The impact of digital voice of customer and product lifecycle management on Quality 4.0: moderating role of AI in SMEs

Received 2 December 2024
Revised 12 March 2025
23 March 2025
Accepted 30 March 2025

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Abstract

Purpose – Advanced technologies such as artificial intelligence (AI) and Quality 4.0 (Q4.0) are crucial for the survival of today's industrial enterprises. In this context, this study reveals the impact of digital voice of the customer (DVoC) and product lifecycle management (PLM) on Q4.0. Furthermore, this study explores the moderating role of AI in enhancing the relationship between DVoC and PLM and Q4.0, which is an important gap in the literature specific to Asian countries and is based on limited empirical evidence.

Design/methodology/approach – This study focuses on small and medium-sized enterprises (SMEs) in the manufacturing sectors of Asia (China, Pakistan and India). Within the scope of this study, data were obtained from 334 SMEs operating in the manufacturing sector in Asia. The data were analyzed using partial least squares structural equation modeling.

Findings – According to the results, the direct impact of DVoC and PLM on Q4.0 is confirmed. The study also revealed that AI enhanced the impact of DVoC and PLM on Q4.0. Another important finding is that AI improves Q4.0-related processes.

Originality/value – This study shows how AI moderates the link between DVoC, PLM and Q4.0. It also identifies important applications for using DVoC and reveals new possibilities for industries to adopt AI to enhance Q4.0 and PLM techniques. These findings have important implications for marketers, practitioners, the manufacturing sector and policymakers.

Keywords Artificial intelligence, Product lifecycle management, Quality 4.0, Manufacturing industry, Digital voice of customer

Paper type Research paper

Erratum: It has come to the attention of the publisher that the article: Armutcu, B., Majeed, M.U., Hussain, Z. and Aslam, S. (2025), "The impact of digital voice of customer and product lifecycle management on Quality 4.0: moderating role of AI in SMEs", *Journal of Manufacturing Technology Management*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JMTM-12-2024-0660 published incorrect affiliations for 2 authors. Muhammad Ussama Majeed's affiliation has been updated from 'Department of Management Sciences, National University of Modern Languages, Islamabad, Pakistan' to 'Department of Management Sciences, National University of Modern Languages, Lahore Campus, Lahore, Pakistan' and Sumaira Aslam's affiliation has been updated from 'Department of Commerce and Accountancy, University of Management and Technology, Lahore, Pakistan' to 'School of Commerce and Accountancy, University of Management and Technology, Lahore, Pakistan'. The publisher sincerely apologises for this error and for any inconvenience caused.

Journal of Manufacturing Technology Management
Vol. 36 No. 6, 2025
pp. 1265-1283

e-ISSN: 1758-7786
p-ISSN: 1741-038X
DOI 10.1108/JMTM-12-2024-0660

Quick value overview

Interesting because – While previous research has primarily focused on manufacturing productivity or been limited to developed economies, this study addresses an important gap by focusing on rapidly industrializing Asian small and medium-sized enterprises (SMEs), where digital transformation and artificial intelligence (AI) integration are particularly challenging. Furthermore, this study uniquely explores how AI technologies, including cognitive analytics and automated decision-making, can enhance digital voice of the customer (DVoC) and product lifecycle management (PLM) practices to promote the adoption of Quality 4.0 (Q4.0), an area that has not been extensively addressed in the existing literature.

Theoretical value – This study theoretically demonstrates that AI plays a moderating role in the relationship between DVoC, PLM and Q4.0. Highlighting the impact of AI on customer-centric quality improvement and adaptive quality management, this study foregrounds the transformative role of AI in the adoption of quality management systems, particularly in Asian SMEs. It also demonstrates that AI is not only an automation tool, but also a tool that empowers innovation and quality management processes. These theoretical contributions fill gaps in the literature and offer important insights into quality management and digitalization in manufacturing SMEs.

Practical value – This study highlights the importance of AI integration in improving quality management systems, revealing that it strengthens the relationship between AIs, DVoC, PLM and Q4.0 through its integration role (see Figure 1). Managers in manufacturing SMEs are recommended to invest in AI technologies to improve their quality management systems. It also highlights the critical importance of building flexible and responsive quality management systems to improve product quality and adapt to changing customer needs by analyzing customer feedback. These findings offer practical insights to policymakers, manufacturers, enterprises, and SMEs in AI-enabled quality management and developing customer-centered strategies.

1. Introduction

The adoption of advanced technologies, such as AI and Q4.0 has a significant impact on the development and competitiveness of industrial enterprises in today's world (Nyamekye *et al.*, 2024; Khan *et al.*, 2023). AI, a computerized technique analyzed through data analytics and predictive modeling, provides significant advantages to industries in many aspects (Lee *et al.*, 2019). Today, industries use AI to monitor the product lifecycle and improve the efficiency and quality of manufacturing operations through data analytics and the Internet of Things (IoT) (Naeem and Di Maria, 2022).

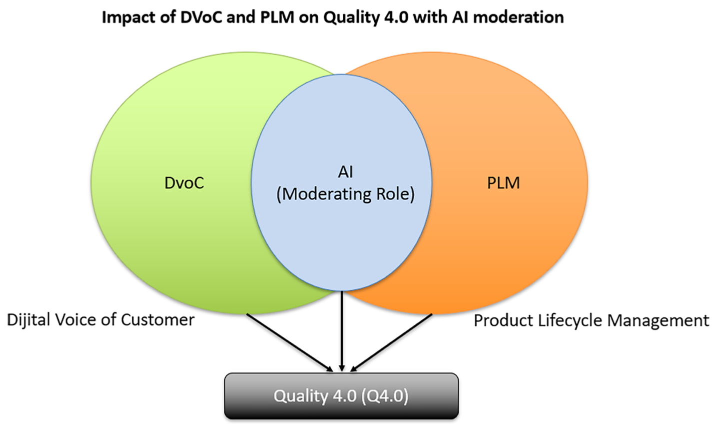

Figure 1. Quick value overview. **Source(s):** Authors' own work

According to Chui *et al.* (2023), the global AI industry reached $400 billion in 2024 and is forecasted to grow at annual pace of 30% to get $1.6 trillion by 2028. In this respect, enhancing effectiveness and quality in businesses requires a significant link between Q4.0 and AI. This demonstrates the importance of AI and Q4.0 implementation on the global impact in terms of speed, quality, and operational costs in industries (Aw *et al.*, 2022). With the help of Industry 4.0, industrial production efficiency has grown from 15% to 20% (Oktavia, 2023). Khan *et al.* (2023) showed that defects in quality management systems can be reduced using AI. AI tools improve the quality of an entire product by enabling more precise surveillance and detection of production faults (McLean *et al.*, 2021). Efficient use of the production process is also an important factor for industrial organizations (Bălan, 2023). Nyamekye *et al.* (2024) found that Q4.0 tactics contributed significantly to the reduction of production costs. Naeem and Di Maria (2022) found that AI predicts machine failures, improves maintenance routines, and minimizes operational inconveniences. Dash *et al.* (2021) discovered that AI improved the adaptability and responsiveness of manufacturing processes by enhancing inventory control and demand forecasting. Rasool *et al.* (2023) found that integrating AI improves workflows to make manufacturing procedures more effective and smooth.

Similarly, Wereda and Woźniak (2019) argued that modern businesses, especially those operating in innovative industries and sectors, should pay special attention to shaping customer relationships. Sony *et al.* (2020) found that the adoption of Q4.0 reduced the number of consumer complaints. They demonstrated that Q4.0's tenets contributed to a decrease in customer complaints. Müller and Däschle (2018) showed that AI sped up the method of testing products. Roslan and Ahmad (2023) discovered that using AI for cognitive analytics enhanced market trend prediction. Khan *et al.* (2023) found that AI significantly contributes to maintaining and upgrading quality requirements. Green *et al.* (2020) found that the use of AI improved the precision of final product quality measurements. Costa and Borsato (2021) emphasized that the application of Q4.0 practices sped up production procedures.

