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Innovation in SMEs, AI Dynamism, and Sustainability: The Current Situation and Way Forward

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Abstract: The purpose of this study is to examine artificial intelligence (AI) dynamism and its impact on sustainability of firms, including small and medium enterprises (SMEs). In addition, this study investigates the moderating effects of technological and leadership support for AI technology deployment and sustainability for manufacturing and production firms. We developed a theoretical model through the lenses of expectation disconfirmation theory (EDT), technology–trust–fit (TTF) theory, contingency theory, and the knowledge contained in the existing literature. We tested the proposed theoretical model using factor-based PLS-SEM technique by analyzing data from 343 managers of SMEs. The findings of this study demonstrate that organizational characteristics, situational characteristics, technological characteristics, and individual characteristics all impacted SMEs' deployment of AI technologies for the purpose of achieving sustainability, with technological and leadership support acting as moderators.

Keywords: AI deployment; sustainability; SMEs; innovation; production and manufacturing firms; AI dynamism

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1. Introduction

Artificial intelligence (AI) is technology that can demonstrate machine intelligence in contrast to human intelligence. It can perform cognitive functions such as learning and problem solving that are usually performed by humans [1,2]. The versatility of AI has attracted the attention of the industrial sector to make use of these abilities in organizational operations. This is because AI uses multi-disciplinary approaches to accurately gather and analyze data and then share that data without human involvement [3,4]. There is great optimism that the applications of AI technology will be able to revolutionize various functionalities of organizations, including innovation, production, and operations. Such applications of AI technology are expected to face several entangled challenges which adversely affect organizational and situational characteristics, technological issues, and specialized employees of organizations [5]. In practical terms, the challenges involved in adopting AI in manufacturing and production firms are considerable [6]. These include compatibility, the complexity of organizations and their preparedness to adopt AI [7–11]. Situational hazards can pose issues as well, including technological dynamism and external competitive pressure [12]. There can be technical challenges if AI solutions are too difficult to implement or incompatible with existing systems [13]. Apart from this, as is always the case in technological adoption, trust factors and the learning abilities of employees are crucial influences on organizational strategies, and help organizations to decide whether or not they should adopt a new system [14–16]. This concept is in conformity with expectation disconfirmation theory (EDT) [17]. Of course, these factors may sometimes facilitate and sometimes impede the adoption of AI in organizations, including SMEs. It is to be noted that the applications of AI in an enterprise can balance the electricity supply and demand in real time from the perspective of optimizing energy use and storage to reduce costs. In a firm, an AI-embedded digital geospatial dashboard can successfully and effectively monitor and manage the environmental systems. It can tackle the inefficient use of electricity and extraction of water, and reduce air pollution, among other things. In the context of AI adoption for manufacturing and production firms, we know that such processes are carried out with a focus on reducing expenditures. At the same time, however, the apprehension that jobs could be lost can hardly be ruled out. The extant literature deals with various contributions of AI in the business processes of enterprises. However, the literature is silent with respect to exhaustive explanations of how appropriate and effective deployment of AI technologies can achieve sustainability of SMEs. In this context, the objectives of this study are as follows:

[i] To determine the antecedents that impact the AI deployment rationale of manufacturing and production firms, including SMEs.

[ii] To investigate the moderation effects of technological support and leadership support on the relationship between AI deployment rationale and its effect on sustainability of manufacturing and production firms, including SMEs.

[iii] To examine whether AI technology can support sustainable automation for SMEs.

The present study contributes knowledge about how organizational characteristics (including complexity, compatibility, and readiness), situational characteristics, (including AI technology dynamism and competitive pressure), and technological characteristics (such as AI-related technological complexity and compatibility) can assist firms in deploying AI-embedded technologies to achieve sustainability under the moderating influences of both technological and leadership support.

