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Measuring barriers to digitalisation in the industry 4.0 environment: scale development and validation in manufacturing organisations

Purpose: The study aims to conceptualize, develop, and validate a multi-dimensional scale for barriers to digitalization in manufacturing organisations within Industry 4.0 contexts.

Design/methodology/approach: The study follows a psychometric scale development procedure, including item generation, selection, refinement, and validation. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are used to develop and refine the scale. Additionally, a competing model strategy is applied to identify the best-fitting and most parsimonious model for assessing barriers to digitalization in Industry 4.0.

Findings: The results of exploratory and confirmatory factor analysis indicate a five-dimensional factor structure of barriers to digitalisation. The comparison among different measurement models suggests that barriers to digitalisation can be operationalised as a second-order factor model involving five dimensions, namely, economic & financial barriers, cultural barriers, strategic barriers, behavioural barriers, and technological barriers, thereby offering a theoretical foundation for future empirical studies in the context of a digitalised supply chain.

Research limitations/implications: Unlike previous studies, this study contributes to the knowledge base by offering a better understanding of the multidimensionality and multifaceted structure of underlying barriers to digitalisation in the Industry 4.0 context, which can be helpful for future digitalisation research.

Originality/Value: This study is one of the most relevant and up-to-date studies for developing a scale for assessing digitalisation barriers in an industry 4.0 context.

Keywords: Digitalisation, Supply Chain, Structural Equation Modelling, Barriers, Survey

Article Classification: Research Paper

Quick value overview

Interesting Because: This study develops and validates the first multi-dimensional scale to measure digitalisation barriers in Industry 4.0 manufacturing. Unlike most earlier studies that relied on single-item measures or lacked theoretical grounding, this research uses both deductive and inductive techniques, including literature review, focus group validation, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA) to establish a robust second-order factor model.

Theoretical Value: This study offers substantive theoretical contributions by conceptualising digitalisation barriers as a second-order construct composed of five interrelated first-order dimensions. The theoretical insights stem from applying a dual-lens framework: the Resource-Based View (RBV) and Resource Dependence Theory (RDT).

Practical Value: This study provides a diagnostic tool that allows practitioners to identify, measure, and prioritise key barriers within their organisations that hinder digitalisation. The study recommends investing in training, revising digital strategies, and collaborating with stakeholders to reduce resistance, improve resource allocation, and support a smoother transformation.

1. Introduction

In the wake of Industry 4.0, the growth of the digital economy has paved a path for future growth, and the adoption of digital technologies has become a strategic priority for firms across all industries to bring coordination, efficiency, and effectiveness to their organisational processes (Sun and Xi, 2024; Yang *et al.*, 2024) and reinforce the operational benefits, such as cost reduction, quality improvement, and efficiency improvement(Bajpai *et al.*, 2023; De Alwis *et al.*, 2023; Ghobakhloo *et al.*, 2022). Studies have suggested that digitalisation in the context of industry 4.0 is a complex process, and firms may encounter unique sets of barriers in this pursuit (Cardinali *et al.*, 2022; Cordeiro *et al.*, 2023; T.S. and Ravi, 2022). Barriers such as institutional concerns, infrastructural issues, a lack of a skilled workforce, financial problems (Salman *et al.*, 2023), legal and contractual ambiguity, high cost, cyber security, and privacy (Chauhan *et al.*, 2021) unfavourably affect value perceptions and thereby adversely influence the adoption of digital technologies.

While several studies reported that barriers to digitalisation arise due to misalignment between different elements of manufacturing organisation, human and technological factors, such as huge implementation costs, shortage of digital skills, and a lack of supportive organisational structure (Chauhan *et al.*, 2021; Chen *et al.*, 2023; Fernando *et al.*, 2022; Salman *et al.*, 2023), majority of the existing studies suffer from few design and methodological issues. The first issue is related to the operationalisation of constructs. Most of the studies to date have used single-item measures to operationalise the different digitalisation barriers (Okanlawon *et al.*, 2023; Brunetti *et al.*, 2020; Kamble, Gunasekaran and Arha, 2019; Kamble *et al.*, 2018; Karadayi-Usta, 2020; Majumdar *et al.*, 2021; Moktadir *et al.*, 2018). Although single-item measures are appropriate for relatively simple and narrowly defined constructs (Venkatraman and Grant, 1986), digitalisation barriers are complex, making the appropriateness of single-item measures questionable. The second issue is related to the generalisability of the studies. The existing studies' sample range, sample homogeneity, and scope of measures limit the generalizability of findings (Chauhan et al., 2021; Kamble et al., 2018a, 2019; Majumdar et al., 2021; Moktadir et al., 2020). The third issue is related to statistical testing. Most of the existing studies on barriers to industry 4.0 technologies have assessed distinct barriers using a single measure for modelling purposes (Bajpai et al., 2023; Salman et al., 2023; Kamble et al., 2018; Majumdar et al., 2021; Ullah et al., 2021). As a result, the lack of empirical studies on digitalisation barriers, particularly in emerging economies contexts (Chauhan et al., 2021; Dalenogare et al., 2018), as well as the wide array of single measures used by several studies, can be considered significant causes of the digitalisation's incomplete state of knowledge (Kamble et al., 2019; Moktadir et al., 2020; Ullah et al., 2021).

Building on these gaps, it becomes evident that, despite the well-recognised benefits of digital transformation, emerging economies continue to face significant challenges in digital transformation (Cordeiro et al., 2023; Dadsena et al., 2024; Huu, 2023). For instance, Egala et al. (2024) examined the barriers impacting the digital orientation of service-based SMEs, while Yan and Liu (2024) highlighted how digital trade barriers influence technological innovation efficiency. However, there remains a pressing need to identify, conceptualise, and measure digitalisation barriers in the manufacturing context, where the adoption of Industry 4.0 technologies is essential yet restricted. This study addresses these gaps through the following research questions:

RQ1. What are the key barriers to digitalisation in the context of Industry 4.0 within manufacturing organizations?

RQ2. How can the different dimensions of digitalisation barriers be conceptualised and assessed in manufacturing settings?

RQ3. How can a validated scale be developed to assess barriers to digitalisation in manufacturing organizations implementing Industry 4.0 technologies?

Therefore, the objective of this study is to conceptualise, operationalise, and validate digitalisation barriers using a systematic approach to uncover the multi-dimensional structure of such barriers within the manufacturing context. The research uses deductive logic to observe and examine phenomena empirically. Resource-based view (RBV) (Barney, 1991) and resource dependency theory (RDT) (Pfeffer and Salancik, 1978) are considered appropriate theoretical lenses to understand constructs related to digitalisation barriers and to develop and evaluate the proposed research model within the Indian manufacturing industry.

This study is highly relevant for the manufacturing sector as it takes a comprehensive approach to identifying and measuring barriers to adopting digital technologies in Industry 4.0. It is the first to develop and validate a multi-item scale specifically for this purpose, offering deeper insight into the challenges manufacturers face. By introducing a rigorous and reliable measurement tool, the study enhances research accuracy and supports practical decision-making. It also advances the operations and supply chain fields by providing a structured framework to assess and address digitalisation barriers in manufacturing organisations.

The remainder of the paper is structured as follows. Section 2 describes the theoretical foundation of this study. Section 3 and Section 4 present the research methodology data analysis, and findings of the study. Discussion and implications are presented in section 5. Lastly, the conclusion, limitations and directions for future research are given in Section 6.

2. Theoretical Background

This section underlines the theoretical lens used in the study. It also sheds light on the digitalisation concept and discusses barriers to the adoption of digitalisation in organisations.

2.1. Underpinning Theory

While transitioning to a digitalized supply chain in an Industry 4.0 environment, firms encounter intrinsic and extrinsic barriers, including limited resources and a lack of required skills, knowledge, and experience. Resource constraints hinder digital technology adoption and its potential benefits (Ryan et al., 2013). Managers must strategically allocate resources to facilitate Industry 4.0 adoption. The Resource-Based View (RBV) aligns with this perspective, emphasizing the bundling of tangible and intangible assets, such as management competence, leadership skills, organizational processes, and knowledge resources (Barney, 2016). Thus, a lack of internal resources and capabilities is a key barrier to digital adoption, making RBV a suitable theoretical framework for understanding intra-firm barriers.

