Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model

Sheshadri Chatterjee
Department of Computer Science & Engineering
Indian Institute of Technology Kharagpur, India
Email: sheshadri.academic@gmail.com

Nripendra P. Rana*
School of Management
University of Bradford, Richmond Road
Bradford, BD7 1DP, UK
Email: nrananp@gmail.com

Yogesh K. Dwivedi
School of Management
Swansea University Bay Campus
Swansea, SA1 8EN, UK
Email: ykdwivedi@gmail.com

Abdullah M. Baabdullah
Department of Management Information Systems
Faculty of Economics and Administration
King Abdulaziz University, Jeddah, Saudi Arabia
Email: baabdullah@kau.edu.sa

*Corresponding Author

Abstract
This study aims to identify how environmental, technological, and social factors influence the adoption of Industry 4.0 in the context of digital manufacturing. The Industry 4.0 era has brought a breakthrough in advanced technologies in fields such as nanotechnology, quantum computing, biotechnology, artificial intelligence, robotics, the Internet of Things, fifth-generation wireless technology, fully autonomous vehicles, 3D printing and so on. In this study, we attempted to identify the socioenvironmental and technological factors that influence the adoption of artificial intelligence embedded technology by digital manufacturing and production organizations. In doing so, the extended technology-organization-environment (TOE) framework is used to explore the applicability of Industry 4.0. A conceptual model was proposed that used an integrated technology acceptance model (TAM)-TOE model and was tested using survey-based data collected from 340 employees of small, medium and large organizations. The results highlight that all the relationships, except organizational readiness, organizational compatibility and partner support on perceived ease of use, were found to be significant in the context of digital manufacturing and production organizations. The results further indicated that leadership support acts as a countable factor to moderate such an adoption.

Keywords: Artificial Intelligence, Industry 4.0, Manufacturing and Production Firms, TOE Framework, TAM, Leadership Support

Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model

1. Introduction

The term *Industry 4.0* is considered to be reminiscent of the fourth industrial revolution. Over almost 200 years, the first three industrial revolutions took place and quickly spread throughout the world. The term *Industry 4.0* was introduced in Germany in 2011. It is considered to be a cyber physical system. It is similar to the industrial Internet introduced by GE (Posada et al., 2015). Prior to this, industries were experiencing several challenges from external and internal environments (Asgari et al., 2017). Organizations felt a desperate need to adopt an advanced digitalized strategy to face the many entangled challenges (Cui & O'Connor, 2012). This necessitated a paradigm shift in the manufacturing and production system (Evans & Gawer, 2016) for which Industry 4.0 came to rescue. The main components defining Industry 4.0 include nanotechnology, cyber physical systems, artificial intelligence (AI), robotics, and the Internet of Things (IoT) (Bag et al., 2021; Demlehner et al., 2021; Grover et al., 2020; Hu et al., 2021; Hughes et al., 2020; Muller et al., 2018; Pillai et al., 2020; 2021; Wang, 2016). Organizations needed to become smart organizations, and digitalization was the demand of the day. PwC estimated that starting in 2020, there will be global investments towards digitalization of industries to the tune of $900 billion yearly. Experts opined that there is a necessity for socioenvironmental, as well as technological development for the digitalization of industries in the context of the Industry 4.0 paradigm (Geissbauer et al., 2016; Reischauer, 2018; Frank et al., 2019).

From this perspective, existing studies have argued that the use of AI in an organization will effectively increase productivity and help people make quick decisions (Duan et al., 2019; Dwivedi et al., 2021; Knight, 2015). In other literature, we find enormous contribution-oriented opportunities for AI in industries (Aghion et al., 2017), but there are impediments to the adoption of AI by industries, as most industries are not ready to adopt this cutting edge technology (Sulaiman et al., 2018). However, it has been argued that the use of AI will bring economic growth to many countries, including China (Li, 2017), India (Vempati, 2016) and the USA (MaKridakis, 2017; Lu, 2017).

A report by Gartner (2017) highlights that by 2016, 6% of organizations had adopted AI, while 59% of industries were still considering the adoption of AI technology. However, it is unclear in this report by Gartner (2017) how the adoption of AI by an industry would improve its business strategy. It is also unclear how AI technology could improve the practices of organizations (Margherita & Braceini, 2020), but studies are available that indicate that the adoption of big data analytics, as well as machine learning could ensure some business and social values in organizations (Dubey et al., 2021; Dwivedi et al., 2021; 2020; Pappas et al., 2018; Mikalef et al., 2020; Shareef et al., 2021). Top management support is also considered a vital challenge in the adoption of any innovative technology in an organization (Pu et al., 2019). Top management should realize the business-oriented benefits of AI and should mobilize finance and technical know-how for such an AI adoption (Alshamaila et al., 2013). Hence, strong leadership support is considered to moderate such adoption issues. It is known that the adoption of any technology in the context of socioenvironmental and technological aspects can be easily interpreted in terms of the technology-organizational-environment (TOE) framework (Hossain & Kuaddus, 2011), as it has been successful in explaining the adoption of e-commerce and cloud computing (Idris, 2015; Yang et al., 2015). As such, this framework has been used to identify the factors affecting the adoption of AI in organizations in the context of the current research.

As already stated, there are studies that have emphasized that the use of Industry 4.0 could improve the business strategy of a manufacturing and production firm. However, how the business strategy of manufacturing and production firms could be improved by the application of AI from a socioenvironmental perspective is still not clear, and this aspect has been underexplored (Hofmann & Rush, 2017; Jabbour et al., 2019; Baryannis et al., 2019; Chen et al., 2020). In addition, how organizations can become ready to utilize the best potential of AI has not been studied exhaustively. Moreover, there are a few studies on how organizational leadership support can facilitate the adoption of innovative technologies, such as AI, in manufacturing and production firms, which has not been investigated in an explicit manner (Pu et al., 2019). Hence, in this context, this study aims to address the following objectives:

[1] To identify the antecedents of AI adoption in manufacturing and production organizations in the digital environment in the context of an extended TOE framework.

[2] To ascertain the readiness of organizations to adopt AI in the context of social, technological, and environmental perspectives.

[3] To determine how leadership support moderates the adoption of AI in organizations.

This study will explain how some factors concerned with the internal and external environment of organizations could impact the intention to adopt AI if organizations find such adoption useful and easy to use (Lee et al., 2003; Yousafzai et al., 2007).

The rest of the paper is structured as follows. First, Section 2 presents the theoretical background and develops a conceptual model. Section 3 discusses the research methodology, while Section 4 analyses the data and presents the results. Section 5 discusses the results with respect to the available literature. Finally, Section 6 provides concluding remarks.

2. Theoretical Background, Conceptual Model and Hypotheses Formulation

2.1 Theoretical Background

It is difficult to apply any existing adoption model in the context of AI adoption in organizations, as it is a complex technology (De Graaf, 2016). AI is a modern technological genre. In this context, it is argued that the TAM (Davis, 1989) and TOE frameworks (Tornatzky & Fleisher, 1990) may best explain AI adoption in organizations. Davis (1989) developed the TAM framework to understand the factors influencing the intention and use of technology. Other acceptance models were subsequently developed. We are aligned to depend on TAM. The reasons are multi-fold. TAM is considered a commonly applied influential model in the field of information systems (Lee et al. 2003). It has a widespread popularity for many reasons. It is an IT specific and parsimonious model. It can explore and predict the acceptance of a wide range of technologies. It is helpful to explain the adoption of any technology in a flexible way with a robust theoretical and strong psychometric base and has strong explanatory power (Maartje et al., 2018). Its two core constructs include many acceptance beliefs exploring behavioural intention and act as the primary determinants of system use (Chen & Tan, 2004; Hong et al., 2006; Benbasat & Barki, 2007; Cagliano et al., 2019). The are many reasons for not considering other acceptance models developed after TAM . These models have highly correlated variables, which create unnaturally high explained variance (Maartje et al., 2018). The TOE framework can exhaustively explain the factors impacting adoption decisions. This framework can explain adoption using technological, organizational and environmental dimensions and can explain any modern technology in the socioenvironmental and technological context (Hossain & Quaddus, 2011). It has found successful applications in the adoption of cloud computing (Yang et al., 2015), e-commerce (Idris, 2015), etc.

The two core variables of TAM (i.e., perceived usefulness and perceived ease of use) can explain at least 40% of the reasons for using the system (Ifinedo, 2011). The TOE framework can explain not only technological and organizational aspects but also external factors that include social and environmental aspects (Wang et al., 2010). Hence, by combining TAM and TOE, it is possible to cover all the internal and external antecedents for the adoption of AI. Thus, in the adoption of Industry 4.0, the TAM-TOE hybrid model is perceived as appropriate for use in interpreting the socioenvironmental and technological aspects of the adoption of AI in organizations. Figure 1 shows the TOE-TAM based framework.

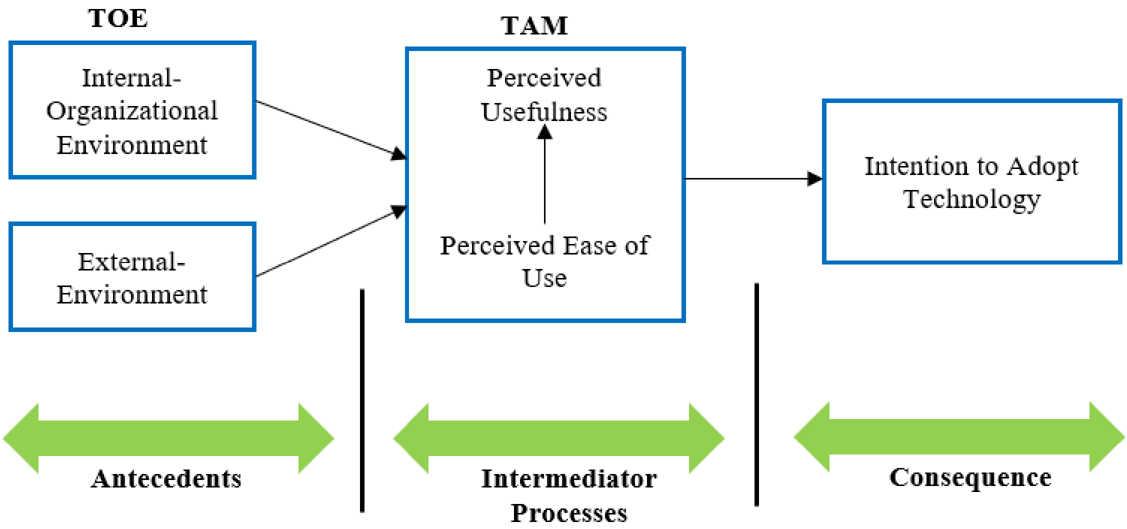

Figure 1: TOE-TAM-based Framework (Sources: Davis 1989; Tornatzky and Fleisher 1990)