The remaining sections of the paper are structured as follows: Section 2 reviews the relevant literature on AI-driven technology; Section 3 proposes the theoretical background, development of the conceptual model, and formulation of hypotheses; Section 4 provides the research methodology, including the research instruments and data collection mechanism; Section 5 analyzes the results. Section 6 provides a discussion of results along with theoretical contributions, practical implications, and limitations along with directions for future research. Finally, Section 7 presents the conclusion of the paper.

2. Literature Review

Previous studies have anticipated that AI-driven technology will improve sustainability in the production and manufacturing systems of various industries. However, until today these have been in the nascent stage [18–21]. AI technology in the form of robots had been placed in 1.3 million industrial robots in different organizations as of 2018 [22]. Several studies have suggested that using AI-enabled technology will allow organizations to improve their sustainability in manufacturing and production processes in an eco-friendly, smart, and flexible manner [23–25].

Several studies have revealed that industries are experiencing challenges in carrying on with their operations using technologies adopted from before Industry 4.0 [26–28]. These constraints have provoked such industries to adopt AI [29,30]. However, other studies have shown that organizations that use AI face several organizational, situational, technological, and individual challenges [5,31]. The ability of an organization to adopt an innovation depends on the extent to which that organization is ready for the technology in question. Many researchers have considered readiness as a state of behavioral, psychological, and structural preparedness which an organization must attain before commencing a specific activity [32–37].

An organization's readiness is associated with organizational compatibility and complexity [7,38,39]. Organizational complexity comprises structural, relational, and behavioral complexity [40,41]. Other studies [42,43] have construed organization to be more effective if the technology in question is not complex.

The adoption of AI by an organization is affected by the organizational context and the mutual compatibility between it and a given technology. The concept of compatibility includes technology–task, technology–organization, and technology–people aspects [44,45]. Organizational compatibility is defined as "the degree to which an innovation is perceived as consistent with the existing values, past experience and needs of potential adopters" ([46], p. 240).

In addition, situational characteristics influence the adoption of a new technology [47]. External competitive pressures can influence the adoption of AI in an organization [48]. If competing organizations perform better, other organizations are pressured to compete as well. With increasing competitive pressure, organizations can use emerging technologies to gain a competitive advantage [49–51]. Studies have found that the development of advanced e-commerce technology with no congenial policies to guide businesses has resulted in uncertainty in the e-commerce environment, which affects employees' level of trust [52–54].

Employees' learning abilities need to be improved in order to assimilate the technological issues of AI in their organizations [55]. When organizations address all the factors that pose challenges to their adoption of AI, it becomes conducive for them to deploy AI. The rationale behind manufacturing and production firms' deployment of AI is to use AI technology to develop sustainability in their firms [56]. However, Alshamaila et al. [57] have suggested that without sincere and effective support from the top levels of management, it is difficult for an organization to adopt new technology.

3. Theoretical Background and Development of Conceptual Model

3.1. Theoretical Background

From a literature review, this study has identified challenging factors impacting manufacturing and production firms in their adoption of AI. In this section, we analyze the extent to which it is possible to theoretically define the antecedents. Technology–Trust–Fit (TTF) theory [58] is usually used in Management Information Science studies to ascertain the fitness and compatibility of technology in an organization. This theory posits that users will use an IT system if the functions that are already available to users become compatible with their activities. If the activities that employees already perform fit the functions that the adopted technology performs, they will prefer to use that technology.

In terms of contingency theory [59,60], an organization is seen to behave in a manner that allows it to adjust to its environment. Its employees' reaction against organizational complexity determines whether the organization is complex or not. This theory posits that an organization is complex if it is diverse, hostile, restrictive, and technologically complex. Technological complexity may be broadly conceptualized as the extent of the difficulties involved in transforming the inputs of technological components into expected outputs [61,62]. Thus, contingency theory ideates both organizational and technological complexity.