On the other hand, RDT posits that firms rely on other actors in their environment to access vital inputs such as materials, the workforce, and technology (Pfeffer and Salancik, 2003). Firms are under tremendous pressure to ensure sustainable production (Cai and Choi., 2019). RDT is particularly relevant to supply chain digitalization, where inter-firm dependencies influence digital adoption. The theory views organizations as systems requiring external support for continuous improvement. Thus, digitalization is examined through RDT to explore external barriers to technology adoption. Consequently, RBV and RDT serve as the primary theoretical anchors to explain barriers to digitalization.

2.2. Digitalisation in the Context of Industry 4.0

The term "Industry 4.0", introduced in 2011 at Hannover Fair, encompasses a wide range of technologies that can be used to revolutionise the value chain of the manufacturing industry through the production of intelligent technologies and concepts (Karadayi-Usta, 2020; Lin *et al.*, 2018). In industry 4.0, digitalisation refers to several interconnected and emerging technologies (Shou *et al.*, 2020), including the Internet of things, 5 G networks, cloud computing, big data analytics, artificial intelligence, and blockchain technology, that can be characterised as a "digital eco-system" (Kalinina, 2020, Choi et al., 2021). It implies the process of using these emerging digital technologies to get globally interconnected on a real-time basis and generate values in novel ways (Ivanov, 2021). Intelligent supply chain networks provide visibility through continuous real-time synchronisation (Hanifan *et al.*, 2014; Kothari *et al.*, 2008) and integration of supply chain partners (Huo *et al.*, 2014). Digitalisation promotes customer-driven, agile, and productive activities to leverage efficient approaches within novel promising technologies such as the internet of things, blockchain, 3-D manufacturing, cloud computing, and data analytics (Büyüközkan and Göçer, 2018). Overall, digitalisation in the industry 4.0 context encourages firms to develop innovative business models and brings value (Spanaki et al. 2018; Jajja et al., 2018).

2.3. Barriers to Digitalisation in Industry 4.0 Context

Despite the well-acknowledged manifold benefits of digitalisation across all industries (Agrifoglio et al., 2017), organisations cannot fully reap the potential of digital technologies due to several barriers that impede the progress towards digitalisation (Dwivedi et al., 2021; Kumar et al., 2020). The challenges in implementing digital technologies are multifaceted (Agrawal et al., 2020; Cichosz et al., 2020; Glass et al., 2018; Kamble et al., 2018; Marcon et al., 2019; Vogelsang et al., 2019). Some of the widely cited barriers in the literature include lack of government support and policies, organisational complacency, lack of industry-specific guidelines, huge implementation cost, shortage of digital skills, threat of cybersecurity and lack of supportive organisational structure (Chauhan et al., 2021; Agrawal et al., 2020; Cichosz et al., 2020; Kumar et al., 2020; Glass et al., 2018; Kamble et al., 2019; Vogelsang et al., 2019; Chauhan et al., 2019; Huh & Lee, 2018; Luthra & Mangla, 2018; Yadav et al., 2018; Kamble et al., 2018; Council, 2017; Müller et al., 2017; Schröder, 2017; Kiel et al., 2017; Raj et al., 2020; Ryan et al., 2017). Although there is a consensus that barriers to digitalisation are multi-dimensional (Chauhan *et al.*, 2021; De Alwis *et al.*, 2023; Govindan, n.d.; Salman *et al.*, 2023), there are fragmented views on the dimensions that need to be studied to assess barriers to digitalisation. Previous studies also reported that the barriers to digitalisation need further exploration and, hence, more empirical investigation (de Sousa Jabbour et al., 2018; Horváth & Szabó, 2019; Kamble et al., 2018; Oesterreich & Teuteberg, 2016; Raj et al., 2020; Xu et al., 2018). Table 1 describes some of the recent studies on barriers to the adoption of Industry 4.0 technologies.

Table 1: Recent studies on Barriers to Industry 4.0 technology adoption

Author	Methodology	Findings
Halmosi, & Aranyossy (2024)	Interviews	Unveils catalysts and barriers of Healthcare 4.0 transformation
Cordeiro *et al.* (2023)	Survey	Found that technological infrastructure, financial constraints, and lack of understanding of the benefits of Industry 4.0 directly affect the adoption of Industry 4.0 technologies
De Alwis *et al.*, (2023)	Case studies	Barriers and strategies to overcome these barriers were identified in the Sri- Lankan manufacturing context.
Bajpai *et al.* (2023)	DANP, TOPSIS	14 critical risk factors related to four different risk dimensions were identified, and their ranking was performed

Okanlawon *et al.*, (2023)	EFA	Technological and socio-economic barriers were identified in the adoption of blockchain technology.
Salman *et al.* (2023)	Delphi, DEMATEL	I4.0 training, Lack of Motivation and Resistance to Change are found to be the most significant barriers to the adoption of Industry 4.0
T.S. and Ravi (2022)	ISM, MICMAC	Analysed and interpreted barriers to supply chain digitalisation
Ghobakhloo *et al.*, (2022)	SLR	The study identified various drivers and barriers of industry 4.0 technology in manufacturing SMEs
Raut *et al.* (2021)	DEMATEL	Lack of data storage facility, IT infrastructure, organisational strategy and uncertain benefits and long-term usage are the widely documented barriers to adopting BDA practices.
Chauhan *et al.* (2021)	Survey	Intrinsic and extrinsic barriers are negatively associated with digitalisation
Kumar *et al.* (2021)	ISM-ANP	The study indicates that lack of government support, incentives, and policies and protocols are significant obstacles to implementing the I4.0-CE model.
Masood and Sonntag, (2020)	Survey	Financial and knowledge constraints are found to be the key challenges in industry 4.0 technology in SMEs
Yadav *et al.* (2020)	ISM-DEMATEL	Lack of government regulation and lack of trust among stakeholders to use blockchain are significant adoption barriers to blockchain in Indian agriculture.
Raj *et al.*(2020)	Grey DEMATEL	Lack of a digital strategy and resource scarcity are the most important barriers in developed and developing economies.
Stentoft *et al.* (2020)	Survey	Lack of perceiving industry 4.0 drivers adversely affects SMEs development of industry 4.0 readiness

2.4. Dimensions of Barriers to Digitalisation

In terms of theories, the study has applied RBV to understand intra-barriers related to firms' resources, capabilities, and procedures. It derives barriers related to competence, leadership skills, organisational processes, and knowledge resources. Further, considering the interdependency of firms for resources, funds, and information, the study has used RDT to explore inter-firm barriers to acquisitions of resources, capabilities, and processes.

Drawing from RBV, *behavioural dimension* generally refers to resistance to change stemming from management structure and a lack of employees' knowledge across about the latest technologies (Chen *et al.*, 2023; Cordeiro *et al.*, 2023; Fernando *et al.*, 2022; Rojo Abollado *et al.*, 2017). *Economic and financial dimension* is an important dimension of digitalisation barrier. Significant investment with uncertain returns, high implementation costs, inadequate budgeting, and insubstantial capital investment are significant concerns that make economic and financial barriers a salient dimension of digitalisation barrier in organisations in the Industry 4.0 context (Bajpai *et al.*, 2023; De Alwis *et al.*, 2023; Moktadir *et al.*, 2018; Nimawat and Gidwani, 2021; Vaidya *et al.*, 2018). Existing studies also provide further evidence that the financial dimension has been extensively adopted in conceptualising and operationalising barriers to digitalisation in a diverse technology context(Cardinali *et al.*, 2022; Salman *et al.*, 2023; T.S. and Ravi, 2022). *The cultural dimension* of a firm refers to its aversion to change and the absence of the appropriate organisational and governance model(De Alwis *et al.*, 2023). The antagonistic culture that prevents employees from implementing digital technologies, such as a lack of digital training & education (Calabrese *et al.*, 2021), and reverse mentoring, can be considered cultural barriers. According to RDT, the challenges for digital transformation include the need to develop novel knowledge across the supply chain, leadership skills to develop trust and commitment, and the need to retrain employees to fit into the new digital culture (Horváth and Szabó, 2019). The lack of necessary competencies related to human resources (Stentoft *et al.*, 2020), the fear of job replacement by machines and robots, and resistance to change are concerns raised by managers and researchers (Marcon *et al.*, 2019). Also, employers' passive attitude towards implementing change management practises in organisations impedes the digitalisation process (Okanlawon *et al.*, 2023; Schroeder *et al.*, 2019)).

