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Implementing challenges of artificial intelligence: Evidence from public manufacturing sector of an emerging economy

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ABSTRACT

The growing Artificial Intelligence (AI) age has been flooded with several innovations in algorithmic machine learning that may bring significant impacts to industries such as healthcare, agriculture, education, manufacturing, retail etc. But challenges such as data quality, privacy and lack of a skilled workforce limit the scope of AI implementation in emerging economies, particularly in the Public Manufacturing Sector (PMS). Therefore, to enhance the body of relevant literature, this study examines the existing challenges of AI implementation in PMS of India and explores the inter-relationships among them. The study has utilized the DEMATEL method for identification of the cause-and-effect group factors. The findings reveal that poor data quality, managers' lack of understanding of cognitive technologies, data privacy, problems in integrating cognitive projects and expensive technologies are the main challenges for AI implementation in PMS of India. Moreover, a model is proposed for industrial decision-makers and managers to take appropriate decisions to develop intelligent AI enabled systems for manufacturing organizations in emerging economies.

1. Introduction

The concept of Artificial Intelligence (AI) has been an area of interest for many decades (Jarrahi, 2018; Jordan, 2019; Spanaki, Sivarajah, Fakhimi, Despoudi, & Irani, 2021). It has been imagined as a dominance of smart machines that will capture the world and perform mundane daily routine operations (Desouza, Dawson, & Chenok, 2020). Due to its benefits and performance outcomes, AI has become an essential part of the business model of many organizations and a strategic system across industries (Burström, Parida, Lahti, & Wincent, 2021). There has been a lot of conceptual and empirical research on AI in the public sector in last few years. Both the academic and practitioner's perspective have shown several examples of AI utilization by local and global government agencies (Wirtz et al., 2021). Moreover, the development of AI enabled systems demonstrates the significance of AI in Public Manufacturing Sector (PMS).

Although AI implementation varies across nations, it is still in the initial phase in developing countries (Wang, Zhang, & Zhao, 2020). The novel approaches of AI have attracted the attention of academicians and researchers (Duan, Edwards, & Dwivedi, 2019). The World Economic Forum (WEF) has examined the potential effect of AI and industrial automation on organizations and its impact on the economy. This identified certain positive and negative impacts on organizations and also a variation in operations across countries. As per the study, more than 20% of existing jobs in developed countries like the United Kingdom will be directly impacted by AI driven technologies (Vinuesa et al., 2020). In developing countries such as India and China, the overall impact assessed is more than 26% in the manufacturing sector. AI technologies have the potential to become key drivers in change and economic growth; it is expected that these technologies will create 133 million jobs in the global market by 2022 through the manufacturing sector in India. Also, it has the growth potential to contribute to 20% of GDP of China (Bora & Timis, 2021). In Europe, AI technology spending has dramatically increased by up to 52% in 2020 (Straus, 2021). Countries around the world are trying to become part of the AI-led digital economy, with an estimation of contributing around $15.7

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trillion to the global economy by 2030 (Dubey et al., 2020). Also, many other countries are actively committing public investment in the area of AI through various initiatives (Korinek & Stiglitz, 2021). Consequently, several AI-based companies are emerging and showing a great value, but also bringing along significant challenges that are crucial to their successful implementation. These challenges are particularly observed in context to AI implementation, ethical issues and value creation for public sector and society (de Sousa, de Melo, Bermejo, Farias and Gomes, 2019).

There is no doubt that AI is shaping the actions and reactions of companies nowadays, bringing innovations to existing business models. It is believed that AI implementation can trigger competitive advantage as it enhances productivity through a degree of innovation. Despite the growing popularity of AI, only a few studies have analyzed AI in context to PMS. Also, very few studies have tried to show how usage and inhibiting factors enable the implementation of AI for inter-organizational competitive advantage and value creation (Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021; Zhang, Chen, Chen, & Chong, 2021; Zuiderwijk, Chen, & Salem, 2021). But, the implementing challenges in context to PMS still need to be examined.

AI has offered ample opportunities in different areas such as healthcare, agriculture, manufacturing and the environment (Kumar, Dwivedi, & Anand, 2021). Gradually, AI is becoming the growth driver of economies and enabling the world to progress into the digital age (Lee & Trimi, 2021). Pattern recognition techniques are being extensively used in combination with AI to develop models for addressing difficult issues across different industries (Dwivedi et al., 2021). On this theme, government initiatives have motivated industries to contribute towards implementation of AI technologies in PMS, seeing this as a valuable tool for making the world a better place (Zuiderwijk et al., 2021). The government, with support from public and private sectors, is investing in national AI strategies to make it an asset for the nation and a source of global competitive advantage. AI has revolutionized businesses in India; the public sector is focused on areas where cognitive technologies can leverage the existing processes and can regenerate them to optimize human-computing interaction. New technology can transform the way individuals, societies and governments interact with each other. Several national governments are strategically defining their AI implementation roadmap to plan a digital future for public services (Kuziemski & Misuraca, 2020; Mikalef et al., 2021). Countries like India are also in the planning phase to set out a broader agenda for future AI initiatives in public sector.

The manufacturing industry has the potential to be one of the prominent sectors in India for AI implementation (Jaiswal, Arun, & Varma, 2021). With 'Make in India' as a policy intervention, manufacturing firms are being encouraged to accelerate the economic growth of the country (NITI Aayog, 2018). Also, the government has decided to target the contribution of manufacturing output as 25% of GDP by 2025 (Rizvi, Haleem, Bahl, & Javaid, 2021). India stands at sixth place globally, as the largest manufacturing nation. In past years, the government has provided motivation to the manufacturing industry by introducing a national manufacturing policy with the objective of creating 100 jobs in new employment. However, the new workforce needs to be skilled in Industry 4.0 technologies or 21st century skills (Chatterjee, 2020). It is a great challenge to drive a skills-based workforce, capable of AI skills.

AI implementation is dependent on an organization's existing practices and planning ability for future technologies.(Chatterjee, Kar and Gupta, 2018) The implementation of AI in Indian PMS has been slow and limited. This low rate of AI implementation PMS in India is hampering the country's prominence in global business as other countries move more quickly to gain advantage through AI (NITI Aayog, 2018). Thus, in this context, an investigation is required to understand why the AI implementation is low in India, particularly PMS? What are the challenges faced by the public manufacturing companies in AI implementation? What are the cause-and-effect relationships between the challenging factors that need to be addressed by policy makers, decision makers and public manufacturing companies in India? This research study serves as a beacon in exploring the challenges faced by emerging economies like India to develop AI based intelligent systems for future success. More specifically, the current research intends to discourse the following research questions (RQs):

RQ1. *What are the challenges faced by the public manufacturing sector in implementation of AI in emerging economies like India?*

RQ2. *What role does the cause-effect relationships between these challenges play in the implementation of AI in public manufacturing sector the in emerging economies like India?*

Therefore, to answer the above questions, the main aim is to examine the key challenges in implementation of AI within the context of an emerging economy. After an extensive literature review, a gap is identified in the literature related to challenging factors for AI implementation. To fill this gap, the following objectives were set:

- To investigate the challenges faced by the public manufacturing sector in implementation of AI in emerging economies like India.
- To understand the cause-effect relationships between the challenging factors and build an influential network relationship map.
- To provide implications/recommendations for the effective implementation of AI in public manufacturing organizations that will help managers in planning and developing AI based systems in their organization to enhance efficiency outcomes.

To achieve the above-mentioned objectives, this study is carried out in three phases. In the first phase, the relevant challenges of AI implementation in PMS were identified through extensive review, experts' opinions and a brainstorming process. To explore the cause-and-effect relationships among the challenges of AI implementation, the DEMATEL method was used.

Based on the causal and effect group factors, opportunities for organizations to improve their current systems have been identified. The findings from this research provide the base for policymakers and decision makers to evaluate the identified challenges and propositions for their decision making. Also, based on the findings, a model is proposed for future empirical research in the third phase of the study.

Following this introduction, the organization of the paper is as follows: Section 2 presents the literature review; this helps in exploring the current challenges of AI implementation in PMS in India. Research methodology is described in Section 3. The real-world applicability and results are presented in Section 4. The discussion of findings with practical implications of the present work are presented in Section 5. In section 6, a conceptual framework has been drawn up for future studies. In the last section, concluding remarks are given with limitations and directions for future research.

2. Literature review

This section examines literature on challenges faced by organizations in implementation of AI. The systematic literature review has been conducted to extract those papers related to the objective of the study.

2.1. Systematic literature review

A systematic literature review was conducted to explore the pertinent published literature on Artificial Intelligence, applications and challenges. The databases "Scopus" and "Web of Science (WoS)" are searched for relevant literature. Search terms such as "Artificial Intelligence", "Challenges of Artificial Intelligence" "Implementation of Artificial Intelligence", "Artificial Intelligence and Emerging Economy", "Artificial Intelligence" and "Public Manufacturing Sector" are used. The multiple keywords are used to search relevant articles. The research is limited to journal articles from "2015–2021". Based on the search terms, a total of 87 articles were found after removal of document types such as theses, reports, technical papers, editorials, magazines, conference proceedings, book series and trade publications. The second extraction was to exclude those articles not in the English language; this left 58 articles. Some duplicated publications were then removed, leaving 48 articles. In the last step only articles that were relevant to the study were selected on the basis of abstract. Finally, a total of 40 articles were selected for the study.

