South African Journal of Economic and Management Sciences
ISSN: (Online) 2222-3436, (Print) 1015-8812

The influence of artificial intelligence on the manufacturing industry in South Africa

Authors:
Manqoba L. Nzama[1]
Gloria A. Epizitone[1]
Smangele P. Moyane[1]
Ntando Nkomo[1]
Peggy P. Mthalane[1]

Affiliations:
[1]Department of Information and Corporate Management, Faculty of Accounting and Informatics, Durban University of Technology, Durban, South Africa

Corresponding author:
Manqoba Nzama,
mashiza91@yahoo.com

Dates:
Received: 29 Jan. 2024
Accepted: 25 June 2024
Published: 21 Aug. 2024

How to cite this article:
Nzama, M.L., Epizitone, G.A., Moyane, S.P., Nkomo, N. & Mthalane, P.P., 2024, 'The influence of artificial intelligence on the manufacturing industry in South Africa', *South African Journal of Economic and Management Sciences* 27(1), a5520. https://doi.org/10.4102/sajems.v27i1.5520

Background: The adoption of artificial intelligence (AI) in manufacturing has the potential to considerably improve productivity, efficiency and sustainability. Artificial intelligence aids with tasks such as data processing and process monitoring, process modelling and optimisation, live fault detection, and process quality assessment in manufacturing processes.

Aim: This study sought to obtain a full understanding of the influence of AI on the South African manufacturing industry by exploring how AI technology is impacting productivity, reshaping the workforce, affecting quality control practices and optimising supply chain management among other issues.

Setting: Data in this study were obtained from 23 qualitative research publications that address the influence of AI on the manufacturing industry in South Africa published on ScienceDirect, Scopus, Springer, Web of Science and Google Scholar.

Method: Multiple correspondence analysis was utilised to analyse associations among quality, productivity, supply chain and workforce transformation in the presence of AI in the South African manufacturing industry.

Results: The findings demonstrate a substantial association between the usage of AI and a range of performance measures, suggesting that those organisations embracing AI technology can benefit from greater productivity, quality control and supply chain management. Additionally, findings emphasised the necessity of workforce transformation because of AI adoption.

Conclusion: The adoption of AI technology positively influenced the South African manufacturing industry, contributing to increased productivity and quality, and optimising the supply chain.

Contribution: This study makes a valuable contribution to the existing body of knowledge as AI adoption in the manufacturing industry in developing countries is only emerging.

Keywords: artificial intelligence; AI; manufacturing; industry; South Africa.

Introduction

Background

The emergence of artificial intelligence (AI) technologies has compelled many industries including the manufacturing sector to adjust with regard to how they operate through what is termed Industry 4.0. In recent times, traditional industries have been compelled to integrate digital technologies as a tactic to sustain their competitiveness in the market environment. Since the early 1970s, these emerging industries have experienced significant trends aimed at increasing the competitiveness of their production processes (Aydalot & Keeble 2018). Various trends and advancements have emerged over the last few decades, transforming the manufacturing field and shaping how businesses operate today. These developments are being driven by technology, which according to Shai, Bakama and Sukdeo (2020) remains critical to the success of any business, regardless of its size or the products or services it offers. Furthermore, it plays a pivotal role in the success of any organisation by increasing efficiency and enabling innovation, regardless of industry or sector (Gaglio, Kraemer-Mbula & Lorenz 2022).

Technology as a crucial driver of rapid change has revolutionised the way modern business is carried out (Shai et al. 2020). Organisation for Economic Co-operation and Development (OECD 2021) recognises technology as a transformative force to economies worldwide reforming how businesses design, market and sell their goods and services; however, despite the decline in broadband costs and increased internet access via low-cost mobile phones in the mid-to-late 2000s, the digitisation gap between high-income and low-income countries remains wide.

This is evident in some developing countries such as South Africa, where the digital divide is widening (OECD 2021).

In the manufacturing sector, Industry 4.0 describes an ongoing process involving industrial automation, digitalisation, and vertical and horizontal value chain integration (Vaidya, Ambad & Bhosle 2018). In the manufacturing sector, the phenomenon aims to improve factory productivity (Maisiri & Van Dyk 2021), improve working conditions (Mayer & Oosthuizen 2021) and stimulate the development of new business models (Oztemel & Gursev 2020). In the assembly lines, technologies such as 3D printing have enabled rapid prototyping, reduced manufacturing lead times and facilitated product customisation (Enrique et al. 2022). Collaborative and autonomous robots improve production efficiency and safety by collaborating with human workers or performing tasks autonomously (Liu et al. 2022). In addition, big data analytics have enabled businesses to extract valuable insights from vast amounts of data, leading to better customer service and better decision-making (Müller, Kiel & Voigt 2018). Wearable devices such as smart glasses and smart gloves are being deployed to improve job performance and provide real-time guidance to workers (Todde et al. 2022). Industry 4.0 reduces unit costs and time (Büchi, Cugno & Castagnoli 2020). It also makes it easier to meet individual customer needs and enables product customisation (Calabrese et al. 2023).

Over the years, the world has evolved towards a digital future, with Industry 4.0 technologies being seen as the way forward (Oztemel & Gursev 2020). The AI is a crucial component of Industry 4.0, driving digital transformation across industries (Trong & Kim 2020). It is one of the most prominent technological concepts alongside blockchain, Internet of Things (IoT) and cloud computing (Reier Forradellas & Garay Gallastegui 2021). The AI can be characterised in its most basic form as a concept that relies on accessible data sets and computational techniques to address emerging problems (Du-Harpur et al. 2020). More explicitly, AI enables a system to understand external inputs accurately, extract key lessons from data and achieve specific goals through flexible changes based on those lessons (Ahmad et al. 2021).

The integration of AI technology is transforming the South African manufacturing industry (Magwentshu et al. 2019). In the aspects such as quality, productivity and workforce, both positive and negative influences have been felt. Although the influence of AI on manufacturing processes, productivity development, quality control and supply chain management (SCM) is recognised worldwide, there are still challenges such as resistance to change and workforce upscaling associated with their integration in the industry (Varshney 2020). Thus, there is a need for solutions that handle these challenges, especially in the South African manufacturing context where there is a lack of insight into its influence (Tjebane, Musonda & Okoro 2022). Furthermore, the limited information available on this topic hinders informed decision-making and strategic planning necessary for successful AI implementation in the industry (Phaladi et al. 2022). The aforementioned disposition on AI integration warrants the need for more studies that delve into exploring the terrain for the optimal benefit of the manufacturing industry. Thus, the rationale for this study enquiry sought to afford practical improvement that would enhance the integration of AI in the manufacturing industry and assist corporate policymaking (Epizitone 2022).