In the context of marketing, planning, and development, production along with distribution, the manufacturing environment has experienced a drastic reduction that warrants digitalization for obtaining sustainable production and manufacturing systems befitting Industry 4.0 (Reischaur, 2018; Frank et al., 2019). Among the different components of Industry 4.0, artificial intelligence (AI) is considered one of the vital components (Wang et al., 2016). Applications of AI embedded technology have been able to revolutionize operations, as well as production processes (Luthra & Mangla, 2018; Jabbour et al., 2018). The manufacturing system has experienced drastic innovation by using AI embedded technology (Sung, 2018; Li, 2018). The use of AI-embedded technology has facilitated manufacturing process systems for developing smart, flexible, ecofriendly production ecosystems (Oesterreich & Teuteberg, 2016; Metallo et al., 2018). Studies have highlighted that industrial engineers and production managers have expressed interest in integrating process innovation with contemporary technological developments for managing sustenance in production systems (Buer et al., 2018). However, several studies have suggested that the managers and executives of organizations are found to have expressed reluctance towards the use of the developed process and operation systems during the transition to Industry 4.0-oriented operations (Muller et al., 2018). In this context, it is important that the managers of organizations manage the environmental and social challenges in production and manufacturing systems in the context of the use of AI (Hofmann & Rusch, 2017; Chen et al., 2020). Studies have revealed that Industry 4.0 has promoted the concept of electronic readiness towards the enhancement of competitiveness, along with better management procedures to utilize available resources in the best possible way (Kalaitzi et al., 2019). Studies have indicated that, using traditional procedures, organizations face several challenges that are multifarious in nature. To remove these constraints, organizational management leaders feel the need to utilize Industry 4.0 cutting-edge technology (Chatterjee et al., 2018; Grover et al., 2020; Moeuuf et al., 2018). Large industries are the backbone of economies, while SMEs are the foundation of large industries (Batta et al., 2020; Chatterjee & Kar, 2020; Dutta et al., 2020; Knight, 2015). Studies have revealed that SMEs are flexible in adopting innovative technologies, and it is easier to study the idea of adopting Industry 4.0 in SMEs (Kar, 2020; Lin et al., 2018; Lu, 2017). The Gartner Report (2017) predicted that by the end of 2020, AI will be pervasive in every software product and connected service. Studies have confirmed that organizations are facing some socioenvironmental and technological challenges to the use of Industry 4.0 (Kar & Navin, 2020; Moeuuf et al., 2018). Limited studies on AI are available where technology has been adopted to obtain improved business benefits (Dutta et al., 2020; Tortorella et al., 2019). Studies have suggested that to identify the antecedents of AI adoption from the perspective of organizational, environmental and technological aspects, the extended TOE framework (Tornatzky & Fleisher, 1990) is perceived to be helpful, as this model has been applied successfully in various socioenvironmental contexts with a focus on technological issues (Yang et al., 2015; Idris, 2015). Studies have highlighted that there is a need to use Industry 4.0 cutting edge technology to remove the challenges organizations face when using traditional procedures (Moeuf et al., 2018). Studies have also emphasized the need to use the TOE framework to identify the determinants for the adoption of AI in organizations in the socioenvironmental context. However, studies covering how AI would help manufacturing and production firms improve their practices to obtain the best business results, how organizations might become ready to adopt AI and how leadership support might facilitate the adoption of Industry 4.0 in manufacturing and production firms to improve their business processes remain underexplored.

2.2 Proposed Conceptual Model and Hypotheses Formulation

The proposed conceptual model contains four organizational- and internal environment-level variables, including organizational competency, organizational complexity, organizational compatibility, organizational readiness and two external environmental variables, i.e., competitive advantage and partner support, whereas perceived ease of use and perceived usefulness are two TAM-based technological variables. Based on the theoretical underpinning of TOE and considering the relevant constructs to be incorporated as a part of technological (e.g., constructs from TAM, such as perceived ease of use and perceived usefulness), organizational (i.e., organizational competency, organizational complexity, organizational readiness and organizational compatibility) and environmental segments (i.e., competitive advantage and partner support), Figure 2 illustrates the proposed research model.

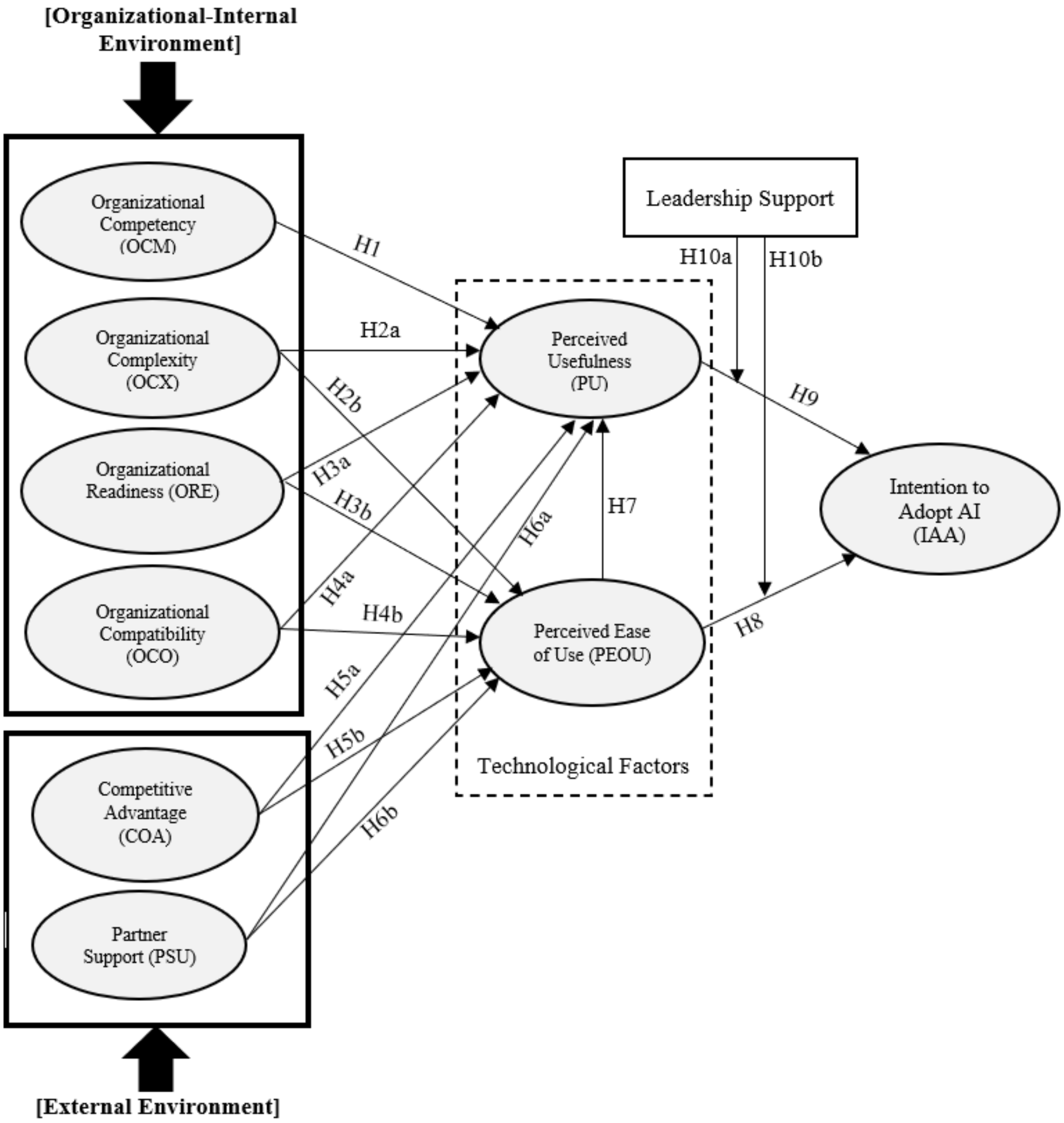

Figure 2: Proposed Conceptual Model (Adapted from: Davis, 1989; Tornatzky and Fleisher 1990)

2.2.1 Organizational competency (OCM)

Organizational competency is associated with the concept of employees' skill, knowledge, capabilities, and other relevant traits essential for effective performance in an employment position (Long et al., 2013). Competency increases by ameliorating the performance of the employees of the firm (Veliu & Manxhari, 2017). The TOE framework indicates the necessity of the competency of organizations (Riyadh et al., 2009). The concept and idea of competency has enormous facets. Employee competency brings about the competency of the organization (Halabi et al., 2017). Its concept is associated with performance (Tortorella et al., 2019). Hence, to ensure a performance-oriented culture in a firm, competent personnel are required (Riyadh et al., 2009). It is natural that if the employees of the organization are competent to use a system, the organization is considered a competent organization (Veliu & Manxhari, 2017). However, if the employees of an organization are not capable of using a technology, they will not perceive the usefulness of that technology (Maduka et al., 2018). Based on the above discussion, the following hypothesis is developed:

H1: Organizational competency has a positive impact on perceived usefulness.

2.2.2 Organizational complexity (OCX)

The concept of complexity in an organization comes from the sense of ease of use lent from TAM, as already discussed. Complexity is defined as the level of inconvenience and constraints towards understanding and using a system (Sonnenwald et al., 2001). From the perspective of AI adoption in an organization, this complexity is considered an internal organizational issue, and it is conceptualized and weighed by measuring the extent that applications are using the AI infrastructure, the time required for performing a task, intelligent decision-making effectiveness, the efficiency of the system functionality and the interface design (Parveen and Sulaiman, 2008). This concept is conceptualized through the sense of ease of use (Chau and Hu, 2001). As the complexity in an organization increases, the usefulness and ease of use decrease (Idris, 2015). If there is complexity in the system of an organization, employees will experience problems in using a new technology with a complex system and will not be able to realize the usefulness of the new system (Sonnenwald et al., 2001). From the above discussion, the following hypotheses are formulated:

H2a: Organizational complexity negatively influences perceived usefulness.

H2b: Organizational complexity negatively influences perceived ease of use.

2.2.3 Organizational readiness (ORE)

Organizational readiness is defined as the accessibility of the required organizational resources for adoption (Iacovou et al., 1995). In any organization, the adoption of any innovative technology is impacted by some specific organizational characteristics, including the organization size and the availability of resources. These are salient factors that are instrumental to measuring organizational readiness (Idris, 2015). The organization’s size directly affects its adoption readiness relating to any innovative technology (Rogers, 2003). Several studies have also subscribed the view of Rogers (2003). Larger organizations need more technical and financial resources (Aboelmaged, 2014; Ransbotham et al., 2017; Gartner, 2017). If an organization is not ready to use a new system such as AI (Industry 4.0), employees will feel constrained regarding the use of the new technology, and the usefulness of this new technology will not be realized by them. The above discussion leads to the formulation of the following hypotheses:

H3a: Organizational readiness has a positive impact on perceived usefulness.

