org/pdf/2001.00804.pdf

Ahmad, H., Hanandeh, R., Alazzawi, F., Al-Daradkah, A., ElDmrat, A., Ghaith, Y., & Darawsheh, S. (2023). The effects of big data, artificial intelligence, and business intelligence on e-learning and business performance: Evidence from Jordanian telecommunication firms. *International Journal of Data and Network Science*, *7*(1), 35-40. doi: 10.5267/j.ijdns.2022.12.009

Al-Slais, Y., & Ali, M. (2023). Robotic Process Automation and Intelligent Automation Security Challenges: A Review. *2023 International Conference On Cyber Management And Engineering (CyMaEn)*, 71-77. doi: 10.1109/CyMaEn57228.2023.10050996.

Asadov, R. (2023). Intelligent Process Automation: Streamlining Operations and Enhancing Efficiency in Management. Available at SSRN 4495188. doi: 10.2139/ssrn.4495188

Baranauskas, G. (2018). Changing patterns in process management and improvement: using RPA and RDA in non-manufacturing organizations. *European Scientific Journal*, *14*(26), 251-264. doi: 10.19044/esj.2018.v14n26p251

Berruti, F., Nixon, G., Taglioni, G., & Whiteman, R. (2017). Intelligent process automation: The engine at the core of the next-generation operating model. Digital McKinsey, Retrieved from https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/intelligent-process-automation-the-engine-at-the-core-of-the-next-generation-operating-model#/

Bhatnagar, N. (2020). Role of Robotic Process Automation in Pharmaceutical Industries. In A. Hassanien, A. Azar, T. Gaber, R. F. Bhatnagar, & M. Tolba (Eds.), *The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2019). Advances in Intelligent Systems and Computing*, 921. Cham: Springer. doi: 10.1007/978-3-030-14118-9_50

Boersma, E. (2020). Intelligent Process Automation Framework Supporting the transformation of a manual process to an automation, Master Thesis. Retrieved from http://essay.utwente.nl/83139/1/Boersma_MA_EEMCS.pdf

Brás, J. R., & Moro, S. (2023). Intelligent Process Automation and Business Continuity: Areas for Future Research. *Information*, *14*(122). doi: 10.3390/info14020122

Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., & Unuvar, M. (2020). From Robotic Process Automation to Intelligent Process Automation. In A. Asatiani et al. (Eds.), *Business Process Management: Blockchain and Robotic Process Automation Forum. BPM 2020*. Lecture Notes in Business Information Processing, 393. Cham: Springer. doi: 10.1007/978-3-030-58779-6_15

Cho, S., Moon, J., Bae, J., Kang, J., & Lee, S. (2023). A Framework for Understanding Unstructured Financial Documents Using RPA and Multimodal Approach. *Electronics*, *12*(4), 939. doi: 10.3390/electronics12040939

Costa, S. A. S., Mamede, H. S., & Silva, M. M. (2022). Robotic Process Automation (RPA) adoption: a systematic literature review. *Engineering Management in Production and Services*, *14*(2), 1-12. doi:10.2478/emj-2022-0012

Devarajan, J. (2019). A Review on Intelligent Process Automation. *International Journal of Computer Applications, 182*(36). doi: 10.5120/ijca2019918374

Feio, I. C. L., & Dos Santos, V. D. (2022). A Strategic Model and Framework for Intelligent Process Automation. In *17th Iberian Conference on Information Systems and Technologies (CISTI),* 1-6. doi: 10.23919/CISTI54924.2022.9820099

Ferreira, D., Rozanova, J., Dubba, K., Zhang, D., & Freitas, A. (2020). On the Evaluation of Intelligent Process Automation. Retrieved from https://arxiv.org/pdf/2001.02639

Flechsig, C. (2021). The Impact of Intelligent Process Automation on Purchasing and Supply Management – Initial Insights from a Multiple Case Study. In U. Buscher, R. Lasch, & J. Schönberger (Eds.), *Logistics Management. Lecture Notes in Logistics.* Cham: Springer. doi: 10.1007/978-3-030-85843-8_5

Furman, J., & Seamans, R. (2019). AI and the Economy. *Innovation Policy and the Economy*, *19*(1), 161-191. doi: 10.1086/699936

Gartner. (2021). Forecast analysis: Low-code development technologies. Tech. rep., Gartner Research. Retrieved from https://www.gartner.com/en/documents/3995846

Geiger, R. S., Yu, K., Yang, Y., Dai, M., Qiu, J., Tang, R., & Huang, J. (2020). Garbage in, garbage out? Do machine learning application papers in social computing report where human-labeled training data comes from? In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, (pp. 325-336). doi: 10.1145/3351095.3372862

Geyer-Klingeberg, J., Nakladal, J. Baldauf, F., & Veit, F. (2018). Process Mining and Robotic Process Automation: A Perfect Match. In *International Conference on Business Process Management*. Retrieved from https://api.semanticscholar.org/CorpusID:52195591

Godbole, M., Rehan, S., & Wasana, B. (2022). Exploring the Nexus Between Process Complexity and Intelligent Automation. In *Proceedings of the Pacific Asia Conference on Information Systems (PACIS). Association for Information Systems*. Retrieved from https://eprints.qut.edu.au/232501/1/pacis22b_sub1477_cam_i26.pdf

Götzen, R., Schuh, G., von Stamm, J., & Conrad, R. (2023). Soziotechnische Systemarchitektur für den Einsatz von Robotic Process Automation. In S. D'Onofrio, & S. Meinhardt (Eds.), *Robotik in der Wirtschaftsinformatik*. Edition HMD. Wiesbaden: Springer Vieweg. doi: 10.1007/978-3-658-39621-3_4

Götzen, R., von Stamm, J., Conrad, R., & Stich, V. (2022). Understanding the Organizational Impact of Robotic Process Automation: A Socio-Technical Perspective. In L. M. Camarinha-Matos, S. Ortiz, X. Boucher, & A. L. Osório (Eds.), *Collaborative Networks in Digitalization and Society 5.0. PRO-VE 2022. IFIP Advances in Information and Communication Technology*, 662. Cham: Springer. doi: 10.1007/978-3-031-14844-6_9

Herm, L. V., Janiesch, C., Reijers, H. A., & Seubert, F. (2021). From Symbolic RPA to Intelligent RPA: Challenges for Developing and Operating Intelligent Software Robots. In A. Polyvyanyy, M. T. Wynn, A. Van Looy, & M. Reichert (Eds.), *Business Process Management. BPM 2021. Lecture Notes in Computer Science*, 12875. Cham: Springer. doi: 10.1007/978-3-030-85469-0_19

Hong, T., Kim, D., Ji, M., Hwang, W., Nam, D., & Park, S. (2022). Bros: A pre-trained language model focusing on text and layout for better key information extraction from documents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, *36*(10), (pp. 10767-10775). doi: 10.48550/arXiv.2108.04539

Huang, F., & Vasarhelyi, M. A. (2019). Applying robotic process automation (RPA) in auditing: A framework. *International Journal of Accounting Information Systems*, *35*, 100433, doi: 10.1016/j.accinf.2019.100433

Jha, N., Prashar, D., & Nagpal, A. (2021). Combining Artificial Intelligence with Robotic Process Automation—An Intelligent Automation Approach. In K. R. Ahmed, & A. E. Hassanien (Eds.), *Deep Learning and Big Data for Intelligent Transportation*. *Studies in Computational Intelligence*, 945. Cham: Springer. doi: 10.1007/978-3-030-65661-4_12

Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y., Dai, W., Madotto, A., & Fung, P. (2023). Survey of hallucination in natural language generation. *ACM Computing Surveys*, *55*(12), 1-38. doi: 10.1145/3571730

Kaarnijoki, P. (2019), Intelligent automation. Assessing artificial intelligence capabilities potential to complement robotic process automation. Retrieved from https://trepo.tuni.fi/bitstream/handle/123456789/27088/Kaarnijoki.pdf?sequence=4

Kassekert, R., Grabowski, N., Lorenz, D. Schaffer, C., Kempf, D., Roy, P., Kjoersvik, O., Saldana, G., & ElShal, S. (2022). Industry Perspective on Artificial Intelligence/Machine Learning in Pharmacovigilance. *Drug Safety*, *45*, 439-448. doi: 10.1007/s40264-022-01164-5

Kedziora, D., & Hyrynsalmi, S. (2023). Turning Robotic Process Automation onto Intelligent Automation with Machine Learning. In *The 11th International Conference on Communities and Technologies (C&T) (C&T '23). ACM, New York*. doi: 10.1145/3593743.3593746

Kholiya, P. S., Kapoor, A., Rana, M., & Bhushan, M. (2021). Intelligent Process Automation: The Future of Digital Transformation. In *10th International Conference on System Modeling & Advancement in Research Trends (SMART)*, (pp. 185-190). doi: 10.1109/SMART52563.2021.9676222

Kortesalmi, H., Aunimo, L., & Kedziora, D. (2023). RPA Experiments in SMEs Through a Collaborative Network. In L. M. Camarinha-Matos, X. Boucher, & A. Ortiz (Eds.), *Collaborative Networks in Digitalization and Society 5.0. PRO-VE 2023. IFIP Advances in Information and Communication Technology*, 688. Cham: Springer. doi: 10.1007/978-3-031-42622-3_54

Kudlak, L. (2019). Don't underestimate the power of robotic process automation. Will the Age of Ultron come to our world? Retrieved from https://medium.com/tech4planet/dont-underestimate-the-power-ofrobotic- process-automation-8ffb8262d62f

Lacity, M., Willcocks, L. P., & Craig, A. (2015). *Robotic process automation: mature capabilities in the energy sector. The Outsourcing Unit Working Research Paper Series (15/06)*. London, UK: London School of Economics and Political Science.

Lamberti, L. J., Wilkinson, M., Donzanti, B. A., Wohlhieter G. E., Parikh, S., Wilkins, R. G., & Getz, K. (2019). A Study on the Application and Use of Artificial Intelligence to Support Drug Development. *Clinical Therapeutics*, *41*(8). doi: 10.1016/j.clinthera.2019.05.018

Lievano-Martínez, F. A., Fernández-Ledesma, J. D., Burgos, D.,Branch-Bedoya,J.W.,&Jimenez-Builes,J.A.(2022). Intelligent Process Automation: An Application in Manufacturing Industry. *Sustainability, 14*, 8804. doi: 10.3390/su14148804

Martínez-Rojas, A., Sánchez-Oliva, J., López-Carnicer, J. M., & Jiménez-Ramírez, A. (2021). AIRPA: An Architecture to Support the Execution and Maintenance of AI-Powered RPA Robots. In J. González Enríquez, S. Debois, P. Fettke, P. Plebani, I. van de Weerd, & I. Weber (Eds.), *Business Process Management: Blockchain and Robotic Process Automation Forum. BPM 2021. Lecture Notes in Business Information Processing*, 428. Cham: Springer. doi: 10.1007/978-3-030-85867-4_4

Mohanty, S., & Vyas, S. (2018). Intelligent Process Automation = RPA + AI. In *How to Compete in the Age of Artificial Intelligence*(pp. 125-141). Berkeley, CA: Apress. doi: 10.1007/978-1-4842-3808-0_5

Moiseeva, A. (2020). Statistical natural language processing methods for intelligent process automation (Doctoral dissertation, lmu). doi: 10.5282/edoc.26681

Moreira, S., Mamede, H. A., & Santos, A. (2023). Process automation using RPA – a literature review. *Procedia Computer Science*, *219*, 244-254. doi: 10.1016/j.procs.2023.01.287

Moulaï, K., Islam, G., Manning, S., & Terlinden, L. (2022). All too human" or the emergence of a techno-induced feeling of being less-able: identity work, ableism and new service technologies, *The International Journal of Human Resource Management*, *33*(22), 4499-4531. doi: 10.1080/09585192.2022.2066982

Navidi, N. (2020). Human/AI interaction loop training as a new approach for interactive learning with reinforcement-learning agents. *Journal of Telecommunications System and Management*, *9*(5), 47. Retrieved from https://www.hilarispublisher.com/open-access/human--ai-interaction-loop-training-as-a-new-approach-for-interactive-learning-with-reinforcementlearning-agents.pdf

Ng, K. K., Chen, C. H., Lee, C. K., Jiao, J. R., & Yang, Z. X. (2021). A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives. *Advanced Engineering Informatics*, *47*, 101246. doi: 10.1016/j.aei.2021.101246

Oliva, P. E. (2022). Cognitive Automation – Automating with Artificial Intelligence at Enterprise scale. *Telecommunications System & Management, 9*(5), 53.

Pacelli, V. (2012). Forecasting Exchange Rates: a Comparative Analysis. *International Journal of Business and Social Science, 3*(10), 31-45. doi: 10.12846/j.em.2015.02.06

Pramod, D. (2022). Robotic process automation for industry: adoption status, benefits, challenges and research agenda. *Benchmarking: An International Journal*, *29*(5), 1562-1586. doi: 10.1108/BIJ-01-2021-0033

Priya, K., Ganesh, N., & Balaraman, P. (2019). Basics of Business Model, Emerging Fintech & Case Insights on Gojek Business Model. *International Journal of Engineering and Advanced Technology (IJEAT*), *8*(5).