In order for an organization to adopt an innovative technology such as AI, it must have the ability to unfreeze, freeze, and refreeze the available resources supported by congenial strategies in the context of dynamic business environments in hyper-competitive markets [63]. This signifies that in order to adopt any innovative technology, an organization should be prepared to continuously change its approach to innovation. This is in consonance with the theory of organizational readiness [64], which posits that organizational readiness is an assessment of an organization's actual state of preparedness for the effective adoption and exploitation of any technology with respect to innovation. Based on organizational readiness theory, we can interpret that state-of-preparedness has an impact if the organization characteristics are conducive to adoption.

Expectation Disconfirmation Theory (EDT) [17,65] posits that users' satisfaction is affected as they compare their expectations and disconfirmations of the performance of a technology [66]. Lewicki et al. [67] considered that trust building is a hybrid process of expectation and disconfirmation. Hence, the sense of trust emerges as a factor from the concept of the EDT. Each employee's learning ability must be continuously refreshed in order to stay relevant in a dynamic marketplace and to explore, exploit, and assimilate any innovative opportunity without constraint. Employees can improve their learning capabilities by creating opportunities to learn, stimulating each other to learn, exchanging feedback with each other, and enhancing mutual help while learning [55]. Employees with enhanced learning ability help their organizations to easily adopt technology for sustainable growth.

3.2. Development of the Conceptual Model and Formulation of Hypotheses

Based on our review of the literature and inputs from different theories, we have identified several challenges, including organizational, situational, technological, and individual issues, that organizations need to address before deploying AI-embedded technology to improve the sustainability of manufacturing and production. In addition, additional leverage from technological and leadership support can help firms to succeed in such deployment.

3.2.1. Organizational Characteristics

The characteristics of organizations are perceived to be critical for their successful deployment of AI to improve their manufacturing and production activities. The time spent installing AI technology in an organization must not be too long. The organization should be able to make effective intelligent decisions with AI applications more smoothly. In brief, there must not be any organizational complexity [68]. Moreover, employees must develop the necessary skills and expertise to adopt a technology such as AI and have the competencies required to use the new technology without any constraints. Employee competency makes the organization compatible [69]. The organization must be well equipped during the adoption of AI in order to be ready to facilitate deployment without any difficulty [8]. Thus, the organization must be able to readily adopt AI to improve its manufacturing and production units.

The organization should not be complex, as was discussed earlier as being one of the relevant organizational characteristics. Complexity is conceptualized as the level of constraint and inconvenience involved in understanding and using a system [68]. The complexity of an organization has to do with its system functionalities and interface designs [70]. This idea is quite in conformity with contingency theory [59]. This indicates that complexity of the organization might affect the rational deployment of AI for improving the sustainability of manufacturing and production firms. This leads us to suggest the following hypothesis:

H1a. *Organizational complexity (OCX) negatively impacts the AI deployment rationale of manufacturing and production firms (ARMP).*

Compatibility has been defined as "the degree to which an innovation is perceived as consistent with the existing values, past experience, and needs of the potential adopters" ([46], p. 240). Compatibility is conceptualized as the extent to which an innovation can easily be assimilated and integrated with the available infrastructure of the organization [69,71]. This concept has been duly supplemented by TTF theory [58]. Thus, it is apparent that if a technology is compatible with an organization, its adoption is facilitated. On the basis of these ideas, the following hypothesis can be derived:

H1b. *Organizational compatibility (OCO) positively influences the AI deployment rationale of manufacturing and production firms (ARMP).*

Organizational readiness can be conceptualized as the ability of an organization to prepare the necessary resources for adopting AI technology [72]. Organizational readiness is an internal characteristic that depends on an organization's IT resources and employees who are trained, skilled, and ready to accept any adoption without interruption [9,48]. This concept is supplemented by organizational readiness theory [8,64]. Hence, organizational readiness is perceived to facilitate deployment of AI in an organization. The above discussion helps to formulate the following hypothesis:

H1c. *Organization readiness (ORE) positively impacts the AI deployment rationale of manufacturing and production firms (ARMP).*

3.2.2. Situational Characteristics

Kaufmann and Carter [73] (2006) argue that dynamism is a crucial variable when considering industrial adoption behavior; an organization needs to adjust itself in order to keep pace with the development of AI. AI technology is characterized by its dynamism [74]. If an organization adopting AI technology is unable to stay updated on the fast-changing situation, it will lag its competitors [75]. In addition, the organization should advance at the same speed as contemporary organizations. This competitive pressure is considered a healthy way to develop competitive advantage [76].