H3b: Organizational readiness has a positive impact on perceived ease of use.

2.2.4 Organizational compatibility (OCO)

Compatibility can be defined as the level to which an innovation is considered to be consistent with the potential users' existing values, previous experiences and requirements (Geczy et al., 2012). Organizational compatibility is an internal organizational issue and is considered relevant for its behavioural pattern, existing values and experience. To what extent these characteristics of the organization are reconcilable with an innovative technology is assessed (Peng et al., 2012). Practically, compatibility is perceived as the extent to which AI innovation (in the context of the present study) can be easily assimilated and integrated with the existing process and available infrastructure of the organization (Geczy et al., 2012). The old production systems of organizations are considered strong inhibitors of innovative adoption, as the system is not compatible with innovation (Chen & Tan, 2004). Based on the above discussion, the following hypotheses are proposed:

H4a: Organizational compatibility has a positive impact on perceived usefulness.

H4b: Organizational compatibility has a positive impact on perceived ease of use.

2.2.5 Competitive advantage (COA)

Competitive advantage is defined as the level at which a technological factor seems to provide a better benefit for organizations (Rogers, 2003). The additional advantages of a technology in comparison to its alternatives play a considerably decisive role towards its adoption in an organization. This external factor is associated with the sense of the threat of losing advantages (Aboelmaged, 2014). The competitive pressure for acquiring a competitive advantage acts as an important factor for the diffusion of an innovative technology (Yang et al., 2015). Since AI is able to create new opportunities and to spur innovation, the adoption of AI in an organization is considered to gain the highest competitive advantage (Gartner, 2017; Fast & Horvitz, 2017). Gaining a competitive advantage over other contemporary organizations will impact the employees of that organization, as they feel complacent when possessing an advantageous position (Press, 2016). Thus, competitive advantage has a socioenvironmental aspect that is developed by organizations through the use of AI embedded technology (Makridakis, 2017). The use of AI-enabled technology means the use of machine learning, deep learning, natural language processing, and so on in organizations. The use of these technologies will help organizations gain competitive advantages (Curran & Pureel, 2017). Properly trained employees will then perceive the usefulness of this technology and perceive the technology to be easy to use. The above discussion helps to formulate the following hypotheses:

H5a: Having a competitive advantage has a positive impact on perceived usefulness.

H5b: Having a competitive advantage has a positive impact on perceived ease of use.

2.2.6 Partner support (PSU)

The potentialities of any innovation cannot be achieved without collaborative support (Haans et al., 2016). In the context of the knowledge-based view, researchers believe that apart from financial support, partner support acts as an external agent to help an organization develop the knowledge repository of employees. It helps to adopt any cutting-age technology, such as Industry 4.0 (here AI) (Zheng et al., 2015). Partner support is external and helps to generate the innovation performance of an organization through knowledge exchange (Koka & Prescott, 2002). The knowledge development of employees through their own and through the help of inputs from partners of the organization would help in the easy adoption of AI embedded technology, and the knowledge gained would help employees realize the usefulness of AI applications in organizations (Asgari et al., 2017). The knowledge assimilated by employees would also help them to use AI, increasing its perceived ease of use. Such an achievement may be deemed to be the contribution of partner support, as partners provide supplemental support to develop the knowledge of employees (Hottenrott & Lopes-Bento, 2016). The above discussions lead to the formulation of the following hypotheses:

H6a: Partners' support positively influences perceived usefulness.

H6b: Partners' support has a positive impact on perceived ease of use.

2.2.7 Perceived usefulness (PU) and perceived ease of use (PEOU)

Perceived ease of use is interpreted as the extent to which a person has a belief that using a new system or a new technology would be free of effort (Davis, 1989). Several studies have used TAM to successfully describe an individual's acceptance of any new system or new technology (Lee et al., 2003). In this study, TAM has been used to explain the use intention of AI adoption in a firm. In addition, PEOU includes the concepts of self-efficacy, perception of external control, anxiety, playfulness, and enjoyment (Venkatesh & Bala, 2008). As already stated, TAM confirms that PEOU is a predictor of usefulness. Therefore, we hypothesize the following:

H7: Perceived ease of use positively influences perceived usefulness.

As per TAM, PEOU acts as a predictor of the intention of users to use a new system or technology. The sense of easiness in using a system motivates users to intend to use the system (Yousafzai et al., 2007). TAM is considered to be the most widely accepted model for the intention to use a new technology (Venkatesh & Morris, 2000). From different studies, including those on the adoption of e-commerce (Kufaris, 2002) and multipurpose information appliances (Hong & Tam, 2006), it has been observed that the intention to use a new system is predicted by the concept of ease of use. These discussions have helped to perceive that intention to adopt AI in any firm is derived from the ease of using a technology. Hence, we formulate the following hypothesis:

H8: Perceived ease of use positively influences the intention to adopt AI.

Perceived usefulness is interpreted as the potential users' subjective possibility that using a system or the application of a system will enhance the job performance of the users within the context of the firm (Lee et al., 2003). Ajzen (1991) believed that the perceived usefulness of a technology will motivate users to intend to use that technology. In this study, TAM has been used to explain use intention by users since this model has demonstrated that there exists a linear relationship between usefulness and intention (Maartje et al., 2019). PU includes the concepts of subjective norms, image, job relevance, output quality, and result demonstrability (Venkatesh & Bala, 2008). These predictors prompted us to construe that individuals form perceived usefulness judgements partly due to cognitively comparing what a system is capable of doing with what they need to accomplish in their job (Venkatesh & Davis, 2000). Hence, it is perceived that a sense of usefulness would lead an individual to intend to use a new technology. Therefore, we hypothesize the following:

H9: Perceived usefulness has a positive impact on intention to adopt AI.

2.2.8 Effects of leadership support as a moderator

Leadership support (LS) is associated with the sincere engagement of a higher ranking leader in the implementation of the new system, which would affect the relation between perceived usefulness and intention, as well as the perceived ease of use and intention (Ifinedo, 2011). Leadership commitment is considered to have a significant impact on the adoption of innovative technology (Yang et al., 2015). As an example, in the context of the research on information science, leadership support was considered important for promoting cloud computing adoption, as well as the adoption of electronic business (Yang et al., 2015). In this study, we considered LS as a variable moderating the two linkages covering H8 (PEOU to IAA) and H9 (PU to IAA). In terms of the above discussions, the following hypotheses are developed:

H10a: Leadership support moderates the linkage between perceived usefulness and the intention to adopt AI.

H10b: Leadership support moderates the linkage between perceived ease of use and the intention to adopt AI.

3. Research Methodology

3.1 Research instrument

The conceptual model and the hypotheses were validated through quantitative studies by conducting surveys. For this, it was essential to prepare a questionnaire. From the literature survey and theory, constructs have been identified. The questionnaire was created using all the items representing the constructs selected for the proposed research model. The meaning and contexts of the questions were designed to represent the measures for all given constructs, which were tested in the pretesting phase of questionnaire development. The questionnaire was first reviewed by academic experts who were experienced in the area of AI. Then, the questionnaire was again piloted with the help of IT experts to ensure that the respondents would be able to understand the measures and provide appropriate responses to the questions. A total of 36 items concerning all the relevant constructs were designed as part of questionnaire in which the responses were answered. We used a 5-point Likert scale for the measures used for constructs for the purpose of data collection, with ‘1’ representing ‘strongly disagree’ and ‘5’ representing ‘strongly agree’. The measurement instrument is shown in Table 1 (see Appendix A).

3.2 Data collection strategy

For the data collection, a purposeful sample was used for the selection of the respondents. Top- and middle-level professionals of IT and other companies where AI is being adopted or contemplated were targeted. Practically, we targeted manufacturing and production organizations from the (official) database of the Bombay Chamber of Commerce and Industry (India). Telephone calls and emails were chosen as the medium to contact the top-level and mid-level IT professionals of the manufacturing and production organizations. Initially, we targeted 800 organizations. Through telephone and email contact, it was ascertained that 562 organizations were interested in adopting or were in the process of adopting AI technology.

Among these 562 organizations, we were able to gather contact information for 857 respondents. We emailed them with a set of 36 questions to gain their feedback. The prospective respondents were informed that the aim of this study was purely academic. They were assured that their anonymity and confidentiality would be strictly preserved. A guideline was also provided to them explaining how to fill in the response sheet. All these initiatives were taken to enhance the response rate (Chidlow et al., 2015). They were asked to respond within 30 days from the date of receipt of the email. During this time window, 391 responses were received, which was a response rate of 45.6%. To analyse the nonresponse bias, the recommendations of Armstrong and Overtone (1977) were followed. Chi-square tests and independent sample t-tests were conducted by considering the first and last 100 responses. From the analysis, no mentionable differences between these two groups were found ($p<0.05$). This confirms that no non-response bias is present. All 391 responses were scrutinized. Out of the 391 replies, 51 were found to be incomplete and, hence, were discarded from further analysis. We started our analysis with 340 usable and valid replies. The details of these 340 respondents are shown in Table 2.

Table 2: Demographic Profile

Category	Criterion of Category	Number of Respondents
Small	Number of Employees ≤ 350	79
Medium	350 < Number of Employees ≤ 800	117
Large	Number of Employees > 800	144

3.3 Data analysis technique

We used a partial least squares (PLS)-based structural equation modelling (SEM) technique to analyse the data. This technique has been adopted because this process gives better results in the analysis of this type of exploratory study (Aktar and Pangil, 2017). This process can also analyse those data that are not normally distributed (Hair et al., 2018). This technique does not impose any sample restriction to conduct the survey (Willaby et al., 2015; Richter et al., 2016). This process involves quantification of responses on a specific scale.

4. Data Analysis and Results

4.1 Measurement model

The internal consistency was estimated by calculating the composite reliability (CR) of all constructs. Similarly, the validity of the constructs was ascertained by calculating the average variance extracted (AVE) of all the constructs. A test of multicollinearity was performed by estimating the variance inflation factor (VIF) of each construct. The constructs' consistency was assessed by computing Cronbach's alpha (α) for each construct. After all these computations, it appears that all the parameters are within acceptable ranges. Hence, the items are reliable, and the constructs are consistent, valid and do not suffer from multicollinearity defects. All the estimations are shown in Table 3.