2.2. AI Implementation in public manufacturing sector

As a branch of computer science, AI can complete tasks that require human intelligence. With the explosion of data expansion due to the power of computers, the world is witnessing rapid developments in AI, machine learning and deep learning, bringing transformations in all sectors of the economy (Panch, Szolovits, & Atun, 2018).

The Public Manufacturing Sector (PMS) has experienced a significant transformation during the Industry 4.0 era. It revolves around real time data and machine leaning to significantly enhance digitization. AI technology deploys machine learning and data analytics to help manufacturers to reduce downtime, enhance efficiency, safety, anticipate requirements and make faster production cycles. AI has the potential to improve the manufacturing process in ways that have never been possible before, using big data, machine learning and analytics to build smarter, more efficient plant operations (Lima & Delen, 2020). With industry 4.0 technologies, developing countries are transforming the industrial sector (Benzidia, Makaoui, & Bentahar, 2021). Yet India has a slow rate of AI implementation in the PMS. The main reasons for this include lack of advanced technology infrastructure, knowledge, skilled people, equipment, capital expenditure, processes, lack of integration and optimization.

The most important challenge of the PMS in India is to upgrade the manufacturing value chain. However, initiatives such as 'Digital India', 'Make in India' and 'Skill India' have supported the PMS in skill enhancement and technology up-grading. AI and machine learning utilization in the manufacturing sector have shown that these technologies demand considerable capital and optimum human resources to develop collaborative models in the working environment. These unique challenges and aspirations, combined with AI technologies and their implementation, require huge transformational interventions supported by the government, the public and private players in the economy. The technical feasibility, regulatory norms, privacy concerns and ethical concerns are indicators in measuring the readiness of a sector for AI implementation.

By 2030, 70% of businesses are expected to implement some form of AI technology in their business processes (Bughin, Catlin, Hirt, & Willmott, 2018). Studies show that higher levels of AI implementation in manufacturing, healthcare and digital marketing are projected (Lee and Yoon, 2021). AI implementation differs from traditional technology implementation, posing new challenges to create a dynamic business environment to embrace the nature of AI and Machine Learning (ML). Issues to be faced are the underlying information theory limitations that apply to all information processing but in specific ways to AI/ML (Davenport & Kalakota, 2019; Dwivedi et al., 2021). The major challenges in PMS in India are elaborated in Table 1.

3. Research methodology

To achieve the objective of this study, a three-phase study was conducted. Fig. 1 illustrates the methodology framework used to conduct the study.

During the first phase, an extensive literature review was conducted to identify the challenges for AI implementation in the PMS. To elaborate on the opinions of the respondents and validate them with the support of relevant literature, a questionnaire was designed for pairwise

Table 1
Challenges of AI implementation in public manufacturing sector.

	Challenges	Implied meaning	References
V1	Difficult to integrate cognitive projects with existing manufacturing processes and systems	There is low rate of AI implementation because of less skilled manpower; there needs to be more education on cognitive technologies and their usage	Davenport and Ronanki (2018); Alshahrani, Dennehy, and Mäntymäki (2021)
V2	Technologies and expertise are too expensive/ affordability issue	Many organizations show reluctance in implementing AI due to its high cost	Dwivedi et al. (2021)
V3	Privacy and data security	Data used in AI based on AL/ML is confidential and thus sensitive in nature	Chatterjee (2020)
V4	Managers lack understanding of cognitive technologies and related functioning	Lack of skilled managers to learn cognitive technologies and their usage. AI requires skilled professionals but currently there is a shortage of trained staff	Chan-Olmsted (2019); Sun and Medaglia (2019); Cubric (2020); Wamba-Taguimdje et al. (2020)
V5	High R & D cost	AI technologies and innovation have high R & D cost	Pan, Froese, Liu, Hu, and Ye (2021)
V6	Lack of agility in production design	Production design is inflexible in implementing AI technology	Cubric (2020); Bag, Pretorius, Gupta, and Dwivedi (2021)
V7	Unstable product quality	The demand for the product and its quality is dynamic	Cubric (2020); Chatterjee (2020); Zhang et al. (2021)
V8	Low availability of infrastructure	There is a lack of appropriate computing infrastructure, hampering the implementation of AI	Chatterjee (2020); Zhang et al. (2021)
V9	Responsibility and accountability	Organizations wary of taking responsibility and accountability in AI implementation and associated risks	Chatterjee (2020); Zhang et al. (2021)
V10	AI safety; compatibility of machine versus human value judgment	There is misconception related to human and machine compatibility and its effect on efficiency	Zhang et al. (2021)
V11	Manager unwillingness	Low managerial trust in AI. Unwillingness to invest in AI and machine learning technologies	Prahl and Van Swol, 2021; Baryannis et al., 2019
V12	Difficulties in capacity management	To identify the appropriate kind of AI driven approach towards capacity management is a challenge for organizations	Cubric (2020); Wamba-Taguimdje et al. (2020)
V13	Trust, transparency and diversity	*Trust* by clarity, transparency in information exchange through AI literacy	Hengstler, Enkel, and Duelli (2016); Robinson (2020); Androutsopoulou, Karacapilidis, Loukis, and Charalabidis (2019); Janssen, Brous, Estevez, Barbosa, and Janowski (2020)
V14			Delgado et al. (2020); Rizvi et al. (2021)

(continued on next page)

Table 1 (*continued*)

	Challenges	Implied meaning	References
	Constraints of access to industry-specific data	Industry specific data has been limited to major players in India.	
V15	Absence of collaborative efforts between various stakeholders	There is a lack of integrated and collaborative effort among stakeholders to implement AI across industries	Le Pennec and Raufflet (2018); De Carlo, Ferilli, d'Angella, and Buscema (2020)
V16	Lack of enabling data ecosystems; absorptive capacity	Firms find difficulties in implementing AI within the existing system. Companies need to enhance their absorptive capacity for AI implementation	Burström et al. (2021)
V17	Lack of integrity and ethics with AI	With the advancement in AI algorithms and its contribution in decision making, ethical challenges are emerging as major challenges	Morley, Floridi, Kinsey, and Elhalal (2020); Bartoletti (2019); Gerpe and Markopoulos (2020)
V18	The bias problem	It is becoming a concern that data-driven algorithms can pick up bias from the data they are fed.	Chatterjee (2020); Morley et al. (2020)
V19	Data scarcity	Due to the perception that the organization is not data-rich, this can hold many operators back from unlocking its full potential	Floridi et al., (2020)
V20	Paucity of awareness of professionals	Insufficient awareness of AI applications among professionals towards decision making problems	Randhawa and Jackson (2020); Chatterjee (2020). Scheetz et al., (2021)
V21	Perception towards loss of job	Perception of people losing their jobs has an impact on economic well-being. It acts as a perceptual barrier in AI implementation	Nam (2019)
V22	Poor data quality	Data is the backbone of AI; hence easy availability of open-source data is crucial for any country to accelerate AI innovation	Cabitza, Campagner, and Balsano (2020); Kim and Park (2017); Morley et al. (2020)
V23	Unattractive intellectual property regime	The lack of an intellectual property regime may restrict the implementation of AI	Schulze-Horn et al. (2020)

comparison of the challenging factors. Experts from the PMS were invited to provide their opinions on the designed questionnaire. The 18 experts from the PMS organizations were selected. The experts have at least 5 years' experience and are placed at managerial positions in their organizations. Experts validated the identified challenges in this phase. In the second phase, the DEMATEL method was applied to examine the cause-and-effect group factors among the challenges already identified from the literature review.

In the third phase a model is proposed for future research work. Based on experts' responses, an influential network relationship map was developed among the factors to understand their cause-effect impact by DEMATEL. The cause-effect map will help managers to not only understand the impact of each challenging factor, but also its influence on other factors. DEMATEL is a widely used method by researchers in different domains (Kumar & Dixit, 2018; Sharma, Joshi, & Kumar, 2020, Yasmin, Tatoglu, Kilic, Zaim, & Delen, 2020).

4. Data analysis and results

This study has attempted to analyses and investigate the challenges of implementing AI in the PMS of India. The identified and validated challenges from the first phase were investigated through DEMATEL in the second phase. DEMATEL was employed in the study to map the interrelationships among the identified challenges into a structural model that is easy to understand. This method is useful in categorizing cause-and-effect factors and is the most suitable method to examine the interdependency among factors in a complex system (Li & Mathiyazhagan, 2018). In this regard, the identified challenges can be ranked and obtained priorities may be utilized for strategic planning and developing a future roadmap. DEMATEL has been used by many researchers (Cui, Chan, Zhou, Dai, & Lim, 2019; Luthra, Kumar, Zavadskas, Mangla, & Garza-Reyes, 2020).