The objective of this study was to analyse the associations among quality, productivity, supply chain management and workforce transformation in the presence of AI in the South African manufacturing industry using multiple correspondence analysis (MCA):

The contributions of the study to the field of knowledge and application are threefold, as outlined below:

- A review of related studies to broadly determine the influence of AI on the manufacturing industry in South Africa.
- The extraction of useful qualitative data from the reviewed studies in a format suitable for statistical analysis.
- Application of MCA to uncover hidden associations in the obtained qualitative data to assist in improving the understanding of the influence of AI on the manufacturing industry in South Africa.

The rest of this chapter is concisely organised as follows. Section Literature review provides the literature review. Section 'Materials and methods' describes the research methods and materials. Section Result and discussion presents the results of the study and discussion. The article is then concluded in Section Five with a brief remark.

Literature review

For many years, automation has been utilised in manufacturing to increase output and efficiency. However, the advent of AI is dubbed to enable major advances in various areas and has made great strides in the manufacturing industry (Acemoglu & Restrepo 2018). From automating repetitive tasks to optimising industrial processes, AI is an important tool for companies that seek to improve efficiency and reduce costs (Sutherland 2020). The AI-powered automation presets repetitive tasks, freeing up employees to focus on more strategic, value-added activities (Mikalef & Gupta 2021). Using predictive analytics and machine learning algorithms, AI enables accurate demand forecasting, inventory management and production planning, resulting in less waste and better responsiveness to consumer demand (Praveen, Farnaz & Hatim 2019). In addition, AI-driven data analysis has provided key insights into consumer behaviour and market trends, enabling companies to adjust their products and marketing strategies to gain a competitive advantage (Accenture 2019). Moreover, AI has received significant interest from academics and practitioners over the past decade as the amount of data and information collected by organisations and put into their operations continue to grow (Mikalef & Gupta 2021).

Theoretical framework

This study aims to gain a thorough perspective for understanding the intricacies of AI implementation within manufacturing companies in South Africa. The study adopted the following three major theories:

The Technology Adoption Theory: This is based on the diffusion of innovation theory and the technology acceptance model (TAM), states that perceived utility, usability, organisational preparedness and outside influences all have an impact on how AI technologies are combined and integrated in manufacturing. (Khan et al. 2023). These conceptual frameworks provide insight into why and how organisations adopt new technologies, thereby enriching the understanding of the AI adoption process in South African manufacturing companies.

The Organisational Change Theory: Deriving from organisational transformation theories such as Lewin's change management model and Kotter's eight-step model, emphasises the need to monitor organisational changes that arise from integrating AI (Madanchian & Taherdoost 2022). It emphasises the importance of leadership, communication, employee engagement and educational efforts to facilitate a successful transition (Firican 2023). Understanding these theoretical principles can help decipher the implications of AI for workforce dynamics and organisational ethics in manufacturing facilities in South Africa.

The Resource-Based View (RBV): From the firm sets that organisations accomplish a competitive edge by capitalising on their particular assets and capabilities (Lubis 2022). When connected to the domain of AI adoption, this system proposes that activities prepared with developed innovative framework, gifted workforce and strong authoritative competencies are in a better position to exploit the points of interest of AI in terms of proficiency, quality assurance and administration of the supply chain (Abrokwah-Larbi & Awuku-Larbi 2023). This perspective can enhance our evaluation of the varying implications of AI adoption in the South African manufacturing industry.

Through the integration of viewpoints from these theoretical systems, this study develops a comprehensive understanding of the influence of AI on the manufacturing industry in South Africa. It observes the consequences of joining AI into operations on productivity and measures, the reshaping of workflow, the upgrade of supply chains and the utilisation of AI developments to accomplish a competitive edge.

Artificial intelligence on productivity

Artificial intelligence offers several potential avenues for improving business output. For example, machine learning advances have led to inexpensive and improved predictive analytics, complete mechanisation of tasks (such as self-driving cars) and new associations that can be combined to generate new ideas and know-how, improve access to knowledge and generate a number of innovations (Cockburn, Henderson & Stern 2019). At a conceptual level, AI, as demonstrated by Aghion, Antonin and Bunel (2019), is an additional input in a company's production process that can affect the performance of a company through its impact on the invention of new ideas and technologies and its usefulness in solving complex problems. According to Brynjolfsson, Rock and Syverson (2018), increasing investment in AI technology can improve productivity and other types of factor inputs, so AI ought to be considered as an added immaterial capital in the firm's manufacturing functions. Effective use of AI technology creates immaterial assets such as data sets, company-specific human skills and the establishment of new business processes. As with any new technology, the productivity benefits of AI technology may not be immediately apparent and may take time to materialise, as organisations will need to adopt a variety of processes and invest in complementary assets to realise the full productivity potential of AI (Brynjolfsson et al. 2018).

Artificial intelligence in the manufacturing industry has led to significant productivity gains in South Africa. Manufacturers have significantly improved operational efficiency, process optimisation and decision-making capabilities through AI technology (Gwagwa et al. 2020). Artificial intelligence-powered automation simplifies repetitive, mundane processes and releases employees to focus on more strategic, value-added activities (IT News Africa 2018). Artificial intelligence enables accurate demand forecasting, inventory management and production planning using predictive analytics and machine learning algorithms, reducing waste and improving consumer-demand responsiveness (TechInsight360 2019). In addition, data analytics based on AI have provided key insights into consumer behaviour and market trends, enabling companies to change their products and marketing strategies to gain a competitive edge (IT News Africa 2018).

Artificial intelligence on quality

Artificial intelligence has become a critical factor in the corporate world, revolutionising and streamlining how companies operate. Quality control is an important aspect that cannot be ignored if a company wants to be successful and meet customer requirements (Villalba-Diez et al. 2019). The AI provides assistance to companies to improve operational efficiency, accuracy, shorter cycle times and better operational compatibility (OECD 2021). The AI has the ability to transform South African manufacturing by improving quality at every stage of production (Ade-Ibijola & Okonkwo 2023). This enables manufacturers to reduce errors, improve productivity and deliver products that meet or exceed customer expectations.

Artificial intelligence has had a substantial impact on quality standards in the South African manufacturing industry. By using AI technology, manufacturers have improved quality control processes, optimised production flows and improved overall product quality (Gaglio et al. 2022). Automated AI-driven quality control systems, including computer vision and image recognition, enable real-time defect detection and prevention, minimising human error and ensuring only high-quality products will reach the market (Trakadas et al. 2020). The AI-driven predictive maintenance systems proactively address equipment failures, reduce downtime and ensure consistent production quality (Gaglio et al. 2022).

In addition, the ability of AI to analyse large data sets and optimise manufacturing processes has increased process efficiency and improved product quality and consistency (Gupta et al. 2022). Real-time quality monitoring by an AI-driven system ensures continuous tracking and intervention in the event of deviations, ensuring compliance with strict quality standards (Park, Phuong & Kumar 2019). In addition, AI-powered insights from customer feedback and market trends have made it easier to optimise product designs and create products that meet customer preferences and expectations (Rathore 2023). As such, the integration of AI into the South African manufacturing industry represents a major advance in improving quality throughout the production lifecycle, driving customer satisfaction and market competitiveness.