Ribeiro, J., Lima, R., Eckhardt, T., & Paiva, S. (2021). Robotic Process Automation and Artificial Intelligence in Industry 4.0 – A Literature review. *Procedia Computer Science*, *181*, 51-58. doi: 10.1016/j.procs.2021.01.104

Richardson, S. (2020). Cognitive automation: A new era of knowledge work? *Business Information Review*, *37*(4), 182-189. doi: 10.1177/0266382120974601

Sarker, I. H. (2022). AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science*, *3*, 158. doi: 10.1007/s42979-022-01043-x

Schulte, A., Klat, W., & Süße, T. (2022). How Does the Implementation of AI Agents Affect Human Agents' Job Profiles? Insights from Two Industrial Cases. In L. M. Camarinha-Matos, A. Ortiz, X. Boucher, A. L. Osório, (Eds.), *Collaborative Networks in Digitalization and Society 5.0. PRO-VE 2022. IFIP Advances in Information and Communication Technology*, 662. Cham: Springer. doi: 10.1007/978-3-031-14844-6_25

Shidaganti, G., Sanjana, R., Shubeeksh, K., Raman, V. M., & Thakshith, V. (2023). ChatGPT: Information Retrieval from Image using Robotic Process Automation and OCR. In *7th International Conference on Intelligent Computing and Control Systems (ICICCS)*, (pp. 1264-1270). doi: 10.1109/ICICCS56967.2023.10142461

Siderska, J. (2020). Robotic Process Automation – a driver of digital transformation? *Engineering Management in Production and Services, 12*(2), 21-31. doi: 10.2478/emj-2020-0009

Siderska, J., Alsqour, M., & Alsaqoor, S. (2023). Employees' attitudes towards implementing robotic process automation technology at service companies. *Human Technology, 19*(1), 23-40. doi: 10.14254/1795-6889.2023.19-1.3

Stolpe, A., Steinsund, H., Iden, J., & Bygstad, B. (2017), Lightweight IT and the IT function: experiences from Robotic Process Automation in a Norwegian bank, Bibsys Open Journal Systems. Retrieved from https://api.semanticscholar.org/CorpusID:208331545

Süße, T., Kobert, M., & Kries, C. (2023). Human-AI interaction in remanufacturing: exploring shop floor workers' behavioural patterns within a specific human-AI system. *Labour and Industry*. doi: 10.1080/10301763.2023.2251103

Süße, T., Kobert, M., Grapenthin, S., & Voigt, B. F. (2023). AI-Powered Chatbots and the Transformation of Work: Findings from a Case Study in Software Development and Software Engineering. In L. M. Camarinha-Matos, X. Boucher, A. Ortiz, (Eds.), *Collaborative Networks in Digitalization and Society 5.0. PRO-VE 2023. IFIP Advances in Information and Communication Technology*, 688. Cham: Springer. doi: 10.1007/978-3-031-42622-3_49

Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. In *Adaptive Computation and Machine Learning series*. MIT Press.

Vajgel, B., Corrêa, P.L., Tóssoli De Sousa, T., Encinas Quille, R.V., Bedoya, J.A., Almeida, G.M., Filgueiras, L.V., Demuner, V.R., & Mollica, D. (2021). Development of Intelligent Robotic Process Automation: A Utility Case Study in Brazil. *IEEE Access, 9*, 71222-71235. doi: 10.1109/ACCESS.2021.3075693

Veale, M., & Borgesius, F. Z. (2021). Demystifying the Draft EU Artificial Intelligence Act—Analysing the good, the bad, and the unclear elements of the proposed approach. *Computer Law Review International, 22*(4), 97-112.

Waefler, T., & Schmid, U. (2021). Explainability is not Enough: Requirements for Human-AI-Partnership in Complex Socio-Technical Systems. In F. Matos (Ed.), *Proceedings of the 2nd European Conference on the Impact of Artificial Intelligence and Robotics (ECIAIR 2020)*, (pp. 185-194. Lisboa, Portugal: ACPIL.

Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelli*gence, *10*(2), 1-37. doi: 10.2478/jagi-2019-0002

Wojciechowska-Filipek, S. (2019). Automation of the process of handling enquiries concerning information constituting a bank secret. *Banks and Bank Systems*, *14*(3), 175-186, doi: 10.21511/bbs.14(3).2019.15

Zeltyn, S., Shlogov, S., Yaeli, A., & Oved, Y. (2022). Prescriptive Process Monitoring in Intelligent Process Automation with Chatbot Orchestration. Retrieved from https://arxiv.org/pdf/2212.06564.pdf

Volume 15 • Issue 4 • 2023

sciendo

received: 26 June 2023
accepted: 15 November 2023

pages: 104-115



# Hierarchical risk communication management framework for construction projects

Mohammad A. Mansour
Nabil Beithou
Moh'd Alsqour
Sultan A. Tarawneh
Khalid Al Rababa'a
Sameh AlSaqoor
Ewa Chodakowska

**Sameh AlSaqoor**
Applied Science Private University, Jordan
Middle East University, Jordan
Tafila Technical University, Jordan
ORCID 0000-0002-0552-8926
Corresponding author:
e-mail: sameh@ttu.edu.jo

**Mohammad A. Mansour**
Applied Science Private University, Jordan
Middle East University, Jordan
ORCID 0000-0001-8701-4007

**Nabil Beithou**
Tafila Technical University, Jordan
ORCID 0000-0002-3283-1402

**Moh'd Alsqour**
Irbid National University, Jordan
ORCID 0000-0003-0167-3429

**Sultan A. Tarawneh**
Applied Science Private University, Jordan
Middle East University, Jordan
Mutah University, Jordan
ORCID 0000-0001-6194-2833

**Khalid Al Rababa'a**
Tafila Technical University, Jordan
ORCID 0000-0001-7091-8587

**Ewa Chodakowska**
Bialystok University of Technology, Poland
ORCID 0000-0003-1724-192X

ABSTRACT
Risk, as an effect of uncertainty, is associated with every human activity. Like any other industry, construction companies are eager to reduce the uncertainty of reluctant events. A well-planned risk communication system could contribute to the success of a construction project. A proper announcement protocol could be a mitigating lever for identified or unidentified risks during planning and monitoring processes. This research aims to present a risk communication management system (RCMS) for construction companies involved in large projects. The proposed model includes a step-by-step communication procedure considering the authority level within the organisational hierarchical structure. The model aims to remove the ambiguity of risk communications during the construction process under uncertain conditions. It leaves no or little room for the emergence of unplanned risks. The proposed communication structure has been implemented in GRC cladding construction projects, and the risk communication time and response have been significantly improved.

KEY WORDS
**risk, uncertainty, risk management, communication, project, risk response plan, construction, model**

**10.2478/emj-2023-0031**

## Introduction

Uncertainty and the resulting risks create challenges for decision-making managers in every sector and every process (Chodakowska, 2020; Sukwadi & Caesar, 2022). Construction is one of the activities that contribute the most to creating added value in countries worldwide; thus, the sector's problems translate into the global economy (Nazarko & Chodakowska, 2017; Urbański et al., 2019). On the other

Mansour, M. A., Beithou, N., Alsqour, M., Tarawneh, S. A., Al Rababa'a, K., AlSaqoor, S., & Chodakowska, E. (2023). Hierarchical risk communication management framework for construction projects. *Engineering Management in Production and Services, 15*(4), 104-115. doi: 10.2478/emj-2023-0031

hand, global economic fluctuations are expected to impact the construction sectors significantly. The present instability in the global economy is predicted to only worsen in the coming years (Lucchese & Pianta, 2020; Yu et al., 2022). Clients, investors, and funders are becoming more demanding, discerning, less willing to accept risks, and want to minimise risk exposure. Therefore, the accounting and project finance practice should be integrated with risk management (Zaleha Abdul Rasid et al., 2011). Large construction companies need to realise the shortage of funds for future projects. Meanwhile, high competition leads the construction industry to low profitability (Davila Delgado et al., 2019).

Driven by the desire to overcome the risks, large construction firms need to have a strategy to minimise costs and improve performance. Risk reduction contributes to long-term financial stability and, as such, should be one of the company's top goals (Ginevičius, 2020). The problem of identifying the sources of uncertainty and the probability and severity of the risks is one of the main impediments that construction companies must overcome. The risk management capability is important to ensure the achievement of goals and to gain a competitive advantage (Saeidi et al., 2019). This has led to increasing attention to risk analysis to guide decision-making in recent years (Drożyner, 2020; Shevchenko et al., 2019).

The research aims to present the risk communication management system (RCMS) for construction companies involved in large projects. The proposed model refers to the communication processes and considers the level of authorisation in the organisation's hierarchical structure. It can be treated as an operationalisation of ISO 310000 and such initiatives as integrated risk management (IRM) or enterprise risk management (ERP). This model allows for eliminating the ambiguity of communication and reducing risk in the context of uncertainty in construction processes. It leaves little to no room for emerging unplanned risks. RCMS supports the achievement of business goals by transparent risk identification and control. The proposed communication structure has been successfully implemented in GRC cladding construction projects.

The article is organised as follows. First, it presents the motivation for the research, the risks and their categories in construction projects. The role of risk communication in risk management is discussed next. Then, the RCMS is introduced. The article ends with conclusions.

# 1. Literature review

Construction companies must be increasingly aware of the problems related to accepting risks of highly vulnerable projects that are difficult to manage and control. Most insurance companies are no longer open to coverage that involves a disproportionate amount of risk (Liu et al., 2007; Roy & Gupta, 2020). The occurrence of risks can significantly hinder the implementation of plans and disturb the development of a construction company in the short, medium, and long term (Moorhead et al., 2022; Raza & Zhong, 2022). The risk management process in construction projects often has many deficiencies that reduce the efficiency and effectiveness of project management and the probability of success (Shevchenko et al., 2019). The inappropriate predominant practice of risk identification and analysis in the construction industry is mostly based on the assessments of individual experts and does not consider the subjectivity of individual perception (Bornschein et al., 2020).

Risks can occur in any construction process and at any level of the project life cycle. They influence project scope, schedule, budget, and quality (Mulholland & Christian, 1999). Large-scale construction projects involve a particularly high risk. Clients take significant financial risks due to their investments. Architects are responsible for design risks (Aksamija, 2016). Contractors take responsibility for the risks associated with construction implementation. Government agencies are responsible for ensuring that regulations and standards have been established at the minimum acceptable level. The insurance industry bears the transferable risk of failure of either party. Suppliers are responsible for the performance risk associated with delivered components and materials (Eriksson & Westerberg, 2011; Ritchie & Brindley, 2007). Besides, risks of hazards, negligence, maintenance, accidents or force majeure can affect everyone involved in the project and contribute considerably to the construction project's success (Jarkas & Haupt, 2015).

Non-industry or sector-specific standard ISO 31000:2018 Risk management — Guidelines (International Organisation for Standardisation, 2018) proposes to express risk in terms of risk sources, potential events, consequences, and likelihood. It introduces a high-level set of principles for effective risk management and establishes a framework for dealing with risk that needs to be adapted to each sector (Almeida et al., 2019; Moraes et al., 2021). Also, it proposed a generally structured approach to risk management (Howlett et al., 2022).

In recent years, several studies have analysed risk factors and explored the key success factors in risk management. Risks can be classified into categories according to various criteria, e.g., macrolevel, mesolevel, and microlevel (Yang et al., 2020). Furthermore, risk factors can be grouped into six categories related to project, government, client, design, contractor, consultant, and market risks (Shen et al., 2006). There are categories such as technical, social, economic, ecological, and political (Kodym et al., 2020) or contractual, environmental, financial, economic, market, logistical, design, construction, and operational risks (Shen et al., 2006). In a hierarchical risk structure for construction projects, external, operational, project management, engineering, and financial categories are distinguished (Rezakhani, 2012). The main risks to a construction project's performance in terms of quality, time and cost are technical, schedule, and financial (cost and funding risks). Technical risks result from incomplete design, inadequate site investigation, and uncertainty about the source or availability of materials and appropriateness of specifications. In particular, logistics risks significantly impact construction projects since they concern the sufficient availability of such resources as construction equipment, spare parts, fuel, labour, and transportation facilities. Risk is sometimes shared among organisational units in the supply or production chain. Risk may be shifted downwards through contractual terms and penalties. Flexible supply chain strategies are often the way to overcome the logistics risk. Construction risks also involve the uncertain productivity of resources, weather or seasonal implications, and industrial relations problems.

Proper communication is believed to be one of the key project success factors. The most common definition of risk communication has been developed by Covello (1992) as "the process of exchanging information among interested parties about the nature, magnitude, significance, or control of a risk" (Gentili et al., 2020). Risk communication is also defined as "any two-way communication between stakeholders about the existence nature, form, severity, or acceptability of risk" (Canadian Standards Association, 1997). Risk communication is traditionally associated with natural disasters, public health, and food safety. The literature emphasises the evolutionary and interdisciplinary character of risk communication (Balog-Way et al., 2020). Risk communications should be viewed as an important business process since there is a need to share information about risks with stakeholders: employees, customers, or the public. The necessity for a practical and effective risk communication model, rather proactive than reactive, should be among the top priorities for risk management, as the way the risk is announced determines a message reception (Freudenstein et al., 2020). Risk communication encourages accountability and ownership of risk and should be a key part of any company's risk management strategy (International Organisation for Standardisation, 2018).

A good communication system in large construction projects should involve all people associated with the construction projects directly or indirectly. At the same time, rules and responsibilities should be comprehensible, and risk communication must consider the actual public concerns (Doyle & Becker, 2022). The risk communication model is intended to clarify ambiguities and provide appropriate guidance to be applied from risk identification to the risk monitoring and control process (Tufano, 1996). The threat of miscommunication during risk management affects the performance and costs of the all-project's aspects. However, these costs can be avoided if a proper and clear communication model is launched and introduced to all team members associated with construction projects (Ceric, 2014).