Table 3: Measurement Properties

Construct/Items	LF	CR	AVE	VIF	t-value	Cronbach's Alpha (α)
Organizational Competency (OCM)		0.93	0.90	4.7		0.94
OCM1	0.89				21.67	
OCM2	0.87				22.11	
OCM3	0.95				23.41	
OCM4	0.90				26.82	
Organizational Complexity (OCX)		0.92	0.89	3.8		0.96
OCX1	0.92				21.11	
OCX2	0.96				23.10	
OCX3	0.95				85.60	
OCX4	0.95				17.11	
Organizational Readiness (ORE)		0.96	0.92	4.1		0.87
ORE1	0.89				17.39	
ORE2	0.98				19.11	
ORE3	0.99				22.46	
ORE4	0.97				26.80	
Competitive Advantage (COA)		0.93	0.89	3.7		0.88
COA1	0.95				27.11	
COA2	0.92				32.13	
COA3	0.96				32.10	
COA4	0.95				30.04	
Organizational Compatibility (OCO)		0.91	0.86	4.7		0.91
OCO1	0.90				30.55	
OCO2	0.90				23.65	
OCO3	0.95				28.48	
OCO4	0.95				26.42	
Partner Support (PSU)		0.94	0.90	3.9		0.89
PSU1	0.90				88.11	
PSU2	0.95				22.11	
PSU3	0.87				23.47	
PSU4	0.89				21.14	
Perceived Usefulness (PU)		0.97	0.93	4.9		0.89
PU1	0.99				23.41	
PU2	0.96				24.54	
PU3	0.99				35.11	
PU4	0.89				21.60	
Perceived Ease Of Use (PEOU)		0.92	0.88	3.8		0.91
PEOU1	0.95				23.22	
PEOU2	0.90				26.42	
PEOU3	0.95				23.12	
PEOU4	0.95				18.11	

Intention to Adopt AI (IAA)		0.93	0.90	3.6		0.97
IAA1	0.95				23.00	
IAA2	0.90				23.16	
IAA3	0.87				27.17	
IAA4	0.89				18.78	

[Note: AVE: Average Variance Extracted, CR: Composite Reliability, LFs: Loading Factors, VIF: Variance Inflation Factor]

4.2 Discriminant validity test

To ascertain whether the items can fully explain their own constructs and weakly connect with other constructs, a discriminant validity test (Fornell & Larcker, 1981) was conducted, which confirmed that the square root of AVE for each construct is greater than the corresponding correlation coefficients of that construct with other constructs. The entire results are shown in Table 4.

Table 4: Discriminant Validity Test

	Leadership Support	OCM	OCX	ORE	OCO	COA	PSU	PU	PEOU	IAA	AVE
Leadership Support	1.00										1.00
OCM	0.21	**0.95**									0.90
OCX	0.26	0.22	**0.94**								0.89
ORE	0.39	0.26	0.24	**0.96**							0.92
OCO	0.37	0.28	0.26	0.21	**0.93**						0.86
COA	0.21	0.30	0.28	0.26	0.23	**0.94**					0.89
PSU	0.31	0.31	0.32	0.21	0.33	0.26	**0.95**				0.90
PU	0.26	0.29	0.33	0.29	0.26	0.31	0.21	**0.96**			0.93
PEOU	0.21	0.31	0.36	0.30	0.28	0.33	0.17	0.33	**0.94**		0.88
IAA	0.36	0.21	0.27	0.31	0.31	0.32	0.29	0.36	0.31	**0.95**	0.90

The square roots of the AVE are shown in the diagonal positions in Table 4, and the correlation coefficients are shown in the off-diagonal positions.

To supplement the Fornell and Larcker criteria, a heterotrait-monotrait (HTMT) correlational ratio test was performed (Henseler et al., 2014). The results show that all the values of the constructs are less than 0.85 (Voorhees et al., 2016). This result confirms the discriminant validity of the constructs. The results are shown in Table 4A.

Table 4A: Discriminant Validity Test (HTMT criteria)

Construct	OCM	OCX	ORE	OCO	COA	PSU	PU	PEOU	IAA
OCM									
OCX	0.34								
ORE	0.46	0.51							
OCO	0.32	0.44	0.46						
COA	0.19	0.33	0.33	0.44					
PSU	0.27	0.26	0.27	0.36	0.28				
PU	0.24	0.19	0.24	0.37	0.37	0.43			
PEOU	0.46	0.17	0.20	0.39	0.46	0.19	0.27		
IAA	0.27	0.32	0.39	0.17	0.29	0.31	0.25	0.34	

4.4 Common Method Bias

This study depends on the inputs from the respondents obtained from structured questionnaires with reference to all the constructs. As such, there is a chance of respondent bias. To eliminate the problems due to bias, at the time of the survey, the respondents were assured that their anonymity and confidentiality would be strictly preserved. This reassurance was given as a pre-emptive measure to ensure unbiased replies. However, to confirm that no bias is present, common method bias is performed. For this, Harman's single factor test was conducted, and the results showed that the first factor was 41.33%, which is less than the highest cut-off value of 50%, as recommended by Podsakoff et al. (2003). Hence, it is concluded that the data does not distort the prediction.

4.5 Hypotheses Testing

The bootstrapping procedure was adopted from the perspective of PLS-SEM analysis for hypothesis testing for which Smart PLS was used. In this procedure, 5,000 resamples were considered with reference to 340 cases (Henseler et al., 2009). This procedure is considered advantageous, as hypotheses can be tested by this procedure without conducting parametric tests (Chin, 2010). To ascertain cross-validated redundancy, omission separation 5 was considered concerning exogeneous factors. The Stone-Geisser Q^2 value that emerged was 0.62 (Stone, 1974; Geisser, 1975). This proves that the results have predictive relevance. Again, to verify whether the model is fit or not, the standardized root mean square residual (SRMR) error was considered a standard index, and its values were 0.061 for PLS and 0.033 for PLSc, with both values being less than 0.08 (Hu & Bentler, 1998). This highlights that the model is acceptable. Through use of this procedure, the path coefficients for all linkages along with probability values could be estimated. The results are shown in Table 6, and the validated model is shown in Figure 3.

Table 6: Results of path weight with R^2

Effects	Hypothesis	Path weightage	R^2	p-value	Sign	Remarks
Effects on PU			0.64			
by OCM	H1	0.41		$p < 0.05$ (*)	+	Supported
by OCX	H2a	0.32		$p < 0.05$ (*)	-	Supported
by ORE	H3a	0.33		$p < 0.01$ (**)	+	Supported
by OCO	H4a	0.47		$p < 0.001$ (***)	+	Supported
by COA	H5a	0.44		$p < 0.05$ (*)	+	Supported
by PSU	H6a	0.58		$p < 0.01$ (**)	+	Supported
by PEOU	H7	0.42		$p < 0.05$ (*)	+	Supported
Effects on PEOU			0.49			
by OCX	H2b	0.29		$p < 0.01$ (**)	-	Supported
by ORE	H3b	0.021		$p > 0.05$ (ns)	+	Not Supported
by OCO	H4b	0.042		$p > 0.05$ (ns)	+	Not Supported
by COA	H5b	0.32		$p < 0.05$ (*)	+	Supported

by PSU	H6b	0.021	p > 0.05 (ns)	+	Not Supported
Effects on IAA		0.71			
by PU	H9	0.59	p < 0.001 (***)	+	Supported
by PEOU	H8	0.57	p < 0.01 (**)	+	Supported
Effects on PU → IAA					
by LS	H10a	0.32	p < 0.01 (**)	+	Supported
Effects on PEOU → IAA					
By LS	H10b	0.23	p < 0.05 (*)	+	Supported

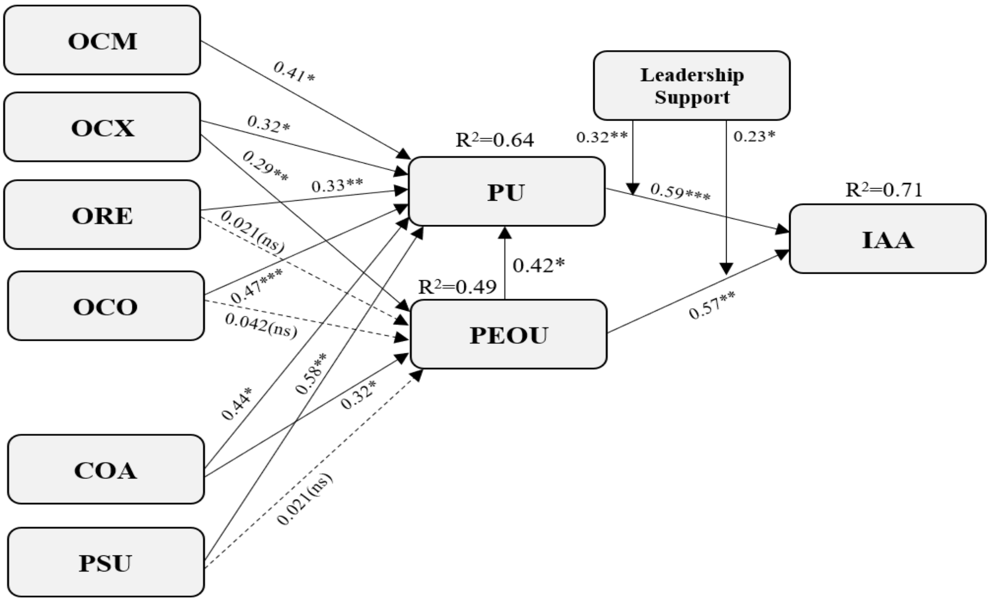

Figure 3: Validated Research Model (*p<0.05, **p<0.01, ***p<0.001)

[Legend: COA: Competitive Advantage; IAA: Intention to adopt AI; OCM: Organizational Competency; OCO: Organizational Compatibility; OCX: Organizational Complexity; ORE: Organizational Readiness; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PSU: Partner Support]

The results show that all the hypotheses were found to be significant except H3b, H4b, and H6b. Between the impacts of OCX on PU and PEOU, the influence of OCX on PU is stronger (β=0.32*). Between the effects of COA on PU and PEOU, the effects of COA on PU are stronger (β=0.44*). The effects of both, i.e., PU and PEOU, on IAA are almost the same, as the path coefficients are very close to each other with varied significance levels (0.59*** and 0.57**). The study further highlights that H3b (ORE → PEOU), H4b (OCO → PEOU), and H6b (PSU → PEOU) are not supported, as is found after validation, as the path coefficients of these three linkages are found to be nonsignificant (0.021^{ns}, 0.042^{ns}, and 0.021^{ns}, respectively). Variables such as OCM, OCX, ORE, OCO, COA, PSU, and PEOU can impact PU, and the variables OCX, ORE, OCO, COA, and PSU can impact PEOU to 64% and 49%, respectively, according to the estimates of the determinant coefficients. PU and PEOU can explain 71% of the variance in IAA, which is the explanatory power of this model. Moreover, the moderator LS has considerable effects on linkages H8 and H9, as the concerned path coefficients are 0.32

($p<0.01$) (H10a) and 0.23 ($p<0.05$) (H10b). This has also already been confirmed by MG analysis.