Rapid change in technology can cause problems in the information processing channel. In this respect, organizations should be vigilant about withstanding the load of information processing and competing in the changing technological environment [77]. Sharfman ([78], p.560) opined that "a mistake in threating environment could be disastrous for the firm, we would expect to find highly rational decision procedures used in such environment." Deployment of AI technology in an organization is perceived to be a very rational approach to decision-making. From this angle, the following hypothesis is formulated:

H2a. *AI technology dynamism (ATD) is positively correlated with the AI deployment rationale of manufacturing and production firms (ARMP).*

Competitive pressure is created by the pace of success of rival organizations. The more success they achieve, the more pressure is placed on other organizations to compete [79]. Competitive pressure acts as a catalyst for an organization to achieve competitive advantage, provided the competition is perceived to be healthy. The competitive environment affects an organization's decision-making strategy [80]. It is perceived to be a situational characteristic that motivates an organization to adopt a technology so that it can enjoy competitive advantage. This concept leads to the following hypothesis:

H2b. *Competitive pressure (COP) is positively related with the AI deployment rationale of manufacturing and production firms (ARMP).*

3.2.3. Technological Characteristics

Complexity and compatibility are two characteristics of an organization's technological environment. Technological compatibility is considered a foundation for assessing a firm's success in a dynamic knowledge-intensive industry [81]. Several technologies exist to justify the concept and to clarify an organization's technological intellectual capital.

Technological complexity is interpreted as the extent of difficulty in realizing how technological components work to transform effective inputs into successful outputs [60]. In other words, a technological system in an organization is said to be complex when it is a combination of elements that produce identical outputs [82,83]. If an organization has complex technology, its employees feel constrained to use the system, which inhibits any adoption approach. This idea helps in developing the following hypothesis:

H3a. *AI technology complexity (ATC) is negatively related with the AI deployment rationale of manufacturing and production firms (ARMP).*

Another aspect which is relevant to the adoption of technology emerges from the idea of technological compatibility [44]. When an employee of an organization believes that an existing technology would help them to assimilate the technology, the employee is seen to exhibit positive use behavior [12,24]. This is because the technology they want to adopt is compatible with the current technology with which they are already acquainted, that is, technology compatibility exists. This leads us to formulate the following hypothesis:

H3b. *AI technology compatibility (AICO) is positively related with the AI deployment rationale of manufacturing and production firms (ARMP).*

3.2.4. Individual Characteristics

When an organization proceeds to adopt a technology, employees' individual characteristics count for a great deal in the context of their trust factor and learning abilities. It is common for employees to initially exhibit a sense of uncertainty regarding outcomes of any technology that their organization adopts. In this context, employees' trust is a factor affecting adoption [84]. Employees' learning abilities impact adoption unless they have proper knowledge about the technology to be adopted. If not, this adversely affects the adoption [55].

It has been observed that trust in technology plays a prominent role in several organizational strategies, such as information systems (IS) in inter-organizational relationship [14] as well as in e-commerce [85]. Employees' trust in technology depends on their expectations and the subsequent satisfaction they gain by using that technology [86]. This concept has been made clear in expectation disconfirmation theory (EDT) [17], which proposes that trust influences employees to subsequently use technology for its outcomes. This leads us to perceive that an organization must gain employees' trust in order to facilitate the adoption of any technology. Based on these discussions, the following hypothesis can be formulated:

H4a. *Employees' trust in AI technology (TAT) in an organization positively influences the AI deployment rationale of manufacturing and production firms (ARMP).*