Artificial intelligence on supply chain management

Artificial intelligence has a major influence on SCM. The AI gives supply chain managers greater visibility across their systems, allowing them to make better decisions and provide better customer service (Toorajipour et al. 2021). Logistics companies can benefit from the ability of AI in monitoring and predicting package movements at scale (Rahimi & Alemtabriz 2022).

Artificial intelligence in the South African SCM has been integrated to transform operations with the AI technology's advanced capabilities. Recent studies have shown that introducing AI into SCM has significantly improved efficiency, accuracy and decision-making (Toorajipour et al. 2021). Furthermore, the data on the impact of AI on SCM in South Africa highlight important developments and opportunities (Gwagwa et al. 2020). For instance, Accenture reports that AI technology could boost productivity in the South African logistics sector by up to 30% (Accenture 2019:12). This increased productivity results in reduced costs, optimised processes and increased customer satisfaction.

South African manufacturers are leveraging AI-powered technology to streamline their supply chain operations. For example, by using predictive analytics and machine learning algorithms to forecast demand, manufacturers can better anticipate market needs, reduce inventory costs and minimise production waste (Mhlanga 2023). This enables manufacturers to achieve higher customer satisfaction while maximising operational efficiency.

Artificial intelligence on workforce transformation

The introduction of AI in South Africa is bringing about major changes in the workforce, reshaping the employment landscape and requiring a paradigm shift in workers' skills and capabilities (Magwentshu et al. 2019). Artificial intelligence integration has presented great challenges and abundant opportunities to the South African labour market. On the bright side, AI could automate repetitive tasks, allowing employees to focus on their more strategic and creative aspects and improving job satisfaction and overall productivity (IT News Africa 2018). In addition, AI-powered tools and systems have streamlined work processes, increasing efficiency and productivity across industries (IT News Africa 2018). In addition, the introduction of AI is creating new jobs in areas related to AI development, maintenance and data analysis, providing opportunities for South African workers in areas of high demand (Gwagwa et al. 2020). In addition, the rapid data analysis capabilities of AI enable employees to make more informed decisions, leading to better business and operational outcomes (Principa 2019). However, this change is not without its challenges as AI automates certain tasks, the risk of job losses increases.

Within the framework of AI adoption, it has become apparent that there is a need to manoeuvre around the issue of potential unemployment and provide retraining for new roles. Bridging the skills gap is paramount, workers need to acquire digital literacy, data analysis and critical thinking skills to adapt to the evolving labour market (Varshney 2020). Ensuring inclusiveness and reducing inequalities in AI integration are also pressing concerns, requiring equal access to AI education and technology to prevent certain people from being left behind (Gwagwa et al. 2020). As AI adoption increases in South Africa, ongoing reskilling and upskilling efforts will be essential to preparing the workforce to thrive in an AI-driven economy (Magwentshu et al. 2019). Furthermore, exploiting the potential of AI while adhering to ethical standards requires a careful reflection of ethical considerations around privacy, AI algorithm bias and impact of AI on human rights (Gwagwa et al. 2020). In summary, the adoption of AI in South Africa presents both unprecedented opportunities and daunting challenges, requiring a proactive and comprehensive approach to workforce transformation to realise the benefits of AI while mitigating its potential downsides.

Materials and methods

This article analysed the influence of AI on manufacturing in South Africa using MCA. Multiple correspondence analysis is a multivariate statistical technique for analysing categorical data to reveal patterns and correlations between variables (Epizitone & Olugbara 2020). The MCA method was selected to study the associations between AI and manufacturing priorities (workforce transformation, productivity, quality and supply chain management) to understand the influence of AI technology on these manufacturing priorities. The MCA is suitable as the article deals with multiple qualitative variables regarded as categorical and it reveals the association among qualitative variables (Olugbara, Letseka & Olugbara 2021).

Data collection

The data in this research article were obtained from qualitative research publications presented in reputable journals and conferences. Studies were selected for their relevance to the research topic and for the purpose of multiple correspondence analysis aimed at examining the impact of AI on multiple parts of an industrial process. The articles were found by searching keywords 'Impact of Artificial Intelligence on the South African Manufacturing Industry' on ScienceDirect, Scopus, Springer, Web of science, and Google Scholar. Search results were filtered by publication date and article type (review articles and research articles). Twenty-three articles covering AI and different aspects of the manufacturing process in South Africa (Supply chain management, productivity, workforce transformation, quality control) were selected. Only publication from the year 2018 to the year 2023 were included in the study to ensure that the study incorporates the most recent, relevant and highest quality research, reflecting the latest technological advances, industry practices and policy contexts. As depicted in Table 1, an inclusion and exclusion criterion was formulated as they are important when selecting data from publications as they help to define the quantity and quality of evidence relevant to the research question. It also helps to eliminate biases and confounding factors that could affect the outcome of a study.

The first search using the search parameters returned a total of 964 articles. After applying pre-defined selection criteria (inclusion criteria), 36 articles on Industry 4.0, automation, AI and manufacturing topics were registered. These 36 articles were screened to determine whether they were relevant to the research context. The quality of the research articles was then assessed and 23 articles were identified for MCA.

TABLE 1: Inclusion and exclusion criteria.

Inclusion criterion	Exclusion criterion
Papers must be from a year between 2018 to 2023 as the publication date for your research article.	Papers published before the year 2018 are excluded.
Only research papers written in the English language were selected.	Papers written in any other language are excluded.
Only journal articles, conference proceedings, and research articles should be selected.	Books, book chapters, dissertations, reviews, reports, or any other type of publication should be rejected.
Research must have been conducted in South Africa or affiliations must be South African.	Research conducted by non-South African researchers and that not conducted in South Africa are excluded.
Studies to be selected are studies that deal with the areas of industry 4.0, automation, artificial intelligence, and manufacturing industries.	Papers that do not focus on these areas or have different context or scope are excluded.

Data coding

The data were encoded to assist in categorising and organising the data during collection from peer-reviewed articles based on the variables of quality, productivity, workforce transformation and supply chain management. The data were classified into quality, productivity, workforce transformation and supply chain management. This is illustrated in Table 2.

As shown in Table 2, five aspects of each of our variables were listed, which will be identified from the research articles, which best describe each variable. When conducting secondary data analysis, researchers adhere to ethical principles and guidelines. These include demonstrating respect for the rights and intentions of the original authors, validating the origin of the data, avoiding plagiarism, guaranteeing the confidentiality and anonymity of the data and disclosing any limitations and biases present in the data.