4.6 Moderation analysis

To examine the effects of the moderator (leadership support), multigroup analysis (MGA) was performed. In doing so, the help of accelerated and bootstrapping (bias-correlated) has been used with consideration of 5,000 resamples to compute the differences in the path weights between the two selected categories, i.e., strong leadership support and weak leadership support. The effects of the moderator are considered relevant with 5% probability regarding error levels. This means that it should be noted whether the p-value difference is either less than 0.05 or greater than 0.95 (Hair et al., 2016). This analysis was conducted by considering the effects of strong and weak leadership support on two linkages, i.e., H8 and H9. These results are presented in Table 5.

Table 5: Effects of moderator

Linkage	Difference in path coefficient	Difference in p-values	Remarks
(PU→IAA) × Leadership Support	0.187	0.002	Significant
(PEOU→IAA) × Leadership Support	0.169	0.023	Significant

5. Discussion

The result shows that organizational competency positively influences perceived usefulness, thus supporting Hypothesis H1. This signifies that the employees of the organization possess the skills, knowledge, and abilities along with other required traits to obtain efficient performance, which will be useful for the organization. Earlier studies (Long et al., 2013; Lee et al., 2017) also found support for this hypothesis (i.e., H1), i.e., that the competency of an organization helps to focus on job-related information and enhances the performance efficiency of the employees of the organization. The results show that organizational complexity negatively impacts perceived usefulness and perceived ease of use, confirming hypotheses H2a and H2b. This concept has been supported in earlier studies (Parveen & Sulaiman, 2008), where it has been asserted that system complexity is inversely proportional to perceived usefulness and perceived ease of use. This indicates that if the users find using a system (AI technology in the present case) difficult, they would perceive the system to be useless and that it cannot be handled effortlessly.

Organizational readiness positively affects perceived usefulness, supporting Hypothesis H3a. This confirms the findings of earlier studies (Ransbotham et al., 2017), which observe that if appropriate financial and technical resources and trained employees are available, there will be no impediment to adopting an innovative technology. However, it has also been hypothesized that organizational readiness has a positive impact on perceived ease of use (H3b). However, upon validation, it appears that this hypothesis (H3b) has not been supported. This is contradictory to earlier studies (Aboelmaged, 2014), which is presumably because this study (Aboelmaged, 2014) was conducted in a Western country where the cultural disposition is completely or partially different from the culture of India, from which responses have been used to test the hypothesis (H3b) in this study.

Indians are initially conservative and resist using new technology. They are found to be reluctant to undertake training to become ready to use a new system. They believe in the existing system, and this has been perceived when attempts were made to convert the legacy system to an ERP system (Gangadharan & Swami, 2004). This reluctance is perhaps why this hypothesis (H3b) is not supported (Rajesh, 2008). Organizational compatibility positively affects perceived usefulness, as the corresponding hypothesis (H4a) has been supported after validation, which is in parity with an earlier study (Peng et al., 2012). In the study by Peng et al. (2012), it was observed that if the existing technologies and practices are found to be compatible with the new technology, the users will intend to use it.

Again, organizational compatibility has no significant impact on perceived ease of use, as Hypothesis H4b has not been supported. There may be many reasons for this finding. The authors perceive that this result was arrived at by analysis of responses from 340 respondents chosen from some firms. Had it been possible to include more respondents, the authors expect that such a contradiction from earlier studies (Geczy et al., 2012) would not have occurred. The inadequate number of respondents might have yielded such a contradictory result because the result arrived at is not construed as a general picture.

Thus, in brief, it is expected that a survey that considers more respondents would have projected a general picture, and in that case, the authors presume that Hypothesis H4b would instead be supported. Competitive advantage has significant effects on perceived usefulness and perceived ease of use in supporting Hypotheses H5a and H5b. This result has received support from earlier studies (Curran & Purcel, 2017), which find that the use of AI technology means the use of ML, NLG and DL in an organization and use of these techniques would provide a competitive advantage to the organization compared to those organizations where these are not used.

Partner support has a significant and positive impact on perceived usefulness, and as such, Hypothesis H6a is supported. This is in agreement with earlier studies (Haans et al., 2016), which highlight that partner support would be helpful for sharing knowledge in addition to financial support, and this would enrich the ability of employees to adopt any innovative technology. However, partner support does not support Hypothesis H6b since the validation shows that partner support has a nonsignificant impact on PEOU (H6b), which contradicts the outcomes of other studies (Koka & Prescott, 2002). This is presumably because, through partner support, organizations may obtain financial help and can acquire knowledge through the sharing of knowledge, but other external conditions might not be conducive to easily using new systems despite the employees having sufficient knowledge of the technology .

The study has highlighted that perceived ease of use positively impacts perceived usefulness (H7), and intention to adopt AI (H8) and perceived usefulness impact the intention to adopt AI (H9). All these findings conform with the concept of TAM (Davis, 1989). The study considered leadership support as a moderator impacting linkages H8 and H9. We considered the effect of weak leadership support and strong leadership support. The study synthesized the effects of this moderator quantitatively by using the MGA process and noticed that in the two contexts (weak and strong leadership support), the use of the moderator achieved considerable significance. The moderator effects were shown through two groups considering the effects of the intention to adopt AI against the perceived ease of use linkage by weak and strong leadership support (see Figure 4) and intention to adopt AI against the perceived usefulness linkage by weak and strong leadership support (see Figure 5).

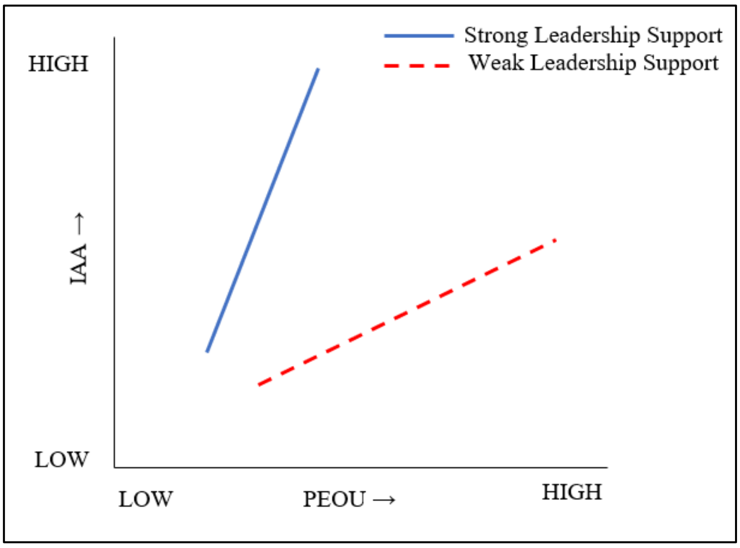

Figure 4: Effect of the moderator with respect to perceived ease of use

The figure 4 has dealt with how the relationship between PEOU and IAA is affected by the moderating effects of strong and weak leadership support. The analysis has been done graphically by plotting IAA against PEOU. Similarly, figure 5 has graphically analysed how the relationship between PU and IAA is impacted by the moderating effects of strong leadership support and weak leadership support. The analysis has been done graphically by plotting IAA against PU. The effects of the moderator have been discussed here through gradient analysis relating to figure 4 and figure 5.

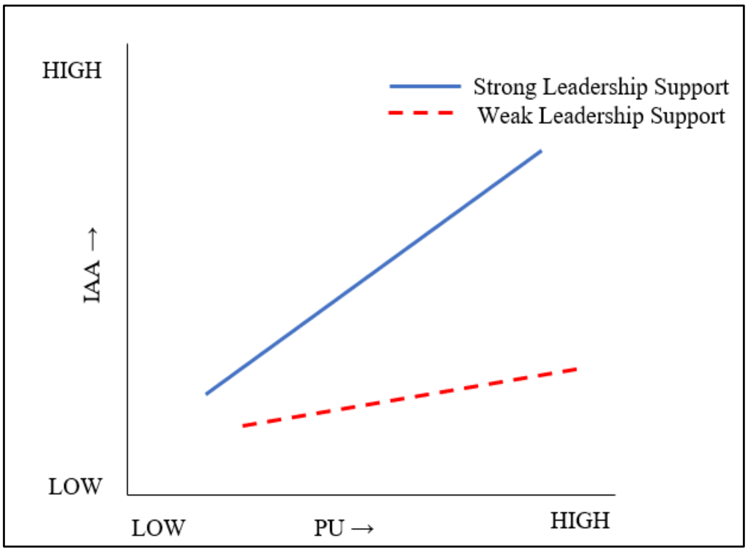

Figure 5: Effect of the moderator with respect to perceived usefulness

It appears that with an increase in perceived ease of use, the impact on intention to adopt AI is enhanced rapidly in the case of strong leadership support (continuous line) compared to weak leadership support (dotted line) (Figure 4) since the gradient of the continuous line is greater than that of the dotted line. The influence is almost identical when we consider the effect on intention to adopt AI by perceived usefulness considering strong and weak leadership support as a moderator (Figure 5). This signifies (in brief) that if strong leadership support exists in an organization, the adoption of AI in that organization will be accelerated. This concept is in agreement with earlier studies (Wang et al., 2010), where it has been mentioned that top management support helps to cultivate a favourable organizational climate to overcome the resistance to change regarding the adoption of innovative technology.

5.1 Theoretical contributions

This study has been able to theorize the environmental, social, and technological developments in the operations of organizations to unlock the digitalization of sustainable manufacturing and production systems. This study has also theorized that such digital systems are compatible in the context of emerging Industry 4.0. In achieving so, this study has imported the concept to interpret the socioenvironmental aspects and technological factors involved in using Industry 4.0; which is, here, AI. For this, the help of a hybrid model, i.e., the integrated TOE-TAM model, has been taken. This hybrid model has been successfully used to explore organizations' intention to adopt AI from social, environmental, and technological aspects. Since few research studies are available to nurture the use of Industry 4.0 in organizations to gain competitive advantage (Muller et al., 2018), this study provides a novel contribution in this context. This study has examined how cultural aspects pose an impediment to adopting a new technology (e.g., big data) in an organization (Lunde et al., 2019), and it has been explained through this study how the TOE framework will help to interpret the situation. The reasons for using the TOE-TAM-based integrated model have been explained in the theoretical background section. The aim of this study is to explain what factors could influence the intention to adopt AI, a component of Industry 4.0. Basically, this study analyses the adoption of AI in organizations. In this context, this study could have used an updated standard adoption model. However, the study has ventured to select better suited antecedents from TOE-TAM-based integrated models.