Moreover, employees' individual learning abilities are perceived as being important to achieving success in an organization [87]. The employees need to improve their knowledge by collecting updated information regarding different technological issues [88]. This information leads to the perception that increasing employees' learning abilities could motivate them to adopt technology. With this idea, the following hypothesis is formulated:

H4b. *Individual learning ability (ILA) of the employees of an organization positively influences the AI deployment rationale of manufacturing and production firms (ARMP).*

3.2.5. AI Deployment Rationale of Manufacturing and Production Firms (ARMP)

Gao et al. [89] found that organizations can be uncertain about achieving success even after adopting technology. Kaufmann et al. [90] stated that such uncertainty occurs because the organization lacks information processing and a decision-making approach. This lacuna hampers organizations and prevents them from achieving sustainability and overall success in the context of such adoption. Researchers have argued that in order to remove this gap, organizations need to focus on procedural rationality to improve information processing and their approach towards decision-making [91]. This implies that in order for manufacturing and production firms to achieve sustainability from the perspective of deploying technology, they must pay attention to different drivers of procedural rationality, such as competitive threat [78] and firm size [92]. These ideas lead us to perceive that an AI deployment rationale which improves procedures after implementation would ensures that firms are able to enjoy sustainable growth in their manufacturing and production units. This leads to the following hypothesis:

H5. *The AI deployment rationale of manufacturing and production firms (ARMP) positively influences their AI technology sustainability (ASMP).*

3.2.6. Moderating Effects of Technology Support (TS) and Leadership Support (LS)

Many organizations encounter problems in sustaining their adoption of technology due to a lack of technical support [93]. If the technology has any issue after it is adopted, there must be a technical support team to restore the system. If this is not ensured, the organization will not derive the full potential of the adopted technology. Therefore, a proper support channel must be available to combat any untoward incident with the technology after it is installed [94]. Leadership support assists in sustaining the adopted solution [95,96] by creating a conducive atmosphere [97]. Leadership support helps to stimulate employees with innovative ideas [98,99]. The above discussions lead us to formulate the following hypotheses:

H6. *Technology support (TS) acts as a moderator between the AI deployment rationale of manufacturing and production firms (ARMP) and the AI technology sustainability of manufacturing and production firms (ASMP).*

H7. *Leadership support (LS) acts as a moderator between the AI deployment rationale of manufacturing and production firms (ARMP) and the AI technology sustainability of manufacturing and production firms (ASMP).*

From all these hypotheses, we developed a research model, which is shown in Figure 1.