Multiple correspondence analysis execution on statistical package for the social sciences

The Statistical Package for the Social Sciences (SPSS) programme is loaded with the data. By allocating numerical quantifications to each variable's categories, optimal scaling makes it possible to apply standard operating procedures to the quantified variables. Based on the procedure's optimising criterion, the ideal scale values are assigned. These scale values have metric features, in contrast to the original labels of nominal or ordinal variables. Maximising the spread of categories is the goal of optimal scaling. To get appropriate scaling in SPSS, the following actions were taken:

Select Dimension Reduction under Analyse, then Optimal Scaling, on the resulting window 'All variables, multiple nominal' was chosen. Single set was selected and a two-dimensional solution was chosen, and the analysis variables were chosen, consisting of Quality, Productivity, Workforce transformation and Supply chain. Under the options tab, Normalisation method was selected as 'Variable principal'. Under the Output tab, Discrimination measures, correlation of transformed variables tables were selected (Epizitone & Olugbara 2020).

The goal of MCA is to arrive at a solution where objects in the same category should be drawn closely together, and objects in different categories should be shown widely apart, according to the MCA solution. Every object is as near as

TABLE 2: Data coding of qualitative data extracted from the research articles.

Quality	Productivity	Workforce transformation	Supply chain management
Q1: Quality control processes	P1: Efficiency improvements	W1: Changes in job roles or responsibilities	S1: Inventory management optimization
Q2: Quality assurance measures	P2: Time savings in production processes	W2: Skills development or upskilling initiatives	S2: Demand forecasting accuracy
Q3: Defect detection and prevention	P3: Reduction in waste or rework	W3: Impacts on employment patterns	S3: Logistics and transportation efficiency
Q4: Customer satisfaction metrics	P4: Increase in output or production capacity	W4: Job displacement or creation	S4: Integration of AI in supply chain processes
Q5: Quality improvement initiatives	P5: Streamlining of operations	W5: Employee engagement and satisfaction	S5: Reduction in lead times or order fulfilment times

feasible to the relevant categories' category points. When variables group objects into the same subgroups within the same categories, they are said to be homogenous (Olugbara et al. 2021). In order to maximise the overall spread for a one-dimensional solution, MCA allocates appropriate scale values (category quantifications) to each category of each variable. Multiple correspondence analysis discovers a second set of quantifications for a two-dimensional solution that are unrelated to the original set. Additionally, MCA provides scores for things; the averages of the item scores within a category serve as the quantifications for that category (Epizitone & Olugbara 2020).

Results

This section provides an in-depth analysis of the influence of AI technology on the South African manufacturing sector's priorities, which are quality, productivity, SCM and workforce transformation, providing a presentation and interpretation of results obtained from MCA.

Extraction of qualitative data for statistical analysis

Table 3 shows the cross-tabulation of all the variables, where each cell represents the frequency of occurrence of the corresponding categories. For example, the cell (S01, Productivity) has a value P1, P3, indicating that Bhagwan and Evans's study reported efficiency improvements and reduction in waste or rework as the impact of AI on productivity. The cell (S18, Quality) has Q1, Q2, Q5, indicating that Sutherland' study shows that AI impacts quality through quality control processes, quality assurance measures and quality improvement initiatives. The cell (S08, SCM) has nothing in it, indicating that Matenga Murena and Mpofu's (2020) study did not report any impact of AI on supply chain management. The cell (S05, Method) has a value of case study, indicating that Daniyar et al.'s study used case study as the research method.

The extracted data were then converted into quantitative data on a scale of 0 (absolutely no impact) to 5 (very high impact), for example, study ID S03; productivity is 2 (low impact), and quantity is 0 (absolutely no impact), SCM is 1 (very low impact) and workforce transformation is 3 (moderate impact).

Data analysis

The data were analysed using MCA. The goal is to minimise the dimensionality of the data by representing rows and columns as points in low-dimensional Euclidean space, with distances reflecting their relatedness. Multiple correspondence analysis can be seen as a generalisation of principal component analysis (PCA) for categorical data or as an extension of correspondence analysis (CA) for more than two categorical variables (Olugbara et al. 2021). Data from the articles is organised into a tabular format and converted into an indicator matrix or Burt table, enabling the application of MCA on the manipulated dataset. An indicator matrix is a binary matrix where each row represents a person, and each column represents a variable category. The Burt table is a symmetric matrix containing all the two-way crosstabs of the variables. The MCA can extract the principal axes that explain the greatest variation in your data and display them graphically as maps of people and categories. These maps can show underlying data structures and patterns, such as groupings of people with similar profiles or correlations between variables in different categories.

Multiple correspondence analysis

Multiple correspondence analysis was conducted using SPSS in order to gain insights into the impact of AI technologies on quality, productivity, workforce transformation and supply chain management practices in the manufacturing sector in South Africa. Based on the MCA study, a two-dimensional MCA solution was determined to be the most appropriate. The first and second dimensions are eigenvalues of 2.773 and 2.619, inertia of 0.693 and 0.655, and Cronbach's alpha of 0.853 and 0.824, respectively (Table 4). A commonly accepted lower bound for Cronbach's alpha value is 0.70, although exploratory studies allow lower values. In this case, both alpha values are above the threshold of 0.70 (Hussey et al. 2023).

TABLE 3: Burt table of codified extracted data from research articles.

SID	Author	Year	Productivity	Quality	Supply chain management	Workforce transformation	Method
S12	Olaitan, Issah and Wayi	2021	P1, P2, P4, P5	Q1, Q5	S1, S3, S5	W2, W4, W5	Literature review
S13	Maisiri and van Dyk	2021	P1, P5	-	-	W1, W2, W4, W5	Qualitative descriptive research
S14	Anakpo and Kollamparambil	2022	P1, P4	-	-	W1, W4, W5	Panel data analysis
S15	Onososen and Musonda	2022	P1, P4	Q1, Q2, Q3	-	W1, W3, W5	ISM
S16	Mfanafuthi, Nyawo and Mashau	2019	P1, P4	-	S4	W3, W4, W5	Exploratory study
S17	Makaula, Munsamy and Telukdarie	2021	P1, P3, P4, P5	Q3, Q5	S1, S4	W2, W4	Sequential literature review
S18	Sutherland	2020	P1, P2, P3, P4, P5	Q1, Q2, Q5	S1, S3, S5	W1, W2, W3, W4	Literature review
S19	Seseni and Mbohwa	2018	P4	Q4, Q5	-	W2, W3, W5	Case study
S20	Rapanyane and Sethole	2020	P3, P4	Q3	-	W2, W4	Case study
S21	Shai, Bakama and Sukdeo	2020	P1, P4	Q4	S3, S5	W1, W2, W3, W4, W5	Quantitative study
S22	Serumaga-Zake and Van der Poll	2021	P4	Q4, Q5	S3, S5	W2, W4	Mixed methods
S23	Gaglio, Kraemer-Mbula and Lorenz	2022	P4	Q5	-	W2	CDM

SID, study identity; VIM, visual inspection and monitoring; ISM, interpretive structural modelling; CDM, crepon-duguet-mairesse; SEM, structured equation modelling; PLS-SEM, partial least square structural equation modelling.