The few existing studies in the literature provide the strongest conclusions about manufacturing efficiency itself, rather than the impact of DvoC and PLM on Q4.0. To the best of our knowledge no study has been conducted in the existing literature assessing the impact of DvoC on the realization of Q4.0. While it is evident that PLM is one of the pillars of industrial management, the literature has not fully examined its interaction with Q4.0 (Costa and Borsato, 2021). AI technologies, particularly cognitive analytics and automated decision-making, facilitate the interpretation of customer data (Roslan and Ahmad, 2023), defect identification (Khan *et al.*, 2023), and production efficiency (Dash *et al.*, 2021). Nevertheless, there are gaps in the literature concerning the contribution of AI to the interactions between DvoC, PLM, and Q4.0. This gap is important because AI could increase the effectiveness of DVoC and assist in PLM for Q4.0. The majority of the existing literature concentrates on developed economies, leaving an eastward gap, particularly in the Asian region's manufacturing domain (China, Pakistan, and India), where SMEs are aggressively undergoing digital transformation (Chui *et al.*, 2023). SMEs face specific challenges regarding quality, digitalization, and AI integration (Rasool *et al.*, 2023). Understanding the role of AI in moderating the relationship between DVoC, PLM and Q4.0 is important for industry and policy leaders. Research regarding the influence of DVoC and PLM on Q4.0 adoption is scarce. In addition, the changing role of AI in reinforcing these relationships has not yet been studied. Moreover, there are no studies related to Asian SMEs undergoing fast-paced industrialization and digitalization. Filling these gaps would enhance the understanding of how customer intelligence and AI-powered lifecycle management systems influence Q4.0 adoption.

To address these gaps, this study investigated the following research questions:

RQ1. What are the main motivators influencing the adoption of Q4.0 in the manufacturing sector?

RQ2. Is there a significant relationship between DVoC, PLM and Q4.0 in the manufacturing sector?

RQ3. Does AI have a moderating role in improving the relationship between DVoC and PLM and Q4.0?

To the best of our knowledge, there has not been a comprehensive examination of how AI and Q4.0 interact with the DVoC, and the limited studies that have been conducted suggest further exploration of the moderating roles of these technologies. This study aimed to close this knowledge gap and investigate how AI enhances the relationship between DVoC and Q4.0. This study first revealed the impact of DVoC and PLM on Q4.0. Furthermore, this study explores the moderating role of AI in improving the relationship between DVoC and PLM and Q4.0, which is an important gap in the literature specific to Asian countries. This will provide valuable insights into Asian countries for literature and policymakers.

In this respect, the study makes important contributions to the related literature b*y (1)* Demonstrating the importance of the DVoC by demonstrating the impact of DVoC on Q4.0, (2) identifying the importance of the PLM for Q4.0 by investigating the impact of PLM on Q4.0, (3) investigating the moderating role of AI in improving the relationship between DVoC and PLM and Q4.0 (4) revealing the impact of cultural differences in the literature with a specific focus on SMEs in Asian (China, Pakistan and India) countries and (5) ensuring the validity and accuracy of the findings obtained using a robust methodological method (partial least squares structural equation modeling).

This study contributes to the limited literature by highlighting the moderating effect of AI on DVoC- and PLM-based quality improvements and offers practical contributions to the industry by helping them better understand the problem. Such knowledge can be useful for manufacturers, policymakers, and business leaders in leveraging AI-driven quality management and customer-centric lifecycle optimization in the context of the integration of Industry 4.0.

The remainder of this paper is organized as follows. Following the introduction (Section 1), Section 2 explains the theoretical background of the study and the hypothesis development process. Section 3 explains the methodological approach of the study, and Section 4 presents the empirical results of the proposed model. Section 5 explains the hypothesis results of the study. Section 6 presents the discussion, theoretical and practical contributions of this study, and future research directions. Finally, Section 7 provides the overall conclusion of the study.

2. Theoretic background and hypothesis development

2.1 Theoretic background

The blending of AI with Q4.0 in the manufacturing industry is initiating unprecedented changes or shifts, but the fundamentals of this phenomenon are yet to be explored. Examining the impact of AI from different theoretical perspectives on quality management, processes, decision-making, and organizational change in Q4.0, in particular, helps us understand these activities and suggests a sound rationale. For example, systems theory explains how the interrelated processes of a production system work towards achieving quality. AI is instrumental, as it provides an understanding of contextualized relationships, dependency, and immediate decision-making in complex datasets (Hussein *et al.*, 2023). The application of AI enables firms to holistically automate production activities, system maintenance, and quality monitoring to enhance Q4.0 (Buhalis and Moldavska, 2022). Contingency theory posits that AI's effectiveness in the execution of Q4.0 can differ with the ever-changing dynamics of industries, markets, and company conditions (Malodia *et al.*, 2021). Sterne and Davenport (2024) argue that externals rely on AI's efficiency in managing quality due to the attributes of the regulatory environment, technology, and workforce. This theory outlines the rationales behind the differences in AI adoption among sectors and even small and medium enterprises situated in different economic regions during Q4.0. In strategic management theory, the integration of AI is significant because it aids in the execution of decisions, facilitates the efficient use of resources, and improves competition (Štverková and Pohludka, 2023). With AI, firms can estimate market changes, minimize losses, and increase output in Q4.0 conditions, which enables them to gain an everlasting competitive edge (Barravecchia *et al.*, 2022a, b, c). Encapsulated in Total Quality Management (TQM) theory is the principle of continuous improvement, customer focus, and complete decision-making as the essence of superior quality results. Applying TQM, AI improved its principles by ranging the automation of defect identification to improve quality assessment models and even active quality control (Chiarini, 2020). Project management theory advocates orderly planning, effective risk management, and work execution. With regard to Q4.0, AI improves project planning and resource allocation, and provides risk estimates (Barravecchia *et al.*, 2022a, b, c). AI-improved virtual modeling and analysis of manufacturing processes allow the reduction of terms of work, decrease of defects, and increase of quality of work performed on manufacturing projects (Dash *et al.*, 2021). Digital transformation theory is the accelerated digitization of industries, automation, and innovation through AI. AI is instrumental in enhancing the processing of real-time data, facilitating smart manufacturing, and enhancing cognitive activities in decision-making within the Q4.0 frameworks (Manuelli *et al.*, 2018). Organizations that utilize AI report better efficiency, lower operational expenditures, and higher responsiveness to market needs (Esmaeili Givi *et al.*, 2023). Innovation in technology theory accounts for AI's role in perturbing typical manufacturing paradigms and enabling radical innovations engendered in Q4.0. These include AI-powered solutions, such as the quality prediction of machine learning, automatic defect classification, and smart supply chain process control, which are transforming the industrial world (Aw *et al.*, 2022). AI contributes to improved product development cycles and greater technological fluidity in manufacturing organizations (Fonseca *et al.*, 2021). The theory of process change emphasizes the manner in which AI infromatics reduces process inefficiency and enhances workflow automation (Müller and Däschle, 2018). An enhancement in operational effectiveness has been achieved through AI-powered analytics in production scheduling, predictive maintenance, and quality inspection (Lee *et al.*, 2019). Access to massive datasets enables AI to facilitate the swift detection of process inefficiency and enhance continuous improvement processes (Wereda and Woźniak, 2019). Organizational learning theory asserts that AI boosts knowledge management, enhances the learning curve, and aids in the optimization of processes (Manuelli *et al.*, 2018). AI tools foster learning, automated data processing, and knowledge sharing across units of production in real time (Khan *et al.*, 2023). This supports rapid decision-making, problem solving, and coping with newly developed standards of quality (Özdağoğlu *et al.*, 2018). In the context of Q4.0, AI makes the process autonomous by contributing to the management of decision support systems and intelligent automation with collected data, which is the focus of information systems theories. Since the emergence of manufacturing processes integrated with AI features, quality monitoring, predictive analytics, and decisions have been made automatically, which increases productivity (McLean *et al.*, 2021). The integration of AI features into enterprise resource planning (ERP) and manufacturing execution system (MES) remarkably improves Q4.0 adoption (Grewal *et al.*, 2022). According to business environment theory, AI facilitates changes in strategy; as a result, industry conditions, consumer needs and overall business progresses are changing rapidly (Rawool *et al.*, 2024). With the use of AI-powered insights, manufacturers can plan for interruptions, improve customer relations with DvoC tactics and further implement quality procedures (Roslan and Ahmad, 2023).

This subsection builds upon relevant theories for better understanding the reasons why AI adoption improves Q4.0. Through the review of existing theories, it was identified that more research on how AI innovations impact quality management, productivity and organizational learning is needed and that there is a gap in the literature in this area. To close the gap, it was proposed that AI and Q4.0 relationships should be investigated not only in terms of technological automation, but also in strategic decision-making, process evolution and learning, which gives a deeper understanding of why AI is applied into Q4.0. These form the basis of the proposed model that looks at the interplay between AI, DVoC, PLM and the adoption of Q4.0 in manufacturing SMEs in Asia.