Analysing the relationship between risk management and risk communication according to ISO 31000:2018, the risk management process starts from context establishment and consists of risk assessment (risk identification, risk analysis, and risk evaluation); the output of the process is risk treatment. Monitoring and review, communication and consultation are related to the entire process (Fig. 1). According to the standard, communication is a continuous and iterative process of providing, sharing, or obtaining information regarding risks and takes place at all stages of the risk management process. The relationship between risk management, risk assessment, and communication could also be viewed as presented in Fig. 2 (Yoe, 2019). From this perspective, risk assessment is a science-based process of describing the character, likelihood, magnitude, and consequences. Risk management is a policy-based process of problem identification, information gathering, evaluation and implementation of actions to reduce the impact and likelihood of problems, shift the unacceptable risk to the tolerable/acceptance level, and monitoring. Risk communication means exchanging infor-

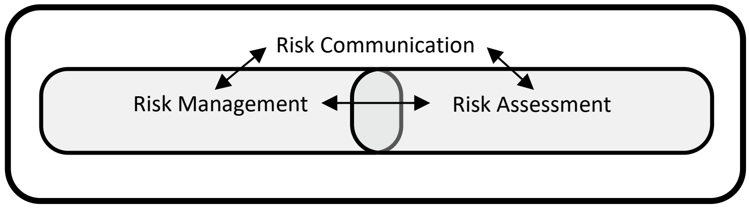



Fig. 1. Risk analysis framework

Source: adapted from Yoe, 2019.

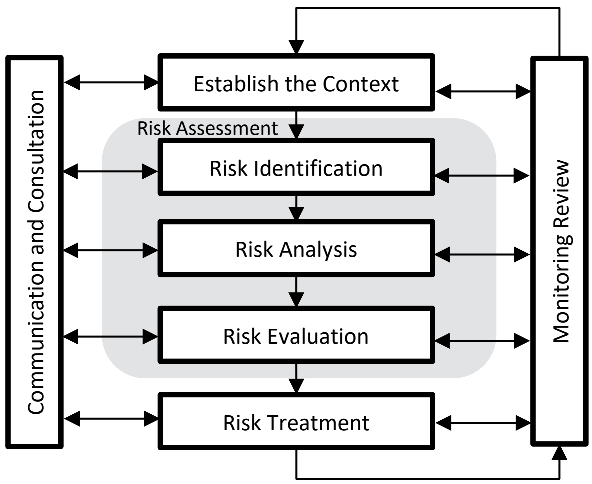



Fig. 2. Risk management process

Source: adapted from the International Organisation for Standardisation, 2018.

mation about risk to better understand it and make improved decisions (Yoe, 2019). Regardless of the approach, it is widely recognised that effective risk communication is a vital and integral part of the risk management process and risk assessment.

This work is related to risk communication that results from the technical and managerial complexity of construction projects and can be linked to the decision-making process in project management tasks in risk management. In this paper, a High Hierarchical Risk Communication Model associated with a Risk Communication Management System is proposed to remove the ambiguity of risk communications in the construction process in uncertain conditions. The main advantages of this risk communication model are (i) consistency and standardisation of procedures, (ii) clear division of responsibilities, and (iii) no or little room for unplanned risks to emerge.

## 2. Risk communication model

The basic steps of risk communication are identifying the risks, the stakeholders and their concerns, and forming and delivering messages (Ndlela, 2019). It can be expanded to assessing the impact of the risk, implementing mitigation activities, and monitoring and reporting the effectiveness of the communication efforts. The communication tasks can be divided into the initiation (identifying stakeholders and scope of issue), preliminary analysis, risk estimation, risk evaluation, risk control, implementation (communication), and monitoring stages (Canadian Standards Association, 1997).

The proposed High Hierarchal Risk Communication (HHRC) for construction consists of twelve steps, starting from risk identification and ending with risk publication. In each step, the responsibility is assigned to the right person. HHRC and the associated Risk Communication Management System (RCMS) are illustrated in Fig. 3 and 4, respectively.

The required input, the detail of the process and the output of each step are as follows:

### 2.1. Risk identification

The RCMS contains the Risk Title, Initiator Name, Date Submitted, Risk Description and Major Areas that might be affected, and Risk Response Action. The risk identification process is a continuous ongoing task throughout the project life cycle and involves anyone, as shown in Fig. 5.

### 2.2. Risk validation

The Risk Manager (RM) should review the candidate risk with the Initiator, as illustrated in Fig. 6., to guarantee that the initial information is correct and complete. The RM clusters the risks into categories and assigns a unique identifier. The consultation should also be carried out with a Subject Matter Expert (SME). The RM determines the validation of

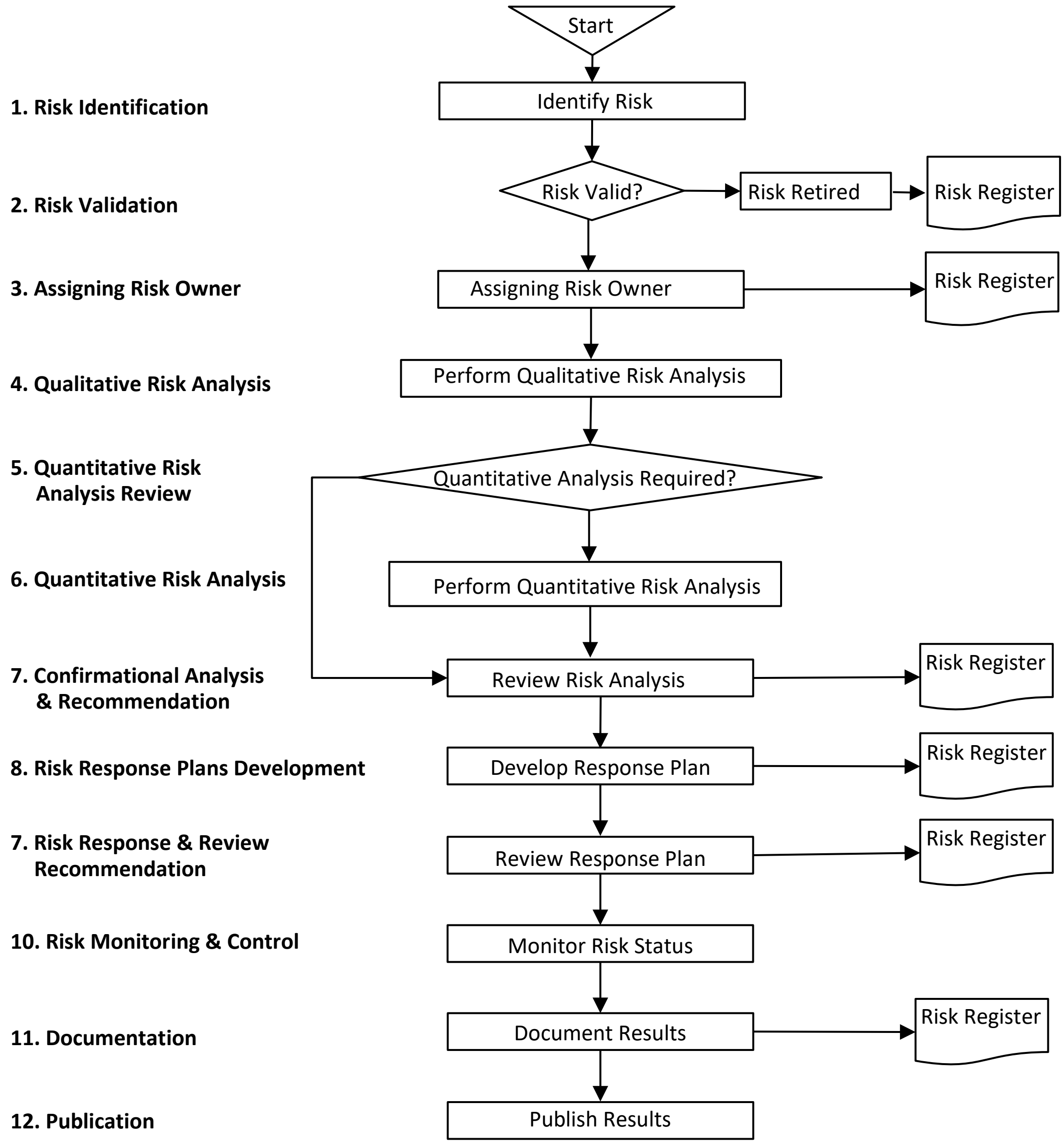



Fig. 3. Flowchart of the High Hierarchical Risk Communication Model

| Risk Communication Management System | | | |
|---|---|---|---|
| I | 1. Risk Identification | (1) | Risk Title |
| | | (2) | Initiator Name |
| | | (3) | Date Submitted |
| | | (4) | Risk Description |
| | | (5) | ☐Schedule ☐Budget ☐Scope ☐Quality<br>Primary Risk Area: |
| | | (6) | Risk Response Action (if any): |
| RM | 2. Risk Validation | (7) | Risk ID #: |
| | | (8) | Risk Validity: ☐Yes ☐No |
| | | (9) | Validation Done by: |
| | | (10) | Validation Date: |
| PM | 3. Assigning Risk Owner | (11) | Risk Owner Name: |
| | | (12) | Risk Assigned: |
| RO | 4. Qualitative Risk Analysis | (13) | Risk Probability Ranking: |
| | | (14) | Risk Impact: |
| | | (15) | Risk Exposure Rating: |
| | | (16) | Risk Priority: |
| RM | 5. Qualitative Risk Analysis Review | (17) | Required Risk Qualitative Analysis: ☐Yes ☐No |
| RO | 6. Quantitative Risk Analysis | (18) | When Risk Will Be Effective: |
| | | (19) | Effect on Critical Path: |
| | | (20) | Contingency Time Reserve: Min… Max… Most likely… Average… Standard deviation… |
| | | (21) | Contingency Cost Reserve: Min… Max… Most likely… Average… Standard deviation… |
| RM | 7. Conformational Analysis & Recommendation | (22) | Analysis Approval: ☐Yes ☐No |
| | | (23) | Risk Critical: ☐Yes ☐No |
| | | (24) | Risk Status: ☐Active ☐Not Active |
| | | (25) | Team Member Name: |
| TM | | (26) | Team Member Recommendation: |
| RO | 8. Risk Response Plan | (27) | ☐Eliminate ☐Mitigate ☐Accept ☐Transfer<br>Select Risk Response Strategy:<br>Describe: |
| | | (28) | Identify Residual Risk: |
| | | (29) | Contingency Trigger: |
| | | (30) | Contingency Plan: |
| | | (31) | Fallback Plan Trigger: |
| | | (32) | Fallback Plan: |
| RM | 9. Risk Response Review & Recommendation | (33) | Risk Response Plan Approval: ☐Yes ☐No |
| RO | 10. Risk Monitoring & Control | (34) | Current Status: |
| RM | 11. Documentation | (35) | Create an Issue Report: |
| PM | 12. Publication | (36) | Publish Risk Status To: |
| I: Initiator, RM: Risk Manager, RO: Risk Owner, PM: Project Manager, TM: Team Member | | | |

Fig. 4. Risk Communication Management System (RCMS)

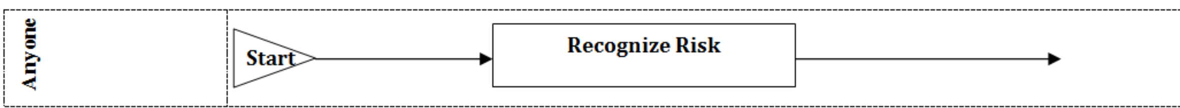



Fig. 5. Risk identification

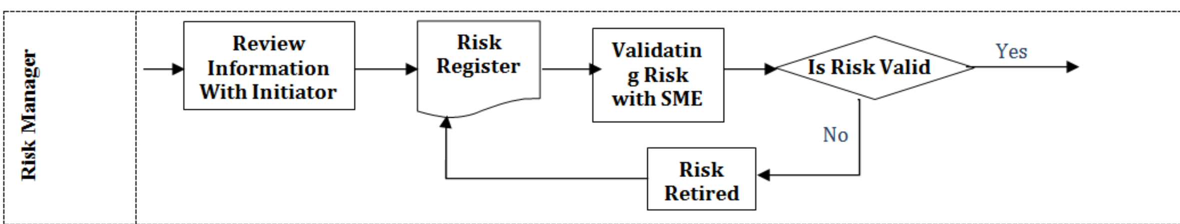



Fig. 6. Risk validation

the candidate risks and determines whether any concern or action is warranted.

### 2.3. Assigning risk owner

When the candidate risk is determined to be unfounded, the risk is withdrawn. If the candidate risk is determined to be valid, the Project Manager (PM) assigns the risk to the Risk Owner (RO) according to RCMS. The RM should meet the RO (and SME) to review the risk, as shown in Fig. 7. The RM delivers the Risk Response Plane Form (RRPF) to the RO and updates the Risk Register.

### 2.4. Qualitative risk analysis

Qualitative risk analysis is a subjective process. This process clears the ambiguity about the risk and sets the roadmap for further investigation and planning. During this process, the Risk Owner can be assisted by a Team Member or SME. The risk probability should be investigated to evaluate the frequency and the impact of the occurring risk according to RCMS, as depicted in Fig. 8.