We employ a heterogeneous configuration to obtain a two-dimensional image of our data, our methodological approaches were performed with this limitation in mind, discrimination measures (Table 5 and Figure 1) display that all the values obtained from dimension one are above the value of ≥ 0.5 (Table 5), and in dimension two only two values were below the value 0.5 that is quality with a distinction of 0.416 and 0.403 (workforce transformation). The most discriminant variables for dimension one hierarchically were workforce transformation (0.848), quality (0.716) and productivity 0.689, with supply chain being the least discriminant at 0.520. The most discriminant variables for dimension two hierarchically were productivity (0.975) and supply chain (0.825) (Table 5). The most discriminant variables in both dimensions are productivity and supply chain management.

In dimension one (Table 6), correlations of transformed variables were as follows: quality is correlated significantly with productivity ($r = 0.430$, $p < 0.001$); quality is correlated significantly with workforce transformation ($r = 0.586$, $p < 0.001$); quality is correlated with supply chain management ($r = 0.317$, $p < 0.001$) and productivity is correlated with workforce transformation ($r = 0.380$, $p < 0.001$). Productivity is correlated significantly with SCM ($r = 0.488$, $p < 0.001$). Workforce transformation has a low correlation ($r = 0.289$, $p < 0.001$) with SCM.

Eigenvalues in a PCA context serve as a representation of the variability present within the data along the principal components. They play a crucial role in indicating the quantity of information that each principal component encapsulates (Karakuzulu et al. 2023). Larger eigenvalues are directly correlated with principal components that hold more significance in the analysis. Furthermore, high eigenvalues are indicative of the fact that the particular principal component is capable of explaining a substantial proportion of the overall data variance (Bao et al. 2022). These eigenvalues, being a fundamental aspect of PCA, hold a strong association with the various dimensions or components within the analysis.

In the realm of PCA, Dimension 1 boasts an eigenvalue of 2.250, which stands out as the dimension that elucidates the highest amount of variance within the data set. On the other hand, the subsequent dimensions possess comparatively lower eigenvalues, such as Dimension 2 with an eigenvalue of 0.844, Dimension 3 with a value of 0.497 and Dimension 4 with a value of 0.409. These eigenvalues serve as crucial indicators shedding light on the extent of variance that each dimension is able to capture. It is noteworthy that higher eigenvalues are indicative of components that hold more significance in the analysis. For instance, in the context of this research article, Dimension 1, focusing on AI adoption, is likely to have a substantial impact on the mentioned variables, whereas the influence of the other dimensions is relatively minor.

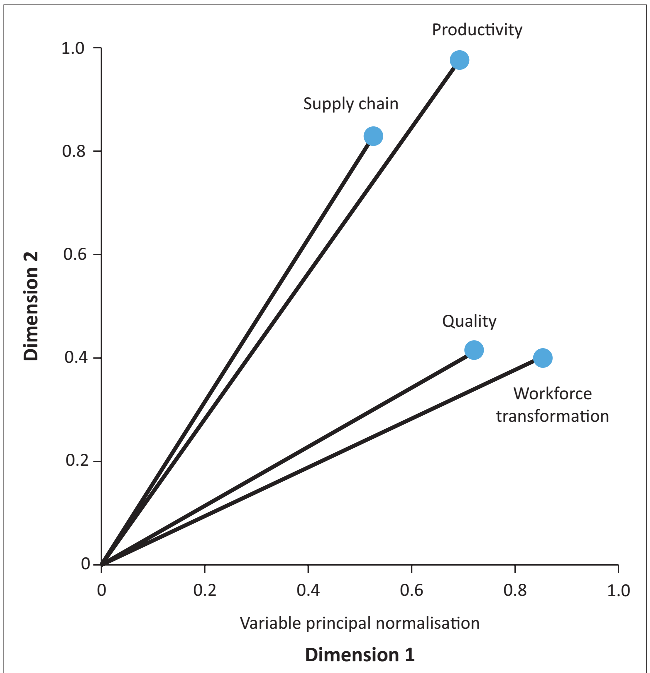

FIGURE 1: Multiple correspondence analysis discrimination measures.

Discussion

The analyses of the study provided some valuable understandings of the influence of AI technologies in the manufacturing sector priorities in South Africa. Artificial intelligence technology has brought about major changes in several areas of the manufacturing industry. This includes efficiency in inventory management, demand forecasting, logistics and transportation, relocation and job creation.

TABLE 4: Model summary of multiple correspondence analysis feasible dimensions and inertia.

Dimension	Cronbach's alpha	Variance accounted for	
		Total (eigenvalue)	Inertia
1	0.853	2.773	0.693
2	0.824	2.619	0.655
Total	-	5.392	1.348
Mean	0.839†	2.696	0.674

†, Mean Cronbach's alpha is based on the mean eigenvalue.

TABLE 5: Multiple correspondence analysis dimensions discrimination measures.

Eigenvalues	Dimension		Mean
	1	2	
Quality	0.716	0.416	0.566
Productivity	0.689	0.975	0.832
Workforce transformation	0.848	0.403	0.625
Supply chain	0.520	0.825	0.672
Active total	2.773	2.619	2.696

TABLE 6: Correlation of transformed variables.

Dimension: 1	Quality	Productivity	Workforce tranformation	Supply chain
Quality†	1.000	0.430	0.586	0.317
Productivity†	0.430	1.000	0.380	0.488
Workforce tranformation†	0.586	0.380	1.000	0.289
Supply chain†	0.317	0.488	0.289	1.000
Dimension†	1.000	2.000	3.000	4.000
Eigenvalue†	2.250	0.844	0.497	0.409

†, Missing values were imputed with the mode of the quantified variable.

In Table 6, correlations showed the relationships between many aspects of the manufacturing sector. Quality and productivity are to a large extent related, suggesting that both are necessary to ensure improved product quality. Achieving high quality in production can improve productivity, impacting a company's profitability and competitiveness. Quality and productivity are crucial in manufacturing sectors such as automotive, as conflicts among the two key concepts can lead to costs such as product recalls, affecting stakeholders and customer satisfaction (Makhanya, Nel & Pretorius 2022). This finding is supported by Phaladi et al. (2022), who found that the interconnected factors of quality and productivity are paramount for the enhancement of product quality when utilising AI technology in South Africa. Quality is correlated significantly with supply chain management so that consumer satisfaction indicators are highly related to logistics and transportation efficiency, highlighting the importance of efficient transportation for customer satisfaction. This finding is evident from the small to medium enterprises in South Africa, which are under pressure to enhance customer satisfaction by means of high-quality products and services, which is enabled by the implementation of efficient supply chain management techniques (Omoruyi & Mafini 2016).