The following section develops hypotheses based on these theoretical perspectives, linking them to empirical findings in the existing literature. With the help of studies and theories supporting the relationship between AI and Q4.0, we developed our proposed model in

Figure 2. In this context, the aim of the study is to gain a deeper understanding of the link between AI and Q4.0 adoption and to conduct a comprehensive impact assessment.

2.2 Hypothesis formulation

2.2.1 Digital voice of customer and quality 4.0. DVoC is becoming an essential technique for businesses. By meticulously archiving and analyzing consumer complaints, thoughts and feedback, businesses gain significant insights into customer requirements and can make more informed corporate decisions (Nyamekye *et al.*, 2024). It's all about leveraging these encounters to truly improve services and drive customer satisfaction (Wereda and Woźniak, 2019). DVoC is data collected through social networks, surveys and online customer connections to improve quality (Malodia *et al.*, 2021). Q4.0 is increasing manufacturing and operation efficiency via IoT, AI and Big Data Analytics (Rachman *et al.*, 2023). The implementation of Q4.0 improves organizational performance and reduces costs (Kuo *et al.*, 2021). Using Q4.0, businesses are leveraging AI that analyzes data and computerized processes to improve production efficiency and quality (Gunasekaren *et al.*, 2019). Hendra *et al.* (2022) discovered that DVoC evaluation offers chances for quality enhancement, which boosts the achievement of Q4.0. Effective utilization of DVoC facilitates Q4.0 adoption and improves product quality (Esmaeili Givi *et al.*, 2023). Hussein and Hapsari (2021) showed that Q4.0 tactics may be implemented with the support of DVoC data evaluation, while customer experiences are used to inform future developments. Carolus *et al.* (2023) found that the adoption of DVoC data played a key role in the accomplishment of Q4.0, which encourages enhancing quality. Sony *et al.* (2020) discovered that DVoC-obtained consumer input improves Q4.0 implementation efficiency and results in enhanced quality. Rawool *et al.* (2024) discovered that DVoC analysis enhances Q4.0 procedures and boosts product efficiency. Silva *et al.* (2024) clarified that Q4.0's based DVoC measures could be effectively performed to satisfy customer demands. Successful application of DVoC promotes quality enhancement and helps Q4.0 succeed (Naeem and Di Maria, 2022). The amalgamation of IoT, Big Data Analytics and AI into Q4.0 has caused a shift in its development as it now has to adopt a more flexible approach to quality control which attends to customer needs and market dynamics (Rachman *et al.*, 2023). The adoption of automated, predictive and self-optimizing systems that replace traditional quality monitoring and evaluation processes with real-time customer participation feedback systems is increasingly predominant (Gunasekaren *et al.*, 2019). DVoC improves digital transformation and quality by facilitating defect prediction, process optimization and raising customer-centric quality standards (Esmaeili Givi *et al.*, 2023). The literature addresses the positive effects of DVoC supported by AI systems in improving

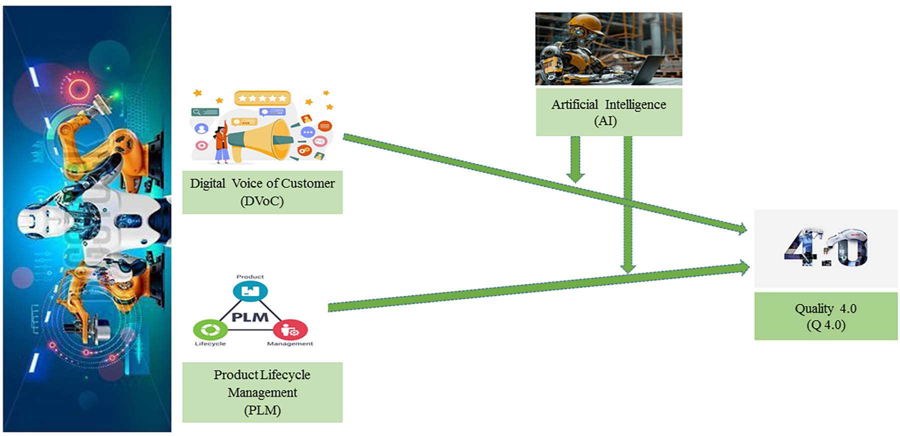

Figure 2. Research design. **Source(s):** Authors' own work

output quality, but leaves many questions unanswered about how effective it is amidst the variability of industries and implementation complexities (Silva *et al.*, 2024). Some researchers contend that DVoC is the backbone of enhanced adoption of Q4.0 due to the provision of feedback in real-time and proactive measures through predictive analytics (Hussein and Hapsari, 2021). Others, however, express concern that excessive dependence on AI-based sentiment scrutiny could result in biased interpretations of consumer needs, leading to an incomplete DVoC model within conventional quality management systems (Rawool *et al.*, 2024). This ongoing discussion underscores the requirement for practical confirmation to determine how much DVoC reinforces the success of Q4.0, notably in sectors where the implementation of AI-enabled quality management is still nascent. This study aims to fill these gaps with a thorough evaluation of the DVoC's effects on Q4.0, so that all organizations are able to utilize it effectively without suffering undue consequences. Based on the available limited empirical evidence in the literature, we propose the following hypothesis:

H1. DVoC has a significant impact on Q4.0.

2.2.2 Product Lifecycle Management and quality 4.0. The framework that oversees every stage of a product's lifecycle including development, creation, manufacturing and dying is known as PLM or PLM (Naeem and Di Maria, 2022). This technique enhances product efficiency and provides advanced knowledge at different stages (Özdağoğlu *et al.*, 2018). PLM involves a systematic process that is used at every stage of the process, from product design to finalization. These process functionalities include all levels necessary to improve the quality of product development, production and product life cycle (Hussein *et al.*, 2023). PLM is a management technique that deals with each stage of developing, producing and launching a product. Its purpose is to enhance profitability and improve product quality and efficiency (Chiarini, 2020). Ramírez-Durán *et al*. (2021) found that the adoption of Q4.0 supports the effectiveness of PLM and its results throughout the entire product lifecycle. Putra (2022) found that PLM with collaborate Q4.0 techniques can enhance whole product efficiency. PLM facilitates Q4.0 and enhances quality efficiency (Malodia *et al.*, 2021). Kuo *et al*. (2021) found that PLM incorporated with Q4.0 enhances product efficiency and quality at each stage of product lifecycle. Fonseca *et al*. (2021) found that PLM improves product efficiency and assists Q4.0 to succeed. Esmaeili Givi *et al*. (2023) found that incorporating PLM improves Q4.0 process by enhancing product lifecycle efficiency. Hamzah *et al*. (2022) show that PLM effectively incorporated with Q4.0 elements enhances product quality and PLM improves Q4.0 elements by extending product life. PLM facilitates Q4.0 adoption and enhances the products efficiency (Lee *et al.*, 2019). On the other hand, Ramírez-Durán *et al*. (2021) provide an opposing perspective by pinpointing integration issues, cost and the overarching difficulty of adopting PLM under a Q4.0 business model. The benefits of PLM as a driver of Q4.0 are still heterogeneous, with some industries still using legacy systems and avoiding AI adoption (Putra, 2022). In addition, other experts view that without broader organizational adjustments, skilled personnel and a sound digital foundation, PLM by itself is insufficient for achieving Q4.0 (Hamzah *et al.*, 2022). These differing viewpoints indicate that there is a gap in research that needs to be addressed in regard to how much PLM affects the adoption of Q4.0 within different industries and operational settings.

The study attempts to contribute to the existing literature by offering strategic guidance on how to better leverage PLM to improve Q4.0 outcomes. In light of the preceding discussion, we suggest:

H2. PLM has a significant impact on Q4.0.