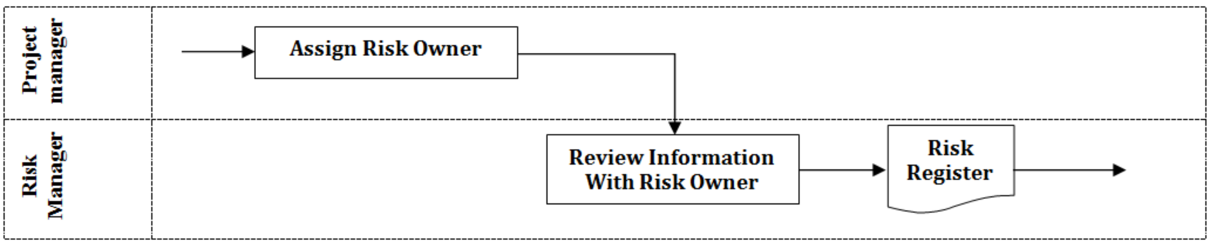



Fig. 7. Assigning risk owner

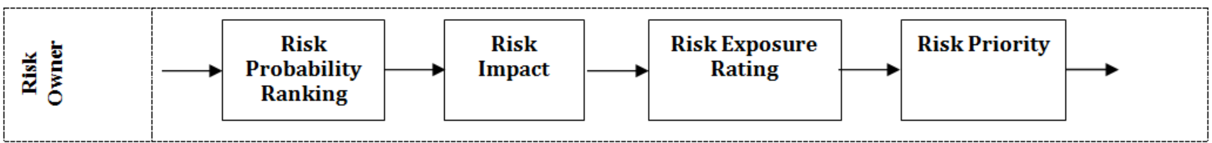



Fig. 8. Qualitative risk analysis

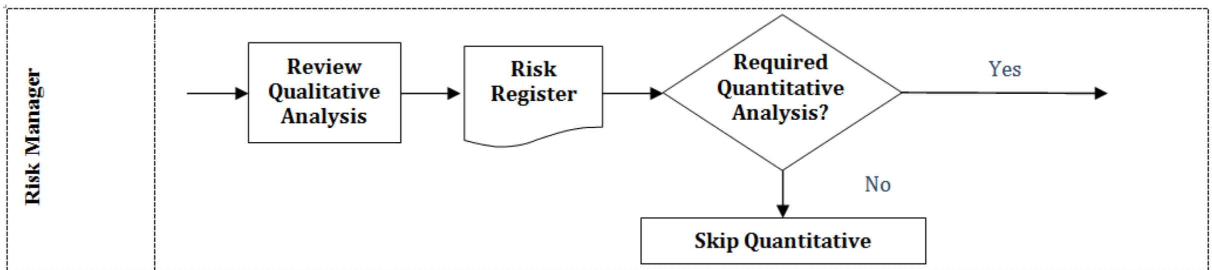



Fig. 9. Qualitative risk analysis review

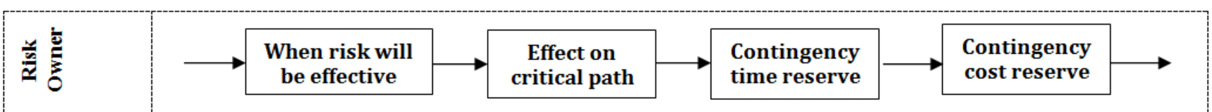



Figure 10. Quantitative risk analysis

## 2.5. Qualitative risk analysis review

The Risk Manager should review the qualitative risk analysis, as illustrated in Fig. 9. The Risk Manager should address and discuss results and findings at the project team meeting. The Risk Register is updated according to the assessment. The Risk Manager is expected to address the need for quantitative analysis.

## 2.6. Quantitative risk analysis

As shown in Fig. 10, the quantitative risk analysis addresses at what time risk is effective, the impact of risk on the critical path, the contingency time, and the cost reserve. Data can be used to extract some statistical scales and parameters for assessment.

## 2.7. Confirm risk analysis and recommendations

The Risk Manager must review and confirm the output from the risk analysis process and address them in the project meetings, as depicted in Fig. 11. If the risk is active, a recommendation from the project Team Members is required for a better risk response plan. The recommendation should follow the RCMS platform. A critical risk should be on the watch list, and the Risk Register must be updated.

## 2.8. Risk response plan

As input from the risk confirmation analysis process, the RO, the RM, and the Team Members should decide upon the best strategy that corresponds

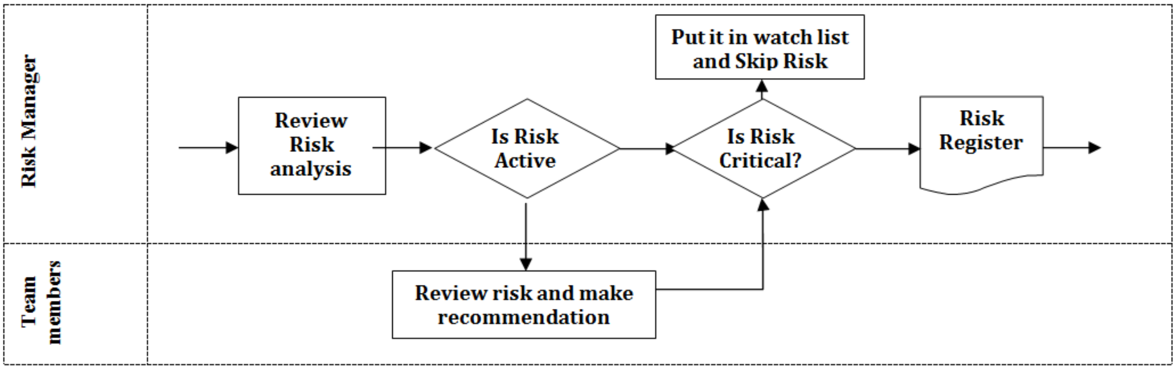



Fig. 11. Confirm risk analysis and recommendation

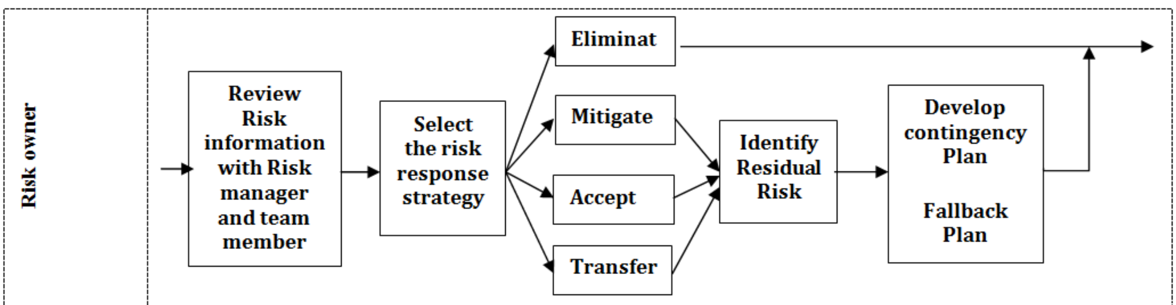



Fig. 12. Risk response plan

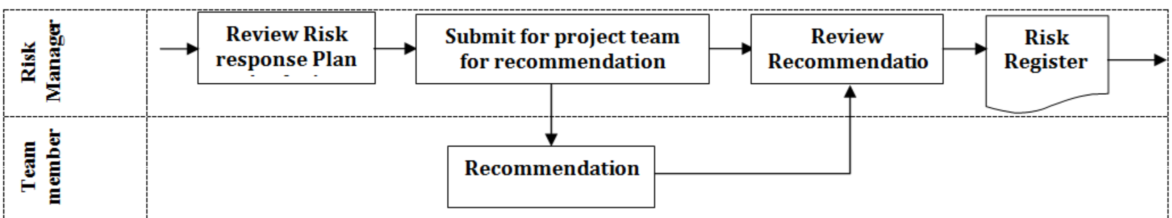



Fig. 13. Risk response review and recommendation

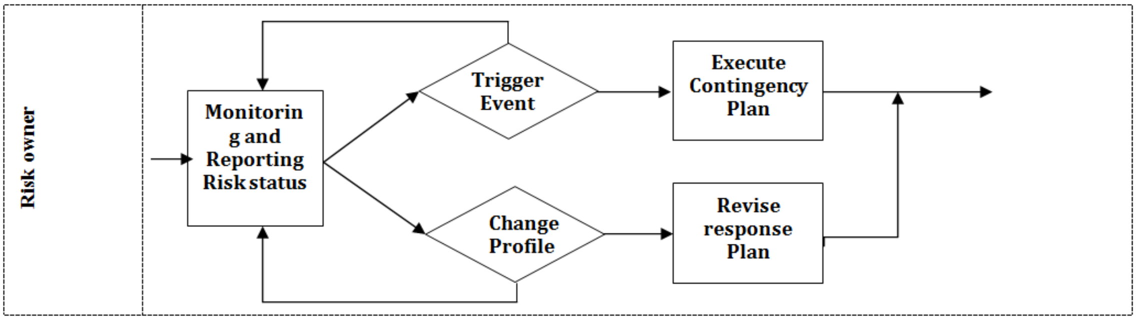



Fig. 14. Risk monitoring and control

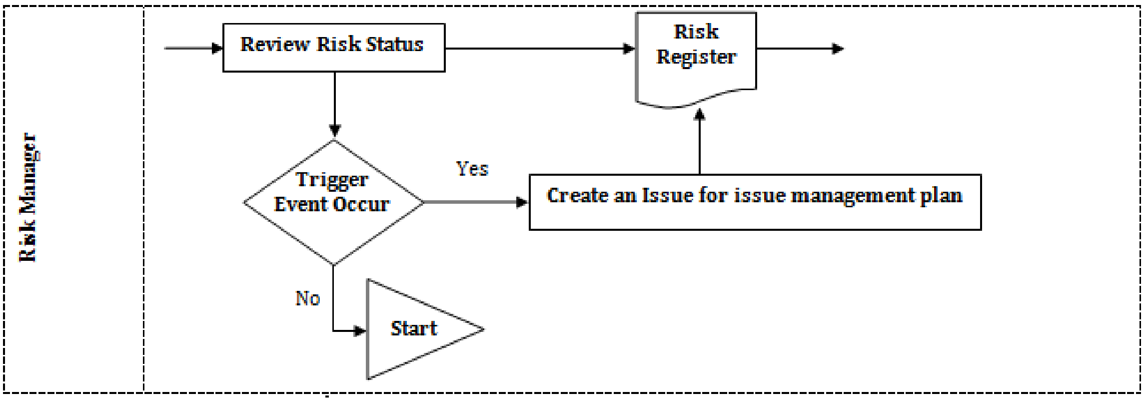



Fig. 15. Risk documentation

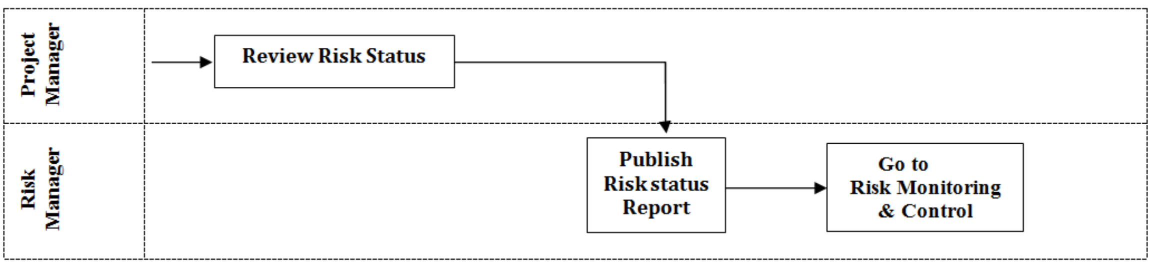



Fig. 16. Risk Publication

to the particular risk. The process is illustrated in Fig. 12. The risk can be eliminated, mitigated, accepted, or transferred to a third party. Based on the selected strategy, the residual risk and risk triggers must be identified to develop a contingency and/or a fallback plan.

## 2.9. Risk response plan review and recommendation

The Risk Manager reviews the risk response plan. A recommendation analysis from the Team Members might be significant to implement the strategy effectively, as illustrated in Fig. 13. As a result, Risk Manager should review the recommendations and update the Risk Register with the proposed suggestions and actions as per the RCMS.

## 2.10. Risk monitoring and control

The risk status should be updated in the RCMS regularly. If a trigger event is recognised, the contingency plan must be executed. On the other hand, if the risk changes its profile or characteristic, the risk response plan must be revised, as shown in Fig. 14.

## 2.11. Risk documentation

The Risk Manager must review the risk status, whether a trigger event occurs, and update the risk register. In addition, the Risk Manager should create a concern for an issue of a management plan if the need emerges, as shown in Fig. 15. The required information of this level should be addressed in the RCMS.

### 2.12. Risk publication

The Risk Manager should review the risk status to take the best advantage of the risk communications system, as shown in Fig. 16. The Project Manager communicates to the Risk Manager the need to publish the risk status report according to the RCMS. Risk monitoring is an ongoing process until the project's closure.

## 3. Research results

Poor communication is one of the leading causes of project failure, which also applies to risk communication. ISO 31000 has introduced a set of principles and paradigms in risk management. It emphasises that effective communication is essential to managing risk and understanding the decision made; however, the guidelines are very general and need to be customised. The proposed model addresses the issue of defining risk communication procedures. The proposed High Hierarchal Risk Communication model includes a detailed plan with the necessary forms compliant with the requirements of ISO and, as such, can be used directly when implementing ISO standards. It makes the process of risk communication transparent and visible to all stakeholders. It clearly defines tasks and responsibilities by describing roles such as Initiator, Risk Manager, Risk Owner, Project Manager, and Team Member. The risk register enables proper collection and archiving of data for further processing, thus facilitating effective risk management.

The risk management policy should include corporate governance objectives in relation to risk. The organisation's strategies should reflect the attitude and risk-aware culture. Each time, the risk acceptance level (based on risk attitude, appetite, and tolerance) must be included to describe and assess the risks. The proposed HHRC risk assessment mechanism has been designed to facilitate risk identification, assessment, and prioritisation.

The presented risk communication structure has been deployed in GRC cladding projects for two years. It significantly improved the communication level. Emerging risks have been identified and reported through the right channels properly. It was estimated that the risk communication model improved the communication time efficacy by 40%. In addition, the proposed communication model proactively identified the status, progress, variance, and trend and reported the risks. The communications occurred internally and externally, vertically and horizontally in all construction activities as outlined by the High Hierarchal Risk Communication plan.

## Conclusions

Large construction organisations are capturing a narrow market and facing risks that are difficult to assess and manage. The proposed Risk Communication Management System is a useful risk management tool throughout the lifecycle of a construction project. The twelve-level, high-hierarchy structure details the communication responsibilities and sequence of steps necessary to effectively manage risk communication to solve conflict issues during the risk management process. The presented procedures transfer the authorisations regarding the risks to the appropriate person directly or indirectly involved in the project to implement the assigned tasks and goals.