DEMATEL has a high capability in developing a map reflecting the relationships for solving decision making problems (Braga et al., 2021). In the present research, specifically, a DEMATEL analysis was conducted not only to establish the cause effect relationship between the challenging factors but also to understand their influence. The mathematical steps carried out through this method were as follows:

Step 1: The respondents assessed the relationships between the challenges on a scale of 0 to 4, where 0 denoted 'no influence' and 4 denoted 'very high influence'. Data from eighteen experts were collected through a snowball sampling method. All the experts had a proper understanding of the research topic and worked in a range of related departments i.e. AI, industry 4.0, operations etc. Eq. 1 was used to calculate the average matrix, as shown in Table 2.

A $n \times n$ matrix is developed as $X^k = [x_{ij}{}^k]$ on the basis of the expert responses. The responses are incorporated from h respondents, direct relation matric 'a_{ij}' is formed through Eq. (1).

$$a_{ij} = \frac{1}{H}\sum_{K=1}^{H} x_{ij}^{k} \tag{1}$$

where H is number of experts, $i, j = 1, \dots n$.

Based on the responses of the experts, an average matrix is derived using eq. (1) as shown in Table 2.

Step 2: The matrix normalization was obtained by applying Eqs. (2) and (3).

$$U = k \times V, \tag{2}$$

$$\mathrm{k} = Min\left[\frac{1}{Max\sum_{j=1}^{n} a_{ij}}, \frac{1}{Max\sum_{i=1}^{n} a_{ij}}\right] \tag{3}$$

A normalized matrix is developed using Eqs. (2) and (3) shown in Table 3.

Step 3: Computing the total relation matrix (T) using Eq. (4):

$$T = N(I - N)^{-1} \tag{4}$$

I denotes the identity matrix.

A total relation matrix is developed using Eq. (4) as shown in Table 4.

Step 4: Drawing the diagraph.where r was defined as $n \times 1$ and c as $1 \times n$ vectors representing the summation of rows and columns of the total relation matrix, respectively. The relation matrix is presented in Table 4. The impact results of implementation are shown in Table 5.

To eliminate minor effects, the threshold value (α) is calculated using Eq. (5).

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left[t_{ij}\right]}{N} = 0.2957 \tag{5}$$

The values obtained in the total relation matrix greater than

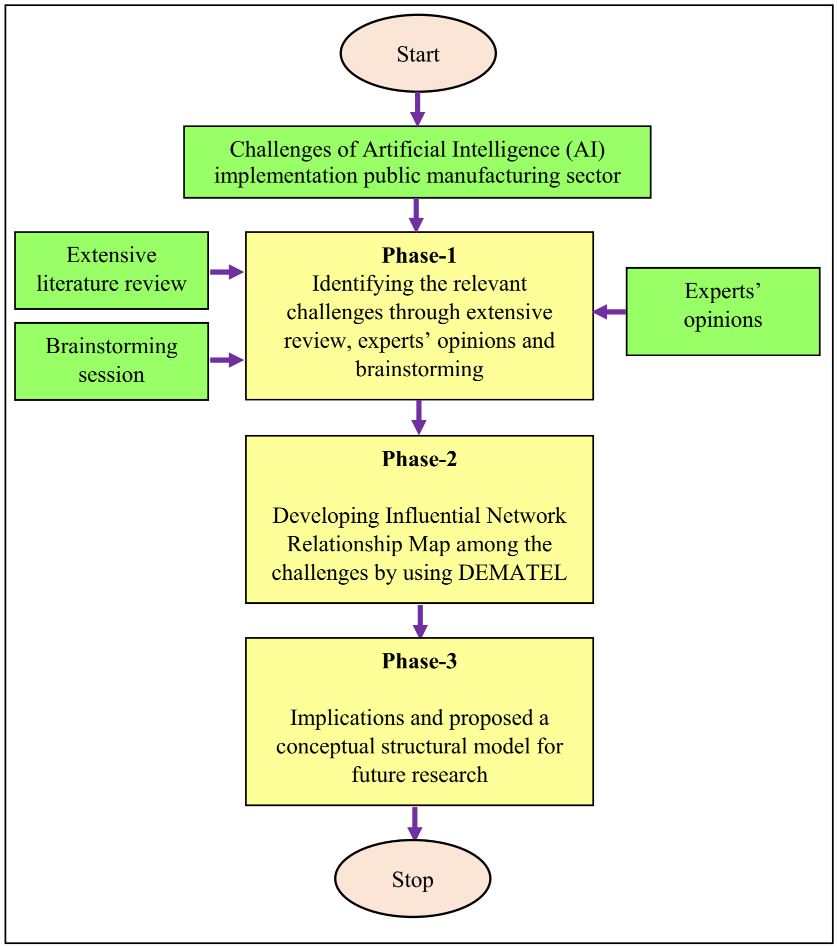

Fig. 1. Proposed research framework.

threshold value of 0.2957 were undertaken to develop a cause-effect model. These values have been shown in italics in Table 4. For instance, as shown in Table 4, V22 has threshold value (α) more than 0.2957 for almost all other factors. Fig. 2 represents the network relation diagraph among all the challenging factors.

5. Discussion of findings

Based on the DEMATEL results, the causal and effect factors categorization is drawn up. The variables - Technologies and expertise are too expensive/Affordability issue (V2), Privacy and Data security (V3), Managers lack understanding of cognitive technologies and how they work (V4), High R & D cost (V5), Low availability of infrastructure (V8), AI safety (V10), Managerial unwillingness (V11), Constraints of access to industry-specific data (V14), Absence of collaborative efforts between various stakeholders (V15), Lack of enabling data ecosystems (V16), Poor data quality (V22) are found to be causal group factors. The variables - Difficult to integrate cognitive projects with existing processes and system (V1), Agility in production design (V6), Unstable product quality (V7), Responsibility and accountability (V9), Difficulties in capacity management (V12), Trust, transparency and diversity (V13), Lack of integrity and ethics with AI (V17), Bias problem (V18), Data scarcity (V19), Paucity of awareness of the professionals (V20), Perception towards loss of job (V21) are effect group factors. As shown in Table 5, the top five most influential causal factors are data quality (V22) followed by Managers lack understanding of cognitive technologies (V4), Constraints of access to industry-specific data (V14), High R & D cost (V5) and Data privacy (V3).

AI implementation is a major challenge of PMS due to its initial cost. Developing countries like India have affordability issues (V2) that restrict organizations in implementing AI. The goal of achieving 'AI for all' needs long term engagement by institutional collaboration among all stakeholders; this includes the citizens of the country (NITI Aayog, 2018). While ensuring a collaborative strategy, the government also needs to act as facilitator, promoter or owner to develop a common platform for all sectors to perform in an integrated manner. The stakeholders include consumers, sellers and others working towards AI; these agencies and individuals are worth researching (McDuie-Ra & Gulson, 2020). Currently, the absence of collaborative efforts between multiple stakeholders in India is one of the causal factors. Organizations need to redesign tasks, jobs, practices and performance goals while implementing AI technologies. Managers lack understanding of cognitive technologies (V4) causes a resistance in an organization towards AI implementation. The automation of task, time allocation and interactive systems etc. needs training for staff members to help them to better understand AI.

The results reveal that Data quality (V22) is the most influential factor, affecting the other variables with a value of 1.246 for r_i-c_j. AI algorithms are intended to offer guidance and information in taking actions, but its impact still needs to be explored. There is less knowledge about the general working of algorithms. When AI based applications carry out market research, can the results be trusted? The data quality has many concerns. There is no doubt that reliable data is the key to understanding consumers and their decision-making process. The generation of huge amounts of consumer data provides insights into how their decisions are made. Thus, AI based systems may provide an opportunity to utilize consumer data to target consumers appropriately. With the help of AI based systems, data can be captured faster and more