2.2.3 Moderating role of artificial intelligence (AI). A technique that deals with machines to react like humans is known as AI (Aw *et al.*, 2022). These technologies help to create computerized tactics and support the evaluation of complicated data and decision-making (Bălan, 2023). AI is an important technique that helps robots understand themselves and make decisions, which increases their work capacity (Özdağoğlu *et al.*, 2018; Müller and Däschle, 2018). Dash *et al*. (2021) found that AI assists the Q4.0 adoption and enhances the link between DVoC and PLM. Wereda and Woźniak (2019) found that AI assists PLM and improves the Q4.0 efficiency and DVoC. Hamzah *et al*. (2022) found that Al supports the Q4.0 adoption and enhances the PLM efficiency and DVoC. Also, AI enhances DVoC and PLM efficiency and assists Q4.0 advancement (Nyamekye *et al*., 2024). Hussein *et al*. (2023) found that AI has capabilities to analyze customer outcomes via DVoC more efficiently. Naeem and Di Maria (2022) found that AI enhances DVoC's efficiency and improves PLM and Q4.0 adoption. Winarko *et al*. (2022) state that AI support has an important role to play on DVoC and PLM linkages. Silva *et al*. (2024) found that AI tactics support the Q4.0 adoption and improves DVoC and PLM efficiency. Sterne and Davenport (2024) found that AI helps to adopt Q4.0 and improve DVoC and PLM. Štverková and Pohludka (2023) found that AI improves DVoC information processing and assists the adoption of PLM and Q4.0. Malodia *et al*. (2021) found that AI enhances DVoC and PLM efficiency and supports the adoption of Q4.0. Martasari (2023) demonstrated that AI boosts the efficacy of Q4.0 and enhances the efficacy of DVoC and PLM methods. Grewal *et al*. (2022) argue that the proficient utilization of AI enhances the effectiveness of DVoC and PLM and has significant importance in the execution of Q4.0. However, some studies challenge the idea that Q4.0 adoption positively impacts AI, pointing to other problems such as algorithm discrimination, data abuse and excessive difficulty of topics (Silva *et al*., 2024). The automation of quality management processes necessitates a high level of digital system support, trained personnel and organizational integration, which many companies find difficult to achieve (Sterne and Davenport, 2024). Moreover, there are issues of excessive dependence on automation leading to simplistic assumptions of the absence of relevant human intelligence in the quality management business (Štverková and Pohludka, 2023). There is, therefore, a gap that should be filled with data to evaluate the impact of AI in the relationship between DVoC, PLM and Q4.0 adoption within various organizational boundaries. Filling this gap, the current study investigates the ways in which AI may beneficially moderate these relationships. Thus, we suggest the following hypotheses.

H3. AI moderates the relationship between DVoC and Q4.0.

H4. AI moderates the relationship between PLM and Q4.0.

The study reveals the impact of DVoC and PLM on Q4.0. Moreover, the study explores the moderating role of AI in improving the relationship between DVoC and PLM and Q4.0. In this context, we develop and propose the model in Figure 3 below to test the hypotheses based on the discussions in the literature.

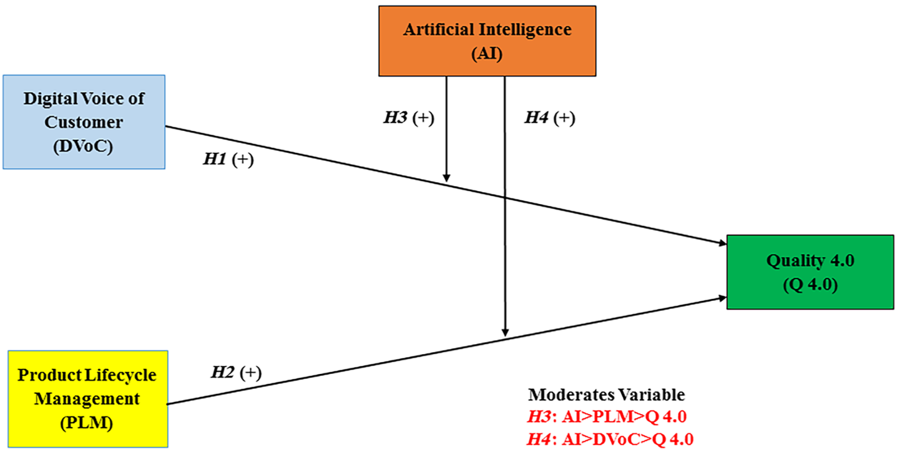

Figure 3. Proposed model. **Source(s):** Authors' own work

3. Methodology

3.1 Research sample and design

For two main reasons, Asian manufacturing SMEs provide a perfect setting for doing empirical research on the contexts and hypotheses. First, the wide differences in digital change among SMEs provide a varied sample. The change of firms is highly valued by the Asian government because of the limitations placed on society, economy and resources. Innovative procedures have the potential to reduce expenses by enhancing the financial health of an organization. Participants included managers and owners of SMEs involved in advanced innovative ventures. The manufacturing industry SMEs that operate in many Asian nations particularly China, Pakistan and India that have the greatest number of SMEs were the subject of a Survey via questionnaire. We emailed owners, managers and other pertinent parties immediately after speaking with the owners of SMEs in the manufacturing industry to clarify the research's goal and reassure them concerning data privacy. From June to August 2024, a three-month period, the survey was conducted. A total of 1,000 questionnaires were sent to businesses via email and telephone and feedback on the survey was received from a total of 350 businesses. Based on the filter question, 334 of the responses were deemed valuable due to their thoroughness and acceptability. 67 (20.1%) were the proprietors of SMEs, 107 (32.2%) were supervisors, 87 (26.0%) were production leaders and 121 (36.3%) were directors among the valid participants (see Figure 4). Because of this, the majority of the participants were executives of departments with extensive knowledge of the subjects addressed.

3.2 Measures

The questionnaire was developed based on a literature review. Although researchers have utilized an identical scale to assess factors in previous research, the Likert-Scale is employed to evaluate replies. The perceptual components of the items were measured using a 7-point Likert-Scale, where 1 represents "strongly disagree" and 7 represents "strongly agree". PLM inside an organization is assessed using a widely recognized scale from earlier studies Roslan and Ahmad (2023). Product development, product procedures, quality control, consumer feedback and lifetime assistance are the five subjects covered. A pre-established scale Hendra *et al*. (2022) has been utilized for assessing the DVoC of an organization. This scale is composed of four components; competitive edge, resource execution, capabilities regeneration and strategic cooperation. The predefined scale Müller and Däschle (2018) is also used to measure the Q4.0 implementation. It can accurately represent improvements in client satisfaction, data integration, real-time tracking and workflow efficiency. Lastly, the predefined scale Ramírez-Durán *et al*. (2021) is also used to measure the moderating factor AI.

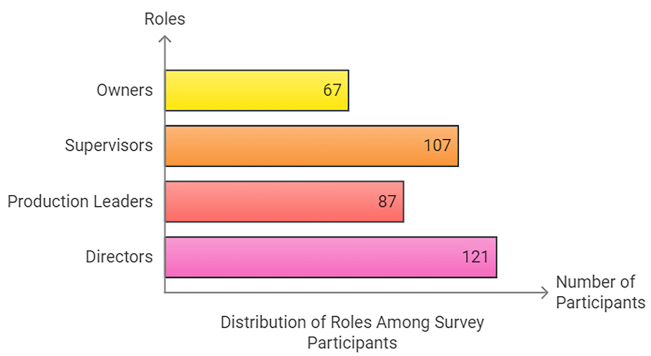

Figure 4. Distribution of participants. **Source(s):** Authors' own work

It includes a number of topics such as industry changes, acceptance of new technologies, innovation velocity and pressure from competitors.

3.3 Data analysis and descriptive data

The first issue that arises when data is gathered with questionnaires is typical method bias. It is necessary to solve common approach bias problems in order to guarantee the participant's genuine response. We examined the problem of typical method bias using Harman's single factor test. Five factors with eigenvalues greater than one are determined to account for more than 50% of the variation, according to the factor estimation findings. As a result, factor evaluation confirms the information rather than implying the presence of one underlying factor. Item loadings were subsequently evaluated.

3.4 Reliability and validity

The item loadings were verified in order to assess the data. All items had their loading rates determined since any item with a loading value less than 0.7 ought to be removed from consideration in the model. Approximately 5% of the items were determined to have been removed. To further confirm the validity and reliability of the instrument, analyses were conducted using Cronbach's alpha, composite reliability and average variance extracted at criteria levels of 0.50, 0.60 and 0.70, respectively. Table 1 shows the study of the instrument's content validity for DVoC, PLM, Q4.0 implementation and AI (Hair *et al.*, 2017).