The risk communication model eliminates ambiguities, reduces the necessary response time, and minimises the effect of uncertainties. In addition, the communication model provides a tool for controlling project meetings by addressing risk regularly during project implementation. Risk communication protocol recognises the significance of involving all people associated with construction projects in identifying, analysing, and designing an effective response plan for risks. By following the presented procedures, monitoring the risk profile and status can be ensured. The proposed communication model positively affects the project's success within scope, budget, time, quality, and essential requirements. In future research, the presented approach is worth verifying in other sectors.

## Acknowledgements

This research was carried out within the framework of the project No. WZ/WIZ-INZ/2/2022 of the Bialystok University of Technology and financed from the subsidy granted by the Minister of Science and Higher Education. The authors appreciate the financial support provided by Applied Science Private University and Tafila Technical University, Jordan.

# Literature

Aksamija, A. (2016). *Integrating innovation in architecture: Design, methods and technology for progressive practice and research*. Wiley.

Almeida, R., Teixeira, J. M., Mira da Silva, M., & Faroleiro, P. (2019). A conceptual model for enterprise risk management. *Journal of Enterprise Information Management*, *32*(5), 843-868. doi: 10.1108/JEIM-05-2018-0097

Balog-Way, D., McComas, K., & Besley, J. (2020). The Evolving Field of Risk Communication. *Risk Analysis*, *40*(S1), 2240-2262. doi: 10.1111/risa.13615

Bornschein, R., Schmidt, L., & Maier, E. (2020). The Effect of Consumers' Perceived Power and Risk in Digital Information Privacy: The Example of Cookie Notices. *Journal of Public Policy & Marketing*, *39*(2), 135-154. doi: 10.1177/0743915620902143

Canadian Standards Association. (1997). *CSA-Q850 Risk Management: Guidelines for Decision-Makers*.

Ceric, A. (2014). Minimizing Communication Risk in Construction: A Delphi Study of the Key Role of Project Managers. *Journal of Civil Engineering and Management*, *20*(6), 829-838. doi: 10.3846/13923730.2013.802739

Chodakowska, E. (2020). A Hybrid Approach in Future-Oriented Technology Assessment. In K. Arai, R. Bhatia, & S. Kapoor (Eds.), *Proceedings of the Future Technologies Conference (FTC)* 2019, Vol. 1069 (pp. 512-525). Springer International Publishing. doi: 10.1007/978-3-030-32520-6_38

Covello, V. T. (1992). Risk Communication: An Emerging Area of Health Communication Research. *Annals of the International Communication Association*, *15*(1), 359-373. doi: 10.1080/23808985.1992.11678816

Davila Delgado, J. M., Oyedele, L., Ajayi, A., Akanbi, L., Akinade, O., Bilal, M., & Owolabi, H. (2019). Robotics and automated systems in construction: Understanding industry-specific challenges for adoption. *Journal of Building Engineering*, *26*, 100868. doi: 10.1016/j.jobe.2019.100868

Doyle, E. E. H., & Becker, J. S. (2022). Understanding the Risk Communication Puzzle for Natural Hazards and Disasters. In E. E. H. Doyle & J. S. Becker, *Oxford Research Encyclopedia of Natural Hazard Science*. Oxford University Press. doi: 10.1093/acrefore/9780199389407.013.208

Drożyner, P. (2020). Risk analysis in maintenance processes. *Engineering Management in Production and Services*, *12*(4), 64-76. doi: 10.2478/emj-2020-0028

Eriksson, P. E., & Westerberg, M. (2011). Effects of cooperative procurement procedures on construction project performance: A conceptual framework. *International Journal of Project Management*, *29*(2), 197-208. doi: 10.1016/j.ijproman.2010.01.003

Freudenstein, F., Croft, R. J., Wiedemann, P. M., Verrender, A., Böhmert, C., & Loughran, S. P. (2020). Framing effects in risk communication messages – Hazard identification vs. Risk assessment. *Environmental Research*, *190*, 109934. doi: 10.1016/j.envres.2020.109934

Gentili, D., Bardin, A., Ros, E., Piovesan, C., Ramigni, M., Dalmanzio, M., Dettori, M., Filia, A., & Cinquetti, S. (2020). Impact of Communication Measures Implemented During a School Tuberculosis Outbreak on Risk Perception among Parents and School Staff, Italy, 2019. *International Journal of Environmental Research and Public Health*, *17*(3), 911. doi: 10.3390/ijerph17030911

Ginevičius, R. (2020). Managerial decisions on the nature and scale of corporate activity diversification in the construction sector. *Engineering Management in Production and Services*, *12*(3), 7-17. doi: 10.2478/emj-2020-0015

Howlett, M., Leong, C., & Sahu, S. (2022). Managing internal policy risk: Australia, the UK and the US compared. *Policy Design and Practice*, *5*(2), 152-163. doi: 10.1080/25741292.2022.2065716

International Organization for Standardization. (2018). *ISO 31000:2018. Risk Management – Guidelines*.

Jarkas, A. M., & Haupt, T. C. (2015). Major construction risk factors considered by general contractors in Qatar. *Journal of Engineering, Design and Technology*, *13*(1), 165-194. doi: 10.1108/JEDT-03-2014-0012

Kodym, O., Kubáč, L., & Kavka, L. (2020). Risks associated with Logistics 4.0 and their minimization using Blockchain. *Open Engineering*, *10*(1), 74-85. doi: 10.1515/eng-2020-0017

Liu, J., Li, B., Lin, B., & Nguyen, V. (2007). Key issues and challenges of risk management and insurance in China's construction industry: An empirical study. *Industrial Management & Data Systems*, *107*(3), 382-396. doi: 10.1108/02635570710734280

Lucchese, M., & Pianta, M. (2020). The Coming Coronavirus Crisis: What Can We Learn? *Intereconomics*, *55*(2), 98-104. doi.: 10.1007/s10272-020-0878-0

Moorhead, M., Armitage, L., & Skitmore, M. (2022). Risk management processes used in determining project feasibility in the property development process early stages by Australia/New Zealand property developers. *Journal of Property Investment & Finance*, *40*(6), 628-642. doi: 10.1108/JPIF-08-2021-0071

Moraes, L. F. B., Rampasso, I. S., Anholon, R., Lima, G. B. A., Santa-Eulalia, L. A., Mosconi, E., & Yparraguirre, I. T. R. (2021). Assessing risk management in Brazilian social projects: A path towards sustainable development. *International Journal of Sustainable Development & World Ecology*, *28*(5), 451-460. doi: 10.1080/13504509.2020.1867251

Mulholland, B., & Christian, J. (1999). Risk Assessment in Construction Schedules. *Journal of Construction Engineering and Management*, *125*(1), 8-15. doi: 10.1061/(ASCE)0733-9364(1999)125:1(8)

Nazarko, J., & Chodakowska, E. (2017). Labour efficiency in construction industry in Europe based on frontier methods: Data envelopment analysis and stochastic frontier analysis. *Journal of Civil Engineering and Management*, *23*(6), 787-795. doi: 10.3846/13923730.2017.1321577

Ndlela, M. N. (2019). A Stakeholder Approach to Risk Management. In M. N. Ndlela (Ed.), *Crisis Communication* (pp. 53-75). Springer International Publishing. doi: 10.1007/978-3-319-97256-5_4

Raza, M. H., & Zhong, R. Y. (2022). A sustainable roadmap for additive manufacturing using geopolymers in construction industry. *Resources, Conservation and Recycling*, *186*, 106592. doi: 10.1016/j.resconrec.2022.106592

Rezakhani, P. (2012). Classifying Key Risk Factors in Construction Projects. *The Bulletin of the Polytechnic Institute of Jassy, Construction. Architecture Section*, *58*(2), 27-38. Retrieved from http://www.bipcons.ce.tuiasi.ro/Archive/292.pdf

Ritchie, B., & Brindley, C. (2007). An emergent framework for supply chain risk management and performance measurement. *Journal of the Operational Research Society*, *58*(11), 1398-1411. doi: 10.1057/palgrave.jors.2602412

Roy, S., & Gupta, A. (2020). Safety investment optimization in process industry: A risk-based approach. *Journal of Loss Prevention in the Process Industries*, *63*, 104022. doi: 10.1016/j.jlp.2019.104022

Saeidi, P., Saeidi, S. P., Sofian, S., Saeidi, S. P., Nilashi, M., & Mardani, A. (2019). The impact of enterprise risk management on competitive advantage by moderating role of information technology. *Computer Standards & Interfaces*, *63*, 67-82. doi: 10.1016/j.csi.2018.11.009

Shen, L.-Y., Platten, A., & Deng, X. P. (2006). Role of public private partnerships to manage risks in public sector projects in Hong Kong. *International Journal of Project Management*, *24*(7), 587-594. doi: 10.1016/j.ijproman.2006.07.006

Shevchenko, G., Ustinovichius, L., & Walasek, D. (2019). The Evaluation of the Contractor's Risk in Implementing the Investment Projects in Construction by Using the Verbal Analysis Methods. *Sustainability*, *11*(9), 2660. doi: 10.3390/su11092660

Sukwadi, R., & Caesar, A. (2022). An integrated approach for supply chain risk management. *Engineering Management in Production and Services*, *14*(1), 38-48. doi: 10.2478/emj-2022-0004

Tufano, P. (1996). Who Manages Risk? An Empirical Examination of Risk Management Practices in the Gold Mining Industry. *The Journal of Finance*, *51*(4), 1097-1137. doi: 10.1111/j.1540-6261.1996.tb04064.x

Urbański, M., Haque, A. U., & Oino, I. (2019). The moderating role of risk management in project planning and project success: Evidence from construction businesses of Pakistan and the UK. *Engineering Management in Production and Services*, *11*(1), 23-35. doi: 10.2478/emj-2019-0002

Yang, M., Chen, H., & Xu, Y. (2020). Stakeholder-Associated Risks and Their Interactions in PPP Projects: Social Network Analysis of a Water Purification and Sewage Treatment Project in China. *Advances in Civil Engineering*, 2020, 1-14. doi: 10.1155/2020/8897196

Yoe, C. E. (2019*). Primer on risk analysis: Decision making under uncertainty (Second edition)*. CRC Press.

Yu, Z., Razzaq, A., Rehman, A., Shah, A., Jameel, K., & Mor, R. S. (2022). Disruption in global supply chain and socio-economic shocks: A lesson from COVID-19 for sustainable production and consumption. *Operations Management Research*, *15*(1-2), 233-248. doi: 10.1007/s12063-021-00179-y

Zaleha Abdul Rasid, S., Rahim Abdul Rahman, A., & Khairuzzaman Wan Ismail, W. (2011). Management accounting and risk management in Malaysian financial institutions: An exploratory study. *Managerial Auditing Journal*, *26*(7), 566-585. doi: 10.1108/02686901111151314

Volume 15 • Issue 4 • 2023

sciendo

received: 5 February 2023
accepted: 30 September 2023

pages: 116-127



# Investigation into the key barriers to achieving UK "Construction 2025" Strategy targets

Krzysztof Dziekonski
Francis Mascarenhas
Abdul Majeed Mahamadu
Patrick Manu

ABSTRACT
The "Construction 2025" is a United Kingdom (UK) Government Strategy introduced in 2013 to improve the construction industry in the United Kingdom by meeting outlined performance targets by 2025. However, with only a few years left to reach the targets, it is unclear how much industry is advancing to meet them. This paper reviews the progress to achieve the Strategy targets. The data collected from 96 UK construction professionals was utilised to assess the key barriers to achieving the UK "Construction 2025" Strategy targets. Results indicate that industry professionals are uncertain about reaching the reduction in overall cost and time targets by 2025. However, they are more positive about reducing greenhouse gas emissions and the trade gap. In terms of the key barriers, the results revealed a reluctance to adopt change, lack of implementation of new technology, fragmentation in the industry, and failure to adopt modern construction methods as the key barriers to the Strategy targets. The research is the first attempt at a comprehensive assessment of the progress and barriers to the UK "Construction 2025" Strategy. The results reinforce the call for government initiatives to transform the industry.

KEY WORDS
**United Kingdom, construction industry, Construction 2025, strategy, barriers**

**10.2478/emj-2023-0032**

**Krzysztof Dziekonski**

University of the West of England,
United Kingdom
ORCID 0000-0001-5396-8582

Corresponding author:
e-mail:
krzysztof.dziekonski@uwe.ac.uk

**Francis Mascarenhas**

University of the West of England,
United Kingdom

**Abdul Majeed Mahamadu**

University College London,
United Kingdom
ORCID 0000-0001-7757-8562

**Patrick Manu**

University of the West of England,
United Kingdom
ORCID 0000-0001-7766-8824

## Introduction

The United Kingdom (UK) construction industry contributed GBP 117 billion (i.e., 6 %) to the UK's economy in 2019. It is responsible for 2.4 million (7 %) jobs in the UK (Rhodes, 2019). The Confederation of British Industry's (2020) research shows that every GBP 1 spent on UK construction creates GBP 2.92 value to the UK. The global market has become more competitive after the 2008–09 economic crisis (Smiley, 2016). As a result, the UK Government formed industrial strategies with several major industries,

Dziekonski, K., Mascarenhas, F., Mahamadu, A. M., & Manu, P. (2023). Investigation into the key barriers to achieving UK "Construction 2025" Strategy targets. *Engineering Management in Production and Services, 15*(4), 116-127. doi: 10.2478/emj-2023-0032

creating long-term strategic alliances with different industry sectors to impact growth significantly. In 2013, the UK Government introduced the Government Industrial Strategy "Construction 2025" to achieve specific targets by 2025 and five key themes crucial for the future of the British construction industry (HM Government, 2013). The Strategy aimed to significantly reduce cost, time, greenhouse gas emissions, and the trade gap by 2025 compared to the respective benchmarks by delivering much faster buildings and infrastructure with better carbon and energy performance and greater life value (Hansford, 2015).