Strategic dimension represents the lack of a strategic plan for implementing novel digital technologies due to a lack of understanding of the strategic importance of digital technologies and the incompatibility of the existing systems used in the organisation with the novel system(Chen *et al.*, 2023). This is in line with the tenant of RDT that suggests that the performance of an organisation is linked to resources it does not directly control.

Technological dimensions of digitalisation barriers generally refer to a lack of technological infrastructure (Moktadir et al., 2018; Kamble et al., 2018), security and privacy risks (Agrawal *et al.*, 2020; Legner *et al.*, 2017), incompatibility of the latest digital technology with their existing processes(Okanlawon *et al.*, 2023), industrial espionage, and threats of cyber-attacks that escalate with digitalisation ((Bajpai *et al.*, 2023; Chen *et al.*, 2023; Fernando *et al.*, 2022; Kamble *et al.*, 2019; Marcon *et al.*, 2019; Moktadir *et al.*, 2018). To conclude, the five dimensions of barriers to digitalisation are comprehensive yet parsimonious and find theoretical support in RBV and RDT. Many other dimensions proposed in the existing digitalisation literature can be reconciled within these five dimensions. Therefore, the dimension offered in the component model of barriers to digitalisation is adopted as the theoretical basis for developing the instrument.

3. Research Methodology

This section delineates the research methodology used in the present study, systematically analysing the research questions through a mixed-method approach. A deductive approach was employed to address the first research question. A comprehensive literature review facilitated the identification of an initial list of 22 barriers to digitalisation grounded in existing research. An inductive approach was incorporated to refine and validate these barriers by conducting two focus group studies with industry practitioners, utilising purposive and snowball sampling. These discussions provided practical insights, leading to a comprehensive list of 26 barriers, ensuring theoretical robustness and practical relevance. Building on this foundation, the second research question was addressed by conceptualizing and categorising the identified barriers into five key dimensions based on insights from the literature and focus groups. The process included item generation and sorting, face validity assessments, and a refinement process, enhancing the clarity, coherence, and relevance of the identified barriers. A rigorous statistical approach was applied to address the third research question to ensure that the instrument developed for assessing digitalisation barriers was reliable and valid. This involved data screening and quality checks, followed by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to validate the instrument's reliability and effectiveness in measuring digitalisation barriers. The details of each of the steps are presented in the following sub-sections.

3.1. Identification of the barriers to digitalisation

With the deductive approach, a systematic search was carried out with keywords, platform, and article topic, which were all factors examined at this stage. Using a combination of keywords like "Digitalisation", "Digital Supply Chain", "Barriers", "Challenges", "Digital transformation", “Industry 4.0,” “Blockchain”, “Internet of things”, “Bigdata technologies”, “Artificial intelligence”, relevant articles from Web of Science and Scopus databases were extracted. Simar search strategy was used to extract relevant papers from specific journals that frequently publish papers on digitalisation, automation, technology and supply chain-related articles like Technological Forecasting & Social Change, Computer & Industrial Engineering, International Journal of Production Economics, IEEE Transactions on Engineering and

Industrial Management & Data System. Data from different databases were integrated, and overlapping and duplicate items were deleted, resulting in a list of 22 items.

3.2. Focus group study

With an inductive approach, following Axelrod's (1975) guidelines, two focus group studies (n = 6*2 = 12) were undertaken with practitioners to understand the barriers and challenges encountered during the digitalisation in Industry 4.0 context. Due to the COVID-19 pandemic, online focus group interviews were conducted over Zoom software (collaborative, cloud-based video conferencing service) in October 2020. Online focus groups provide participants with fast and spontaneous reactions to diverse aspects of research questions and are a very efficient and flexible research method compared to offline focus group interviews. The focus group participants were selected using the purposive and snowball sampling methods, and the following criteria were applied for their recruitment: i) Each participant understands the digitalisation concept in the industry 4.0 context ii) Participants are somehow part of the digital transformation in their organisation; iii) participants are representatives of their respective firms. The profile of the focus group participants is given in Table 2.

Before the focus group interviews, participants were briefed on the study's purpose and procedures. A semi-structured interview protocol (Appendix Table A1) guided discussions on challenges faced by practitioners. Disagreements were addressed through clarification, fostering a shared understanding of technological adoption issues. Each session lasted 60 to 90 minutes and continued until theoretical saturation was reached**.** Discussions were recorded, transcribed, and analysed using Goulding's (2005). guidelines, following by McQuarrie & Krueger (1989) criteria. Themes were developed using a grounded theory approach, balancing open-minded analysis with existing theoretical frameworks.

Construct validity was ensured through triangulation, while internal validity was established via pattern matching and literature-based explanation building. After refining the initial list by removing three ambiguous items and adding seven from focus interviews, participants confirmed a final set of 26 items, with no further changes.

Table 2. Sample characteristics of Focus group (N =12)

Particulars		No.
Gender	Male	9
	Female	3

Domain	Supply Chain	2
	Production	1
	Maintenance	1
	Research & Development	2
	Information Technology	4
	Product Development	2
Experience	5 Years - 8 years	4
	8 years - 10 Years	5
	More than 10 Years	3
Education	Bachelors	8
	Masters	4
Industry	Automobile and auto ancillary	3
	Apparel manufacturing	2
	Food Manufacturing	2
	Computer and electronics products	3
	Electronic Equipment Manufacturing	2

3.3. Item generation and face validity

A final list of 26 items was generated using both the deductive and inductive approaches. Further, the sorting of items was independently done by two researchers, and these items were also clustered into 5 dimensions of barriers to digitalisation. The face validity of the 26-item list was then evaluated. The experts (2 professors, 3 practitioners, and 5 respondents) were given the background of the study and were suggested to retain the items based on the meaningfulness, unambiguity, and relevance of the items. Subsequently, 6 items were modified, and an ambiguous item was dropped. Finally, a questionnaire with 25 items was developed using a seven-point Likert scale (1 = "strongly disagree" and 7 = "strongly agree"). The 25 items included in the questionnaire are presented in Table 3. The questionnaire is included in the appendix in Table A2.

Table 3. Items used in the study

Barriers	Items	Related Studies	Focus Group Interview Support
Technical Barriers (TCB)	Inadequate storage capacity to move in for digital technologies	N.A.	Yes
	Potential risk of data protection and cyber security issues in my organisation due to implementation of industry 4.0 technologies	(Marcon *et al.*, 2019), (Agrawal *et al.*, 2020)	Yes

	Most of the machines and equipment do not have an open interface to take out relevant data, or maker support is readily available.	(Bajpai *et al.*, 2023; Chen *et al.*, 2023)	Yes
	Incompatibility of existing processes and systems with advanced digital technologies in the industry 4.0	(Bajpai *et al.*, 2023; Chen *et al.*, 2023; De Alwis *et al.*, 2023).	Yes
	Perceived fear of confidential data breach in management's thoughts regarding the advanced digital system	(Bajpai *et al.*, 2023; Chen *et al.*, 2023; Prause, 2019)	Yes
	Lack of technical expertise in engineers to manage digital technologies	(Mckinsey&Company, 2016), (Deloitte, 2017)	Yes
Economic & Financial Barriers (EFB)	Unwillingness to digitalise the existing supply chain process due to an increase in manufacturing cost	(Agrawal *et al.*, 2020; Chen *et al.*, 2023)	Yes
	No economies of scale exist if we digitise our processes.	N.A.	Yes
	Unable to quantify the benefits of advanced technologies in terms of ROI	(Bajpai *et al.*, 2023; Chen *et al.*, 2023; De Alwis *et al.*, 2023; Marcon *et al.*, 2019)	Yes
	Budgetary constraints to implement digital technology	Marcon et al. (2019	
	The upgradation of existing systems shall also involve a considerable cost that cannot be recovered.	(Bajpai *et al.*, 2023; De Alwis *et al.*, 2023; Okanlawon *et al.*, 2023; Salman *et al.*, 2023).	Yes
	Lack of investment in training & development programs to facilitate the adoption of digital technology	(Chen *et al.*, 2023; Marcon *et al.*, 2019)	Yes
Behavioural Barriers (BHB)	Employees fear job security due to the introduction of robots and other technologies to reduce human efforts.	(De Alwis *et al.*, 2023)	Yes
	Employees' reluctancy to use advanced systems due to prolonged engagement in the conventional process	(Chen *et al.*, 2023; Okanlawon *et al.*, 2023; Prause, 2019)	Yes
	Unable to foresee the relative advantage of recent technologies	(Prause, 2019), (Marcon *et al.*, 2019)	Yes
	Lack of trust between top management and employees that hinders the implementation of advanced technologies	(Marcon *et al.*, 2019)	Yes
Strategic Barriers (STB)	Lack of a dynamic strategic plan for the implementation of the latest digital technologies	(Bajpai *et al.*, 2023; Mckinsey&Company, 2016; Salman *et al.*, 2023), (Deloitte, 2017)	Yes
	Fear of adverse environmental impact of digital technology	N.A.	Yes
	Lack of capabilities to reconfigure existing processes to support the implementation of the latest digital technology	(Marcon *et al.*, 2019)	Yes