Making sure the estimated amount for the parameter is smaller than the identical number for every other factor in the identical column and row is how discriminatory validity analysis is done (Rachman *et al.*, 2023). Table 2 lists the computed values used to guarantee discriminatory validity. The structural model's evaluation was followed by the discriminant validity study with the use of the bootstrapping method. A bootstrapping representation of 5,000 was selected in order to assess the hypothesis and broad structure by determining the

Table 1. Content validity and reliability

Factors	Items	Loadings	CA	CR	AVE
Product lifecycle management	PLM1	0.841	0.865	0.911	0.703
	PLM2	0.849			
	PLM3	0.869			
Digital voice of customer	DVoC1	9.852	0.812	0.891	0.723
	DVoC2	0.753			
	DVoC3	0.912			
	DVoC4	0.847			
Quality 4.0 implementation	Q4.0-1	0.778	0.923	0.938	0.612
	Q4.0-2	0.767			
	Q4.0-3	0.763			
	Q4.0-4	0.839			
	Q4.0-5	0.773			
	Q4.0-6	0.818			
	Q4.0-7	0.795			
	Q4.0-8	0.771			
	Q4.0-9	0.723			
Artificial intelligence	AI1	0.844	0.867	0.908	0.651
	AI3	0.812			
	AI5	0.832			
	AI6	0.788			
	AI8	0.753			

Note(s): CA: customer analytics, AVE: average variance extracted and CR: composite reliability
Source(s): Authors' work

Table 2. Discriminant validity

	Product lifecycle management	Digital voice of customer	Quality 4.0	Artificial intelligence
PLM	0.841			
DVoC	0.489	0.851		
Q 4.0	0.465	0.653	0.779	
AI	0.796	0.581	0.554	0.811

Source(s): Authors' work

relevance of the associations. According to the analyses, it is seen that the model provides discriminant validity (Hair *et al.*, 2017; Fornell and Larcker, 1981).

4. Results

4.1 Direct effects

In order to fill in the gaps within the literature, the investigation looked into the systematic structural framework and validated the concepts that were developed to answer the hypotheses. Information on the direct effect values indicating a significant relationship is shown in Table 3 and Figure 4. Table 3's estimated numbers, which examined the direct impacts, indicated that PLM had an important influence on Q4.0 ($\beta = 0.195$, $t = 2.361$, $p = 0.017$), while DVoC also had a substantial effect on Q4.0 ($\beta = 0.561$, $t = 6.91$, $p = 0.000$).

4.2 Moderating effects

Once it was established that PLM and Q4.0 had a large direct impact, AI was examined as a moderator to fill in the discrepancies in the literature addressing discordant results. The results showed (Table 4) that AI has a moderating effect on the linkages among PLM, DVoC, and Q4.0 in addition to having considerable effects on Q4.0. As a result, Table 4 and Figure 5 display the moderating impact results for every factor. According to the above-described examination, AI

Table 3. Direct effects

	Original sample	Sample mean	Std. deviation	*t*-statistics	*p*-values
PLM > Q 4.0	0.195	0.209	0.084	2.361	0.017
DVoC > Q 4.0	0.561	0.564	0.086	6.991	0.000

Source(s): Authors' work

Table 4. Moderating effects

	Original sample	Mean sample	Std. deviation	*t*-statistics	*p*-values
AI > PLM > Q 4.0	0.225	0.224	0.111	2.061	0.036
AI > DVoC > Q 4.0	0.241	0.238	0.119	2.081	0.031
AI > Q 4.0	0.277	0.269	0.159	1.737	0.000

Source(s): Authors' work

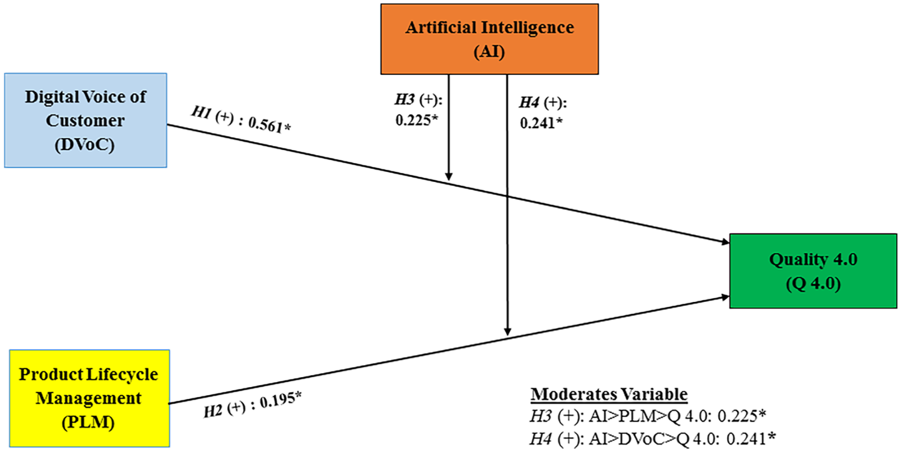

Figure 5. Model results. **Source(s):** Authors' own work

has a significant moderating impact on the connection between PLM and Q4.0 ($\beta = 0.225$, $t = 0.224$, $p = 2.061$), and it additionally has a significant moderating influence on the connection between DVoC and Q4.0 ($\beta = -0.241$, $t = 2.081$, $p = 0.031$). Similarly, AI and Q4.0 are also directly related ($\beta = 0.277$, $t = 1.737$, $p = 0.000$).

4.3 Predictive relevance

Once the general significance of the framework has been established, it is equally vital to ascertain whether the model has predictive relevance. That is, theoretical importance should be established if an approach which is comparable is studied in similar conditions and produces identical outcomes. Researchers employed the Blindfolding approach via Construct Cross-Validated Redundancies through the Stone–Geisser Q2 Test, which was recommended by Putra (2022), to verify the predictive relevance (McLean *et al.*, 2021). Table 5 lists the outcomes of the construct cross-validated redundancy. According to Table 5's construct cross-validated redundancy results, Stone-Geisser's Q2 has an estimated value of greater than zero, or Q4.0 (0.288), indicating that the framework has a considerable predictive significance.

4.4 General summary of results

The aim of this investigation was to investigate the moderating effect of AI on the adoption of Q4.0, PLM and DVoC. 334 small and medium-sized firms (SMEs) in the Asian manufacturing sector provided data for analysis in this study. The findings demonstrate that AI has a significant moderating effect and enhances the DVoC procedure through integrating with Q4.0 and PLM. The study emphasized the critical role AI in putting Q4.0, DVoC and PLM into practice. The findings demonstrated the close connection between PLM and Q4.0. Also, DVoC

Table 5. Construct cross-validated redundancy

	SSO	SSE	*Q*^2(= 1-SSE/SSO)
Q 4.0	800.000	641.531	0.288

Note(s): SSO: smart system optimization and SSE: smart sustainable enterprise
Source(s): Authors' work

has a significant impact on Q4.0. This represents a highly significant finding that demonstrates the enormous benefits of integrating the DVoC into the Q4.0 process. The impact of AI on Q4.0 also indicates that using AI can enhance Q4.0. The Stone–Geisser Q2 test yielded an effective model significance of 0.288 for Q4.0 confirming the predictive relevance of the framework. These findings demonstrate that every one of these criteria combined enhance this cutting-edge management system and that they have a substantial and statistically noteworthy impact on the adoption of Q4.0. The investigation found that AI has improved PLM and DVoC's interaction with Q4.0 in addition to having direct effect on it. This paper shows that AI enhances the impacts of DVoC and PLM on Q4.0. Businesses have capacity to adopt Q4.0 and satisfy customers via AI. The results show that organizational culture is significantly related to the adoption of Q4.0. This shows a close link between quality management and organizational culture. Innovative technologies increase quality control systems. This shows that technologies enhance organization's quality control. The adoption of customer input has significantly improved the quality process. The findings are supported by Aw *et al*. (2022) showing that AI significantly affect industry transitions and improve organizational capabilities. The results are supported by Green *et al*. (2020), who found a significant relationship between DVoC and Q4.0. Q4.0 adoption techniques were analyzed by Hussain *et al*. (2024). Fonseca *et al*. (2021) found a significant relationship between PLM and customer responses. Q4.0 has significant effects on DVoC and PLM (Chiarini, 2020). Naeem and Di Maria (2022) found that AI improves the Q4.0 efficiency. These results support our findings. Mevcut çalışmanın sonuçları, yapay zekanın kalite 4.0'ın benimsenmesini artırdığını gösteren Hussein ve diğerleri (2021) tarafından desteklenmektedir. Further, this study is supported by Carolus *et al*. (2023) reporting the significance effect of AI on customer satisfaction.