After publishing the Strategy, there was much criticism against its targets. Gruneberg (2018) addressed the flaw in the method of reaching these targets, which is neither clear nor transparent. Green (2013) argued that most construction professionals do not think the Strategy would succeed as the previous initiatives failed to reach the targets. Gruneberg (2018) also believed that failure to achieve all of the "Construction 2025" Strategy targets would give an unjustified impression of the construction industry's failure.

The progress of the Strategy targets was not examined in any of the previous research. While a few studies have focused on various aspects of the Strategy (Smiley, 2016; Gruneberg, 2018; Green, 2013), none have evaluated the key barriers to attaining the targets. This study focuses on the literature review of the progress of the "Construction 2025" Strategy targets and investigates the potential barriers. The main aim is to identify the key barriers hindering the progress of the Strategy targets to reach the specified target by 2025.

# 1. Literature review

Buildings provide housing, protection, and a sense of community for households and are a vital source of wealth, with construction goods totalling GBP 3620 billion (CIOB, 2020). The construction industry is crucial in creating the nation's wealth.

The construction industry employed over three million workers across the UK in 2013, with output totalling GBP 112.6 billion (approx. 7 % of UK GDP and equivalent to 10 % of total UK jobs). Hence, the Government developed industrial strategies with various major industries, developing long-term strategic partnerships with industry sectors. Furthermore, the UK government backed the construction industry, which was expected to be a key driver of potential growth in the UK economy, creating more value-added and employment. A good strategy could enhance an industry's competitive position and add customer value (Mongkol, 2021). In July 2013, the Government published the "Construction 2025" Strategy: a partnership between the Government and the industry. The Strategy outlined how the UK would place itself as a global leader in construction (HM Government, 2013). The Government and the construction industry jointly aspired to achieve the following four targets by 2025 (HM Government, 2013):

1. A 33 % reduction in both the initial cost of construction and the whole life cost of assets based on the 2009/2010 benchmarks.
2. A 50 % reduction in the overall time from inception to completion for newly built and refurbished assets, compared to 2013 levels.
3. A 50 % reduction in greenhouse gas emissions in the built environment versus a 1990 baseline.
4. A 50 % reduction in the trade gap between total exports and total imports for construction products and materials (using 2012's trade gap of GBP 6 billion as the starting point).

This Strategy (HM Government, 2013) has also set out five non-specific aspirations, which are based on the following five key themes: People: An industry that is known for its talented and diverse workforce; Smart: An industry that is efficient and technologically advanced; Sustainable: An industry that leads the world in low-carbon and green construction; Growth: An industry that drives growth across the entire economy; Leadership: An industry with clear leadership from the Construction Leadership Council (CLC).

## 1.1. Progress of the "Construction 2025" Strategy targets

The core of implementing a strategy is to follow a schedule and milestones. The lack of control over the implementation process can lead to failure (Ivančić et al., 2021). The CLC was responsible for monitoring and measuring the progress of the Strategy's targets. However, the CLC members admitted that they do not monitor or measure these goals (Construction Index, 2017). Moreover, CLC did not publish any document — no annual assessment and no performance evaluation — informing how the industry is doing to meet the Strategy targets.

#### 1.1.1. 33 % reduction in both the initial cost of construction and the whole life cost of assets

According to Latham (1994), if his report's guidelines were followed, a 30 % savings could have been achieved by 1999. In Egan's report (1998), one of the ambitious targets was to reduce construction costs by 10 % annually. The UK government was looking into the construction industry to see how it could experiment with pre-fabrication and procurement methods like those used by European builders. In Belgium, Holland, Germany, and Scandinavia, many clients claim buildings are 20–30 % cheaper than in the UK (Symonds et al., 2015). As a result, the Government Construction Strategy (GCS) 2011–2015 programme was launched in 2011 with the primary goal of lowering the cost of public sector building by up to 20 % by the end of the Parliament in 2015 (Cabinet Office, 2011). While the Strategy aimed to save GBP 8.8 billion a year by the end of the Parliament, the GCS 2016–2020 found that only GBP 3 billion was saved over 2011–2015. By the end of the Parliament, the GCS 2016–20 predicted productivity gains of GBP 1.7 billion, much less than the GCS 2011–2015 (IPA, 2016). This reflects the challenge of lowering costs on which the industry must focus. No sufficient data has been published regarding the target's progress after 2015.

#### 1.1.2. 50 % reduction in the overall time from inception to completion for newly built and refurbished assets

The CITB (2018) surveys indicate that 63 % of projects were completed on time or better in 2018, whereas in 2013, it was 45 %. However, in 2018, only 53 % of the projects completed the design phase within the time agreed upon at the start of that phase. A major limitation in assessment is the unavailability of sufficient data to illustrate the progress of the target.

#### 1.1.3. 50 % reduction in greenhouse gas emissions in the built environment

The UK is leading the world in carbon reductions, with the Government pledging to achieve net-zero emissions by 2050 (National Federation of Builders, 2019). UK construction accounts for 10 % of the total country's emissions, and the whole built environment impacts 47 % of all emissions through the built assets (Committee on Climate Change, 2019). The Green Construction Board (GCB) (2013) has created the Low Carbon Route map for the Built Environment to meet the UK Government's goal of reducing greenhouse gas (GHG) emissions by 80 % by 2025 compared to 1990 baseline levels. The "Construction 2025" Strategy aimed to cut emissions by half by 2025 compared to the 1990 baseline. Therefore, the target for 2025 is an integral part of the Low Carbon Routemap. The UK has been successful in reducing emissions (Priestley, 2019). In 2018, emissions were 43.8 % lower than in 1990, indicating that the country has met its first and second carbon budget goals and is on track to meet the third, ending in 2022 (BEIS, 2019). This seems to be the only target that can be met compared to others (Construction Index, 2017).

#### 1.1.4. 50 % reduction in the trade gap between total exports and total imports for construction products and materials

In 2013, the UK exported GBP 6 billion in building materials and components while importing GBP 12 billion, resulting in a GBP 6 billion trade deficit (ONS, 2013). Exports have risen steadily since then, reaching GBP 7.7 billion in 2019. On the other hand, imports have risen as well, reaching GBP 17.8 billion. After introducing the "Construction 2025" Strategy, the trade deficit has not been reduced but has widened from GBP 6 billion to more than GBP 10 billion (ONS, 2019).

### 1.2. Barriers to the "Construction 2025" Strategy targets

Considering the factors that impacted the UK construction industry in the last ten years, industry reports and recent studies have been reviewed to identify potential barriers to the "Construction 2025" Strategy targets.

According to Bingham (2013), these targets' representation implies that the industry is too expensive and idle. Steer (2015) referred to these as "random goals" and mentioned the industry's scepticism about meeting them. Gruneberg (2018) argued that the targets are not clear and transparent. Furthermore, the targets have distorted how construction projects are delivered, shifting the focus away from what is expected of the sector and towards achieving unattainable and conflicting targets. The contradictory nature of the targets would result in not achieving all the targets and could reflect the construction industry's failure and incompetence (Gruneberg, 2018; Bingham, 2013).

A CITB (2019) report indicated that the UK construction industry would face a shortfall to match the demand. Based on Farmer's (2016) review, the industry could see as much as a 25 % decline in its available labour force within a decade, mainly due to the retirement of older workers. Arcadis' (2017) report indicated that the UK construction industry needs to employ over 400 000 people each year to meet housing and infrastructure demands. Meanwhile, the impact of Brexit will widen this gap even more (Mohamed et al., 2017). Brexit might result in a loss of up to 214 000 EU employees in the construction industry in the UK (Arcadis, 2017). The shortage of skills and labour would mainly impact the reduction in time and cost targets.

For several decades, the construction industry in the UK has been warned that it must modernise to improve (Latham, 1994; Egan, 1998; Farmer, 2016). The white paper on housing released by the Government in 2018 reiterated this barrier, highlighting innovation, modernisation, and productivity problems (Ministry of Housing, Communities & Local Government, 2018). The construction industry seems trapped in conventional and dysfunctional structures and techniques (Farmer, 2016). Even today, most construction firms still rely on very traditional production approaches. Nazir et al. (2020) argued that modular housing could resolve the UK's affordable housing crisis. The McKinsey & Company report (2019) highlighted two critical benefits of modular methods for construction clients: a 50 % cut in time to complete projects and reduced costs of up to 20 % (Steinhardt and Manley, 2016). Modular methods of construction (MMC), like offsite construction, offer the potential to reduce construction time and cost (Miles and Whitehouse, 2013). According to Azman et al. (2012), pre-fabrication can solve major problems in the UK construction sector, such as a skilled labour shortage, expedited completion, higher costs, and transportation issues. Also, prefabricated buildings have lower embodied and operational carbon emissions than traditional buildings (Teng et al., 2018). However, the UK has been slower to embrace the technique. Only around 10 % of Britain's housebuilders use MMC (Savills, 2020).

Construction News (2020) stated, "We build too slowly, too expensively, and with too little reliability". Rogers (2018) and Madanayake and Çidik (2019) believed digitalisation could solve the construction productivity problem. Between 2013 and 2020, BIM adoption increased significantly, from 39 % to 73 % (NBS, 2020). Meanwhile, Raza et al. (2019) argued that BIM efficiently reduces carbon emissions if used effectively in the building design phase. However, since these technologies are regarded as costly, their adoption is limited.

Sarhan and Fox (2013) argued that the wide adoption of lean construction management principles would improve quality and efficiency. However, their study also revealed a lack of adequate lean awareness and understanding, top management commitment, and cultural and human attitudinal issues as the main barriers to adopting lean management in the UK. Meng (2019) suggested that integrating lean construction with the supply chain would make lean construction more effective and accelerate lean transformation. An integrated supply chain will increase the industry's productivity and reduce waste (Al-Werikat, 2017; Magill et al., 2020).

Both Latham's (1994) and Egan's (1998) reports mentioned the lack of collaboration as one of the main barriers to the industry's growth. Also, the "Construction 2025" Strategy report (HM Government, 2013) addressed the lack of collaboration and knowledge-sharing as one of the industry's weaknesses. Oraee et al. (2019) showed that collaboration is fundamental for improving the industry's efficiency, resource utilisation, increasing profit and enhancing quality. The lack of collaboration surrounding the construction industry's activities has been closely attributed to the industry's poor efficiency, such as delays and cost overruns, as construction processes frequently take place sequentially, and parties usually operate in isolation with limited interfaces between them (Riazi et al., 2020).

The "Construction 2025" report (HM Government, 2013) highlighted the higher degree of fragmentation as a threat to the UK construction industry's growth. It arises from a high proportion of self-employment and many small and micro-businesses driving the industry. The Government Construction Strategy 2016–2020 (IPA, 2016) reported that the industry was dominated by 956 000 SMEs, which accounted for 99 % of businesses. Most of the work is done by small enterprises, with only 25 % going to the top 20 main contractors. In Sweden, on the other hand, the top three companies are responsible for 40 % of the work (Construction News, 2019). Naoum et al. (2010) identified the fragmentation of the construction industry as the main barrier to innovation. The industry's fragmentation causes the industry to underperform, such as delays, cost overruns, low satisfaction, etc. (Riazi et al., 2020). The Government oversight of the construction industry is distributed across many departments, each taking responsibility for a different policy. The Department of Business, Innovation, and Skills (BIS) is responsible for the "Construction 2025" Strategy (HM Government, 2013), whereas the Infrastructure and Projects Authority (IPA) is responsible for the "Government Construction Strategy 2016–2020" (IPA, 2016). This indicates some fragmentation in the governance structures adopted to manage the major delivery of programmes. The depreciation of the British pound causes price increases in imports, forcing companies to raise their prices to avoid lower profit margins (Elcheikh et al., 2020). While a lower pound increases export competitiveness, it does not guarantee economic growth because exporters may raise their prices to maximise profits, resulting in unchanged export volumes. However, a weaker currency could improve competitiveness between British firms (Competition & Markets Authority, 2020).

The "Construction 2025" report (HM Government, 2013) addressed the challenges of inefficient procurement, which leads to high construction costs and increased GHG emissions. Ivalua's (2019) report revealed that inefficient procurement processes cost UK firms almost GBP 2 million per year. The industry and clients need to change the procurement routes to transform the industry (Marshall, 2020).

After considering the challenges that the industry faced over the last decade and analysing their impact on the revolutionary industrial Strategy, the study identified thirteen potential barriers to the "Construction 2025" Strategy targets: the contradictory nature of the "Construction 2025" Strategy targets, skilled labour shortage, reluctance to adopt change, failure to adopt modern construction methods, lack of implementation of new technology, lack of implementation of new methods of management, failure to adopt sustainable building design and construction strategies, lack of collaboration and limited knowledge sharing, fragmentation in the industry, the weakening value of

Tab. 1. Respondents' characteristics

| Characteristics | Percentage |
|---|---|
| **Construction Experience** | |
| less than a 1 year | 9.30% |
| 1 to 5 years | 21.90% |
| 6 to 10 years | 18.80% |
| more than 10 years | 50.00% |
| **Professional Role** | |
| Architect | 11.00% |
| Building Surveyor | 8.00% |
| Civil Engineer | 5.00% |
| Construction Manager | 7.00% |
| Design Manager | 4.00% |
| Director | 16.00% |
| Project Manager | 26.00% |
| Quantity Surveyor | 12.00% |
| Site Manager | 4.00% |
| Other | 7.00% |
| **Awareness of the "Construction 2025" Strategy targets** | |
| Aware | 69.00% |
| Not aware | 31.00% |

Note: 96 participants; all categories add up to 100 %.

the pound sterling, lack of trust in the supply chain, traditional procurement approaches, and poor record of tackling climate change.

## 2. Research methods

A questionnaire survey was used to obtain a generic view of industry professionals' perceptions about the attainment level of performance targets and barriers to achieving them. The questionnaire consisted of two main parts:

Part 1. Collect data on the demographic profile of the respondents.