	Centralised decision-making in an organisation	(Prause, 2019)	Yes
Cultural Barriers (CLB)	Lack of digital education for employees to promote digitalisation	(Agrawal *et al.*, 2020; Brunetti *et al.*, 2020; Chen *et al.*, 2023), (Brunetti *et al.*, 2020; De Alwis *et al.*, 2023)	Yes
	Lack of encouragement to promote digitally skilled workers	(Brunetti *et al.*, 2020; Salman *et al.*, 2023)	Yes
	Lack of investment in reverse mentoring to promote digitalisation	(Brunetti *et al.*, 2020)	Yes
	Lack of efforts to break down resistance to digitalisation	(Bajpai *et al.*, 2023; Brunetti *et al.*, 2020)	Yes
	Lack of formal training to implement and use the latest technology	(Brunetti *et al.*, 2020; Chen *et al.*, 2023)	Yes

3.4. Sample and data collection

The targeted population for this study comprises Indian manufacturing firms belonging to thirteen industries from all over India as per the EMIS ISI emerging database (Table 3). The rationale for choosing various sectors is as follows: First, the selected industries for data collection were consistent with the earlier empirical studies on digitalisation (Marcon *et al.*, 2019; Prause, 2019; Zangiacomi *et al.*, 2020). Second, using diverse industries in the sample offers an opportunity to address the robustness of the digitalisation concept and its applicability across various industries. To ensure the appropriateness of firms, the following screening criteria were applied. First, respondents were asked whether their firms have recently implemented or are in the process of implementing any emergent digital technologies, such as blockchain, the Internet of Things, and big data. A firm that has implemented or is implementing novel technologies was considered suitable for this study. Second, firms implementing novel technologies, either new to their respective industries or new to their respective firms and industries, were qualified to study. Thus, this study did not include firms implementing novel technologies already established in their respective industries or used by competitors' firms.

The study targeted middle and senior management professionals in supply chain, manufacturing, design, R&D, and product development using purposive and snowball sampling. To ensure clarity, the questionnaire included an explanation of digitalization within the industry 4.0 context, defining it as the integration of technologies like IoT, cloud computing, AI, big data analytics, and cybersecurity. The cover page outlined the questionnaire's purpose, while the instructions specified that all questions pertain to Industry 4.0, with relevant examples provided.

Two screening criteria were applied to finalize the respondents. First, they had to be engaged in digitalization-related activities within their organizations. Second, they needed at least three years of experience to understand their firm's digitalization practices. To address the low response rate, a stratified random sample of 1,200 manufacturing firms was initially contacted with a cover letter. After two rounds of telephone follow-ups, 640 respondents expressed interest in participating. These 640 targeted firms were contacted at least twice via telephone to encourage participation. Ultimately, 246 usable and valid responses were received. Table 4 presents the sample characteristics.

Table 4. Sample Characteristics of the study

Particular		*No. of Responses*	*Particular*	*No. of Responses*
Industry Broad Classification	*NAICS Code*		*Ownership of the firm*	
Apparel Manufacturing	315	21	Joint Venture	17
Chemical Industry	325	18	Private Domestic Player	81
Communication Equipment Manufacturing	334290	16	Private Foreign Player	58
Computer and Peripheral Equipment Manufacturing	334100	7	PSU	4
Computer and Electronics Products	334	17	Public Limited	86
Computer Terminal and Other Computer Peripheral Equipment Manufacturing	334118	6		
Electronic Equipment Manufacturing	33531	17	*Age of Firm*	
Food Manufacturing	311	17	Less than 5 Years	22
Household Appliances	423620	23	5 years to 10 Years	13
Machine Manufacturing	333	37	10 years to 15 Years	14
Motor Vehicle Manufacturing	3361	16	15 years to 20 years	16
Motor Vehicle Part Manufacturing	3363	13	More than 20 years	181
Semiconductor and Other Electronic Component Manufacturing	33441	10		
Others (Pharma, Plastic, Rubber, Steel, Fertiliser, Ventilation Airconditioning, etc)		28		
Informants Job Title			*Number of Employees*	
AGM/DGM/GM		26	Up to 1000	65
Assistant Manager/Deputy Manager		131	1000-5000	33
CEO/President/Vice President/COO/Owner		11	5000-10000	23
Engineer		72	More than 10000	125

3.5. Data Screening

The responses were screened carefully to identify any unusual patterns, outliers, non-response bias, and common method bias (Hair et al., 2009). Outliers do not appear on the Likert scale, as extreme responses (either 1 or 7) do not represent outlier behaviour. Outliers in terms of unengaged responses were prevented by keeping reverse-coded questions in the questionnaire. Non-response was assessed using exploration and the subjective method (Armstrong and Overton, 1977). The respondents' profile characteristics were compared with non-respondents' profile characteristics in terms of industry, total experience, profile, and designation (Armstrong and Overton, 1977). The profile characteristics of respondents and non-respondents were not significantly different. Common method bias was controlled through study design (ex-ante) and statistical techniques (ex-post), ensuring response anonymity, clear questionnaire construction, and multiple respondents to minimize systematic error(Podsakoff *et al.*, 2003). A common latent factor (CLF) analysis confirmed no significant bias, with factor loading differences below 0.2. Endogeneity was addressed through a thorough literature review, though instrumental variable tests were limited due to sample size and the cross-sectional nature of the data.

Reliability and item-to-total correlation were calculated to initiate data analysis. The minimum acceptable value of Cronbach's coefficient alpha for a new scale is 0.6 and 0.7 for the existing scale (Hair et al., 2009). Cronbach's coefficient alpha value was found to be 0.94. All the item-to-total correlations were greater than the threshold limit of 0.3, indicating an acceptable level of reliability (Nunnally, 1978).

3.6. Data Analysis & Findings

The data analysis method includes a series of statistical analyses, including exploratory factor analysis using SPSS software, confirmatory factor analysis, and competing model analysis using AMOS software. In the following subsections, findings from data analysis have been presented.

3.7. Exploratory factor analysis

Exploratory Factor Analysis (EFA) was conducted to assess the suitability of 25 items in explaining the five dimensions of barriers to digitalization using Principal Component Analysis with varimax rotation in SPSS 21.0. The results showed a Kaiser-Meyer-Olkin (KMO) value of 0.92, significant Bartlett's test of sphericity, and communalities ranging from 0.61 to 0.88. Four items were removed: one due to factor loadings below 0.5, another for communality below 0.5, and two for cross-loading. After three iterations, five factors emerged, explaining 71.29% of the variance, with 16% non-redundant residuals indicating a good model fit (Hair et al., 2009). Cronbach's alpha values ranged from 0.75 to 0.90, all above the suggested onset of 0.7 (Nunnally and Bernstein, 1994). The findings from EFA and reliability analysis are given in Table 5.