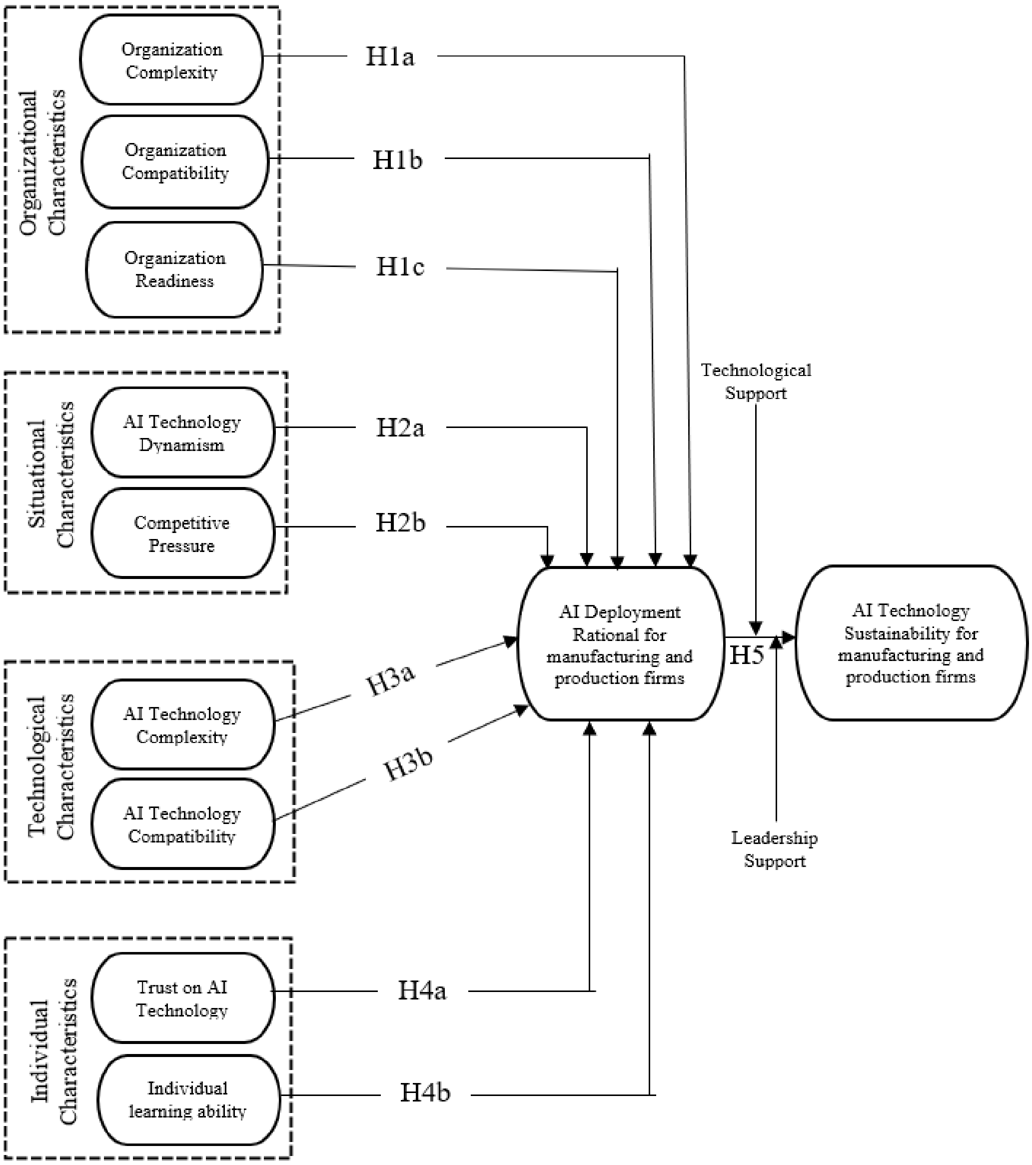

Figure 1. Proposed conceptual model.

4. Research Methodology

We tested the hypotheses for the proposed model with the help of the PLS-SEM approach. This approach is considered convenient because this study is exploratory in nature and the approach does not require any restriction in sample size [100]. For this study, we conducted a survey with 343 respondents. We used Smart PLS 2.0 M3 to analyze the data.

4.1. Research Instruments

The literature and the concepts of the constructs helped to frame the items for the questionnaire. We initially prepared 41 questions in the form of statements. To enhance the comprehensiveness and readability of the questions, a pilot test was conducted. Five experts in the adoption of Industry 4.0 technology by firms were consulted. Then, 30 employees at different levels of management from 11 manufacturing and production firms were interviewed. These employees were chosen on a random basis. Responses from the experts and the interviews helped to finalize the 41 questions with necessary corrections.

Figure 1 illustrates the four groups of organizational characteristics of the proposed conceptual model. Complexity, compatibility, and readiness are organizational specialties. Technological dynamism and competitive pressure are situational characteristics. AI-embedded technological complexity and compatibility are organizations' technological characteristics, and trust in AI technology and individual learning ability are employees' competencies. They are exogenous factors which could impact the firms to deploy AI-embedded technologies to achieve sustainability with the moderating influence of leadership and technological support.