Part 2. Use a 10-point Likert scale, which allowed the respondents to express their perception of the probability of achieving "Construction 2025" targets. The more the value tends towards 1, the more it is considered "Highly Impossible"; and the more it tends towards 10, the more it represents "Highly Possible". Additionally, respondents were asked to use the same 10-point Likert scale to rate 13 factors identified as potential barriers to the "Construction 2025" Strategy targets.

A Cronbach's alpha test was calculated to assess the research instrument's reliability. The result (0.862) indicates a good internal consistency of the questionnaire.

The questionnaire was deployed via an online survey using Qualtrics. The questionnaire was distributed to UK construction professionals through the online professional network LinkedIn platform between March–April 2021. A total of 96 respondents completed the survey. The respondents' characteristics are shown in Table 1.

## 3. Research results

### 3.1. Possibility of achieving the strategy targets by 2025

A one-sample t-test was run to compare the mean scores to a test value of 5. The test results, indicating respondents' opinions on the possibility of achieving "Construction 2025" Strategy targets, are shown in Table 2.

Results show the respondents' perception of the likelihood of achieving the targets. All mean values are close to 5 (the middle of a scale), indicating high uncertainty among respondents. Construction industry professionals in the UK are unsure if the industry can achieve a 33 % reduction in costs and a 50 % reduction in time by 2025. The uncertainty in the reduction in time and cost targets reflects the opinions of many industry professionals, who believe the target is a tall order for the industry (Gruneberg, 2018; Green, 2013; Bingham, 2013). Additionally, no clear data has shown the progress of these two targets since 2013.

However, results demonstrate that respondents are more positive in their view of a 50 % reduction in greenhouse gas emissions, with mean values significantly above 5. It reflects the UK's successful history in reducing emissions by 43.8 % from 1990 to 2018 (BEIS, 2019).

Tab. 2. Possibility of achieving "Construction 2025" Strategy targets

| S/N | Target | Mean | Standard deviation | t-value | p-value |
|---|---|---|---|---|---|
| 1 | A 33 % reduction in both the initial cost of construction and the whole life cost of assets | 5.06 | 2.27 | 0.27 | 0.79 |
| 2 | A 50 % reduction in the overall time from inception to completion for newly built and refurbished assets | 5.12 | 2.51 | 0.49 | 0.63 |
| 3 | A 50 % reduction in greenhouse gas emissions in the built environment | 5.85 | 2.56 | 3.27 | 0.00* |
| 4 | A 50 % reduction in the trade gap between total exports and total imports for construction products and materials | 5.49 | 2.14 | 2.23 | 0.02* |

Note: statistically significant values $p<0.05$ have been marked with an asterisk.

The respondents are also positive about a 50 % reduction in the trade gap. However, the mean value, close to the middle of a measure scale, shows an uncertainty. Brexit could impact this target, as 62 % of materials imported by the UK construction industry come from EU countries (Construction Index, 2021). However, it is difficult to assess the full impact of Brexit on the industry.

### 3.2. Barriers to the "Construction 2025" Strategy targets

Thirteen factors were listed as potential barriers to attaining the strategy targets. As previously, the one-sample t-test was run to compare the mean scores of a barrier to a test value of 6.5. A higher test value has been chosen to identify barriers perceived as a considerable obstacle to successfully implementing the "Construction 2025" Strategy targets. The list of barriers and results of the one-sample t-test are shown in Table 3.

The results reveal four statistically significant barriers to the "Construction 2025" Strategy targets: reluctance to adopt change, lack of implementation of new technology, fragmentation in the industry, and failure to adopt modern construction methods.

A principal component analysis was run to observe any relationships and correlations in the whole data set. To verify the adequacy of the data for factor analysis, the Kaiser–Meyer–Olkin (KMO) test and Barlett's test of sphericity were used. Results are shown in Table 4.

The KMO measure of this study, with a value of 0.819, and significant Bartlett's test results (Table 4) suggest the adequacy of the data for the factor analysis (Field, 2005; George and Mallery, 2020).

The data collected was subject to principal component analysis (PCA) with Varimax rotation. The choice of the principal components was made using criteria of the variance explained by the principal components and the criterion of a scree plot (Cangelosi and Goriely, 2007). Table 5 shows eigenvalues,

Tab. 3. Barriers to the successful implementation of the "Construction 2025" Strategy targets

| Barriers | Mean | Standard deviation | t-value | p-value |
|---|---|---|---|---|
| Reluctance to adopt change | 7.22 | 2.63 | 2.67 | 0.00* |
| Lack of implementation of new technology | 7.08 | 2.53 | 2.25 | 0.02* |
| Fragmentation in the industry | 7.05 | 2.40 | 2.25 | 0.02* |
| Failure to adopt modern construction methods | 6.98 | 2.30 | 2.03 | 0.04* |
| Failure to adopt sustainable building design and construction strategies | 6.92 | 2.25 | 1.85 | 0.06 |
| Shortage of skilled labour | 6.90 | 2.82 | 1.41 | 0.16 |
| Lack of implementation of new methods of management | 6.85 | 2.23 | 1.55 | 0.12 |
| Lack of collaboration and limited knowledge sharing | 6.76 | 2.29 | 1.11 | 0.27 |
| Traditional procurement approaches | 6.76 | 2.35 | 1.08 | 0.28 |
| Poor record of tackling climate change | 6.70 | 2.37 | 0.85 | 0.39 |
| Lack of trust in the supply chain | 6.27 | 2.26 | -0.99 | 0.32 |
| Weakening value of the pound sterling | 5.92 | 2.15 | -2.65 | 0.00* |
| Contradictory nature of the "Construction 2025" Strategy targets | 5.89 | 2.13 | -2.77 | 0.00* |

Note: Statistically significant values p<0.05 have been marked with an asterisk.

Tab. 4. Kaiser–Meyer–Olkin (KMO) and Barlett's test of sphericity results

| Kaiser–Meyer–Olkin Measure of Sampling Adequacy | | 0.819 |
|---|---|---|
| Bartlett's Test of Sphericity | Approx. Chi-Square | 530.666 |
| | Df | 78 |
| | Sig. | 0.000 |

cumulative eigenvalues, and the explanatory power — the percentage of variance explained — of a particular principal component.

A threshold of at least 70 % of explained variability has been used to establish the number of selected principal components (Jolliffe, 2002). Four principal components have been extracted. The variance of each component has been visualised on a scree plot (Fig. 1).

The plot shows a drop for Component 1 and Component 2. The line stabilises from Component 4 onwards, indicating that the first four components collectively account for most of the total variance in the dataset. Four principal components, cumulatively explaining 70.23 % of the variance in the dataset, have been extracted. Table 6 presents the results of the rotated component matrix.

Tab. 5. Eigenvalues and cumulative variance explained by principal components

| Component | Initial Eigenvalues | | |
|---|---|---|---|
| | Total | % of Variance | Cumulative % |
| 1 | 5.229 | 40.224 | 40.224 |
| 2 | 1.580 | 12.156 | 52.380 |
| 3 | 1.429 | 10.991 | 63.371 |
| 4 | 0.892 | 6.862 | 70.233 |
| 5 | 0.722 | 5.557 | 75.790 |
| 6 | 0.625 | 4.805 | 80.595 |
| 7 | 0.484 | 3.727 | 84.321 |
| 8 | 0.462 | 3.556 | 87.877 |
| 9 | 0.423 | 3.254 | 91.131 |
| 10 | 0.371 | 2.857 | 93.989 |
| 11 | 0.323 | 2.486 | 96.475 |
| 12 | 0.276 | 2.123 | 98.597 |
| 13 | 0.182 | 1.403 | 100.000 |

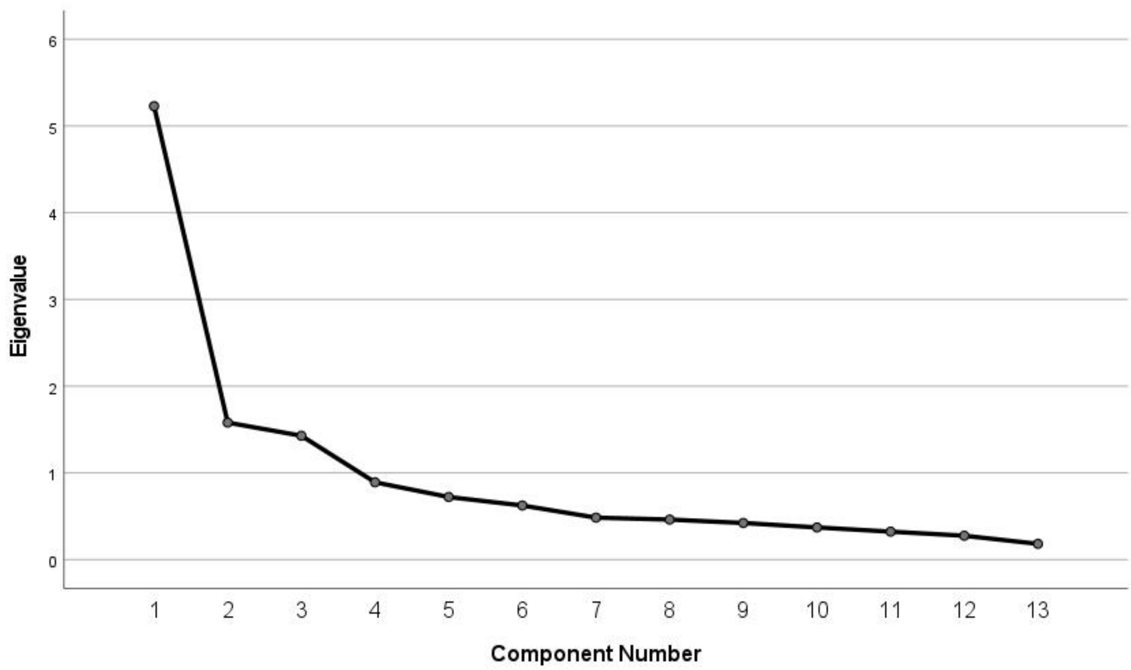



Fig. 1. Scree plot

Tab. 6. Component loadings matrix — varimax rotation normalised

| **Barriers** | **Component** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| Contradictory nature of the "Construction 2025" Strategy targets | 0.228 | -0.248 | 0.244 | <u>0.785</u> |
| Shortage of skilled labour | <u>0.859</u> | 0.061 | 0.039 | 0.127 |
| Reluctance to adopt change | <u>0.705</u> | 0.155 | 0.379 | -0.171 |
| Failure to adopt modern methods | 0.312 | <u>0.720</u> | 0.090 | 0.063 |
| Lack of implementation of new technology | 0.237 | <u>0.739</u> | 0.314 | -0.307 |
| Lack of implementation of new management methods | -0.018 | <u>0.729</u> | 0.346 | 0.078 |
| Failure to adopt sustainable building design and construction strategies | 0.415 | 0.560 | 0.262 | 0.289 |
| Lack of collaboration and limited knowledge sharing | <u>0.695</u> | 0.402 | 0.102 | -0.169 |
| Fragmentation in the industry | 0.553 | 0.133 | 0.554 | 0.214 |
| Weakening value of the pound sterling | -0.263 | 0.404 | -0.024 | <u>0.752</u> |
| Lack of trust in the supply chain | 0.195 | 0.251 | <u>0.762</u> | 0.116 |
| Traditional procurement approaches | 0.115 | 0.288 | <u>0.824</u> | 0.038 |
| Poor record of tackling climate change | 0.494 | 0.464 | 0.275 | 0.063 |

Note: underlined loadings are >0.60.

To interpret factors, only loadings offering statistical significance at 0.05 level have been used. Following Hair et al. (2019) guidelines for identifying significant component loadings based on sample size, the cut-off point for interpretation purposes is all loadings greater than 0.60. Component loadings greater than 0.60 have been underlined (Table 6).

Since component loadings represent the correlation between the original variable and its factor (expressing the influence of each original variable within the component), the following components' labels are proposed:

Component 1 accounts for 40.2 % of the total variance explained and reports high loadings for three variables (shortage of skilled labour, reluctance to adopt change, lack of collaboration and limited knowledge sharing) related to the industry's hermetic and unappealing nature.

Component 2 comprises three variables (failure to adopt modern methods, lack of implementation of new technology, lack of implementation of new management methods) representing reluctance to adopt innovation, which explains 12.15 % of the dataset's variance;

Component 3 indicates inefficient procurement systems (with two variables: lack of trust in the supply chain and traditional procurement approaches), explaining 10.99 % of the variance;

Component 4 accounts for 6.86 % of the total variance in the data set representing economic/government support factors.

## 4. Discussion

It has been almost 25 years since Latham (1994) and Egan's (1998) report called for the industry to modernise and be more collaborative. However, construction professionals still report the old problems of the industry's conventional approach. Half of the variance in the data set (Component 1 and Component 3) is explained by variables that could be attributed to the traditional, labour-intensive approach to the construction process. Interestingly, Component 2, an indicator of the approach to innovation, explains only 12 % of the variance in the data. Despite the industry being slow in adopting MMC (panelised MMC accounts for around 10 % to 15 % of builds while volumetric MMC accounts for less than 2% of current builds (CITB 2019)) respondents do not see the slow adoption of MMC as one crucial barrier to achieving "Construction 2025" targets. ONS report (ONS, 2021) indicates 43 000 vacancies in the construction industry in July–September 2021, which is the highest level in the records. It is believed that adopting MMC will significantly reduce labour pressure and might contribute to the reduction of GHG (Lords' Science and Technology Committee, 2018; CITB, 2019). Recent government guidance (HM Government, 2020) promoting standardised and interoperable components and enhanced BIM interoperability, clearly incentivising MMC adoption, may provide the industry with more certainty to invest in new technologies. Undoubtedly, MMC will not be adopted as long as consumers continue to demand a traditional building; therefore, a demand-led change is crucial to accelerating the use of MMC (CITB, 2019).