Table 5. EFA and Reliability analysis

Constructs (KMO Value = 0.92, Bartlett's test of sphericity =3238.14($p < 0.001$) , Total variance extracted = 71.29%, non-redundant residual = 16% ($p > 0.05$)					
Parameters	EFB	CLB	STB	BHB	TCB
No. of indicator	6	5	4	4	3
Factor loading (Range)	0.75-0.69	0.79-0.69	0.65-0.83	0.70-0.81	0.73-0.83
Communality (Range)	0.62-0.72	0.63-0.79	0.71-0.88	0.61-0.74	0.64-0.70
Reliability	0.88	0.90	0.89	0.82	0.75
Item-to-total-correlation	0.65-0.77	0.67-0.79	0.64-0.89	0.59-0.71	0.55-0.61

3.8. Confirmatory factor analysis

Confirmatory Factor Analysis (CFA) with maximum likelihood estimation was conducted using AMOS 26.0. A two-step process was followed: first, individual measurement models were assessed for goodness-of-fit indices and measurement properties; then, an overall measurement model validated the factor structure of 21 items derived from EFA. Model fit criteria and parameter estimates were evaluated (Byrne, 2013). The standardised residual values between the item measures were discovered to be less than 2.58 (Jöreskog and Sörbom, 1996). The fit indices for each measurement model and the parameter estimate for each measurement model are presented in Table 6.

Table 6. Measurement properties of factors

Constructs (No. of items)	Item Reliability (SMC)*	Standardised regression weight (range)**	Fit indices						
			CFI	GFI	NFI	TLI	SRMR	RMSEA	AIC
			> 0.90#	> 0.90#	> 0.90#	> 0.90#	< 0.10#	<0.08#	Smaller is better#
EFB (5)	0.40-0.78	0.70-0.88	0.99	0.99	0.99	0.97	0.02	0.09	33.25
CLB (5)	0.44-0.74	0.66-0.86	0.98	0.97	0.97	0.95	0.03	0.10	42.75
STB (4)	0.48-0.9	0.69-0.98	0.99	0.99	0.99	0.99	0.01	0.07	20.53
BHB (4)	0.42-0.68	0.65-0.82	0.99	0.99	0.99	0.99	0.02	0.05	19.05
TCB (3)	0.43-0.56	0.65-0.75	1		1		0.00	.4	12

*Threshold value for SMC > 0.3 (Hair, J. F., Black, W. C., Babin, 2009)

** Threshold value for Standardised regression weight > 0.6 (Hair, J. F., Black, W. C., Babin, 2009)

Threshold value for the goodness of fit criteria (Fornell and Larcker, 1981)

The five-factor measurement model was examined using frequently used goodness-of-fit indices. Preliminary model results showed a good model fit, and the value of all the fit indices was found to be greater than a permissible threshold limit (Table 7). The model was iterated to improve the model fit.

Table 7. Model fit indices of Measurement Models

	Threshold	Initial Model (21 items)	Revised Model (Covary two items of EFB)
$\frac{\chi^2}{d.f}$	$1 < \frac{\chi^2}{d.f} < 3$ *	1.98	1.85
CFI	> 0.90*	0.94	0.95
NFI	> 0.90 *	0.89	0.90
TLI	> 0.90*	0.94	0.94
SRMR	<0.10*	0.05	0.05
RMSEA	<0.08*	0.06	0.05
AIC	Smaller is better*	457.99	435.52
CAIC	Smaller is better*	692.27	674.31

* Threshold value for fit indices (Fornell and Larcker, 1981), (Hair, J. F., Black, W. C., Babin, 2009)

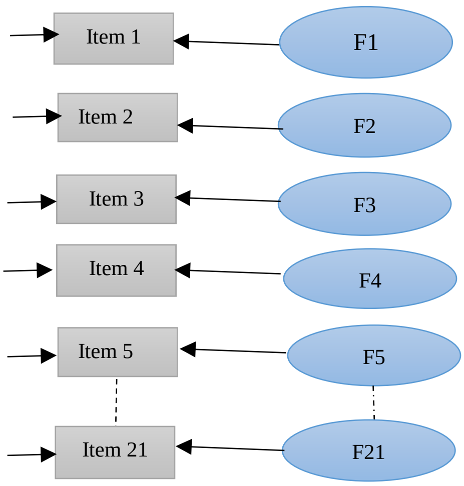
3.9. Competing Models Analysis

Following the guidelines of Xia and Lee (2005), five alternative models were built and assessed (Figure 1). The five alternative competing models are as follows: Model 1 represents a null model, ii) Model 2 illustrates a model with one single first-order factor, iii) Model 3 represents five uncorrelated first-order factors, iv) Model 4 represents five correlated first-order factors, and v) Model 5 signifies a second-order factor of barriers to digitalisation. The model-fit indices of the five models are summarised in Table 8. Only Model 4 and Model 5 met the threshold and showed correct parameter estimates and statistical significance, which were accepted, as shown in Figures 2 and 3.

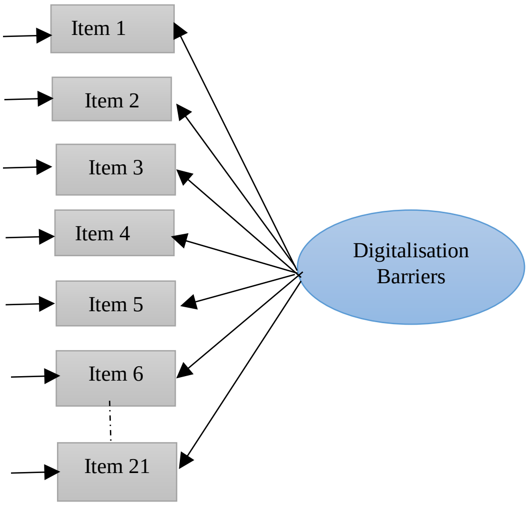
Table 8. Results of the competing models

	Threshold	Model 1	Model 2	Model 3	Model 4	Model 5
$\frac{\chi^2}{d.f}$	$1 < \frac{\chi^2}{d.f} < 3$*	---	6.59	4.22	1.85	1.83
CFI	> 0.90*	1	0.66	0.81	0.95	0.95
NFI	> 0.90*	1	0.63	0.76	0.90	0.90
TLI	> 0.90*	--	0.63	0.78	0.94	0.94
SRMR	<0.10*	--	0.16	0.33	0.06	0.06
RMSEA	<0.08*	0.25	0.15	0.12	0.06	0.06
AIC	Smaller is better*	462.00	1333.74	878.85	435.52	431.68
CAIC	Smaller is better*	1502.73	1518.46	1072.58	674.31	647.94

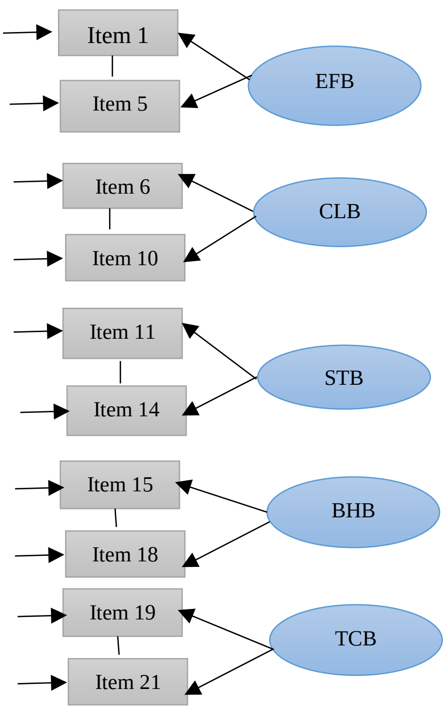
*(Hair, J. F., Black, W. C., Babin, 2009), (Fornell and Larcker, 1981)