Quality is correlated significantly with workforce transformation; therefore, quality is positively associated with work streamlining programmes and skill development or skill-up programmes, indicating that these factors contribute to quality improvement. This finding is a mirror representation of quality correlation with workforce in the South African manufacturing industry (Makhanya et al. 2022). Moreover, reducing waste and rework is highly related to skill development and qualification activities, meaning that skill enhancement can lead to waste reduction in the South African manufacturing sector (Saba & Ngepah 2024).

Productivity is correlated with workforce transformation, as changes in job roles and responsibilities are associated with increased efficiency and impact employment patterns, indicating that changes in job roles can affect both efficiency and employment. In South Africa, this association significantly affects the manufacturing sector in the presence of AI (Bhagwan & Evens 2023). Productivity is correlated significantly with supply chain management such that optimising inventory management is associated with reducing waste and rework, streamlining operations, personnel training and upskilling programmes, and streamlining logistics and transportation, thereby highlighting the importance of these factors to effective inventory management. This finding is aligned with Taljaard and Gerber (2022), who alluded the importance of implementing upskilling programmes to provide the necessary training for personnel involved in AI-integrated supply chains in South Africa.

The minimal association between supply chain and workforce transformation shows that workforce transformation may not have as big of an impact on supply chain management as previously thought. Overall, the results indicate that the variables related to the impact of AI on the South African industry are closely associated with the transformation taking place in the manufacturing sector (Mhlanga 2023). Quality, productivity, workforce transformation and supply chain management are all interrelated and influence each other. This connectivity highlights the complexity of the impact of AI on the manufacturing industry in South Africa (Ngepah, Saba & Kajewole 2024).

Two dimensions were uncovered from the MCA as displayed in Figure 1 and were constructed within the manufacturing sector to be:

- **Workforce Quality Transformation:** The employment of AI systems enables the streamlining of operations, which in turn enables the discovery and pinpointing of faults in goods or operations, thereby diminishing mistakes and improving client contentment. Artificial intelligence possesses the capability to enable workers to focus on more vital and pioneering assignments, thereby boosting their expertise and career advancement.
- **Supply Chain Productivity Management:** The AI-driven systems are capable of examining extensive amounts of data to detect patterns and trends, facilitating more precise demand prediction and inventory enhancement. This aids manufacturers in South Africa in mitigating stock shortages, reducing surplus inventory and enhancing the efficiency of the entire supply chain. These advancements have led to enhanced efficiency, decreased waste and rework, and heightened production output and capacity, thereby contributing to a general boost in productivity. The adoption of AI technologies has empowered improved decision-making, elevated transparency and heightened efficiency in overseeing the supply chain, resulting in an overall enhancement in supply chain performance and customer contentment.

The outcomes of this article pave a way for further investigation through a quantitative lens, which may systematically explore the determinants of AI adoption within South African manufacturing firms. Through the collection of survey data from various stakeholders and the application of statistical analysis methods, researchers can objectively evaluate the factors influencing decisions regarding AI adoption and measure their effects on productivity, quality control, workforce dynamics and supply chain management. Furthermore, they can evaluate the strength and direction of relationships, workforce quality transformation and supply chain productivity management.

Conclusion

The impact of AI is clear on the manufacturing industry's quality and productivity and can be seen within the optimised supply chains and the changing workforce. The utilisation of AI has enabled advanced quality control processes, error detection and prevention, and quality improvement activities. This has then resulted in the reduction of scrap and rework, improved efficiency and increased production capacity. The integration of AI into supply chain processes has also improved inventory management, demand forecasting accuracy, and logistics and transportation efficiency. Artificial intelligence-powered solutions have improved decision-making, increased transparency and increased supply chain efficiency. Therefore, the adoption of AI technology in the South African manufacturing industry has yielded positive results. The results of MCA provided insight into the relationships between quality, productivity, workforce transformation and supply chain management; however, more research is required to fully capture the dissimilarities of these relationships in particular data sets. As a result, future research that dives into quantitatively assessing AI in the manufacturing sector is needed to empirically validate the study's findings.

Acknowledgements

The authors would like to express profound gratitude to Dr Murimo Bethel Mutanga for their generous dedication of time and expertise in conducting the review and providing invaluable insights on this research. Dr Mutanga provided constructive criticism and valuable counsel that substantially elevated the calibre of the material.

Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

M.L.N. wrote the manuscript with support from G.A.E. and S.P.M. Both, N.N. and P.P.M., helped to supervise the project.

Ethical considerations

This article followed all ethical standards for research without direct contact with human or animal subjects.

Funding information

This article received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

Data availability

The data that support the findings of this study are available on request from M.N., the corresponding author.

Disclaimer

The views and opinions expressed in this article are those of the authors and are the product of professional research. It does not necessarily reflect the official policy or position of any affiliated institution, funder, agency or that of the publisher. The authors are responsible for this article's results, findings and content.

References

Abrokwah-Larbi, K. & Awuku-Larbi, Y., 2023, 'The impact of artificial intelligence in marketing on the performance of business organizations: Evidence from SMEs in an emerging economy', *Journal of Entrepreneurship in Emerging Economies* 16(4), 1090–1117. https://doi.org/10.1108/JEEE-07-2022-0207

Accenture, 2019, *Artificial intelligence: The future of growth in South Africa*, viewed 19 June 2023, from https://www.accenture.com/_acnmedia/PDF-106/Accenture-AI-Future-of-Growth-in-South-Africa.pdf.

Acemoglu, D. & Restrepo, P., 2018, 'Artificial intelligence, automation, and work', in A. Agrawal, J. Gans & A. Goldfarb (eds.), *The economics of artificial intelligence: An agenda*, pp. 197–236, University of Chicago Press, Chicago, IL.

Ade-Ibijola, A. & Okonkwo, C., 2023, 'Artificial intelligence in Africa: Emerging challenges', in J.D. Kabutha, B.O. Okanda & K. Nyamai (eds.), *Responsible AI in Africa: Challenges and opportunities*, pp. 101–117, Springer International Publishing Cham, Cham.

Aghion, P., Antonin, C. & Bunel, S., 2019, 'Artificial intelligence, growth and employment: The role of policy', *Economie et Statistique/Economics and Statistics* 510-511-512, 150–164. https://doi.org/10.24187/ecostat.2019.510t.1994

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y. & Chen, H., 2021, 'Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities', *Journal of Cleaner Production* 289, 125834. https://doi.org/10.1016/j.jclepro.2021.125834

Aydalot, P. & Keeble, D. (eds.), 2018, *High technology industry and innovative environments: The European experience*, Routledge, London.