The industry is now on the verge of the fourth industrial revolution, with digitisation significantly impacting the work itself and how the industry collaborates (RICS, 2020). Digital technologies are regarded as costly; therefore, their adoption is limited. At least 60–70 % of construction companies are not engaging with any digitalisation at all, which is hampering them in a competitive market (Construction News, 2019). The industry should be encouraged to invest more in IT technologies and become more digital, as it can lead to overall improvements in productivity. Interestingly, COVID-19 has accelerated the digital adoption in the industry (RICS, 2020) and changed some work models. It is expected that the industry will continue to transform. Without an innovative approach to business models and more value-adding processes, the UK construction industry will still be criticised for being inefficient and outdated (Baran, 2007).

## Conclusions

This study has reviewed the progress of the "Construction 2025" Strategy targets of the UK construction industry and has ascertained the progress of those targets based on the views of construction professionals. The analysis indicates that none of the targets is on course to be met by 2025. However, UK construction professionals are more positive in their view of a 50 % reduction in greenhouse gas emissions and a 50 % reduction in the trade gap by 2025.

The analysis also reveals three significant barriers to achieving the "Construction 2025" Strategy targets: the industry's hermetic and unappealing nature, reluctance to adopt innovation and inefficient procurement systems. The UK's construction industry seems trapped in conventional and dysfunctional structures and techniques, obstructing rapid change by 2025.

It is recommended that a more robust and comprehensive approach to analysing the industry's attainment of targets is implemented through tailored KPIs. There should also be mechanisms for measuring and reporting them. Further Government initiatives are required to address some barriers, particularly incentives to adopt MMCs and technologies and digital innovation using similar initiatives, such as the UK's national BIM strategy and the Transforming Construction Programme.

## Literature

Al-Werikat, G. (2017). Supply Chain Management In Construction; Revealed. *International Journal of Scientific and Technology Research, 6*(3), 106-110.

Arcadis. (2017). *Arcadis talent scale: The real extent of Britain's construction labour crisis*. Retrieved from http://www.infrastructure-intelligence.com

Azman, M. N. A., Ahamad, M. S. S., & Wan Husin, W. M. (2012). Comparative Study on Prefabrication Construction Process. *International Surveying Research Journal, 2*(1), 45-58.

Baran M. (2007). Efektywność strategii innowacji technologicznych w sferze produkcji (na przykładzie przemysłu maszynowego) [Effectiveness of technological innovation strategies in manufacturing (on the example of the engineering industry)]. In A. Strychalska-Rudzewicz (Ed.), *Innowacje i jakość jako czynniki konkurencyjności przedsiębiorstwa* [*Innovation and quality as factors of company competitiveness*] (pp. 85-90). Olsztyn, Poland: UWM.

BEIS. (2019). *2018 UK greenhouse gas emissions, provisional figures.* National Statistics. London: Crown.

Bingham, T. (2013). Construction 2025: You cannot be serious. *Building*. Retrieved from https://www.building.co.uk/comment/construction-2025-you-cannot-be-serious/5059021.article

Cabinet Office. (2011). *Government Construction Strategy*. London: Cabinet Office.

Cangelosi, R., & Goriely, A. (2007). Component retention in principal component analysis with application to cDNA microarray data. *Biology Direct, 2*(2). doi:10.1186/1745-6150-2-2

CIOB. (2020). *The Real Face of Construction 2020.* Retrieved from https://policy.ciob.org/wp-content/uploads/2020/02/The-Real-Face-of-Construction-2020.pdf

CITB. (2018). *UK Industry Performance Report: 2018* CITB. Bircham Newton: CITB.

CITB. (2019). *The impact of modern methods of construction on skills requirements for housing*. Bircham Newton: CITB.

Committee on Climate Change. (2019). *Net Zero: The UK's contribution to stopping global warming.* Committee on Climate Change. London: Committee on Climate Change.

Competition & Markets Authority. (2020) *The State of UK Competition: November 2020*. London: Competition & Markets Authority.

Confederation of British Industry. (2020). *Fine margins: Delivering financial sustainability in UK construction.* London: Confederation of British Industry.

Construction Index. (2017). *Industry targets are not being measured.* Retrieved from https://www.theconstructionindex.co.uk/news/view/industry-targets-are-not-being-measured

Construction News. (2019). *2020: The year construction turns a corner on digitisation.* Retrieved from https://www.constructionnews.co.uk/agenda/opinion/2020-year-construction-turns-corner-digitisation-11-10-2019

Construction News. (2020). *Our low productivity is the biggest economic crisis.* Retrieved from https://www.constructionnews.co.uk/agenda/opinion/our-low-productivity-is-the-real-economic-crisis-25-08-2020

Egan, S. J. (1998). *Rethinking Construction.* Department of Trade and Industry. London: Crown.

Elcheikh, M., Cojocaru, A., Theaker, M., & Alsheikh, D. (2020). Analyzing the Effect of Brexit on the British Construction Industry Using Fuzzy Sets Theory. *Frontiers in Built Environment, 6.* doi: 10.3389/fbuil.2020.00008

Farmer, M. (2016). *Modernise or Die: The Farmer Review of the UK Construction Labour Model.* Construction Leadership Council. Retrieved from https://www.gov.uk/government/publications/construction-labour-market-in-the-uk-farmer-review

Field, A. (2005). *Discovering Statistics Using SPSS for Windows.* London: Sage Publications.

George D. & Mallery, P. (2020). *IBM SPSS Statistics 26 Step by Step*. Oxon: Routledge.

Green Construction Board. (2013). *Low Carbon Routemap for the UK Built Environment.* London: Green Construction Board.

Green, S. (2013). At it again: Critique of UK government's industrial strategy for construction. *Construction Research and Innovation*, *4*(3), 12-15. doi: 10.1080/20450249.2013.11873892

Gruneberg, S. (2018) *A strategic approach to the UK construction industry.* Oxon: Routledge.

Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2019). Multivariate data analysis, 8th ed. Andover: Cengage.

Hansford, P. (2015). Continuing to transform UK construction – 'Construction 2025'. *Innovation and Research Focus*. Retrieved from https://www.innovationresearchfocus.org.uk

HM Government. (2013). *Construction 2025. Industrial Strategy: Government and industry in partnership.* Department for Business, Innovation and Skills. London: Cabinet Office.

HM Government. (2020). *The construction playbook. Government Guidance on sourcing and contracting public works projects and programmes.* London: Cabinet Office.

IPA. (2016). *Government Strategy GCS 2016-2020.* London: Crown.

Ivalua. (2019). *Inefficient Procurement processes are costing UK businesses almost £2m per year.* Retrieved from https://www.ivalua.com/newsroom/inefficient-procurement-processes-are-costing-uk-businesses-almost-2m-per-year-reveals-research

Ivančić, V., Jelenc, L., & Mencer, I. (2021). The strategy implementation process as perceived by different hierarchical levels: The experience of large Croatian enterprises. *Journal of Entrepreneurship, Management and Innovation, 17*(2), 99-124. doi.org/10.7341/20211724

Jolliffe, I. (2002). *Principal Component Analysis.* New York: Springer.

Latham, S. M. (1994). *Latham Report - Constructing the Team Joint Review of Procurement and Contractual Arrangements in the United Kingdom Construction Industry.* London: Crown.

Lords' Science and Technology Committee. (2018). *Science and Technology Select Committee Off-site manufacture for construction: Building for change.* Retrieved from https://publications.parliament.uk/pa/ld201719/ldselect/ldsctech/169/16902.htm

Madanayake, U. H., & Çidik, M. S. (2019). The potential of digital technology to improve construction productivity. In C. Gorse & C. J. Neilson (Eds.), *Proceedings 35th Annual ARCOM Conference*, 2-4 September 2019, Leeds Beckett University (pp. 416-425). Leeds: UK Association of Researchers in Construction Management.

Magill, L. J., Jafarifar, N., Watson, A. & Omotayo, T. (2020). 4D BIM integrated construction supply chain logistics to optimise on-site production. *International Journal of Construction Management, 22*(12), 2325-2334. doi:10.1080/15623599.2020.1786623

Marshall, J. (2020). Plan to modernise construction needs procurement to change. *Building*. Retrieved from https://www.building.co.uk/news/plan-to-modernise-construction-needs-procurement-to-change-former-civil-service-head-says/5109446.article

McKinsey & Company. (2019). *Modular construction: From projects to products.* Retrieved from https://www.mckinsey.com/business-functions/operations/our-insights/modular-construction-from-projects-to-products

Meng, X. (2019). Lean management in the context of construction supply chains. *International Journal of Production Research, 57*(11), 3784-3798. doi: 10.1080/00207543.2019.1566659

Miles, J., & Whitehouse, N. (2013). *Offsite Housing Review.* London: Construction Industry Council.

Ministry of Housing, Communities & Local Government. (2018). *Government response to the housing White Paper consultation: Fixing our broken housing market*. London: Crown.

Mohamed, M., Pärn, E. A., & Edwards, D. J. (2017). Brexit: measuring the impact upon skilled labour in the UK construction industry. *International Journal of Building Pathology and Adaptation, 35*(3), 264-279. doi: 10.1108/IJBPA-05-2017-0023

Mongkol, K. (2021). A comparative study of a single competitive strategy and a combination approach for enterprise performance. *Polish Journal of Management Studies, 23*(2), 321-334. doi: 10.17512/pjms.2021.23.2.19

Naoum, H. G, Lock, K., & Fong, D. (2010). Is fragmentation of the UK construction industry the main barrier to innovation? The architects' views? *The 6th International Conference on Innovation in Architecture, Engineering & Construction (AEC).* Pennsylvania: Pennsylvania State University.

National Federation of Builders. (2019). *Transforming Construction for a Low Carbon Future*. Cheshire: National Federation of Builders.

Nazir, F. A., Edwards, D. J., Shelbourn, M., Martek, I., Thwala, W. D. D., & El-Gohary, H. (2020). Comparison of modular and traditional UK housing construction: a bibliometric analysis. *Journal of Engineering, Design and Technology, 19*(1), 164-186. doi: 10.1108/JEDT-05-2020-0193

NBS. (2020). *10th annual BIM Report 2020.* Newcastle: NBS. Retrieved from https://architecturaltechnology.com

ONS. (2013). *Construction Statistics, Great Britain: 2013*. London: Office for National Statistics.

ONS. (2019). *Atmospheric emissions: greenhouse gas emissions by economic sector and gas*. London: Office for National Statistics.

ONS. (2021). *Vacancies and jobs in the UK: October 2021.* London: Office for National Statistics.

Oraee, M., Hosseini, M. R., Edwards, D. J., & Li, H. (2019). Collaboration barriers in BIM-based construction networks: A conceptual model. *International Journal of Project Management, 37*(6), 839-854. doi: 10.1016/j.ijproman.2019.05.004

Priestley, S. (2019). *UK Carbon Budgets. London: House of Commons.* Retrieved from https://commonslibrary.parliament.uk/research-briefings/cbp-7555/

Raza, M. S., Kumar, D. & Nawab, H. (2019). Building Information Modelling (BIM): an approach for reducing carbon emissions of buildings. In: *First International Conference on Carbon Neutral Built Environment (CNBT–I) "A Step Towards Sustainable Future"*. December 20-21, Karachi, Pakistan.

Rhodes, C. (2019). *Construction Industry: Statistics and policy.* London: House of Commons. Retrieved from https://commonslibrary.parliament.uk/research-briefings/sn01432/

Riazi, S. R. M., Zainuddin, M. F., Nawi, M. N. M., Musa, S. & Lee, A. (2020). A critical review of fragmentation issues in the construction industry. *Journal of Talent Development and Excellence, 12*(2), 1510-1521.

RICS. (2020). *The Future of BIM: Digital transformation in the UK in construction.* London: RICS.

Rios, F. C., Chong, W. K. & Grau, D. (2015). Design for Disassembly and Deconstruction - Challenges and Opportunities. *Procedia Engineering*, *118*, 1296-1304. doi: 10.1016/j.proeng.2015.08.485

Rogers, D. (2018). We have the technology: How digitalisation could solve UK construction's productivity problem, starting now. *Construction Research and Innovation*, *9*(3), 60-63. doi: 10.1080/20450249.2018.1513226

Salama, W. (2017). Design of concrete buildings for disassembly: An explorative review. *International Journal of Sustainable Built Environment, 6*(2), 617-635. doi: 10.1016/j.ijsbe.2017.03.005

Sarhan, S. & Fox, A. (2013). Barriers to Implementing Lean Construction in the UK Construction Industry. *The Built and Human Environment Review,* 6, 1-17.

Savills. (2020). *Spotlight: Modern Methods of Construction.* Retrieved from https://www.savills.co.uk/research_articles/229130/301059-0

Smiley, J. P. (2016). *Exploring Policy Discourses in the UK Construction Sector : An Interpretive Analysis. PhD thesis.* Loughborough: Loughborough University. Retrieved from https://dspace.lboro.ac.uk/2134/22913

Steer, R. (2015) Construction 2025: Where were you? *Building*. Retrieved from https://www.building.co.uk/comment/construction-2025-where-were-you/5075634.article

Steinhardt, D. A. & Manley, K. (2016). Adoption of prefabricated housing-the role of country context. *Sustainable Cities and Society, 22*, 126-135. doi: 10.1016/j.scs.2016.02.008

Symonds, B., Barnes, P., & Robinson, H. (2015). New Approaches and Rules of Measurement for Cost Estimating and Planning. In B. Robinson, H. Symonds, B. Gilbertson, & B. Ilozor (Eds.). *Design Economics for the Built Environment: Impact of Sustainability on Project Evaluation* (pp. 31-46). Oxford: Wiley-Blackwell.

Teng, Y., Li, K., Pan, W., & Ng, T. (2018). Reducing building life cycle carbon emissions through prefabrication: Evidence from and gaps in empirical studies. *Building and Environment, 132*, 125-136. doi:10.1016/j.buildenv.2018.01.026