Table 2
Average matrix.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23
V1	0	2.278	2.000	1.722	2.278	2.500	2.833	2.278	2.889	3.444	2.278	3.111	2.444	2.667	2.833	3.444	2.333	1.500	2.111	3.778	1.889	2.500	2.056
V2	1.833	0	3.667	3.778	2.833	1.889	2.333	2.056	2.389	2.889	2.278	2.333	1.889	2.889	2.333	3.333	2.833	2.833	1.889	2.833	2.833	2.833	2.833
V3	2.722	2.833	0	2.278	2.833	2.278	2.889	2.056	2.833	2.833	2.944	2.778	2.833	3.278	1.833	3.056	3.167	3.167	2.722	1.889	2.833	2.722	2.333
V4	1.722	2.833	1.889	0	3.611	1.889	2.889	2.111	3.667	2.833	2.833	3.500	3.667	1.889	2.056	2.889	2.056	1.889	2.278	3.000	3.722	1.889	1.833
V5	2.722	1.889	3.722	2.833	0	1.889	1.111	1.833	1.722	1.833	1.722	2.833	2.056	1.889	3.056	3.389	3.611	2.833	1.889	3.444	3.778	3.778	3.611
V6	1.500	2.833	2.000	0.944	0.944	0	1.389	2.000	1.556	2.111	2.889	1.556	2.167	2.667	2.500	2.722	2.833	2.833	3.611	3.222	2.833	2.833	2.722
V7	2.944	2.833	2.833	1.889	1.889	2.833	0	0.944	1.889	0.944	2.778	3.778	1.889	1.889	3.333	2.056	2.889	1.889	2.833	3.778	2.333	2.833	3.556
V8	2.833	1.889	2.000	2.833	1.833	2.833	2.833	0	0.944	2.833	2.722	2.556	2.889	2.000	2.667	2.000	2.778	3.778	2.833	2.833	2.944	2.833	2.444
V9	2.833	3.778	2.389	2.833	3.722	1.889	2.833	2.833	0	2.833	3.056	2.444	2.833	1.889	2.278	1.889	1.889	2.833	1.889	2.833	3.000	2.000	2.389
V10	2.778	0.000	2.833	1.889	2.833	2.833	2.833	2.833	1.889	0	2.944	3.778	1.889	1.889	2.833	2.778	2.833	2.833	3.778	2.833	2.222	2.833	2.778
V11	3.056	2.833	3.722	1.278	1.889	2.833	1.889	1.889	3.778	3.778	0	1.889	2.833	2.833	2.833	2.778	2.833	2.778	2.833	1.889	3.778	2.833	2.778
V12	3.444	2.889	2.444	1.944	3.389	1.000	3.722	2.722	1.056	3.333	3.778	0	1.889	2.833	3.389	1.889	1.889	1.889	2.833	2.833	2.833	1.889	1.722
V13	2.722	1.889	0.944	2.833	2.889	3.778	2.833	2.833	2.833	1.056	2.833	1.889	0	1.889	1.389	1.889	2.833	2.833	2.833	2.111	3.000	2.833	2.333
V14	2.833	2.833	1.889	3.111	2.944	2.833	2.833	2.833	3.667	1.944	2.778	3.778	3.778	0	1.889	1.889	2.833	2.833	1.889	1.889	3.000	1.889	2.111
V15	1.778	2.500	2.444	3.111	2.778	3.556	2.833	2.889	1.833	1.889	2.667	2.833	2.833	2.833	0	0.944	2.778	1.889	2.833	2.833	2.222	2.833	2.833
V16	2.000	2.111	2.889	2.000	1.889	3.167	2.000	1.889	2.833	1.944	1.889	2.889	3.722	2.833	2.833	0	2.833	3.778	2.833	1.000	2.833	2.389	2.333
V17	2.056	3.556	1.833	1.722	2.556	2.611	2.833	3.333	3.778	2.833	2.833	3.556	1.389	2.778	2.778	2.389	0	0.944	3.778	3.778	2.833	1.389	2.000
V18	2.833	1.278	0.944	2.833	2.056	4.278	2.833	3.389	1.889	2.667	2.833	1.889	1.500	1.889	2.778	1.444	1.889	0	2.833	3.778	1.889	1.500	1.889
V19	1.889	2.833	3.778	2.833	0.944	2.833	1.944	1.111	2.778	2.833	1.889	3.444	3.722	1.111	1.889	1.056	3.778	2.833	0	2.667	2.667	2.833	2.833
V20	1.667	2.833	3.778	2.833	1.722	1.889	2.833	2.833	3.778	1.889	2.833	2.778	1.278	2.833	0.944	2.833	2.833	2.833	1.889	0	1.889	2.833	3.778
V21	3.778	1.889	1.889	0.944	2.500	2.833	1.889	1.889	2.833	2.833	1.889	1.889	1.889	2.833	2.833	3.778	2.833	3.778	2.833	1.889	0	1.889	3.778
V22	3.389	2.833	2.833	1.889	2.667	1.889	3.556	2.833	2.833	3.778	2.833	2.833	3.778	2.778	2.833	3.778	2.833	1.889	2.833	2.833	2.833	0	3.778
V23	1.889	2.778	2.333	1.000	2.389	2.500	2.833	2.778	3.778	1.500	2.111	2.333	3.000	1.944	2.833	1.444	2.778	2.833	3.778	2.222	1.889	1.611	0

Table 3
Normalized matrix.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23
V1	0	0.0354	0.0311	0.0268	0.0354	0.0389	0.044	0.0354	0.0449	0.0535	0.0354	0.0484	0.0380	0.0415	0.0440	0.0535	0.0363	0.0233	0.0328	0.0587	0.0294	0.0389	0.0320
V2	0.0280	0	0.0570	0.0587	0.0440	0.0294	0.0363	0.0320	0.0371	0.0449	0.0354	0.0363	0.0294	0.0449	0.0363	0.0518	0.0440	0.0440	0.0294	0.0440	0.0440	0.0440	0.0440
V3	0.0420	0.0440	0	0.0354	0.0440	0.0354	0.0449	0.0320	0.0440	0.0440	0.0458	0.0432	0.0440	0.0509	0.0285	0.0475	0.0492	0.0492	0.0423	0.0294	0.0440	0.0423	0.0363
V4	0.0270	0.0440	0.0294	0	0.0561	0.0294	0.0449	0.0328	0.057	0.0440	0.0440	0.0544	0.0570	0.0294	0.0320	0.0449	0.0320	0.0294	0.0354	0.0466	0.0579	0.0294	0.0285
V5	0.0420	0.0294	0.0579	0.0440	0	0.0294	0.0173	0.0285	0.0268	0.0285	0.0268	0.0440	0.0320	0.0294	0.0475	0.0527	0.0561	0.0440	0.0294	0.0535	0.0587	0.0587	0.0561
V6	0.0230	0.0440	0.0311	0.0147	0.0147	0	0.0216	0.0311	0.0242	0.0328	0.0449	0.0242	0.0337	0.0415	0.0389	0.0423	0.0440	0.0440	0.0561	0.0501	0.0440	0.0440	0.0423
V7	0.0460	0.0440	0.044	0.0294	0.0294	0.0440	0	0.0147	0.0294	0.0147	0.0432	0.0587	0.0294	0.0294	0.0518	0.032	0.0449	0.0294	0.0440	0.0587	0.0363	0.0440	0.0553
V8	0.0440	0.0294	0.0311	0.044	0.0285	0.0440	0.0440	0	0.0147	0.0440	0.0423	0.0397	0.0449	0.0311	0.0415	0.0311	0.0432	0.0587	0.0440	0.0440	0.0458	0.0440	0.0380
V9	0.0440	0.0587	0.0371	0.044	0.0579	0.0294	0.044	0.0440	0	0.0440	0.0475	0.0380	0.0440	0.0294	0.0354	0.0294	0.0294	0.0440	0.0294	0.0440	0.0466	0.0311	0.0371
V10	0.0430	0.0000	0.0440	0.0294	0.0440	0.0440	0.044	0.0440	0.0294	0	0.0458	0.0587	0.0294	0.0294	0.0440	0.0432	0.0440	0.0440	0.0587	0.0440	0.0345	0.0440	0.0432
V11	0.0470	0.0440	0.0579	0.0199	0.0294	0.0440	0.0294	0.0294	0.0587	0.0587	0	0.0294	0.0440	0.0440	0.0440	0.0432	0.0440	0.0432	0.0440	0.0294	0.0587	0.0440	0.0432
V12	0.0540	0.0449	0.038	0.0302	0.0527	0.0155	0.0579	0.0423	0.0164	0.0518	0.0587	0	0.0294	0.0440	0.0527	0.0294	0.0294	0.0294	0.0440	0.0440	0.0440	0.0294	0.0268
V13	0.0420	0.0294	0.0147	0.0440	0.0449	0.0587	0.0440	0.0440	0.0440	0.0164	0.0440	0.0294	0	0.0294	0.0216	0.0294	0.0440	0.0440	0.0440	0.0328	0.0466	0.0440	0.0363
V14	0.0440	0.0440	0.0294	0.0484	0.0458	0.0440	0.0440	0.0440	0.0570	0.0302	0.0432	0.0587	0.0587	0	0.0294	0.0294	0.0440	0.0440	0.0294	0.0294	0.0466	0.0294	0.0328
V15	0.0280	0.0389	0.0380	0.0484	0.0432	0.0553	0.0440	0.0449	0.0285	0.0294	0.0415	0.0440	0.0440	0.0440	0	0.0147	0.0432	0.0294	0.0440	0.0440	0.0345	0.0440	0.0440
V16	0.0310	0.0328	0.0449	0.0311	0.0294	0.0492	0.0311	0.0294	0.044	0.0302	0.0294	0.0449	0.0579	0.0440	0.0440	0	0.0440	0.0587	0.0440	0.0155	0.0440	0.0371	0.0363
V17	0.0320	0.0553	0.0285	0.0268	0.0397	0.0406	0.0440	0.0518	0.0587	0.0440	0.0440	0.0553	0.0216	0.0432	0.0432	0.0371	0	0.0147	0.0587	0.0587	0.0440	0.0216	0.0311
V18	0.0440	0.0199	0.0147	0.0440	0.0320	0.0665	0.0440	0.0527	0.0294	0.0415	0.0440	0.0294	0.0233	0.0294	0.0432	0.0225	0.0294	0	0.0440	0.0587	0.0294	0.0233	0.0294
V19	0.0290	0.0440	0.0587	0.0440	0.0147	0.0440	0.0302	0.0173	0.0432	0.0440	0.0294	0.0535	0.0579	0.0173	0.0294	0.0164	0.0587	0.0440	0	0.0415	0.0415	0.0440	0.0440
V20	0.0260	0.0440	0.0587	0.0440	0.0268	0.0294	0.0440	0.0440	0.0587	0.0294	0.0440	0.0432	0.0199	0.0440	0.0147	0.0440	0.0440	0.0440	0.0294	0	0.0294	0.0440	0.0587
V21	0.0590	0.0294	0.0294	0.0147	0.0389	0.0440	0.0294	0.0294	0.044	0.0440	0.0294	0.0294	0.0294	0.0440	0.0440	0.0587	0.0440	0.0587	0.0440	0.0294	0	0.0294	0.0587
V22	0.0530	0.0440	0.044	0.0294	0.0415	0.0294	0.0553	0.0440	0.044	0.0587	0.0449	0.0440	0.0587	0.0432	0.0440	0.0587	0.0440	0.0294	0.0440	0.0440	0.0440	0	0.0587
V23	0.0290	0.0432	0.0363	0.0155	0.0371	0.0389	0.044	0.0432	0.0587	0.0233	0.0328	0.0363	0.0466	0.0302	0.0440	0.0225	0.0432	0.044	0.0587	0.0345	0.0294	0.0250	0