5. Discussion

The results of this investigation underscore the moderation effect of AI in the adoption of Q4.0, DVoC, and PLM in the context of 334 SMEs in the Asian manufacturing industry. The findings suggest that AI contributes to the integration of DVoC and PLM in Q4.0, which supports the argument that AI can qualitatively transform and streamline processes as well as enhance productivity. These results support other studies which show the increasing role of AI in improving quality management systems, transforming manufacturing systems and enhancing quality. Naeem and Di Maria (2022) noted that AI facilitated greater Q4.0 effectiveness through automating data mining, predictive quality assurance and real-time decision-making processes. A significant model Stone-Geisser Q^2 test value of 0.288, which is in line with Hussain *et al.* (2024) who pointed out the adoption of AI in quality strategies, confirmed the importance of our model and the results of our research. In relation to DVoC, our findings are also consistent with Green *et al*. (2020) and Hussein and Hapsari (2021), who noted a robust relationship between customers' feedback evaluation and the advances provided in Q4.0. The results indicate that AI-based DVoC can shorten the time within which quality improvements are realized, increase the agility of responding to the customer's needs and enable preemptive action against defects as noted by Carolus *et al*. (2023), who discuss customer satisfaction with AI systems which capture feedback in real time. With regards to PLM, our research confirms Fonseca *et al.* (2021) who reported a positive correlation between optimization of the product lifecycle and improvements in quality. Chiarini (2020) have also pointed out that PLM helps to foster adoption of Q4.0 because it automates the processes of design, production and maintenance, which our results also support. Our research adds the knowledge base on AI as a moderator by demonstrating that its effect is not just additive, but radical. Differently from other studies that focused on the effect AI had on Q4.0 directly (Naeem and Di Maria, 2022; Silva *et al*., 2024), this research attempts to explain the aspect of AI's influence on the integration of DVoC, PLM and Q4.0. This elucidates the missing link between customer-driven information and productive efficiency within the literature. Moreover, our results stress the important relationship between AI and organizational culture for the implementation of

Q4.0. The analysis indicates that organizations with an innovation focused culture stand to gain from quality dilution through the use of AI, as Aw *et al*. (2022) argued in regard to the impact of digitalization on organizational abilities. Further contribution is the finding pertaining to "the responsibility of AI in outsourcing work through automation and data processing" that goes further into suggesting strategy of paying attention to evolving customer needs and business constraints. In this respect, AI has been found to act as a driver for dynamic quality improvement for Wereda and Woźniak (2019), whereas for other scholars, like Štverková and Pohludka (2023), this widens the gap claim of AI letting every business to adopt it without consequences. There are unarguable claims which find AI accompanied with improved operational efficiency- but this depends on the infrastructure, workforce availability and alignment of the business with a strategy. Defending previous studies, findings do not support deterministic beliefs for AI to always serve as a panacea for quality management problems. Grounding from AI dominating authors like Sterne and Davenport (2024) who see AI as a tool that only enhances quality, our study finds that context such as data, algorithms and organizational AI proficiency alters the degree of moderation AI provides. Contrary to Winarko *et al*. (2022) who preliminary argued that AI replaces the function of the out-of-date quality control processes, we found the outmost advantage in AI-enhanced processes in a less dominative role to AI. This poses a stronger issue on how much management of assuring quality needs to give decision-making to AI versus assisting decision-making through the use of AI, something that has to be studied in coming research. Alongside the practical implications, the theoretical scope of this study adds to the existing literature on Q4.0 and digital transformation by proving that AI-driven quality management should be seen as an interactive system instead of a mere technological tool for improvement. The possibility of AI to moderate adoption of DVoC and PLM implies that there is more for businesses to do than just deploying AI technology; they also need to re-engineer their processes based on AI output. Practically, the conclusions suggest that firms need to approach investments in AI not only as automation resources, but as a fundamental risk in transformational adaptive quality management. A business committed to Q4.0 needs to devote more resources to AI-enabled customer analytics and lifecycle management, provided that the organizational culture is willing to undergo a digital transformation. Therefore, this research illustrates the role of AI as a moderator in the relationship between DVoC, PLM and Q4.0 adoption and underscores its importance. The results illustrated the role of AI in customer-driven quality enhancement, product life cycle process and adaptive quality management. The results of this study also call for an understanding context in which AI is implemented as there are varying degrees of effectiveness depending on the organizational preparedness and data centered capabilities. Further studies should look into the effects of AI integrations like machine learning, predictive analytics and IoT on the adoption of Q4.0 in different cultural and industrial contexts.

6. Conclusions, practical and theoretical implications

6.1 Conclusion

The moderating function of AI among the deployment of Q4.0, PLM and digital voice of customer is thoroughly examined in this study. Its findings showed that the combination of AI with PLM and DVoC greatly enhances the Q4.0 procedure. We find this conclusion noteworthy as it demonstrates how AI approaches can improve PLM, consumer input and quality throughout industries. Studies have indicated that AI plays a significant moderating impact in the relationship between Q4.0 and PLM. Using PLM, AI may enhance consumer feedback, inspections and developing products. Furthermore, the incorporation of AI results in an expansion of Q4.0 procedures, enhancing workflow effectiveness and user contentment. AI has expended the consequences of DVoC by enabling improved decision-making according to consumer experiences and suggestions. AI enables prompt and precise analysis of client feedback leading to more precise and efficient solutions. Studies have indicated that PLM and Q4.0 are positively and significantly related. AI has the potential to expand by enhancing product development and quality management throughout industries. AI enables SMEs adopt PLM and Q4.0 more effectively, which boosts their operational effectiveness. This study shows that using AI is essential for enhancing consumer experiences, streamlining manufacturing operations and boosting entire corporate success. This study establishes new directions for additional studies considering the significance of AI's participation in industrial operations. AI may assist sectors in modernizing their procedures and resisting against fresh difficulties, which bodes well for their ongoing success and continued development. All things considered, this study offers a complete and exhaustive grasp regarding how AI may enhance the deployment of PLM and Q4.0 and increase the efficacy of the DVoC in terms of offering SMEs managerial and strategic advantages.

In conclusion, integration of AI with PLM and DVoC was found to dramatically increase the adoption of Q4.0 which maintains AI's role as a transformative factor in quality management, customer feedback and processes optimization. The examined role of AI in the integration of PLM and Q4.0 accepted AI's function in enhancing product development, customer feedback analysis and quality control. AI-based insights enable organizations to automate workflows, make more accurate decisions and increase customer satisfaction. Further analysis proved that DVoC has a positive influence on the adoption of Q4.0, while AI also enhances this relationship by providing frontline customer insights, predictive information and automated feedback mechanisms. In addition, the results stressed the significance of AI for SMEs in bettering production efficiency, competitive edge and flexibility to industry shifts. AI-initiated PLM applications improve product life cycle processes, whereas AI-augmented DVoC systems enable firms to proactively deal with customers, anticipate market needs and improve service quality.

6.2 Practical implications

This paper shows that PLM and Q4.0 could be significantly improved by adopting AI. AI adoption may help SMEs improve their customers' responses, quality control and production procedures. AI improves DVoC's process by analyzing customer service effectively. By doing this, businesses improve customer experiences and their competitive advantage. AI enhances Q4.0 adoption, which improves workflow efficiency, quality control and production processes. SMEs should enhance their manufacturing efficiency and adopt AI alternatives. SMEs enhance their product or service quality through AI's support to gain a competitive advantage. This helps businesses to resolve customer issues and fulfills demands and industry developments. AI helps industries to sustain development and resilience. AI helps SMEs update their business strategies and solve their problems effectively.

Overall, the findings of the study help SMEs, policy makers and industry players in myriad ways. Businesses are using AI technologies to assess customer feedback more seamlessly, which leads to efficient modifications in quality that increases customer satisfaction. AI-enabled workflow automation, along with defect detection and predictive maintenance, helps SMEs minimize waste and errors while maximizing production accuracy. Adopting AI improves the qualitative standards of products and services leading to a market edge, allowing SMEs to react promptly to changes in the business environment. PLM and DVoC solutions powered by AI improve the automation of business processes and enhance efficiency, which results in improved sustainable practices in the manufacturing lifecycle. AI further enables real-time decision-making, allowing businesses to react to insights as they emerge, thereby improving the strategic approach to quality management.