Bao, Z., Ding, X., Wang, J. & Wang, K., 2022, 'Statistical inference for principal components of spiked covariance matrices', *The Annals of Statistics* 50(2), 1144–1169. https://doi.org/10.1214/21-AOS2143

Bhagwan, N. & Evans, M., 2023, 'A review of industry 4.0 technologies used in the production of energy in China, Germany, and South Africa', *Renewable and Sustainable Energy Reviews* 173, 113075. https://doi.org/10.1016/j.rser.2022.113075

Brynjolfsson, E., Rock, D. & Syverson, C., 2018, 'Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics', in A. Agrawal, J. Gans & A. Goldfarb (eds.), *The economics of artificial intelligence: An agenda*, pp. 23–57, University of Chicago Press, Chicago, IL.

Büchi, G., Cugno, M. & Castagnoli, R., 2020, 'Smart factory performance and industry 4.0', *Technological Forecasting and Social Change* 150, 119790. https://doi.org/10.1016/j.techfore.2019.119790

Calabrese, A., Costa, R., Tiburzi, L. & Brem, A., 2023, 'Merging two revolutions: A human-artificial intelligence method to study how sustainability and Industry 4.0 are intertwined', *Technological Forecasting and Social Change* 188, 122265. https://doi.org/10.1016/j.techfore.2022.122265

Cockburn, I.M., Henderson, R. & Stern, S., 2019, '4. The impact of artificial intelligence on innovation: An exploratory analysis', in A. Agrawal, J. Gans & A. Goldfarb (eds.), *The economics of artificial intelligence*, pp. 115–148, University of Chicago Press, Chicago, IL.

Du-Harpur, X., Watt, F., Luscombe, N. & Lynch, M., 2020, 'What is AI? Applications of artificial intelligence to dermatology', *British Journal of Dermatology* 183(3), 423–430. https://doi.org/10.1111/bjd.18880

Enrique, D.V., Marcon, É., Charrua-Santos, F. & Frank, A.G., 2022, 'Industry 4.0 enabling manufacturing flexibility: Technology contributions to individual resource and shop floor flexibility', *Journal of Manufacturing Technology Management* 33(5), 853–875. https://doi.org/10.1108/JMTM-08-2021-0312

Epizitone, A., 2022, 'The simulation of Big Data to revolutionize the effectiveness of corporate policy', *Interdisciplinary Journal of Economics and Business Law* 11(4), 86–104.

Epizitone, A. & Olugbara, O.O., 2020, 'Multiple correspondence analysis of critical success factors for enterprise resource planning system implementation', *Journal of Management Information and Decision Sciences* 23(3), 175–186.

Firican D., 2023, 'Change management in the context of digital transformation: A comparison between a theoretical model and successful approaches in organizations', in R. Pamfilie, V. Dinu, C. Vasiliu, D. Pleșea & L. Tăchiciu (eds.), *9th BASIQ International Conference on New Trends in Sustainable Business and Consumption, Constanța, Romania*, ASE, Bucharest, June 08-10, 2023, pp. 472–479.

Gaglio, C., Kraemer-Mbula, E. & Lorenz, E., 2022, 'The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises', *Technological Forecasting and Social Change* 182, 121785. https://doi.org/10.1016/j.techfore.2022.121785

Gupta, S., Modgil, S., Kumar, A., Sivarajah, U. & Irani, Z., 2022, 'Artificial intelligence and cloud-based collaborative platforms for managing disaster, extreme weather and emergency operations', *International Journal of Production Economics* 254, 108642. https://doi.org/10.1016/j.ijpe.2022.108642

Gwagwa, A., Kraemer-Mbula, E., Rizk, N., Rutenberg, I. & De Beer, J., 2020, 'Artificial Intelligence (AI) deployments in Africa: Benefits, challenges and policy dimensions', *The African Journal of Information and Communication* 26, 1–28. https://doi.org/10.23962/10539/30361

Hussey, I., Alsalti, T., Bosco, F., Elson, M. & Arslan, R.C., 2023, *An aberrant abundance of Cronbach's alpha values at. 70*, Center for Open Science, Charlottesville, VA.

IT News Africa, 2018, *How artificial intelligence will impact the South African workforce*, viewed 02 July 2023, from https://www.itnewsafrica.com/2018/03/how-artificial-intelligence-will-impact-the-south-african-workforce/.

Karakuzulu, C., Gumus, İ.H., Guldal, S. & Yavas, M., 2023, 'Determining the number of principal components with Schur's theorem in principal component analysis', *Bitlis Eren Üniversitesi Fen Bilimleri Dergisi* 12(2), 299–306. https://doi.org/10.17798/bitlisfen.1144360

Khan, A.N., Jabeen, F., Mehmood, K., Soomro, M.A. & Bresciani, S., 2023, 'Paving the way for technological innovation through adoption of artificial intelligence in conservative industries', *Journal of Business Research* 165, 114019. https://doi.org/10.1016/j.jbusres.2023.114019

Liu, L., Guo, F., Zou, Z. & Duffy, V.G., 2022, 'Application, development and future opportunities of collaborative robots (cobots) in manufacturing: A literature review', *International Journal of Human–Computer Interaction* 40(4), 915–932. https://doi.org/10.1080/10447318.2022.2041907

Lubis, N.W., 2022, 'Resource based view (RBV) in improving company strategic capacity', *Research Horizon* 2(6), 587–596. https://doi.org/10.54518/rh.2.6.2022.587-596

Madanchian, M. & Taherdoost, H., 2022, 'The impact of digital transformation development on organizational change', in H. Taherdoost (ed.), *Driving transformative change in E-Business through applied intelligence and emerging technologies*, pp. 1–24, IGI Global, Hershey, PA.

Magwentshu, N., Rajagopaul, A., Chui, M. & Singh, A., 2019, *The future of work in South Africa digitisation, productivity and job creation*, Mckinsey & Company, Johannesburg, South Africa.

Maisiri, W. & Van Dyk, L., 2021, 'Industry 4.0 skills: A perspective of the South African manufacturing industry', *SA Journal of Human Resource Management* 19, 1416. https://doi.org/10.4102/sajhrm.v19i0.1416

Makhanya, B.B., Nel, H. & Pretorius, J.H.C., 2022, 'Factors affecting the cost of poor quality management in the South African manufacturing sector: Structural equation modelling', *International Journal of Learning and Change* 14(5–6), 600–624. https://doi.org/10.1504/IJLC.2022.126423

Matenga, A., Murena, E. & Mpofu, K., 2020, 'Application of artificial intelligence to an electrical rewinding factory shop', *Procedia CIRP* 91, 735–740. https://doi.org/10.1016/j.procir.2020.04.135

Mayer, C.-H. & Oosthuizen, R.M., 2021, 'Positive intercultural management in a diverse and global workplace: A four-stage I4. 0 management model', in M. Chavan & L. Taksa (eds.), *Intercultural management in practice: Learning to lead diverse global organizations*, pp. 157–171, Emerald Publishing Limited, Bingley.