Table 4
Total relation matrix.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23
V1	0.252	0.282	0.282	0.251	0.277	0.296	0.301	0.273	0.304	0.301	0.297	0.321	0.290	0.279	0.293	0.295	0.308	0.284	0.304	0.329	0.300	0.282	0.299
V2	0.291	0.259	0.317	0.290	0.296	0.298	0.305	0.280	0.310	0.304	0.308	0.322	0.294	0.293	0.297	0.305	0.327	0.315	0.313	0.327	0.326	0.297	0.321
V3	0.310	0.307	0.268	0.274	0.302	0.311	0.319	0.286	0.322	0.310	0.324	0.335	0.314	0.304	0.296	0.306	0.339	0.326	0.332	0.321	0.333	0.302	0.320
V4	0.286	0.297	0.288	0.232	0.304	0.294	0.309	0.277	0.323	0.299	0.312	0.334	0.315	0.275	0.289	0.295	0.312	0.298	0.314	0.326	0.336	0.281	0.304
V5	0.303	0.287	0.316	0.275	0.253	0.297	0.287	0.277	0.300	0.289	0.299	0.328	0.295	0.278	0.306	0.305	0.338	0.314	0.313	0.335	0.338	0.310	0.332
V6	0.254	0.271	0.262	0.221	0.237	0.239	0.259	0.250	0.266	0.262	0.284	0.276	0.266	0.260	0.267	0.264	0.294	0.283	0.305	0.299	0.292	0.267	0.287
V7	0.293	0.290	0.293	0.251	0.269	0.298	0.257	0.252	0.289	0.264	0.302	0.328	0.280	0.267	0.298	0.273	0.314	0.287	0.313	0.327	0.304	0.285	0.318
V8	0.297	0.279	0.284	0.269	0.273	0.305	0.304	0.242	0.280	0.295	0.306	0.316	0.299	0.272	0.293	0.277	0.318	0.320	0.319	0.320	0.318	0.290	0.307
V9	0.303	0.312	0.296	0.275	0.306	0.296	0.309	0.289	0.270	0.301	0.316	0.320	0.304	0.276	0.293	0.282	0.311	0.313	0.310	0.325	0.326	0.284	0.313
V10	0.301	0.257	0.301	0.258	0.291	0.308	0.308	0.287	0.297	0.257	0.314	0.339	0.290	0.274	0.300	0.291	0.323	0.310	0.337	0.324	0.312	0.294	0.316
V11	0.318	0.310	0.326	0.262	0.291	0.322	0.308	0.287	0.339	0.326	0.283	0.325	0.317	0.301	0.313	0.305	0.338	0.324	0.337	0.324	0.349	0.306	0.330
V12	0.306	0.293	0.292	0.257	0.295	0.277	0.316	0.281	0.281	0.302	0.320	0.278	0.285	0.284	0.304	0.275	0.305	0.292	0.317	0.319	0.317	0.277	0.297
V13	0.283	0.268	0.257	0.258	0.276	0.305	0.290	0.271	0.294	0.258	0.295	0.292	0.244	0.258	0.263	0.264	0.305	0.294	0.305	0.296	0.307	0.278	0.293
V14	0.308	0.303	0.292	0.282	0.300	0.314	0.314	0.293	0.329	0.292	0.317	0.344	0.322	0.251	0.292	0.285	0.329	0.317	0.315	0.317	0.331	0.285	0.312
V15	0.282	0.289	0.291	0.274	0.287	0.314	0.304	0.284	0.293	0.282	0.306	0.320	0.299	0.284	0.253	0.262	0.318	0.293	0.318	0.320	0.309	0.290	0.313
V16	0.280	0.277	0.290	0.253	0.269	0.304	0.286	0.265	0.301	0.277	0.289	0.314	0.307	0.279	0.290	0.240	0.312	0.314	0.313	0.287	0.311	0.277	0.299
V17	0.293	0.312	0.291	0.261	0.291	0.307	0.311	0.297	0.328	0.303	0.315	0.339	0.285	0.290	0.302	0.289	0.285	0.288	0.339	0.340	0.325	0.277	0.309
V18	0.274	0.249	0.247	0.249	0.253	0.302	0.280	0.270	0.270	0.270	0.284	0.282	0.257	0.249	0.272	0.247	0.281	0.241	0.294	0.309	0.279	0.249	0.276
V19	0.277	0.288	0.303	0.263	0.255	0.297	0285	0.253	0.300	0.289	0.288	0.322	0.305	0.254	0.275	0.257	0.325	0.299	0.270	0.310	0.308	0.283	0.306
V20	0.280	0.294	0.310	0.269	0.272	0.289	0.304	0.283	0.321	0.282	0.307	0.319	0.277	0.284	0.268	0.289	0.318	0.306	0.304	0.276	0.303	0.288	0.325
V21	0.306	0.275	0.278	0.238	0.279	0.301	0.286	0.267	0.303	0.291	0.289	0.302	0.282	0.280	0.292	0.298	0.314	0.316	0.314	0.301	0.270	0.272	0.322
V22	0.342	0.329	0.333	0.288	0.321	0.328	0.352	0.318	0.346	0.345	0.346	0.361	0.350	0.318	0.332	0.338	0.359	0.331	0.358	0.358	0.356	0.284	0.366
V23	0.268	0.278	0.274	0.230	0.266	0.283	0.288	0.268	0.304	0.260	0.281	0.296	0.285	0.256	0.280	0.252	0.301	0.290	0.315	0.294	0.287	0.257	0.254

Table 5
Impact results.

	Sum ri	Sum cj	ri + cj	ri-cj	Impact
V1	6.700	6.7063	13.41	−0.007	Effect
V2	6.998	6.6045	13.60	0.393	Cause
V3	7.159	6.6906	13.85	0.468	Cause
V4	6.901	5.9803	12.88	0.921	Cause
V5	6.973	6.4613	13.43	0.512	Cause
V6	6.164	6.8855	13.05	−0.722	Effect
V7	6.654	6.8813	13.54	−0.227	Effect
V8	6.782	6.3478	13.13	0.434	Cause
V9	6.929	6.9679	13.90	−0.039	Effect
V10	6.890	6.6575	13.55	0.232	Cause
V11	7.241	6.9829	14.22	0.258	Cause
V12	6.769	7.3139	14.08	−0.545	Effect
V13	6.454	6.7616	13.22	−0.308	Effect
V14	7.042	6.3666	13.41	0.676	Cause
V15	6.786	6.6701	13.46	0.116	Cause
V16	6.633	6.4958	13.13	0.138	Cause
V17	6.978	7.2753	14.25	−0.298	Effect
V18	6.184	6.9572	13.14	−0.774	Effect
V19	6.611	7.2585	13.87	−0.648	Effect
V20	6.766	7.2823	14.05	−0.517	Effect
V21	6.678	7.2357	13.91	−0.558	Effect
V22	7.760	6.5136	14.27	1.246	Cause
V23	6.365	7.1187	13.48	−0.753	Effect

effectively and can be used for segmentation and targeting appropriate consumers. In the absence of data, an AI algorithm cannot learn or process. AI algorithms need access to data to provide accurate predictions and recommendations. The availability of data does not solve the issue completely; available data has to be AI ready. Public manufacturing organizations have been collecting data for a number of decades, but it is now essential to collect data with AI in mind. Another issue is industry specific data that is accessible to a few major players only (Chatterjee, 2020). This limits SMEs and start-ups; they are not able to access data and are unable to implement AI for decision making (Hansen & Bøgh, 2021).