From the perspective of consideration of leadership support as a moderator to impact the intention to adopt AI, the concept of previous literature has been taken. Studies have revealed that in the context of e-commerce and cloud computing adoption, leadership support has been considered an important factor to promote such an adoption (Yang et al., 2015). This construct was used in this study to consider leadership support as a moderator to adopt AI. One study revealed that in SMEs in Kosovo, competency impacted business performance (Veliu & Manxhari, 2017). From this perspective, this study has used competency as one of the factors that help in the adoption of AI. A review of different literature from other studies has helped to enrich the proposed research model. This theoretical model has been developed for the adoption of AI in organizations to improve the digitalization of production and manufacturing systems, which is a unique context and contribution. By using perceived usefulness and perceived ease of use as two mediating variables to trigger the intention to adopt AI, lending ideas from Davis (1989), this study has been able to bridge the several factors covering social, environmental, and technological aspects with the intention to adopt AI technology and provide a unique way to present the TOE-TAM-based integrated model using perceived ease of use and perceived usefulness as mediating variables.

5.2 Managerial implications

In terms of the findings of this study, managerial implications can be developed to guide the future development of AI technology acceptance intentions in organizations. The vital endogenous variables impacting the intention to adopt AI in organizations are perceived usefulness and ease of use (Davis, 1989). Managers of manufacturing and production firms must be sincere to make clear to all stakeholders the utility of AI technology in organizations. The designers and developers of AI technology must be vigilant so that the use of this technology may not be complex. The importance of the usefulness of this adoption of AI technology must be apprised by the managers of the organization so that its acceptance by all stakeholders is not hindered. This is in support of the observations made in earlier studies (Fink et al., 2013).

Since competency impacts usefulness, managers should try to appropriately train the employees of the organization to enhance their expertise and skill. This will enhance the intention to adopt AI by employees, which would facilitate the organizational authority to adopt AI in an easier way. Since the readiness factor acts as a vital predictor of usefulness and ease of use for adoption of AI in organizations, managers should clearly define the strategy for adoption, ensure strong and committed sponsorship (resource mobilization), active support of mid-level managers, keep stakeholders apprised about the urgent needs for such adoption, ensure that the data to be analysed by AI after adoption are trustworthy and actionable and ensure effective availability of conducive infrastructure (Williams, 2004).

In this way, managers will attempt to keep the organization ready for the adoption of AI. As competitive advantage has a strong impact on PU and PEOU in the context of adoption of AI in an organization, it should be the duty of the managers of organizations contemplating the adoption of AI technology to emphasize the strategic importance, such as mobility, scalability, etc. This will help the users of the organizations (users of AI technology in future after adoption) to realize that the use of AI would make the organizations more productive compared to the other organizations. Managers need to make users realize the importance of competitive advantages by using AI technology, which might lead to better results by ensuring greater employee productivity and reducing inventory costs with enhanced coordination with partners. A developed understanding of these various advantages of AI technology over the existing system would improve customer relationship management, which would be beneficial for organizations.

Compatibility strongly impacts perceived usefulness, as ascertained from the study, since this AI technology has been found to be consistent with the existing format, existing technological architecture and other available structural data. If in any organization there exists an installation of many complex applications, it should be the duties of the managers to implement initiatives to change the existing processes to meet compatibility needs of the AI technology. AI adoption should also be befitting and compatible with the policy of organizations, business essentialities and the environment for IT development (Lin & Chen, 2012). Managers of organizations need to focus on these points. It has been hypothesized that compatibility positively impacts PEOU (H4b). However, while testing the hypotheses through a statistical approach, it appears that this hypothesis has not been supported. This was presumably (with other reasons) because the users of organizations perceived that, for adopting AI in the organization, it will be necessary to make major changes in their work style and nature of jobs, which is why this hypothesis was not supported. The managers of the organization need to focus on this point and should arrange to ensure that in the adoption of AI in the organization, users are apprehensive regarding changes to nature of jobs and work style. The findings in this study highlight that the adoption of AI in organizations is necessarily driven by the support of partners. Hence, managers approaching AI adoption in organizations should encourage the formation of networks for the sharing of knowledge and resources so that the needs of customers are fulfilled.

Regarding leadership support as a moderator, unless there is strong leadership support, the adoption of any innovative technology in an organization will not be successful. Top management is required to perform an effective and pragmatic role to convince their employees to motivate their functional behaviour. This will ensure a conducive environment to facilitate adoption. Managers need to focus on this point. Hence, this study provides various recommendations to managers of organizations to facilitate the adoption of AI in organizations.

5.3 Limitations and future research directions

Like any other study, this research is not without limitations. In validating the conceptual model by survey, the data were analysed based only on 340 responses only. This number is not perceived as a large sample size, and the results obtained should be considered cautiously while generalizing it for the other contexts. The survey was conducted with selected manufacturing and production firms in India. Therefore, the findings of this research should be tested in the context of other developing countries. Additionally, as this research has analysed the cross-sectional data gathered at only one point in time, future research should collect longitudinal data to see how the model performs using data collected from the same employees after a certain period of time. In India, the adoption of AI in organizations is in the preliminary stage, and survey responses have been gathered from nonadopters. Hence, proper precautions need be taken when the findings of this research are applied to adopters. Additionally, experimental research (Balakrishnan & Dwivedi, 2021) can be conducted to show high internal validity in such research. This study has not considered the vulnerable issues of security and privacy that might impede the progress of adoption of AI in organizations. Also, the present study deals with the issues of technology acceptance. The present study can be further extended and improved by using the application of fuzzy-set Qualitative Comparative Analysis (fsQCA) (Ragin, 2009). The application of fsQCA technique allows to get much deeper insights into the data. Also, fsQCA technique enables the researchers to identify the required necessary and sufficient conditions for an outcome to occur (Woodside, 2017; Pappas & Woodside, 2021; Woodside, 2017). To extend the present study, the future researchers can examine which factors from organizational-internal environment and organizational-external environment, or a combination of both the factors, are necessary or sufficient for explaining PU, PEOU, intention to adopt, or how the leadership support, which is a moderator in this study, can be used as a condition that will enable case by case analysis. There are few previous studies in this area which successfully applied fsQCA technique in the technology adoption studies for explaining behavioral intentions and demonstrated how the application of fsQCA technique allows the researchers to go back to the cases to get a much richer understanding of the data (Pappas, 2018; Park et al., 2020; Pappas & Woodside, 2021). Future researchers can also use the integrated TAM-TOE model used in this study and can further analyse using fsQCA technique for identifying the patterns in the dataset of the study which will allow better understanding of adoption of AI in the manufacturing and production firms. All these uncovered issues could be left for future researchers to investigate.

6. Conclusion

This study has investigated how the manufacturing environment has undergone remarkable transformation owing to the use of disruptive Industry 4.0 technology by reshaping production processes and operations (Luthra & Mangle, 2018), leading to a more advanced manufacturing system (Sung, 2018). This study has been able to explain how using Industry 4.0 technology transforms the production system of organizations into a smart system composed of several smart interconnected machines with the help of the IoT (Metallo et al., 2018). This study has focused on the essential environmental, social, and technological developments in organizations' operational techniques for effectively digitalizing manufacturing and production systems through the use of disruptive Industry 4.0 technology. This study aimed to identify the socioenvironmental and technological factors that help organizations adopt AI, a component of Industry 4.0 technology. To identify the antecedents, the study successfully utilized a TOE-TAM-based hybrid model. The TAM helped to identify technological issues, while the TOE mainly helped to identify socioenvironmental issues. As few studies have examined the adoption of Industry 4.0 in organizations in the context of socioenvironmental issues with a focus on technological aspects, this study is deemed to be a special endeavour.

References

Aboelmaged, M. G., 2014. Predicting E-Readiness at Firm-Level: An Analysis of Technological, Organizational and Environmental (TOE) Effects on E-Maintenance Readiness in Manufacturing Firms. *International Journal of Information Management, 34*(5), 639-651.

Aghion, P., Jones, B. F., Jones, C. I., 2017. Artificial Intelligence and Economic Growth. *National Bureau of Economic Research*, Available at: http://www.nber.org/ papers/ w23928.

Ajzen, I., 1991. The theory of planned behavior. Organizational Behavior and Human Decision Processes. *Organizational Behavior and Human Decision Processes, 50*(2), 179–221.

Aktar, A., Pangil F., 2017. The relationship between employee engagement, HRM practices and perceived organizational support: Evidence from banking employees. *International Journal of Human Resource Studies*, *7*(3), 1-22.

Alshamaila, Y., Papagiannidis, S, Li, F., 2013. Cloud computing adoption by SMEs in the north east of England: a multi-perspective framework. *Journal of Enterprise Information Management*, *26*(3), 250-275.

Armstrong, J. S., Overton, T. S., 1977. Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396–402.

Asgari, N., Singh, K. Mitchell, W. 2017. Alliance portfolio reconfiguration following a technological discontinuity. *Strategic Management Journal, 38,* 1062–81.

Bag, S., Pretorius, J. H. C., Gupta, S., Dwivedi, Y. K., 2021. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, 163, Article 120420.

Balakrishnan, J., Dwivedi, Y. K., 2021. Role of cognitive absorption in building user trust and experience. *Psychology & Marketing*, 38 (4), 643-668.

Baryannis, G., Validi, S., Dani, S., Antoniou, G., 2019. Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research, 57*(7), 2179-2202.

Batta, A., Gandhi, M., Kar, A. K., Loganayagam, N., Ilavarasan, V. 2020. Diffusion of blockchain in logistics and transportation industry: an analysis through the synthesis of academic and trade literature. *Journal of Science and Technology Policy Management.* In Press. https://doi.org/10.1108/JSTPM-07-2020-0105.

Benbasat, I., Barki, H., 2007. Quo Vadis, TAM? *Journal of the Association for Information Systems, 8*, 211–218.

Buer, S. V., Strandhagen, J. O., Chan, F. T., 2018. The link between Industry 4.0 and lean manufacturing: mapping current research and establishing a research agenda. International. *Journal of Production Research*, *56*(8), 2924-2940.

Cagliano, R., Canterino, F., Longoni, A., Bartezzaghi, E., 2019. The interplay between smart manufacturing technologies and work organization: The role of technological complexity. *International Journal of Operations & Production Management, 39*(6/7/8), 913-934.

Chatterjee, S., Kar, A. K., 2018. Effects of successful adoption of information technology enabled services in proposed smart cities of India. *Journal of Science and Technology Policy Management*, *9*(2), 189-209.

Chatterjee, S., Kar, A.K., 2020. Why do small and medium enterprises use social media marketing and what is the impact: Empirical insights from India. *International Journal of Information Management*, *53*, No.102103.

Chau, P., Hu, P., 2001. Information technology acceptance by individual professionals: a model of comparison approach. *Decision Sciences*, 32(4), pp. 699-719.

Chen, J., Gao, M., Mangla, S. K., Song, M., Wen, J., 2020. Effects of technological changes on China's carbon emissions. *Technological Forecasting and Social Change*, *153*, 119938.

Chen, L., Tan, J., 2004. Technology adaptation in e-commerce: key determinants of virtual stores acceptance. *European Management Journal*, *22*(1), 74-86.