4.2. Data Collection Mechanism

A survey was conducted with usable respondents who replied to 41 items. These were quantified by a 5-point Likert scale. To collect data, we utilized purposeful sampling to select qualified respondents. From the database of the Bombay Chamber of Commerce, 765 small, medium, and large manufacturing and production firms were randomly selected, and their top officials were contacted by telephone. Most of them were unwilling to participate in the survey; however, 219 managers agreed to cooperate with the survey. We then collected a list of 926 senior, middle, and junior managers that included their email addresses. We sent the questionnaire to the managers by email and requested that they respond within two months (April 2020 to May 2020) to those 41 questions. Within 30 days, they were reminded to respond within time. By the end of two months, 392 responses were obtained, a response rate of 42.3%. To analyze potential nonresponse bias, the method of Armstrong and Overton [101] was followed. A chi-squared test and an independent sample t-test were conducted considering the first and the last 110 respondents. No appropriate difference between these two groups was noted ($p < 0.05$). This highlights that there was no non-response bias. We found that 49 of the 392 responses were incomplete. Therefore, analysis was undertaken after quantifying 343 usable responses. The demographic statistics of 343 respondents are shown in Table 1.

Table 1. Demographic statistics (N = 343).

Particulars	Character	Number	Percentage (%)
Micro-enterprises	Employees < 250	81	23.6
Small firms	250 < Employees < 700	190	55.4
Medium firms	700 < Employees < 1200	72	21.0
	Senior Managers	103	30.0
Professional position	Middle Managers	176	51.3
	Junior Managers	64	18.7

5. Data Analysis and Results

5.1. Measurement Model and Discriminant Validity Test

The loading factor (LF) of each item was measured to identify indicator reliability. Estimations of composite reliability (CR), average variance extracted (AVE), Cronbach's alpha (α), and variance inflation factor (VIF) for each construct were measured to assess internal reliability, validity, consistency, and multicollinearity defects. The results (see Table 2) show that all the estimates are within limits.

Table 2. Measurement properties.

Construct/Items	LF	AVE	CR	α	t-Value	VIF	No. of Items
OCX		0.85	0.88	0.91		3.5	3
OCX1	0.90				21.17		
OCX2	0.95				26.12		
OCX3	0.92				31.19		
OCO		0.82	0.86	0.92		4.7	4
OCO1	0.88				21.72		
OCO2	0.84				25.05		
OCO3	0.98				23.11		
OCO4	0.91				19.98		
ORE		0.93	0.95	0.97		4.2	4
ORE1	0.88				27.12		
ORE2	0.84				31.42		
ORE3	0.91				33.62		
ORE4	0.98				34.04		
ATD		0.92	0.94	0.96		3.8	3
ATD1	0.95				21.17		
ATD2	0.90				26.07		
ATD3	0.90				29.12		
COP		0.84	0.87	0.89		4.3	4
COP1	0.93				29.11		
COP2	0.88				27.04		
COP3	0.89				32.88		
COP4	0.96				33.44		
ATCX		0.83	0.86	0,89		4.6	5
ATCX1	0.86				31.12		
ATCX2	0.84				33.44		
ATCX3	0.88				35.06		
ATCX4	0.97				37.18		
ATCX5	0.99				32.17		
AICO		0.92	0.94	0.97		3.9	3
AICO1	0.91				21.72		
AICO2	0.99				26.41		
AICO3	0.98				29.09		
TAT		0.88	0.91	0.93		4.1	4
TAT1	0.95				29.17		
TAT2	0.95				38.14		
TAT3	0.90				39.41		
TAT4	0.95				36.72		
ILA		0.93	0.95	0.98		4.7	4
ILA1	0.99				31.46		
ILA2	0.96				33.47		
ILA3	0.89				35.78		
ILA4	0.99				39.12		
ARMP		0.90	0.93	0.95		3.8	4
ARMP1	0.90				39.64		
ARMP2	0.95				32.11		
ARMP3	0.87				33.13		
ARMP4	0.89				31.72		

Table 2. *Cont.*

Construct/Items	LF	AVE	CR	α	t-Value	VIF	No. of Items
ASMP		0.82	0.86	0.89		3.6	3
ASMP1	0.97				33.34		
ASMP2	0.86				31.01		
ASMP3	0.89				36.42		

It appears that square roots of AVE of the constructs are all greater than the respective correlation coefficients, confirming discriminant validity. The result for discriminant validity is shown in Table 3.