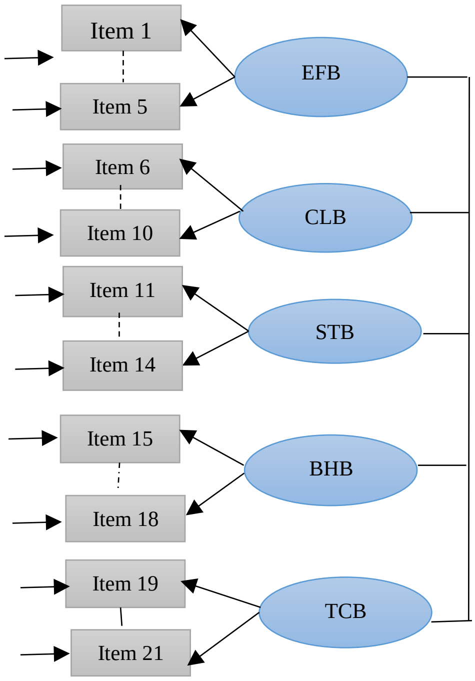
Model 1 Null Model



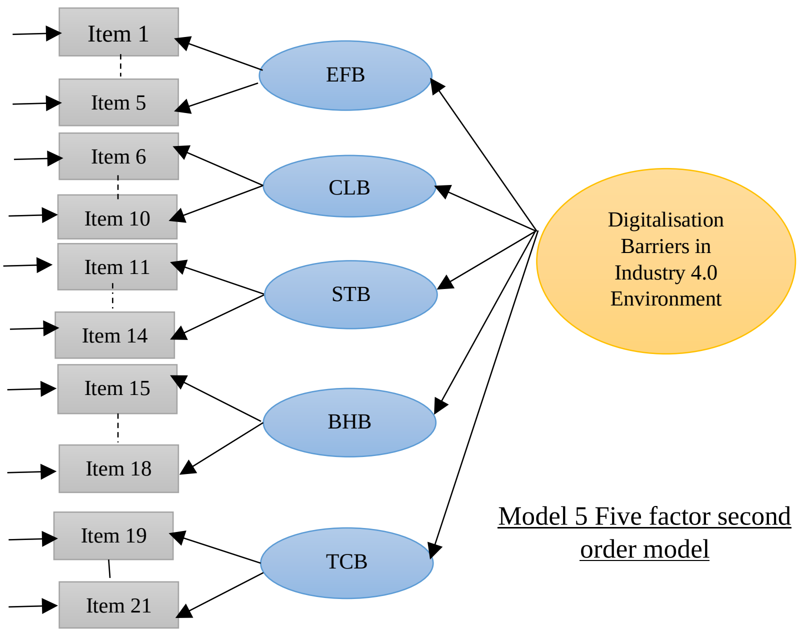
Model-2 One factor-first order model



Model 3 Uncorrelated five first order factor model



Model 4 Correlated five first order factor model



Model 5 Five factor second order model

Figure 1: Competing Models

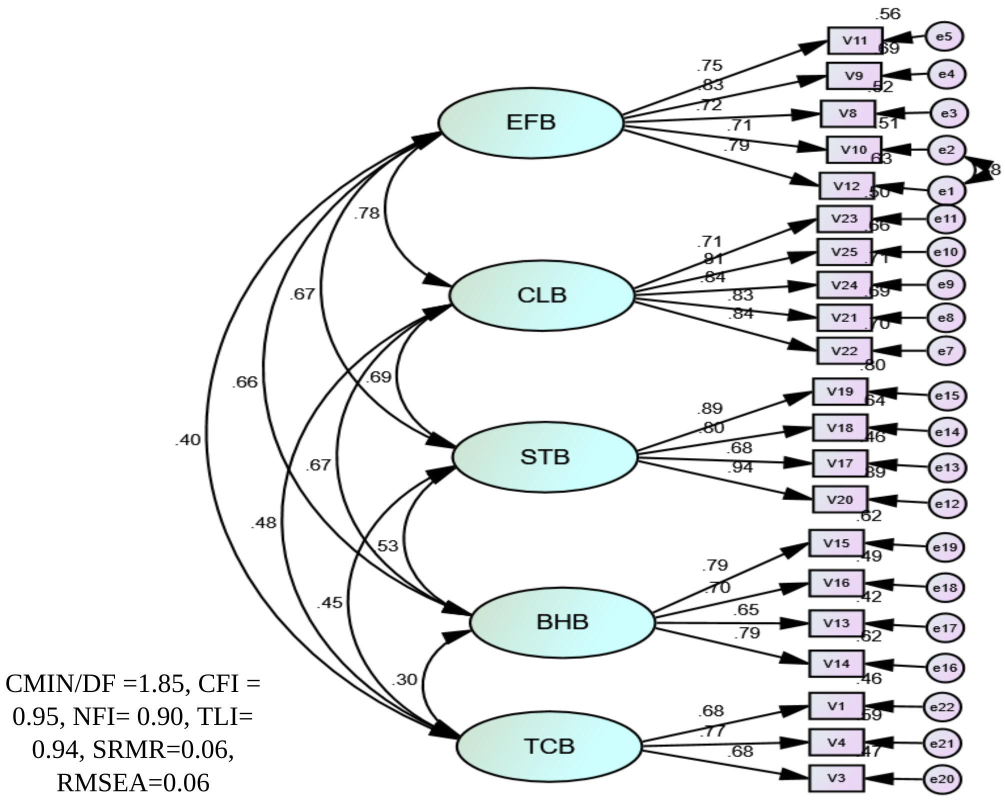


Figure 2 Correlated five-factor model of barriers to digitalisation

To assess the parsimony of the models, AIC and CAIC of model 4 and model 5 were compared. The lower value of AIC and CAIC of model 5 demonstrates better parsimony than model 4. Overall, the second-order model implies more parsimonious indication of observed co-variances and offers additional information regarding the relationships between the higher-order construct and the lower order constructs in terms of standardised path coefficients (EFB = 0.87, CLB = 0.90, STB = 0.76, BHB = 0.73, TCB= 0.51) rather than in terms of correlations (EFB-CLB= 0.78, EFB-STB=0.67, EFB-BHB=0.66, EFB-TCB=0.40, CLB-STB=0.69, CLB-BHB=0.67, CLB-TCB=0.49, STB-BHB= 0.53, STB-TCB=0.45 and BHB-TCB=0.30). Further, the five-factor second-order model confirms the structure of barriers to digitalisation, with all regression weights being significant and correctly signed.

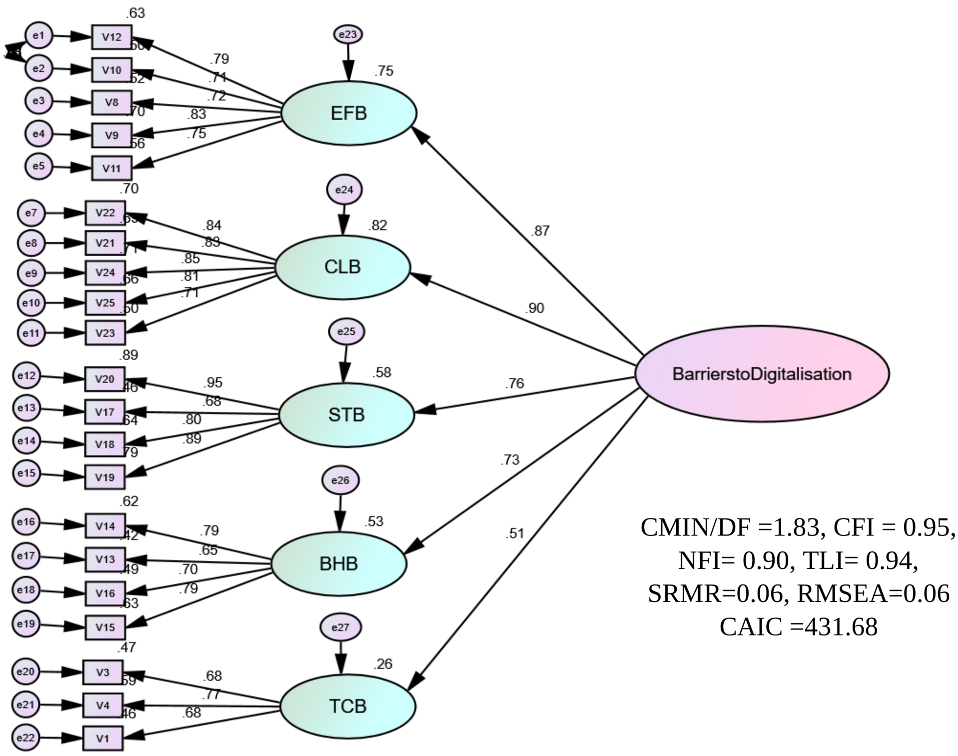


Figure 3 Five-factor second-order model

4. Validity and reliability assessment

4.1. Construct Reliability

Construct reliability was measured using Cronbach's alpha and composite reliability (C.R.). Internal reliability was investigated using Cronbach's alpha. Cronbach's alpha value was found to be in the range of 0.75 to 0.90. Further, the item-to-total correlation was found to be greater than 0.3. Composite reliability implies the internal consistency of indicators measuring a particular construct (Fornell and Larcker, 1981). The value of C.R. was found to be statistically significant and exceeded the acceptable threshold limit of 0.7 (Hair et al., 2009), thereby ensuring the reliability of constructs (Table 7).