6.3 Theoretical implications

This study presents new innovative ideas and models by highlighting AI functions in the context of PLM and Q4.0. To fully comprehend the advantages and difficulties of AI integration, additional investigations on the subject and its effects in empirical research are required. AI has the potential to improve current concepts and frameworks while transforming business procedures. AI's relationship to PLM and Q4.0 may be expanded upon. With the use of AI, novel theoretical frameworks may be created to comprehend how PLM and Q4.0 connect. This study highlights the necessity of using AI to enhance the function and implications of AI and proposes issues and subjects for novel studies. In the future, these can be investigated in greater depth as they present new opportunities and avenues for the field of study. The growth of novel patterns and concepts in universities and businesses could benefit from the significant empirical and theoretical consequences of this study.

6.4 Further research directions and limitations

Additional investigation can be conducted to examine the ways in which AI's expandable features of AI affect different facets of PLM and Q4.0. Specifically, the efficiencies of various AI algorithms and concepts can be examined to identify the best methods. One can investigate the interactions among AI, DVoC, PLM and Q4.0 across multiple industry domains. One may contrast the effects of AI in the banking, healthcare, and service sectors. A study should be conducted on the economic and social implications of using AI to accomplish DVoC and Q4.0. This could involve the evaluation of the economic rewards, employment implications, and social acceptability of AI. It is possible to perform additional studies on how to use AI to enhance the client experience. Specifically, AI can enhance the examination of client grievances and comments. Studies can conduct study on legislation and policies pertaining to the implementation of AI, DVoC, PLM and Q4.0. Determining data security, morality and guidelines may fall under this category. It is possible to conduct study on the rate at which various businesses and geographical areas embrace emerging AI technical advancements. It might also take into account the effects of various cultural and socioeconomic settings. AI may be employed to study a variety of metrics and simulations for increasing manufacturing efficiency. It is possible to conduct additional study regarding how cutting-edge analytical methods like machine learning and deep learning might enhance PLM and Q4.0. These areas of study can shed light on fresh opportunities in the academics and commercial domains while aiding in the comprehension of AI and its many facets.

Only SMEs from Asian countries such as China, India and Pakistan were used as the basis for this study. It could be challenging to extrapolate the results to other areas or larger sectors, owing to the narrow geographic limits of the study. This study only examined industries in the manufacturing sector. Additional studies are necessary to determine whether AI is beneficial for other industries, including agriculture and services. Since the research relied on self-reporting for data collection, self-reported data by participants may contain biases or misrepresentations. The data used in this study might not correspond to recent advancements in AI, which could have an impact on the study's conclusions. These improvements have continued to occur. To better comprehend the impact of AI in various scenarios, more in-depth information on its moderating impact is needed. These restrictions have a significant impact on how the study constraints produce more thorough and accurate outcomes.

References

Aw, E.C.X., Tan, G.W.H., Cham, T.H., Raman, R. and Ooi, K.B. (2022), "Alexa, what's on my shopping list? Transforming customer experience with digital voice assistants", *Technological Forecasting and Social Change*, Vol. 180, 121711, doi: 10.1016/j.techfore.2022.121711.

Bălan, C. (2023), "Chatbots and voice assistants: digital transformers of the company–customer interface-a systematic review of the business research literature", *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 18 No. 2, pp. 995-1019, doi: 10.3390/jtaer18020051.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2022a), "Digital voice-of-customer processing by topic modelling algorithms: insights to validate empirical results", *International Journal of Quality and Reliability Management*, Vol. 39 No. 6, pp. 1453-1470, doi: 10.1108/IJQRM-07-2021-0217.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2022b), "KA-VoC Map: classifying product Key-attributes from digital voice-of-customer", *Quality Engineering*, Vol. 34 No. 3, pp. 344-358, doi: 10.1080/08982112.2022.2057805.

Barravecchia, F., Mastrogiacomo, L., Tavani, L. and Franceschini, F. (2022c), "Statistical Process Control techniques to monitor quality determinants in digital Voice-of-Customer", *In Proceedings of the 5th ICQEM Conference*, pp. 120-141.

Buhalis, D. and Moldavska, I. (2022), "Voice assistants in hospitality: using artificial intelligence for customer service", *Journal of Hospitality and Tourism Technology*, Vol. 13 No. 3, pp. 386-403, doi: 10.1108/JHTT-03-2021-0104.

Carolus, A., Augustin, Y., Markus, A. and Wienrich, C. (2023), "Digital interaction literacy model–Conceptualizing competencies for literate interactions with voice-based AI systems", *Computers and Education: Artificial Intelligence*, Vol. 4, 100114, doi: 10.1016/j.caeai.2022.100114.

Chiarini, A. (2020), "Industry 4.0, quality management and TQM world. A systematic literature review and a proposed agenda for further research", *The TQM Journal*, Vol. 32 No. 4, pp. 603-616, doi: 10.1108/TQM-04-2020-0082.

Chui, M., Hazan, E., Roberts, R., Singla, A., Smaje, K., Sukharevsky, A., Yee, L. and Zemmel, R. (2023), *The Economic Potential of Generative AI: the Next Productivity Frontier*, McKinsey & Company, New York.

Costa, A.R.V. and Borsato, M. (2021), "Digital mock-up and voice of the customer in the context of physical product development", *International Journal of Agile Systems and Management*, Vol. 14 No. 1, pp. 53-78, doi: 10.1504/IJASM.2021.114906.

Dash, G., Kiefer, K. and Paul, J. (2021), "Marketing-to-Millennials: marketing 4.0, customer satisfaction and purchase intention", *Journal of Business Research*, Vol. 122, pp. 608-620, doi: 10.1016/j.jbusres.2020.10.016.

Esmaeili Givi, M., Keshavarz, H. and Kargar Azad, Z. (2023), "Quality assessment of E-learning website using asymmetric impact–performance analysis and Kano's customer satisfaction model: a case study based on WebQual 4.0", *Information Discovery and Delivery*, Vol. 51 No. 1, pp. 35-46, doi: 10.1108/IDD-08-2021-0083.

Fonseca, L., Amaral, A. and Oliveira, J. (2021), "Quality 4.0: the EFQM 2020 model and industry 4.0 relationships and implications", *Sustainability*, Vol. 13 No. 6, p. 3107, doi: 10.3390/su13063107.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18, pp. 39-50.

Green, W., Cluley, R. and Gasparin, M. (2020), "Mobile market research applications as a new voice of customer method: implications for innovation and design management", *Research-Technology Management*, Vol. 63 No. 1, pp. 49-55, doi: 10.1080/08956308.2020.1686297.

Grewal, D., Guha, A., Schweiger, E., Ludwig, S. and Wetzels, M. (2022), "How communications by AI-enabled voice assistants impact the customer journey", *Journal of Service Management*, Vol. 33 Nos 4/5, pp. 705-720, doi: 10.1108/JOSM-11-2021-0452.

Gunasekaran, A., Subramanian, N. and Ngai, W.T.E. (2019), "Quality management in the 21st century enterprises: research pathway towards Industry 4.0", *International Journal of Production Economics*, Vol. 207, pp. 125-129, doi: 10.1016/j.ijpe.2018.09.005.

Hair, J.F., Jr., Sarstedt, M., Ringle, C.M. and Gudergan, S.P. (2017), *Advanced Issues in Partial Least Squares Structural Equation Modeling*, SAGE Publications, Los Angeles.

Hamzah, M.L., Rahmadhani, R.F. and Purwati, A.A. (2022), "An integration of Webqual 4.0, importance performance analysis and customer satisfaction index on E-campus", *Journal of System and Management Sciences*, Vol. 12 No. 3, pp. 25-50, doi: 10.33168/JSMS.2022.0302.

Hendra, S., Wahono, A., Setiawan, I. and Purba, H. (2022), "Quality 4.0 implementation to reduce customer complaints on plastic packaging products in the manufacturing industry", *In Proceedings of the 1st International Conference on Social, Science, and Technology, ICSST 2021*, Tangerang, 25 November 2021, doi: 10.4108/eai.25-11-2021.2318844.

Hussain, M.A., Gupta, R., Kushwaha, A., Samanta, P., Khulbe, M. and Ahmad, V. (2024), "Transforming technology for online marketing with focus on artificial intelligence: a qualitative approach", *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, pp. 1-5.

Hussein, A.S. and Hapsari, R. (2021), "Determining bank 4.0 customer loyalty", *BISTIC Business Innovation Sustainability and Technology International Conference (BISTIC 2021)*, Atlantis Press, pp. 268-272. doi: 10.2991/aebmr.k.211115.039.

Hussein, A.S., Sumiati, S., Hapsari, R. and Abu Bakar, J. (2023), "Bank 4.0 experiential quality and customer loyalty: a serial mediating role of customer trust and engagement", *The TQM Journal*, Vol. 35 No. 7, pp. 1706-1721, doi: 10.1108/TQM-11-2021-0344.