In India, there is a lack of skilled AI managers, limiting implementation in the PMS. As per the NITI Aayog Report of India, only 4% of AI professionals have any experience of working in advance technologies such as deep learning, neural networks etc. A re-skilling of the current workforce is required. This needs integration of skilling initiatives and new platforms to improvise the learning outcomes. It will also add to new methods of employment generation. This view is in line with previous research conducted by Sun and Medaglia (2019) and Grover, Kar, and Dwivedi (2020). Customized or innovative applications, such as automation in manufacturing, healthcare, retail sectors etc. are transforming existing processes (Kumar et al., 2021). The cost of carrying out new innovations, experimentation and trials is very expensive. Governments of developed nations have taken initiatives towards investment in strengthening research and development but developing nations like India are limited in implementing such projects. There are issues around trust and privacy with AI in PMS of India. People often share their data unknowingly without knowing the purpose. This needs to be resolved by enhancing awareness among individuals. People need to know the significance of consent, ethics and privacy when faced with technological solutions to managing privacy risks (V3) (Siau & Wang, 2020).

The effect group factors need to be managed so that their impact can be minimized. Many challenges will affect the performance of the systems in the organization - Difficult to integrate cognitive projects (V1), the production design is inflexible in implementing AI technology (V6), Unstable product quality (V7), Responsibility and accountability (V9), Difficulties in capacity management (V12), Trust, transparency and diversity (V13) and Organizations find it difficult to integrate AI in their traditional business models (V16). With AI advancement in products and algorithms and their contribution to decision making, ethical challenges are emerging as a major challenge for AI service providers (V17). With

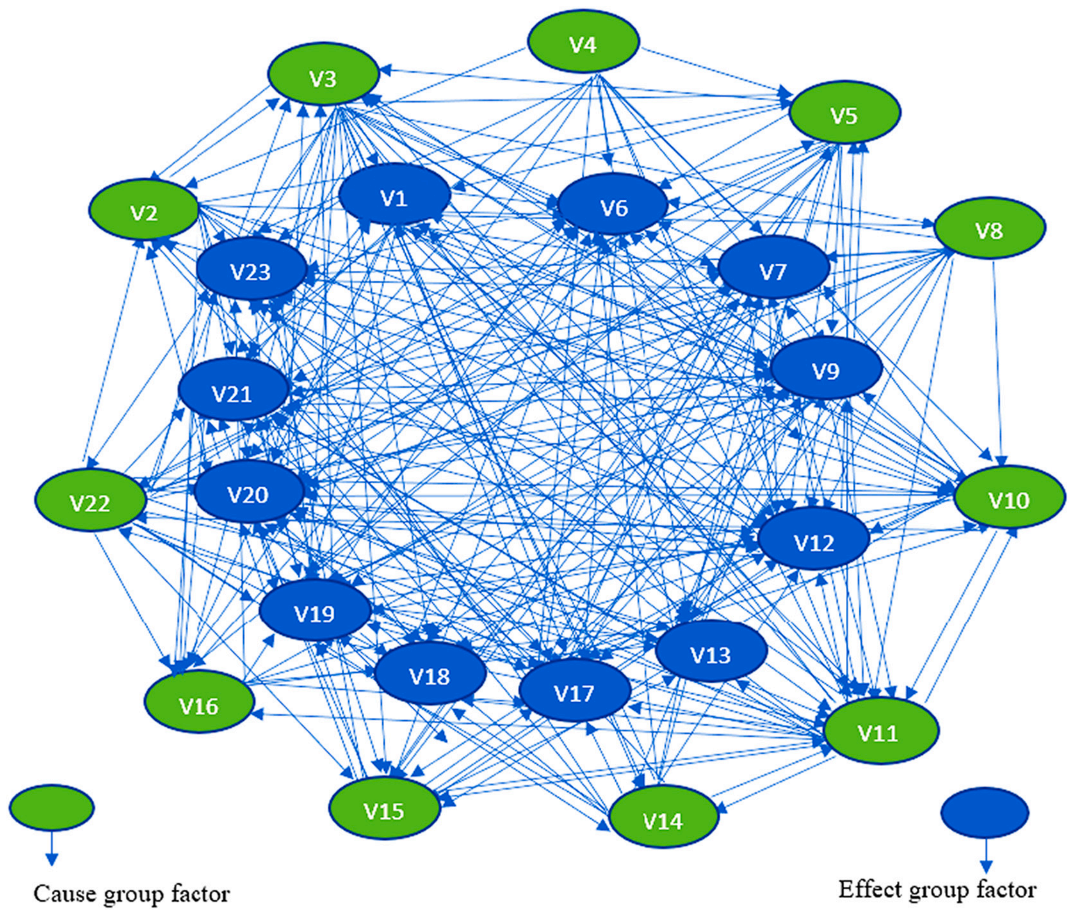

Fig. 2. Network map diagram.

the advent of AI, it has become a growing concern that data-driven algorithms can pick up bias from the data they are fed. The perception that we are not data-rich can hold many operators back from unlocking its full potential - data scarcity (V19). Insufficient awareness of AI applications towards solving business problems creates issues in India - paucity of awareness of the professionals (V20). The fear of loss of jobs is also an effect factor that needs to be properly managed. This finding is in line with previous literature showing that perception and fear among organizations towards implementing AI completely will affect the number of jobs negatively (Dwivedi et al., 2021).

5.1. Theoretical contributions

This study provides some key contributions to the theory in this area of research. The fundamental purpose of any academic research is to examine a research question with a view to producing knowledge (Collins and Hussey, 2013). With this in mind, there has been little research on AI implementation in general and in the context of India in particular. This research will be helpful in understanding the overall issues related to AI implementation in PMS.

This study has made several theoretical contributions to AI implementation and the impact of several challenges. Firstly, it contributes to the understanding of specific AI implementation challenges existing in PMS of India. Despite an AI strategy being developed by the government of India, implementation is still very low due to factors such as poor data quality, data accessibility and lack of skilled labor. There has been practically no research on AI implementation challenges in PMS from an Indian perspective; exploring these areas would help researchers to understand the key issues affecting implementation. Secondly, no research study has categorized the challenging factors into causal and effect variables to uncover their nature. Using DEMATEL techniques, this study has grouped the challenging factors into causal and effect groups. Also, the impact of each factor is computed and the inter-relationships existing among them are identified. Thirdly, a conceptual model is developed on the most influential factors to further extend the study. Development of an AI implementation model is necessary for future cross-sectional research across industries.

Finally, this study is a pioneer in developing a framework to meet the challenges of AI implementation in PMS through data collection from AI experts. The DEMATEL method has been employed to develop a framework that provides more-in-depth information about the cause-and-effect factors in AI implementation.

In summary, this is the preliminary study to facilitate a comprehensive assessment of the AI implementation challenges in PMS through independent and dependent variables. Previous studies on AI implementation did not explore and collate challenges, nor did they establish any causal links. This study is a value addition to current research on AI implementation in PMS. Challenges have been explored from several sources with DEMATEL used to position them as independent, dependent or mediating variables to enable a conceptual model to be developed. This study is insightful for managers and policymakers to help plan and take strategic actions for organizations in developing countries like India. The study can serve as a stepping stone for the theoretical model extension. We hope that future researchers can validate the proposed model through empirical analysis.

5.2. Managerial and policy implications

A flexible framework according to the local context needs to be developed for AI implementation. It is expected that the complexities in one technology can be perceived differently for users depending on the country they are operating in and also the industry they are serving. Governance is needed to understand what liability the company assumes while implementing AI. Based on the causal and effect group factors, opportunities have been found for public manufacturing organizations to improve their current systems. The findings from this research have provided a base for policymakers and decision makers to evaluate the identified challenges and propositions to improve their decision making. The five most influential causal factors are Data quality (V22), Managers lack understanding of cognitive technologies (V4), Constraints of access to industry-specific data (V14), High R & D cost (V5) and Data privacy (V3). These five factors have high impact on all other variables and thus are the areas where decision makers have to place most focus. Practitioners and policy makers can benefit from this study by considering the challenges identified and making efforts to address them to ensure successful AI implementation in PMS of India. Thus, this study is significant in determining the cause-effect factors for AI implementation while providing suggestions for its enhancement.