4.2. Validity Assessment

Content validity implies the extent to which measured variables signify all facets of a given construct (Hair, J. F., Black, W. C., Babin, 2009). Using both deductive (literature review) and inductive approach (focus group interview method), measured variables were identified to represent their respective constructs.

Construct validity was assessed using convergent and discriminant validity (Fornell and Larcker, 1981; Hair, J. F., Black, W. C., Babin, 2009). Convergent validity was confirmed as all measurement items had significant factor loadings, with standardized factor loadings and AVE values exceeding 0.5. Additionally, C.R. values were greater than AVE, further supporting validity (Table 8). Discriminant validity was established as AVE for each construct exceeded its shared variance with other constructs, with AVE values surpassing squared inter-construct correlations (Hair, J. F., Black, W. C., Babin, 2009)(Table 9).

Table 9. Convergent and Discriminant validity measure

	CR	AVE	MSV	EFB	CLB	STB	BHB	TCB
EFB	0.881	0.598	0.582	0.773				
CLB	0.904	0.654	0.582	0.763***	0.809			
STB	0.901	0.698	0.472	0.666***	0.687***	0.835		
BHB	0.823	0.539	0.442	0.661***	0.665***	0.525***	0.734	
TCB	0.754	0.507	0.235	0.401***	0.485***	0.448***	0.302***	0.712

Significance of Correlations: *** $p < 0.001$

Nomological validity was assessed by hypothesising a negative relationship between barriers to digitalisation and digitalised operational practices, consistent with prior studies. Consistent with the prior studies (Kamble *et al.*, 2020; Xu *et al.*, 2018), the construct of digitalised operational practices was measured with six items, namely, use of smart work procedure, storage of data in cloud/common drive, use of internet of things, use of big data analytics, use of additive manufacturing and use of e-kanban for to offer real-time visibility.

The reliability and validity of digitalised operational practices were verified before structural model analysis. The structural model is given in Figure 4. Cronbach's α values, C.R.s and AVEs of the digitalised operational practices construct are 0.86, 0.86 and 0.52, respectively. Fit indices demonstrated excellent goodness of fit (CFI=0.96, GFI = 0.96, AGFI =0.90, NFI =0.95, IFI =0.96 SRMR=0.04, RMSEA = 0.10. The structural model confirms that digitalisation barriers negatively impact digitalised operational practices, with all paths significant and model fit indices acceptable (CFI=0.92, IFI=0.92, TLI=0.91, SRMR=0.08, RMSEA=0.06), supporting the nomological validity of the scale.

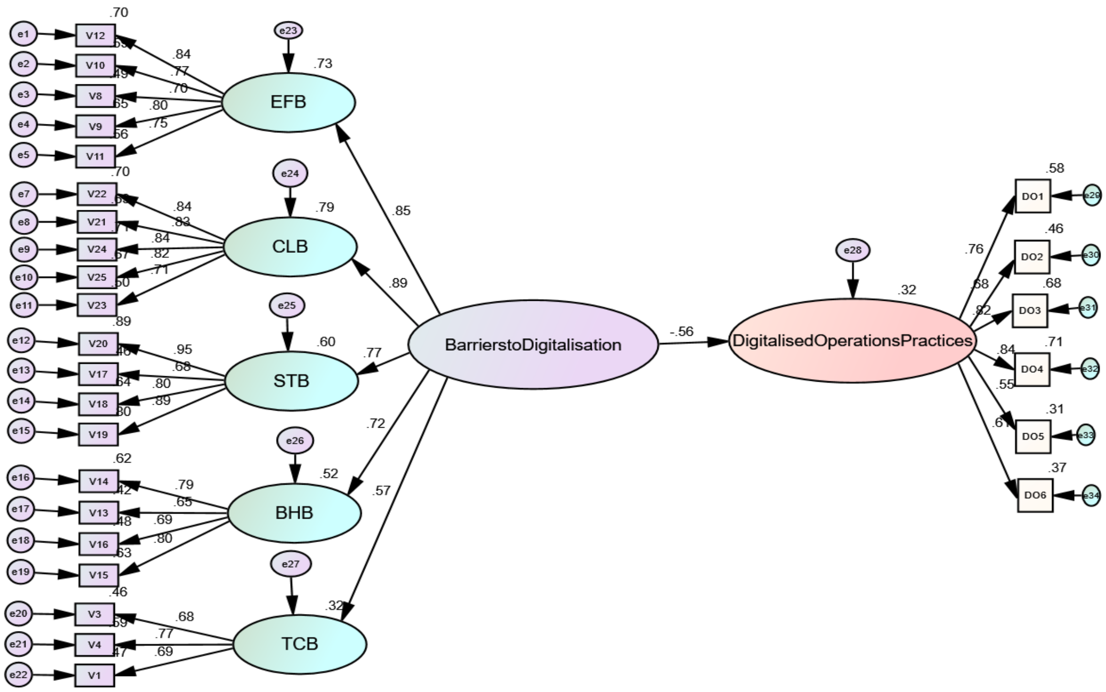


Figure: 4 Results of the Structural Model

5. Discussion & Implications

The study conceptualises, develops, and validates barriers to digitalisation in manufacturing within the Industry 4.0 context. In line with the earlier studies on digitalisation (Bajpai *et al.*, 2023; Chen *et al.*, 2023; Cordeiro *et al.*, 2023; Fernando *et al.*, 2022; Luthra and Mangla, 2018) and anchored in the Resource-Based View (RBV), economic and financial barriers emerged as significant hurdles to digital transformation in manufacturing organisations. The RBV posits that firms' ability to leverage internal resources, including financial capital, determines their competitive advantage. Limited financial resources restrict manufacturing firms from acquiring, developing, and deploying digital technologies, which hinders manufacturers from building unique, value-generating capabilities. The financial constraints include inadequate funding for employee upskilling, capital-intensive investment in smart factories and concerns about cost recovery when upgrading legacy systems. Furthermore, the inability to quantify potential returns from digital transformation often leads to underinvestment, limiting firms' ability to create sustainable competitive advantages, as posited by RBV (Deloitte, 2017). The findings align with prior studies indicating financial constraints as a critical barrier to Industry 4.0 adoption across manufacturing firms and supply chains(Chen *et al.*, 2023; Salman *et al.*, 2023).

Next, cultural barriers, which are deeply linked to inter-firm dependencies in manufacturing ecosystems, were found to be the second most significant hindrance to digitalisation, reinforcing the Resource Dependence Theory (RDT). As highlighted in the literature (Brunetti *et al.*, 2020; Marcon *et al.*, 2019; T.S. and Ravi, 2022), cultural factors—such as inadequate digital education among factory workers, lack of formal training, resistance to transparency, and absence of reverse mentoring—shape manufacturing firms' ability to navigate digital transformation. RDT emphasises that manufacturers depend on external entities for critical digital resources, including skilled personnel, knowledge, and technology, which may create power imbalances and interdependencies that either facilitate or impede digitalisation. The absence of structured training programs and incentives to promote digital adoption exacerbates this issue. Additionally, manufacturing firms struggling with talent acquisition and retention due to external market conditions often face knowledge gaps that weaken their capacity for technological adaptation, as explained by RDT(Deloitte, 2017; Elg *et al.*, 2020).

Manufacturing firms must understand and assess the need for novel knowledge and skills to become part of industry 4.0 ecosystem (Chauhan *et al.*, 2021; Fernando *et al.*, 2022; Okanlawon *et al.*, 2023). Emerging tools, techniques, and processes create skill gaps that need to be filled(Cardinali *et al.*, 2022). Firms need to develop and encourage a digital culture within their operational environment to continuously promote the skills required to innovate, foresee a path of training activities, and focus on digital transformation skills (Martínez-Caro *et al.*, 2020; Zangiacomi *et al.*, 2020). Lack of digital education, incentive encouragement, and formal training adversely influence digitalisation. Less effort to break down transparency-oriented behaviour and a lack of reverse mentoring also create hurdles digital transformation in factories. Manufacturing firms must understand the importance of novel, innovative approaches for internalising training activities among business practises (Brunetti *et al.*, 2020). Understanding technologies through learning experiences is essential for ensuring smooth digital transformation. This factor provides critical insight for developing measures to facilitate the adoption of the digitalisation process.