Mhlanga, D., 2023, 'Artificial intelligence and machine learning for energy consumption and production in emerging markets: A review', *Energies* 16(2), 745. https://doi.org/10.3390/en16020745

Mikalef, P. & Gupta, M., 2021, 'Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance', *Information & Management* 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Müller, J.M., Kiel, D. & Voigt, K.-I., 2018, ‚What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability', *Sustainability* 10(1), 247. https://doi.org/10.3390/su10010247

Ngepah, N., Saba, C.S. & Kajewole, D.O., 2024, 'The impact of industry 4.0 on South Africa's manufacturing sector', *Journal of Open Innovation: Technology, Market, and Complexity* 10(1), 100226. https://doi.org/10.1016/j.joitmc.2024.100226

OECD, 2021, *Artificial intelligence, machine learning and Big Data in finance: Opportunities, challenges, and implications for policy makers*, viewed 06 June 2023, from https://www.oecd.org/finance/artificial-intelligence-machine-learningbig-data-in-finance.htm.

Olugbara, C.T., Letseka, M. & Olugbara, O.O., 2021, 'Multiple correspondence analysis of factors influencing student acceptance of massive open online courses', *Sustainability* 13(23), 13451. https://doi.org/10.3390/su132313451

Omoruyi, O. & Mafini, C., 2016, 'Supply chain management and customer satisfaction in small to medium enterprises', *Studia Universitatis Babes-Bolyai Oeconomica* 61(3), 43–58. https://doi.org/10.1515/subboec-2016-0004

Oztemel, E. & Gursev, S., 2020, 'Literature review of industry 4.0 and related technologies', *Journal of Intelligent Manufacturing* 31, 127–182. https://doi.org/10.1007/s10845-018-1433-8

Park, H.S., Phuong, D.X. & Kumar, S., 2019, 'AI based injection molding process for consistent product quality', *Procedia Manufacturing* 28, 102–106. https://doi.org/10.1016/j.promfg.2018.12.017

Phaladi, M.G., Mashwama, X.N., Thwala, W.D. & Aigbavboa, C.O., 2022, 'A theoretical assessment on the implementation of Artificial Intelligence (AI) for an improved learning curve on construction in South Africa', *IOP Conference Series: Materials Science and Engineering* 1218(1), 012003. https://doi.org/10.1088/1757-899X/1218/1/012003

Praveen, U., Farnaz, G. & Hatim, G., 2019, 'Inventory management and cost reduction of supply chain processes using AI based time-series forecasting and ANN modeling', *Procedia Manufacturing* 38, 256–263. https://doi.org/10.1016/j.promfg.2020.01.034

Principa, 2019, *AI and the South African workforce: A balancing act*, viewed 06 June 2023, from https://principa.co.za/finding-the-balance-between-ai-and-the-south-african-workforce/

Rahimi, A. & Alemtabriz, A., 2022, 'Providing a model of LeAgile hybrid paradigm practices and its impact on supply chain performance', *International Journal of Lean Six Sigma* 13(6), 1308–1345. https://doi.org/10.1108/IJLSS-04-2021-0073

Rathore, B., 2023, 'Integration of Artificial Intelligence& it's practices in apparel industry', *International Journal of New Media Studies: International Peer Reviewed Scholarly Indexed Journal* 10(1), 25–37. https://doi.org/10.58972/eiprmj.v10i1y23.40

Reier Forradellas, R.F. & Garay Gallastegui, L.M., 2021, 'Digital transformation and artificial intelligence applied to business: Legal regulations, economic impact and perspective', *Laws* 10(3), 70. https://doi.org/10.3390/laws10030070

Saba, C.S. & Ngepah, N., 2024, 'The impact of artificial intelligence (AI) on employment and economic growth in BRICS: Does the moderating role of governance Matter?', *Research in Globalization* 8, 100213. https://doi.org/10.1016/j.resglo.2024.100213

Shai, I., Bakama, E.M. & Sukdeo, N., 2020, 'The impact of smart manufacturing approach on the South African manufacturing industry', in *Proceedings of 2020 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*, August 6–7, 2020, pp. 1–5.

Sutherland, E., 2020, 'The fourth industrial revolution–the case of South Africa', *Politikon* 47(2), 233–252. https://doi.org/10.1080/02589346.2019.1696003

Taljaard, T. & Gerber, A., 2022, 'The preparation of South African companies for the impact of artificial intelligence', in *Southern African conference for Artificial Intelligence Research*, pp. 348–367, Springer Nature Switzerland, Cham.

TechInsight360, 2019, 'South Africa Artificial Intelligence (AI) in manufacturing industry report 2019–2025', *Market Research.com*, viewed 04 July 2023, from https://www.marketresearch.com/TechInsight360-v4166/South-Africa-Artificial-Intelligence-AI-12296144/.

Tjebane, M.M., Musonda, I. & Okoro, C., 2022, 'Organisational factors of artificial intelligence adoption in the South African construction industry', *Frontiers in Built Environment* 8, 823998. https://doi.org/10.3389/fbuil.2022.823998

Todde, G., Sara, G., Pinna, D., Artizzu, V., Spano, L.D. & Caria, M., 2022, 'Smart glove: Development and testing of a wearable RFID reader connected to mixed reality smart glasses', in M. di Prisco, S.-H. Chen, I. Vayas, S.K. Shukla, A. Sharma, N. Kumar, et al. (eds.), *Proceedings of Conference of the Italian Society of Agricultural Engineering*, pp. 949–956, Springer, Cham.

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P. & Fischl, M., 2021, 'Artificial intelligence in supply chain management: A systematic literature review', *Journal of Business Research* 122, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009

Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A.P. et al., 2020, 'An artificial intelligence-based collaboration approach in industrial IoT manufacturing: Key concepts, architectural extensions and potential applications', *Sensors* 20(19), 5480. https://doi.org/10.3390/s20195480

Trong, H.B. & Kim, U.B.T., 2020, 'Application of information and technology in supply chain management: Case study of artificial intelligence – A mini review', *European Journal of Engineering and Technology Research* 5(12), 19–23. https://doi.org/10.24018/ejeng.2020.5.12.2254

Vaidya, S., Ambad, P. & Bhosle, S., 2018, 'Industry 4.0 – A glimpse', *Procedia Manufacturing* 20, 233–238. https://doi.org/10.1016/j.promfg.2018.02.034

Varshney, D., 2020, 'Digital transformation and creation of an agile workforce: Exploring company initiatives and employee attitudes', in M.A. Turkmenoglu and B. Cicek (eds.), *Contemporary global issues in human resource management*, pp. 89–105, Emerald Publishing Limited, Leeds.

Villalba-Diez, J., Schmidt, D., Gevers, R., Ordieres-Meré, J., Buchwitz, M. & Wellbrock, W., 2019, 'Deep learning for industrial computer vision quality control in the printing industry 4.0', *Sensors* 19(18), 3987. https://doi.org/10.3390/s19183987