Furthermore, AI challenges of PMS play a crucial in the development of the nation. Due to the technological transformation, it is difficult for the government to keep the pace of development and draft comprehensive regulations. Also, it is difficult for the government to meet the variety of challenges and satisfies the ethical concerns. The policy makers should keep in mind that challenges like non-understanding of cognitive technologies and lack of expertise could be resolved with the training and workshops for their employees to develop AI specific skills. Also, such development programs might help the PMS to deal with data quality, data security and privacy issues. To deal with the current challenges, re-skilling of the current workforce is required.

5.2.1. *Data quality improvement and accessibility*

To eradicate data related concerns, the government should initiate the development of data sets. These data sets should be created during normal business processes and at the time when an intervention is launched. The data sets need to be open for public use in a machine-readable format. The open availability of datasets will be a huge support to start-ups and entrepreneurial ventures and will facilitate AI implementation more easily. The quality of data has to be improved and thus annotation of data images with speech text should be made available. The 'AI for All' strategy by the government is achievable when all public and private players take initiatives collaboratively. To bring meaningful change in the economy, the government and public manufacturing organizations have to take the lead.

5.2.2. *Developing 21st century skilled manpower*

Estimation claims by the Niti Aayog Report are that only 4% of AI professionals have experience of working in advance technologies such as deep learning, neural networks etc. It is evident that the low rate of AI implementation is in part because of less skilled manpower. In India, people are less aware of AI. The government should make joint initiatives to set up training and workshops to enhance the awareness and knowledge related to AI among the public sector manufacturing organizations. Industry professionals need to understand that AI does not aim to replace humans; rather it will support humans in their decision making. With the changing industry 4.0 business model, AI has to be a priority for manufacturing and other industries a re-skilling of the current workforce is required. This is possible with integration of relevant skilling initiatives, developing new platforms to improvise learning and new methods of employment generation through AI promotion.

5.2.3. *Data support for start-ups*

Industry specific data is accessible to few major players in the economy. It is difficult for new entrants to compete with giant companies like Google, Facebook etc. Thus, start-ups face problems in implementation of AI. This limits SMEs and start-ups as they are not able to access data and unable to implement AI for crucial decision-making. To develop a culture of sustainable AI based solutions with reasonable costs, sectors such as health, education and agriculture need the support of their stakeholders. Currently it is difficult for SMEs, start-ups or new entrants to integrate all their processes and implement AI before entering into the market. A common platform needs to be developed for integrating value chain processes.

5.2.4. *Collaborative/participative value chain*

To enhance the pace of AI, a collaborative approach should be followed across sectors and across industries. The government can develop a collaborative model to bring together academic institutes, public and private firms. The goal of achieving 'AI for all' needs long term engagement through institutional collaboration among stakeholders, including the general population. While ensuring a collaborative strategy, the government needs to act as facilitator, promoter or owner for the development of a common platform for all sectors to perform in an integrated manner.

6. Proposed Theoretical Model and Propositions

Grounded on the causal and effect relationship, we choose the causal factors to develop a potential model for AI implementation in the PMS for future validation. These factors support existing research studying the obstacles to AI implementation in public manufacturing organizations. Causal factors such as data quality, skilled manpower, constraints of access to industry-specific data, managers lack understanding of cognitive technologies and difficulty in integrating cognitive projects have been mapped to develop the conceptual model shown in Fig. 3.

6.1. *Data quality*

Data is the key to understanding consumers and their decision making. The implementation of AI depends upon the data captured or collected (Cabitza et al., 2020; Morley et al., 2020). An AI based system can be developed that can enhance the speed of data capture. The planning, strategies and decision-taking will be dependent on the AI based applications for targeting and segmenting customers. Hence, data quality needs to be improved for appropriate decision making. Today, businesses realize that data driven expectations cannot be fulfilled unless the data fits with AI powered analytics systems. The current challenge is data quality, as most of the data is 'unclean'. The current figures indicate that 76% of businesses aim to leverage their data extraction but only 15% have accessibility to fulfil it. Data quality must be improved. Therefore, we propose;

P1: Data quality has a direct and significant effect on successful AI implementation.

6.2. *Managers' lack of understanding of cognitive technologies and related functioning*

AI requires highly trained and skilled professionals. There is a low rate of AI implementation since the current less skilled workforce needs to learn cognitive technologies and their usage. Industry professionals need to understand that AI does not aim to replace humans; rather it will support humans in their decision making. With the changing industry 4.0 business model, AI has to be a priority for manufacturing and other industries. A re-skilling of the current workforce is required. This can be made possible with integration of relevant skilling initiatives, developing new platforms to improvise learning and new methods of employment generation through AI promotion. Therefore, we propose;

P2: Managers' lack of understanding of cognitive technologies has a direct and significant effect on successful AI implementation.

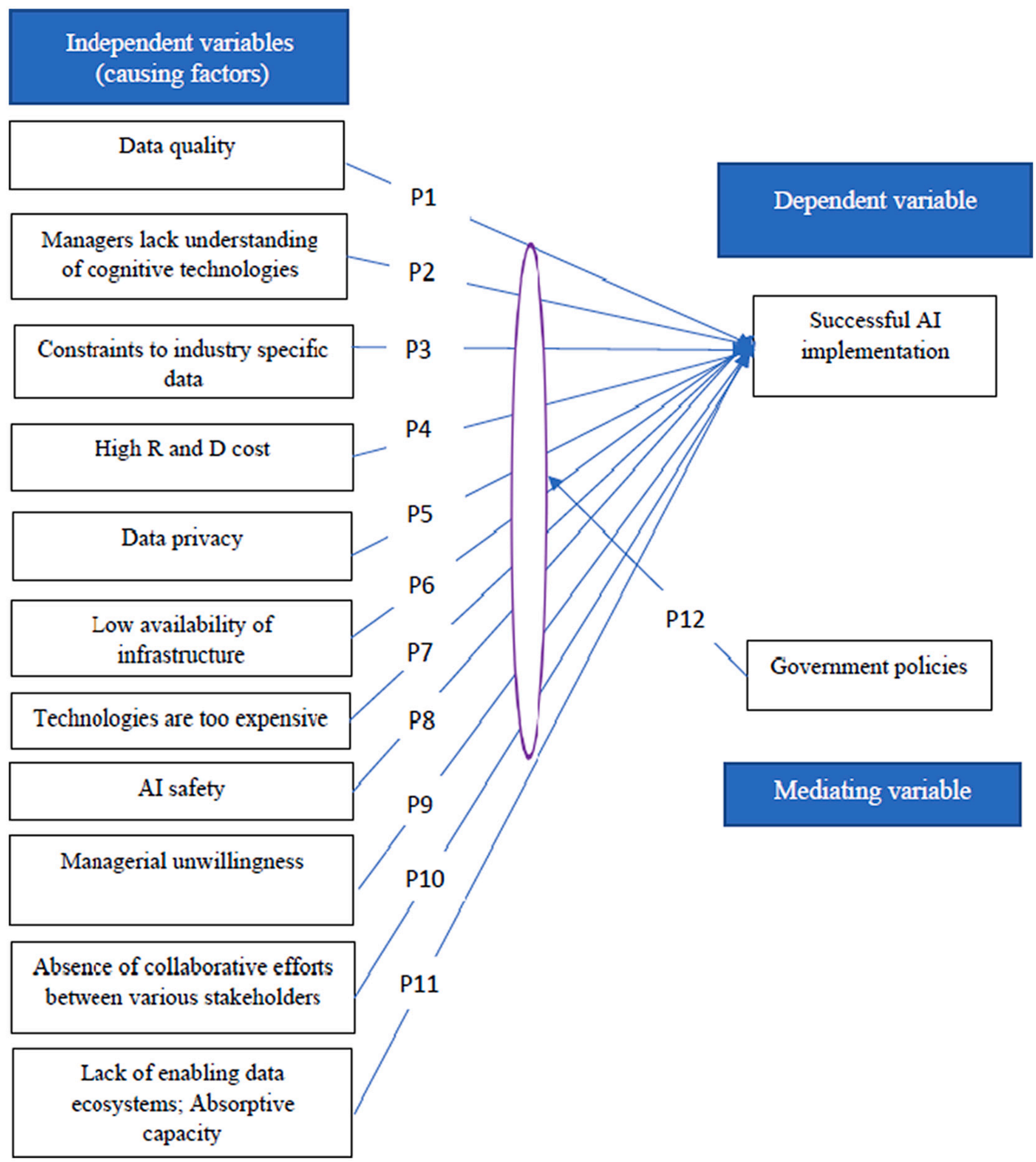

Fig. 3. Proposed conceptual model.

6.3. Industry specific data

Most of the important industry-specific data necessary for providing solutions and decision making has been limited to only a few major players in India (Rizvi et al., 2021; Rodriguez-Delgado & Bergillos, 2021). All organizations, including SMEs/start-ups/new entrants, wishing to implement AI need to have access to industry data for appropriate decision making (Hansen & Bøgh, 2021). The SMEs/start-ups/new entrants need to understand the market and customers, segmentation, targeting customers and taking appropriate decisions. With enhanced accessibility to industry-specific data, SMEs/start-ups/new entrants will gain momentum and increase their productivity. Therefore, the effect of accessibility to industry-specific data can be measured by the following proposition;

P3: Accessibility to industry-specific data has a direct and significant effect on successful AI implementation.