Strategic barriers were found to be the third important barrier to digitalisation in manufacturing. A study by Zangiacomi et al. (2020) revealed that manufacturing firms often approach digital investment as a tactical decision rather than a long-term strategic initiative, failing to integrate it within their broader competitive positioning. From an RDT perspective, firms dependent on external actors for digital expertise or technology adoption may face constraints due to power asymmetries in the supply chain, limiting their ability to make autonomous strategic decisions.

Additionally, centralised decision-making and rigid organisational structures create bottlenecks, making it difficult to reconfigure existing processes for technological integration, aligning with findings from Cardinali et al.(2022), which suggests organisational processes and lack of integration between activities in the supply chain are significant barriers to industry 4.0 adoption in the supply chain. The lack of coordination across supply chain activities further exacerbates bottlenecks for manufacturing firms in implementing smart supply chain.

RBV also underpins behavioural barriers, which emerged as a fourth significant obstacle to Industry 4.0 digitalisation in manufacturing. Employees' reluctance to embrace automation and AI-driven production workflows,coupled with an inability to perceive their strategic advantages, weakens manufacturing firms' capacity to develop human capital as a key internal resource (Cardinali *et al.*, 2022). Lack of trust between top management and factory workers and fear about job security make the digitalisation process difficult. The findings corroborated the earlier study by Legner et al. (2017), Chen et al.(2023) and De Alwis et al.(2023), which suggested that technologies can negatively influence user behaviours such as technostress, addictive behaviours, or privacy issues. Finally, technical barriers were the least significant compared to other constraints related to manufacturing digitalisation. Inadequate storage capacity, cybersecurity risks, lack of digital expertise, and incompatibility with legacy systems continue to present technical challenges. However, firms with strong internal resource capabilities (as per RBV) are more likely to overcome these issues by investing in digital infrastructure, advanced analytics and cybersecurity measures.

5.1. Theoretical Implications

The present study responds to the recent calls for empirical research into the barriers impeding digital transformation within the manufacturing sector under Industry 4.0 paradigm (Cardinali et al., 2022; Fernando et al., 2022; T.S. and Ravi, 2022) and thereby contributes to the literature in several ways: *First*, the study provides empirical evidence to the conceptual notion of barriers to digitalisation in manufacturing organisations by introducing a rigorously developed and diligently validated scale for assessing barriers to digitalisation. Therefore, the scale offers future researchers a validated tool to assess and analyse the factors that inhibit digitalisation in manufacturing context. *Second*, unlike earlier fragmented approaches, this study proposes a second-order construct model comprising five interrelated dimensions that collectively define the complexity of digitalisation barriers in Industry 4.0 manufacturing environments (Bajpai *et al.*, 2023; Chen *et al.*, 2023; De Alwis *et al.*, 2023; Okanlawon *et al.*, 2023; Salman *et al.*, 2023), the study contributes to the theory by providing a sound understanding of the multidimensionality and multifaceted structure of underlying barriers to digitalisation in the Industry 4.0 context, which can be helpful for future digitalisation research. The current study identifies five interconnected dimensions, which, taken together, represent five dimensions of barriers to digitalisation. The study developed a valid and reliable instrument for digitalisation barriers and evaluated it through rigorous statistical methodologies, including EFA, CFA and validation of second-order constructs. *Third*, against the background of digitalisation literature that is limited to identifying and modelling diverse barriers related to industry 4.0 technologies(Bajpai *et al.*, 2023; De Alwis *et al.*, 2023; Govindan, n.d.; Salman *et al.*, 2023; T.S. and Ravi, 2022), the study applies a dual-theoretical lens to deepen understanding of digitalisation barriers in manufacturing. This study best reflects and captures multi-dimensional digitalisation barriers using complementary applications of RBV and RDT. While RBV offers theoretical support for variables linked with intra-firm barriers, such as resistance to change stemming from management structure, the need for significant investment with uncertain returns, high implementation costs, inadequate budgeting, and substantial capital investment, RDT provides foundational support for variables linked with inter-firm barriers, including the need to develop novel knowledge across the supply chain, leadership skills to build trust and commitment. By synthesizing the Resource-Based View (RBV) and Resource Dependence Theory (RDT), this study presents a comprehensive second-order model explaining how barriers related to internal capability development and external dependencies interact to shape the trajectory of digitalization within manufacturing organizations. Therefore, the study can serve as a foundation for future empirical studies with insights into the conceptualisation and operationalisation of barriers to digitalisation in future empirical research in an Industry 4.0 context.

5.2. Managerial Implications

The findings of this study offer significant insights to manufacturing practitioners on how to facilitate the digitalisation process. The operationalisation of the construct in this study provides manufacturing firms with a tool to evaluate barriers within their organisations and, as a result, take necessary steps to overcome these barriers. It serves as a diagnostic tool to assess the extent of key barriers and manage them by prioritising and implementing strategies for a smoother digital transformation in manufacturing.

In line with RBV, an improved understanding of barriers to digitalisation is crucial for preparing manufacturing firms internally, helping them identify, assess, and address various obstacles to digitalisation. The economic impact of these barriers significantly influences adoption in the manufacturing sector. High investment costs, uncertain return on investment, and budgetary limitations are major deterrents for firms. Given the high cost of advanced manufacturing technologies, SMEs in manufacturing face challenges in digital adoption due to limited economies of scale and financial constraints. Despite the operational efficiency that Industry 4.0 technologies bring, financial barriers continue to slow down the diffusion of digital manufacturing solutions. Therefore, consistent with RBV, the study highlights the need for financial support, policy interventions for manufacturing SMEs, and cost-sharing models to facilitate adoption.

It is also essential to improve relationships with relevant stakeholders, such as suppliers, logistics providers, and technology partners, as digital technologies necessitate structural changes in manufacturing organisations, aligning with RDT. Top management involvement and financial investments are critical for education, employee training, and upgrading digital manufacturing infrastructure. To overcome resistance towards digital manufacturing technologies, top management should actively engage employees from an early stage, conducting advanced internal training to help them adapt to and embrace digital transformation in manufacturing.

5.3. Societal Implications

The study suggests that cultural and behavioural barriers hinder the adoption of digital transformation in manufacturing. Employees often do not favour digital adoption in manufacturing processes due to concerns related to job security, fearing that automation and advanced manufacturing technologies might replace their role in the workplace. Further, the digital skills gap in manufacturing will also widen, which can exacerbate employment disparities. Therefore, it is essential for manufacturing organisations to implement capacity-building programs to ensure that employees adapt to the latest technological demands of smart manufacturing. Another significant challenge is the lack of strategic vision of top management in manufacturing firms, which can derail the adoption process of Industry 4.0 technologies. From an RDT perspective, manufacturing organisations need to collaborate with educational institutions, establish workforce reskilling initiatives, and promote digital literacy in manufacturing to address these barriers. Therefore, investment in continuous learning and upskilling of the manufacturing workforce should be made to enable an inclusive and sustainable digital transformation in the manufacturing sector.

6. Conclusion, Limitations & Future Research

This study develops and empirically validates a five-dimensional model of digitalisation barriers in the manufacturing sector. A systematic literature review identified initial barriers, which were then tested using focus groups, EFA, CFA, and competing model analysis. Findings suggest that 21 items, assessed in a second-order factor model, demonstrated satisfactory measurement properties. Nomological validity was established by examining the relationship between barriers to digitalisation and digitalised operational practices in manufacturing. The significant path coefficients and acceptable fit indices confirmed that the model behaves as theoretically expected.

This study makes a significant contribution to manufacturing theory and practice, particularly in understanding and measuring barriers to digitalisation within the Industry 4.0 landscape. However, it has certain limitations. First, due to sample constraints, the findings were not validated across multiple datasets, which limits their statistical generalisability within the manufacturing sector. Future studies should replicate the research in diverse manufacturing contexts beyond India to enhance robustness. Second, barriers to digitalisation in manufacturing are inherently complex, shaped by factors such as industry type (e.g., automotive, textiles, electronics), firm size, and competitive intensity. Broader validation across various sub-sectors of manufacturing is essential to improve applicability. Third, respondents assessed digitalisation in general, without distinguishing between specific Industry 4.0 technologies like IoT, AI, or robotics, which may involve unique challenges for adoption. Future research should explore these technology-specific barriers within manufacturing.

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