Chidlow, A., Ghauri, P., Yeniyurt, S., Cavusgil, S. T., 2015. Establishing rigor in mail survey procedures in international business research. *Journal of World Business*, *50*(1), 26–36.

Chin, W.W. 2010. How to write up and report PLS analyses. In Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (Eds.), Handbook of partial least squares. 655–690. Berlin, Heidelberg, Springer.

Cui, A.S., O'Connor, G., 2012. Alliance portfolio resource diversity and firm innovation. *Journal of Marketing*, *76*, 24–43.

Curran, R., Purcell, B., 2017. *The Forrester Wave: Artificial Intelligence Technologies* Q1, 5.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

De Graaf M.M.A., 2016. An ethical evaluation of human-robot relationships. *International Journal of Social Robotics*, *8*(4), 589–598.

de Graaf, M. M., Ben Allouch, S., van Dijk, J. A., 2019. Why would I use this in my home? A model of domestic social robot acceptance. Human–Computer Interaction, 34(2), 115-173.

de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., Filho, M.G., 2018. When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, *132*, 18-25.

Demlehner, Q., Schoemer, D., Laumer, S., 2021. How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. *International Journal of Information Management*, 58, Article 102317.

Duan, Y., Edwards, J. S., Dwivedi, Y. K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management*, 48, 63-71

Dubey, R., Bryde, D. J., Foropon, C., Tiwari, M., Dwivedi, Y., Schiffling, S. 2021. An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. *International Journal of Production Research*, 59(5), 1586-1605.

Dutta, G., Kumar, R., Sindhwani, R., Singh, R.K., 2020. Digital transformation priorities of India's discrete manufacturing SMEs – a conceptual study in perspective of Industry 4.0. *Competitiveness Review*, *30*(3), 289-314.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ...Williams, M. D., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, Article 101994.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ...Wang, Y. 2020. Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 102168, doi: https://doi.org/10.1016/j.ijinfomgt.2020.102168

Erboz, G., 2017. *How To Define Industry 4.0: Main Pillars Of Industry 4.0.* Available online at https://bit.ly/33fTGMa on 24 November 2020.

Evans, P., Gawer, A., 2016. *The Rise of the Platform Enterprise: A Global Survey*, *Global Enterprise*, The Emerging Platform Economy Series, 5-8.

Fast, E., Horvitz, E. 2017. Long-Term Trends in the Public Perception of Artificial Intelligence. AAAI, 963-969.

Fink, J., Bauwens, V., Kaplan, F., Dillenbourg, P., 2013. Living with a vacuum cleaning robot: A 6-month ethnographic study. *International Journal of Social Robotics, 5*(3), 389–408.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Frank, A.G., Mendes, G. H., Ayala, N. F., Ghezzi, A., 2019. Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technological Forecasting and Social Change*, *141*, 341-351.

Gangadharan, G.R., Swami, S.N., 2004. *Business Intelligence Systems: Design and Implementation Strategies*. Conference of Information Technology Interfaces, IEEE Press.

Gartner, 2017. *Applying Artificial Intelligence to Drive Business Transformation: A Gartner Trend Insight Report*, 2-7.

Geczy, P., Izumi, N., Kôiti, H., 2012. Cloud sourcing: managing cloud adoption. *Global Journal of Business Research, 6*(2), 57-70.

Geissbauer, R., Vedso, J., Scharauf, S. 2016. Industry 4.0: Building the Digital Enterprise. Available online at https://pwc.to/3pZhZbd, accessed on 24th November 2020.

Geisser, S., 1975. The predictive sample reuse method with applications. *Journal of the American Statistical Association*, *70*(350), 320-328.

Grover, P., Kar, A. K., Dwivedi, Y. K., 2020. Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Annals of Operations Research*, 1-37, doi: https://doi.org/10.1007/s10479-020-03683-9

Grover, P., Kar, A. K., Dwivedi, Y. K., 2020. Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Annals of Operations Research*, In Press. https://doi.org/10.1007/s10479-020-03683-9.

Grover, P., Kar, A. K., Janssen, M., Ilavarasan, P. V., 2019. Perceived usefulness, ease of use and user acceptance of blockchain technology for digital transactions–insights from user-generated content on Twitter. *Enterprise Information Systems*, *13*(6), 771-800.

Haans, R. F., Pieters, C., Zi-Lin, H., 2016. Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal, 37*, 1177–1195.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., Sarstedt, M., 2016. *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, Sage Publications.

Hair, J. F., Risher, J., Sarstedt, M., Ringle, C. M., 2018. When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.

Halabi, T., Esquivel, R., Siles, B. 2017. Intrapreneurial competencies: development and validation of a measurement scale. *European Journal of Management and Business Economics, 26*(1), 86-111.

Henseler, J., Ringle, C.M., Sinkovics, R.R., 2009. The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*(1), 277–319.
Henseler, J., Ringle, C.M., Sarstedt, M., 2014. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.
Hofmann, E., Rüsch, M., 2017. Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry*, *89*, 23-34.
Hong, S., Tam, K. Y., 2006. Understanding the adoption of multi-purpose information appliances: The case of mobile data services. *Information Systems Research*, *17*, 162–179.
Hong, S., Thong, J.Y.L., Tam, K.Y., 2006. Understanding continued information technology usage behavior: a comparison of three models in the context of mobile internet. *Decision Support Systems*, *42*(3), 1819-1834.
Hossain, M.A., Quaddus, M., 2011. The adoption and continued usage intention of RFID: an integrated framework. *Information Technology & People*, *24*(3), 236-256.
Hottenrott, H., Lopes-Bento, C., 2016. R&D partnerships and innovation performance: Can there be too much of a good thing? *Journal of Product Innovation Management*, *33*, 773–94.
Hu, L., Bentler, P. M., 1998. Fit indices in covariance structure modeling: Sensitivity to under parameterized model misspecification. *Psychological Methods*, *3*(4), 424–453.
Hu, Q., Lu, Y., Pan, Z., Gong, Y., Yang, Z., 2021. Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management*, 56, 102250.
Hughes, L., Dwivedi, Y. K., Rana, N. P., Williams, M. D., Raghavan, V., 2020. Perspectives on the future of manufacturing within the Industry 4.0 era. *Production Planning & Control*, 1-21, doi: https://doi.org/10.1080/09537287.2020.1810762
Iacovou, C.L., Benbasat, I., Dexter, A.S., 1995. Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology. *MIS quarterly*, *19*(4), 465-485.
Idris, A. O., 2015. Assessing a Theoretically Derived E-Readiness Framework for E-Commerce in a Nigerian SMEs. *Evidence Based Information Systems Journal,* 1(1), 1-20.
Ifinedo, P., 2011. Internet/e-business technologies acceptance in Canada’s SMEs: An exploratory investigation. *Internet Research*, *21*(3), 255–281.
Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Sarkis, J., Godinho Filho, M., 2019. Unlocking the circular economy through new business models based on large-scale data: An integrative framework and research agenda. *Technological Forecasting and Social Change*, *144*, 546-542.
Kalaitzi, D., Matopoulos, A., Bourlakis, M, Tate, W., 2019. Supply chains under resource pressure: Strategies for improving resource efficiency and competitive advantage. *International Journal of Operations & Production Management*, *39*(12), 1323-1354.
Kar, A. K. Navin, L., 2020. Diffusion of blockchain in insurance industry: An analysis through the review of academic and trade literature. *Telematics and Informatics*, *58*, No.101532.
Kar, A.K., 2020. What affects usage satisfaction in mobile payments? Modelling user generated content to develop the “digital service usage satisfaction model. *Information Systems Frontiers,* In Press. https://doi.org/10.1007/s10796-020-10045-0.
Knight, R., 2015. *Convincing Skeptical Employees to Adopt New Technology*. Harvard Business Review. Available at: https://hbr.org/2015/03/convincing-skeptical-employees-to-adopt-new-technology (Last accessed 24 December 2019)

Koka, B.R, Prescott, J.E., 2002. Strategic alliances as social capital: A multi-dimensional view. *Strategic Management Journal*, *23*, 795–816.

Koufaris, M., 2002. Applying the technology acceptance model and flow theory to online consumer behavior. *Information Systems Research*, *13*, 205–223.

Lee, D., Kirkpatrick-Husk, K, Madhavan, R., 2017. Alliance diversity and firm performance: A meta-analysis. *Journal of Management*, *43*, 1472–1497.

Lee, Y., Kozar, K. A. Larsen, K. R. T., 2003. The technology acceptance model: Past, present and future. *Communications of the Association for Information Systems*, *12*(1), 752–780.

Li, L., 2017. China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0". *Technological Forecasting and Social Change*, *135*, 66-74.

Lin, A, Chen, N.-C., 2012. Cloud computing as an innovation: perception, attitude, and adoption. *International Journal of Information Management*, *32*(6), 533-540.

Lin, D., Lee, C.K.M., Lau, H., Yang, Y., 2018. Strategic response to Industry 4.0: an empirical investigation on the Chinese automotive industry. *Industrial Management & Data Systems*, *118*(3), 589-605.

Long, C.S., Wan Ismail, W.K, Amin, S.M., 2013. The role of change agent as mediator in the relationship between HR competencies and organizational performance. *The International Journal of Human Resource Management*, *24*(10), 2019-2033.

Lu, Y., 2017. Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, 6, 1–10.

Lunde, T.Å., Sjusdal, A.P., Pappas, I.O., 2019. *Organizational Culture Challenges of Adopting Big Data: A Systematic Literature Review*. In Conference on e-Business, e-Services and e-Society (pp. 164-176. Springer, Cham.

Luthra, S., Mangla, S. K., 2018. Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. *Process Safety and Environmental Protection*, *117*, 168-179.

Maduka, N., Edwards, H., Greenwood, D., Osborne, A, Babatunde, S., 2018. Analysis of competencies for effective virtual team leadership in building successful organizations. *Benchmarking: An International Journal*, *25*(2), 696-712.

Makridakis, S., 2017. The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms. *Futures*, *90*(6), 46-60.

Margherita, E. G., Braccini, A. M., 2020. Industry 4.0 Technologies in Flexible Manufacturing for Sustainable Organizational Value: Reflections from a Multiple Case Study of Italian Manufacturers. *Information Systems Frontiers*, In Press. https://doi.org/10.1007/s10796-020-10047-y

Metallo, C., Agrifoglio, R., Schiavone, F., Mueller, J., 2018. Understanding business model in the Internet of Things industry. *Technological Forecasting and Social Change*, *136*, 298-306.

Mikalef, P., Pappas, OI., Krogstie, J., Pavlou, P., 2020. Big data and business analytics: A research agenda for realizing business value. *Information & Management*, *57*(1), 103237.