Khan, A., Hamid, A.B.A., Saad, N.M., Hussain, Z. and Arif, A.R. (2023), "Effectiveness of artificial intelligence in building customer loyalty: investigating the mediating role of chatbot in the tourism sector of Pakistan", *International Journal of Academic Research in Business and Social Sciences*, Vol. 13 No. 9, pp. 657-671, doi: 10.6007/IJARBSS/v13-i9/18422.

Kuo, C.M., Chen, W.Y., Tseng, C.Y. and Kao, C.T. (2021), "Developing a smart system with Industry 4.0 for customer dissatisfaction", *Industrial Management and Data Systems*, Vol. 121 No. 6, pp. 1353-1374, doi: 10.1108/CR-11-2023-0277.

Lee, S.M., Lee, D. and Kim, Y.S. (2019), "The quality management ecosystem for predictive maintenance in the Industry 4.0 era", *International Journal of Quality and Innovation*, Vol. 5 No. 1, p. 4, doi: 10.1186/s40887-019-0029-5.

Malodia, S., Islam, N., Kaur, P. and Dhir, A. (2021), "Why do people use Artificial Intelligence (AI)-enabled voice assistants?", *IEEE Transactions on Engineering Management*, Vol. 71, pp. 491-505, doi: 10.1109/tem.2021.3117884.

Manuelli, L.L., Piombino, C., Cugnach, F. and Piccini, F. (2018), "From voice of customer analysis to digital strategy development: the digital challenge of a leading international player in the power generation industry", *In Proceedings of the International MultiConference of Engineers and Computer Scientists*, Vol. 2.

Martasari, G.W. (2023), "Impact of industrial technology 4.0 in improving service quality and customer experience on E-commerce platforms: literature review", *International Journal of Social Service and Research*, Vol. 3 No. 6, pp. 1427-1435, doi: 10.46799/ijssr.v3i6.407.

McLean, G., Osei-Frimpong, K. and Barhorst, J. (2021), "Alexa, do voice assistants influence consumer brand engagement?–Examining the role of AI powered voice assistants in influencing consumer brand engagement", *Journal of Business Research*, Vol. 124, pp. 312-328, doi: 10.1016/j.jbusres.2020.11.045.

Müller, J.M. and Däschle, S. (2018), "Business model innovation of industry 4.0 solution providers towards customer process innovation", *Processes*, Vol. 6 No. 12, p. 260, doi: 10.3390/pr6120260.

Naeem, H.M. and Di Maria, E. (2022), "Customer participation in new product development: an Industry 4.0 perspective", *European Journal of Innovation Management*, Vol. 25 No. 6, pp. 637-655, doi: 10.1108/EJIM-01-2021-0036.

Nyamekye, M.B., Andoh, J.A.S., Husseini, M.M. and Agbemabiese, G.C. (2024), "Do AI-based voice assistants influence brand continuous usage? The mediating role of AI-driven customer experience", *The Journal of Applied Business and Economics*, Vol. 26 No. 2, pp. 14-27, doi: 10.33423/jabe.v26i2.6973.

Oktavia, C. (2023), *Bloomberg – Are You a Robot? (2023)*, Bloomberg, New York.

Özdağoğlu, G., Kapucugil-Ikiz, A. and Celik, A.F. (2018), "Topic modelling-based decision framework for analysing digital voice of the customer", *Total Quality Management and Business Excellence*, Vol. 29 Nos 13-14, pp. 1545-1562, doi: 10.1108/IJQRM-07-2021-0217.

Putra, A.H.P.K. (2022), "Editorial notes: transformation customers' needs in the aspect of client value in industry 4.0", *Golden Ratio of Marketing and Applied Psychology of Business*, Vol. 2 No. 1, doi: 10.52970/grmapb.v2i1.186.

Rachman, N., Nimran, U., Yulianto, E. and Pangestuti, E. (2023), "Influence of social responsibility and quality of service 4.0 on customer satisfaction meiated by company reputation", *Journal of Legal, Ethical and Regulatory Issues*, Vol. 26, p. 1, doi: 10.2139/ssrn.4603525.

Ramírez-Durán, V.J., Berges, I. and Illarramendi, A. (2021), "Towards the implementation of Industry 4.0: a methodology-based approach oriented to the customer life cycle", *Computers in Industry*, Vol. 126, 103403, doi: 10.1016/j.compind.2021.103403.

Rasool, F., Greco, M. and Strazzullo, S. (2023), "Understanding the future kpi needs for digital supply chain", *Supply Chain Forum: An International Journal*, Vol. 25 No. 4, pp. 550-561, doi: 10.1080/16258312.2023.2253524.

Rawool, V., Foroudi, P. and Palazzo, M. (2024), "AI-powered voice assistants: developing a framework for building consumer trust and fostering brand loyalty", *Electronic Commerce Research*, pp. 1-33, doi: 10.1007/s10660-024-09850-5.

Roslan, F.A.B.M. and Ahmad, N.B. (2023), "The rise of AI-powered voice assistants: analyzing their transformative impact on modern customer service paradigms and consumer expectations", *Quarterly Journal of Emerging Technologies and Innovations*, Vol. 8 No. 3, pp. 33-64.

Silva, A.C., Machado, J. and Sampaio, P. (2024), "Predictive quality model for customer defects", *The TQM Journal*, Vol. 36 No. 9, pp. 155-174, doi: 10.1108/TQM-09-2023-0302.

Sony, M., Antony, J. and Douglas, J.A. (2020), "Essential ingredients for the implementation of Quality 4.0: a narrative review of literature and future directions for research", *The TQM Journal*, Vol. 32 No. 4, pp. 779-793, doi: 10.1108/TQM-12-2019-0275.

Sterne, J. and Davenport, T.H. (2024), "Improving voice of the customer analysis with generative AI", *Applied Marketing Analytics*, Vol. 10 No. 1, pp. 32-41, doi: 10.69554/vypb2186.

Štverková, H. and Pohludka, M. (2023), "Quality management for assurance value of the customer in industry 4.0 times", in *In Quality Management, Value Creation, and the Digital Economy*, Routledge, pp. 129-141, doi: 10.4324/9781003404682.

Wereda, W. and Woźniak, J. (2019), "Building relationships with customer 4.0 in the era of marketing 4.0: the case study of innovative enterprises in Poland", *Social Sciences*, Vol. 8 No. 6, p. 177, doi: 10.3390/socsci8060177.

Winarko, T., Parapak, E.R., Virananda, S.A., Yulianti, R. and Istijanto, I. (2022), "The effect of perceived value and marketing 4.0 on customer satisfaction and purchase intention in e-commerce context", *International Journal of Electronic Commerce Studies*, Vol. 13 No. 3, pp. 69-98, doi: 10.7903/ijecs.2121.

Further reading

AL-Khatib, A.w., Shuhaiber, A., Mashal, I. and Al-Okaily, M. (2024), "Antecedents of Industry 4.0 capabilities and technological innovation: a dynamic capabilities perspective", *European Business Review*, Vol. 36 No. 4, pp. 566-587, doi: 10.1108/EBR-05-2023-0158.

Antony, J., Sony, M., Furterer, S., McDermott, O. and Pepper, M. (2022), "Quality 4.0 and its impact on organizational performance: an integrative viewpoint", *The TQM Journal*, Vol. 34 No. 6, pp. 2069-2084, doi: 10.1108/TQM-08-2021-0242.

Barravecchia, F., Mastrogiacomo, L. and Franceschini, F. (2023), "Product quality tracking based on digital Voice-of-Customers", *Total Quality Management and Business Excellence*, Vol. 34 Nos 11-12, pp. 1386-1409, doi: 10.1080/14783363.2023.2177147.

Fernandes, T. and Oliveira, E. (2021), "Understanding consumers' acceptance of automated technologies in service encounters: drivers of digital voice assistants adoption", *Journal of Business Research*, Vol. 122, pp. 180-191, doi: 10.1016/j.jbusres.2020.08.058.

Hasan, S., Jatininngrum, C. and Gumanti, M. (2022), "The contribution of customer satisfaction towards company image and its impact in revolution industry 4.0 era", *Nama Jurnal: IJEBD International Journal of Entrepreneurship and Business Development*, Vol. 5 No. 2, pp. 398-368, doi: 10.29138/ijebd.v5i2.1795.

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