6.4. High research and development cost

The cost of implementing new innovations, experimentation and trials is highly expensive. The governments of developed nations have taken initiatives towards investing in strengthening research and development, while developing nations like India are limited in implementing such projects. There are also issues around trust with AI in India (Siau & Wang, 2020). The limited funds available mean that there are constraints for conducting research in the area of AI. Therefore, we propose;

P4: Research and Development costs have a direct and significant effect on successful AI implementation.

6.5. Data privacy

AI powered systems have many potential benefits. Yet, there are still concerns related to data privacy and data sharing. Users are hesitant to share their personal data. There is a need to define standard practices to be followed to preserve privacy. This would help to attract international organizations to come forward to facilitate AI implementation in India. The government needs to focus on enhancing research facilities that will address issues related to privacy and ethical concerns to accelerate successful AI implementation in PMS of India (Chatterjee, 2020). Therefore, to explore the impact of data privacy on AI implementation, the following proposition is made;

P5: Data privacy has a direct and significant effect on successful AI implementation.

6.6. Low availability of AI infrastructure

Firms need to be flexible, particularly in respect to infrastructure. Technologies, including cloud solutions, will act as the foundation of AI as substantial amounts of data are required. AI implementation in public manufacturing organizations needs significant computing resources and infrastructure. This is the basis of the cognitive infrastructure. It is more complex than traditional infrastructural systems. Therefore, to assess the impact of low availability of infrastructure for AI implementation, we propose;

P6: AI infrastructure has a direct and significant effect on successful AI implementation.

6.7. Expensive technologies

Investing in technologies can help an organization to stay ahead of the competition. With AI, the cost may decrease in future to build the next generation of decision-support systems (Keding, 2021). But currently many organizations are unable to implement AI due to its high initial cost. Recent literature suggests that AI implementation by public manufacturing organizations is increasing but it involves high upfront costs with long term, unquantifiable benefits (Berman and Dalzell-Payne, 2018). Thus, to explore the relationship between the expenditure on technologies for AI implementation, the following proposition is made;

P7: Expensive technologies have a direct and significant effect on successful AI implementation.

6.8. AI safety, human and machine compatibility

There is a misconception related to human and machine compatibility and its effect on efficiency. AI systems require technologies where human and computer interaction should be connected with the information flow (Keding, 2021). The public manufacturing organizations face unnecessary challenges where there is a lack of strategy to implement AI (Sun & Medaglia, 2019). There is a need to understand the human cognitive flexibility and the capacity for learning skills (Keding, 2021). The difference in the enigma of AI algorithms and compatibility with human decision-making leads to a challenge. Therefore, we propose;

P8: AI safety has a direct and significant effect on successful AI implementation.

6.9. Managerial unwillingness

Due to common misconceptions about AI, there exists a level of managerial mistrust (Jöhnk, Weißert, & Wyrtki, 2021). Previous research has presented an unwillingness by public manufacturing organizations to invest in AI and machine learning technologies due to a lack of awareness related to potential AI benefits for the business (Desouza et al., 2020). Schneider and Leyer (2019) examined the factors that influenced managerial willingness to delegate tasks to AI. Further, Logg et al. (2019) challenged the assumption that people preferred human to algorithmic judgment (Prahl and Van Swol 2021; Dietvorst et al. 2018). Based on this discussion, we propose;

P9: Managerial unwillingness has a direct and significant effect on successful AI implementation.

6.10. Absence of collaborative efforts between various stakeholders

With a government strategy of "AI for All', there is a need for long-term institutional collaboration among all stakeholders (Chatterjee, 2020). AI implementation will be successful with a collaborative approach involving stakeholders. But currently, there is a lack of integrated and collaborative effort among stakeholders to implement AI in PMS (De Carlo et al., 2020; Le Pennec & Raufflet, 2018). The role of stakeholders, including consumers, sellers and brands related to AI, needs further research. The current production design is inflexible in implementing AI technology (Bag et al., 2021; Cubric, 2020). To uncover the impact of collaborative efforts on AI implementation, we propose;

P10: Collaborative efforts of stakeholders have a direct and significant effect on successful AI implementation.

6.11. Lack of enabling data ecosystems; absorptive capacity

Due to the technical characteristics and complexity of AI, it is difficult for any public sector manufacturing organization to implement new technology in the current environment. Compared to other digital technologies, AI is not easy-to-use and easy-to-deploy and thus needs businesses to enhance their absorptive capacity. Existing systems are not able to integrate AI technology, so that current data structures can be an obstacle for AI implementation. Therefore, to explore an organization's ability to implement AI, current data ecosystems can be addressed by the following proposition;

P11: Data ecosystems have a direct and significant effect on successful AI implementation.

6.12. Mediating effect of government policies

In the context of an AI-led economy, India with a strategy 'AI for All' has a unique opportunity to become a main contributor in AI based solutions that may revolutionize healthcare, agriculture, manufacturing, education and other sectors. The 'AI for All" strategy has a vast pool of AI trained workers and an emerging start-up system. AI enabled systems in India have been implemented in several areas including healthcare for detection and prevention of diseases. It is projected that AI based systems will have a ripple effect on economic growth and prosperity. It will add $957 billion to the Indian economy by 2035 (Dwivedi et al., 2021). Based on current literature, it is accepted that the Government of India is focusing on AI. Setting out standardized policies is crucial at this time. Thus, in developing nations like India, the goal of achieving AI for all is a long-term target. Engagement and institutional collaboration among all stakeholders, including the general public, is needed (Dwivedi et al., 2021). The government can take joint initiatives to organize training and workshops to enhance awareness and knowledge related to AI among the public sector manufacturing organizations. AI implementation and maintenance costs are very high and are beyond the financial reach of SMEs/start-ups/new entrants (Hansen & Bøgh, 2021). For cyber threat detection, the system has to be robust and needs high investment. Thus, based on research of the sector, government policies and financial support are proposed as mediating variables; both will enhance the relationships between challenging factors such as data quality, accessibility etc., and successful AI implementation. Therefore, we propose;

P12: Government policies will mediate the relationship between cause factors and successful AI implementation.

7. Conclusion

The aim of the study was to explore the challenges and their interrelationships for AI implementation in PMS of India. AI has the potential to revolutionize the designs and systems of an organization and make a positive impact on industries such as healthcare, manufacturing, education and agriculture. If AI is planned and implemented appropriately, it can create new jobs, improve ways to manage daily operations, introduce new business models and bring valuable contributions to our society. The current study has identified major challenges such as managerial lack of understanding cognitive technologies, poor data quality, difficulty in integrating cognitive projects with existing processes and systems plus affordability issues. These need to be addressed to speed up the pace of AI technology implementation. The public sector manufacturing organizations need to skill, train and enhance the knowledge pool of their workforces. Improved data quality and integration among key stakeholders are the main requisites for AI implementation. As AI has revolutionized the landscape, businesses and customers are bound to be classified on the adoption, implementation and integration of new applications and workflows. Most importantly, business organizations and government authorities should prioritize areas where AI can bring about widespread visible and quick, positive benefits.

This needs all stakeholders to invest in enhancing existing resources and workflows for cost reduction and higher efficiency. The government needs to develop a comprehensive strategy for implementing AI in addition to other technologies such as machine learning and IoT to harness potential to the fullest extent in manufacturing processes.

7.1. Limitations and future directions for research

The challenges are identified in the context of the PMS of India, and thus the findings of the study need to be cautiously implemented in the context of private sector organizations. The study has a few limitations. Firstly, there was an absence of face-to-face discussion with experts due to remote collection of data. The faults and connection issues responsible for disturbance in the process might have interrupted the discussion and consequently the interpretation. Secondly, the pairwise comparisons are based on expert judgments and hence the results may be biased. Thirdly, the study has collected data from a single country that has certain contextual factors which might have an impact on the results. Future studies can be conducted to investigate AI implementation in other industries, understanding that there may be a different perspective from stakeholders. The research questions are appropriate to explore the impact of agility, data quality, integration and skilled manpower on AI powered enabled systems in private and public sector organizations. Similarly, challenges of AI in the public sector including efficiency, effectiveness and political legitimacy need to be addressed. Future, research should include the ethical challenges in AI implementation as data privacy issues are rising day by day. Also, how government initiatives are supporting AI implementation in developing countries such as India needs to be explored in future. Such studies may employ structural equation modelling to empirically validate the conceptual framework. Also, DEMATEL can be further extended to GREY-DEMATEL or FUZZY-DEMATEL to evaluate key challenges of AI implementation. Also, in future research, the challenges identified may be analyzed with some other MCDM techniques such as ANP, Pythagorean AHP etc. to prioritize the obstacles towards implementation with sensitivity analysis.

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