Mir, U. B., Sharma, S., Kar, A. K., Gupta, M. P., 2020. Critical success factors for integrating artificial intelligence and robotics. *Digital Policy, Regulation and Governance*. *22*(4), 307-331.

Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S, Barbaray, R., 2018. The industrial management of SMEs in the era of Industry 4.0. *International Journal of Production Research*, *56*, 1118–1136.

Muller, J.M, Buliga, O. and Voigt, K.I., 2018. Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, *132*, 2–7.

Oesterreich, T. D., Teuteberg, F., 2016. Understanding the implications of digitization and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Computers in Industry, 83,* 121-139.
Pappas, I. O., Woodside, A. G., 2021. Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management*, *58*, 102310.
Pappas, I.O., 2018. User experience in personalized online shopping: a fuzzy-set analysis. *European Journal of Marketing*, *52*(7/8), 1679-1703.
Pappas, I.O., Mikalef, P., Giannakos, M.N., Krogstie, J., Lekakos, G., 2018. Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. *Information Systems and e-Business Management*, *16*(3),479-491.
Park, Y., Fiss, P. C., El Sawy, O. A., 2020. Theorizing the multiplicity of digital phenomena: The ecology of configurations, causal recipes, and guidelines for applying QCA. *MIS Quarterly*, *44*(4), 1493-1520.
Parveen, F, Sulaiman, A., 2008. Technology complexity, personal innovativeness, and intention to use wireless internet using mobile devices in Malaysia. *International Review of Business Research Papers, 4*(5), 1-10.
Peng, R., Xiong, L, Yang, Z., 2012. Exploring tourist adoption of tourism mobile payment: an empirical analysis. *Journal of Theoretical and Applied Electronic Commerce Research, 7*(1), 21-33.
Pillai, R., Sivathanu, B., Dwivedi, Y. K., 2020. Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, 57, 102207.
Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., Dwivedi, Y. K., 2021. Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control*, 1-17, doi: https://doi.org/10.1080/09537287.2021.1882689
Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., de Amicis, R., Pinto, E.B., Eisert, P., Döllner, J, Vallarino, I., 2015. Visual computing as a key enabling technology for industry 4.0 and industrial internet. *IEEE Computer Graphics and Applications*, *35*(2), 26-40.
Press, P. H., 2016), *Preparing for the Future of Artificial Intelligence*. CreateSpace Independent Publishing Platform, 2-12.
Pu, X., Chong, A., Cai, Z., Lim, M, Tan, K., 2019. Leveraging open-standard interorganizational information systems for process adaptability and alignment: An empirical analysis. *International Journal of Operations & Production Management, 39*(6/7/8), 962-992.
Ragin, C.C., 2009. *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press Publication, USA.
Rajesh, K.V.N., 2008. Business Intelligence for Enterprises. *The ICFAI Journal of Information Technology*, *35*, 45-54.
Ransbotham, S., David, K., Philipp, G, Reeves, M., 2017. *Reshaping Business with Artificial Intelligence*. MIT Sloan, 3-12.
Reischauer, G., 2018. Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing. *Technological Forecasting and Social Change*, *132*, 26-33.
Richter, N.F., Sinkovics, R., Ringle, C.M., Schlägel, C., 2016. A critical look at the use of SEM in international business research. *International Marketing Review*, 33(3), 376-404.
Riyadh, A.N., Akter, M.S, Islam, N., 2009. The adoption of e-banking in developing countries: a theoretical model for SMEs. *International Review of Business Research Papers, 5*(6), 212-230.

Rogers, E.M. 2003. *Diffusion of Innovations*. The Free Press, New York, NY.
Shareef, M. A., Kumar, V., Dwivedi, Y. K., Kumar, U., Akram, M. S., Raman, R., 2021. A new health care system enabled by machine intelligence: Elderly people's trust or losing self control. *Technological Forecasting and Social Change*, 162, 120334.
Sonnenwald, D.H., Maglaughlin, K.L, Whitton, M.C., 2001. *Using innovation diffusion theory to guide collaboration technology evaluation.* IEEE 10th International Workshop on Enabling Technologies, Work in progress, Infrastructure for Collaborative Enterprises, Cambridge, MA.
Stone, M., 1974. Cross validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society*, *36*(2), 111-147.
Sulaiman, A., Cheung, Y, Messom, C., 2018. *Artificial Intelligence Adoption: AI-readiness at Firm-Level.* Twenty-Second Pacific Asia Conference on Information Systems, Japan.
Sung, T. K., 2018. Industry 4.0: A Korea perspective. Technological Forecasting and Social Change, *132*, 40-45.
Tornatzky, L.G, Fleischer, M., 1990), *The Processes of Technological Innovation*, Lexington books, Lexington, MA.
Tortorella, G., Giglio, R, van Dun, D., 2019. Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement. *International Journal of Operations & Production Management*, 39(6/7/8), 860-886.
Tortorella, G.L., Giglio, R., van Dun, D.H., 2019. Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement. *International Journal of Operations & Production Management*, *39*(6/7/8), 860-886.
Veliu, L, Manxhari, M., 2017. The impact of managerial competencies on business performance: SME's in Kosovo. *Vadyba Journal of Management, 1*(30), 59-65.
Vempati, S.S., 2016. *India and the Artificial Intelligence Revolution*. Carnegie Endowment for International Peace.
Venkatesh, V., Bala, H., 2008. Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, *39*(2), 273-315.
Venkatesh, V., Davis, F. D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*, 186–204.
Venkatesh, V., Morris, M. G., 2000. Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24,* 115–139.
Voorhees, C.M., Brady, M.K., Calantone, R., Ramirez, E., 2016. Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, *44*, 119-134.
Wang, S., Wan, J., Li, D., Zhang, C., 2016. Implementing Smart Factory of Industry 4.0: An Outlook. *International Journal of Distributed Sensor Networks, 12*(4), 1–10.
Wang, Y., Wang, Y, Yang, Y., 2010. Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting & Social Change, 77*(5), 803-815.
Willaby, H.W., Costa, D.S.J., Burns, B.D., McCAnn, C., Roberts, R.D., 2015. Testing complex models with small sample sizes: A historical overview and empirical demonstration of what partial least squares (PLS) can offer differential psychology. *Personality and Individual Differences*, *84*, 73-78.
Williams, S., Williams, N., 2004. Assessing BI Readiness: A Key to BI ROI. *Journal of Business Intelligence, 9*, 15-23.
Woodside, A.G., 2017. *The complexity turn: Cultural, management, and marketing applications*. Springer Publication.

Yang, Z., Sun, J., Zhang, Y., Wang, Y., 2015. Understanding SaaS Adoption from the Perspective of Organizational Users: A Tripod Readiness Model. *Computers in Human Behavior, 45*, 254-264.
Yousafzai, S.Y., Foxall, G.R., Pallister, J.G., 2007. Technology acceptance: A meta-analysis of the TAM: Part 1. *Journal of Modeling in Management*, *2*(3), 251–280.
Zhang, D., Pee, L. G., Cui, L., 2021. Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management*, 57, 102304.
Zheng, Y, Yang, H., 2015. Does familiarity foster innovation? The impact of alliance partner repeatedness on breakthrough innovations. *Journal of Management Studies*, *52*, 213–230.

Appendix A

Table 1: Measurement Instrument

Constructs	Sources	Measurement Item
Organizational Competency (OCM)	Long et al. 2013	OCM1: We have enough technological resources to sustain and support any eventuality that may arise due to the integration of an existing legacy system with AI.
	Maduka et al. 2018	OCM2: Having specialized technological resources at the organization level is important for the smooth adoption of AI technology.
		OCM3: We have experts in the AI domain in our organization.
		OCM4: Organizations with trained manpower in the AI domain will obtain competitive advantages.
Organizational Complexity (OCX)	Sonnenwald et al. 2001	OCX1: Using AI technology is more flexible for manufacturing and production than the existing legacy system.
	Idris 2015	OCX2: AI technology for manufacturing and production can be risky, as most of the processes are automated and technology dependent.
	Parveen and Sulaiman 2008	OCX3: Integrating AI technology with the existing legacy system is a difficult task for our organization.
		OCX4: Resistance to change is high regarding migrating from the legacy system to an AI based manufacturing and production system.
Organizational Readiness (ORE)	Iacovou et al. 1995	ORE1: The AI based manufacturing and production technology procedure is easily understandable to me.
	Aboelmaged 2014	ORE2: I have all the readiness resources for learning the AI based manufacturing and production system in my firm.
	Idris 2015	ORE3: We have different ways (virtual, in person, etc.) of training in our organization.
		ORE4: It is easy for me to learn AI technology.
Organizational Compatibility (OCO)	Peng et al. 2012	OCO1: We have a good plan to integrate AI technology with the existing legacy system in our organization.
	Geczy et al. 2012	OCO2: Our partner helps us to integrate AI technology into the existing legacy system.
		OCO3: AI technology is compatible with the existing legacy system for production and manufacturing in our firm.
		OCO4: Customization is easier for AI based manufacturing and production systems.
Competitive Advantage (COA)	Rogers 2003	COA1: I am aware that an AI based manufacturing and production system is being implemented by a few of our competitors.
	Yang 2015	COA2: I understand that by using an AI based manufacturing and production system, my firm will have a competitive advantage.
	Makridakis 2017	COA3: I believe that an AI based manufacturing and production system is necessary for sustaining our industry.
		COA4: I am aware that many firms are moving towards AI based manufacturing and production systems.

Partner Support (PSA)	Zheng et al. 2015	PSA1: I believe that partner support is essential during the migration process from an existing legacy system to an AI based manufacturing and production system.
	Haans et al. 2016	PSA2: Excellent partner support makes things easier to adopt.
		PSA3: Partner support is essential for solving any technical issue quickly.
		PSA4: I believe that partner support is cost effective for our organization.
Perceived Usefulness (PU)	Davis, 1989	PU1: I agree that using an AI based manufacturing and production system makes our firm more efficient.
	Lee et al. 2003	PU2: I believe that the use of an AI based manufacturing and production system increases productivity in our organization.
		PU3: I can achieve things in a quicker way using an AI based manufacturing and production system.
		PU4: AI based systems reduce production costs.
Perceived Ease Of Use (PEOU)	Lee et al. 2003	PEOU1: The process of using an AI based system is easily understandable by me.
	Yousafzai et al. 2007	PEOU2: It is easy for our organization to operate an AI based manufacturing and production system.
		PEOU3: I will be able to use the AI based manufacturing and production system in our organization.
		PEOU4: I agree that all the related employees can quickly learn about the usage of AI based technology.
Intention to Adopt AI (IAA)	Yousafzai et al. 2007	IAA1: I think that the AI based manufacturing and production system is advantageous for our firm.
		IAA2: I am in favour of an AI based manufacturing and production system.
		IAA3: I would like to use the AI based technology to its full potential.
		IAA4: Overall, I think using AI based technology will enhance our organization's productivity.