Table 3. Discriminant validity test.

Construct	OCX	OCO	ORE	ATD	COP	ATCX	AICO	TAT	ILA	ARMP	ASMP	AVE
OCX	0.92											0.85
OCO	−0.21	0.91										0.83
ORE	0.26 **	0.19 *	0.96									0.93
ATD	0.27	0.22	0.28 ***	0.96								0.92
COP	0.29	0.24	0.26 **	0.24 **	0.92							0.84
ATCX	0.34 ***	0.29 **	0.25	0.22 **	−0.26	0.91						0.92
AICO	−0.41	0.31	0.12 *	0.23	0.27	0.28	0.96					0.92
TAT	0.46	0.33	0.17	0.26 **	−0.29	0.27 ***	0.13 *	0.94				0.88
ILA	0.37	0.37 **	0.29	−0.27	0.41 *	0.39 *	0.19 *	−0.31	0.96			0.93
ARMP	−0.23	−0.41	0.31 **	0.39	0.39	−0.31	−0.21	0.39 **	0.31	0.95		0.90
ASMP	0.19 *	0.30	−0.42	0.41 *	0.37	0.17	0.26	0.29	0.32 *	0.37 *	0.91	0.82

Note: p * < 0.05; p ** < 0.01; p *** < 0.001.

5.2. Moderator Analysis

With the help of multigroup analysis (MGA) and the bias-correlated (accelerated) procedure of bootstrapping, we conducted MGA considering 600 resamples. The results show that for the two moderators, that is, TS and LS, the p-value difference for each linkage referring to two categories of TS (High TS and Low TS) and LS (Strong LS and Weak LS) is less than 0.05, confirming that the effects of these two moderators on the linkage H5 are significant [102]. The results for the interaction effect of the moderators are shown in Table 4.

Table 4. MGA (for moderator analysis).

Path	Moderator	p-Value Difference	Remarks
(ARMP → ASMP) × TS	Technology Support	0.02	Significant
(ARMP → ASMP) × LS	Leadership Support	0.04	Significant

5.3. Hypotheses Testing

Using the PLS-SEM approach, we used the bootstrapping (bias-correlated) system to consider 6000 resamples of the 343 cases in order to test the hypotheses [103] while avoiding a parametric test [104]. It was possible to calculate the path coefficient of each linkage, including the moderators, by assessing the probability value. The R^2 values were computed as well. The entire results are shown in Table 5.

With all these results, the validated model is shown in Figure 2.

Table 5. Estimates of path coefficients, *p*-values with moderators, and R2.

Linkages	Hypotheses	R^2/Path Coefficients	*p*-Values	Remarks
Effects on ARMP		0.48		
by OCX	H1a	−0.32	* $p < 0.05$	Supported
by OCO	H1b	0.17	** $p < 0.01$	Supported
by ORE	H1c	0.44	*** $p < 0.001$	Supported
by ATD	H2a	0.37	** $p < 0.01$	Supported
by COP	H2b	0.33	** $p < 0.01$	Supported
by ATCX	H3a	−0.39	** $p < 0.01$	Supported
by AICO	H3b	0.26	* $p < 0.05$	Supported
by TAT	H4a	0.34	** $p < 0.01$	Supported
by ILA	H4b	0.49	** $p < 0.001$	Supported
Effects on ASMP		0.69		
by ARMP	H5	0.51	*** $p < 0.001$	Supported
Effects on ARMP → ASMP				
by TS	H6	0.32	* $p < 0.05$	Supported
by LS	H7	0.26	** $p < 0.01$	Supported

Note: $p < 0.05$ (*); $p < 0.01$ (**); and $p < 0.001$ (***).

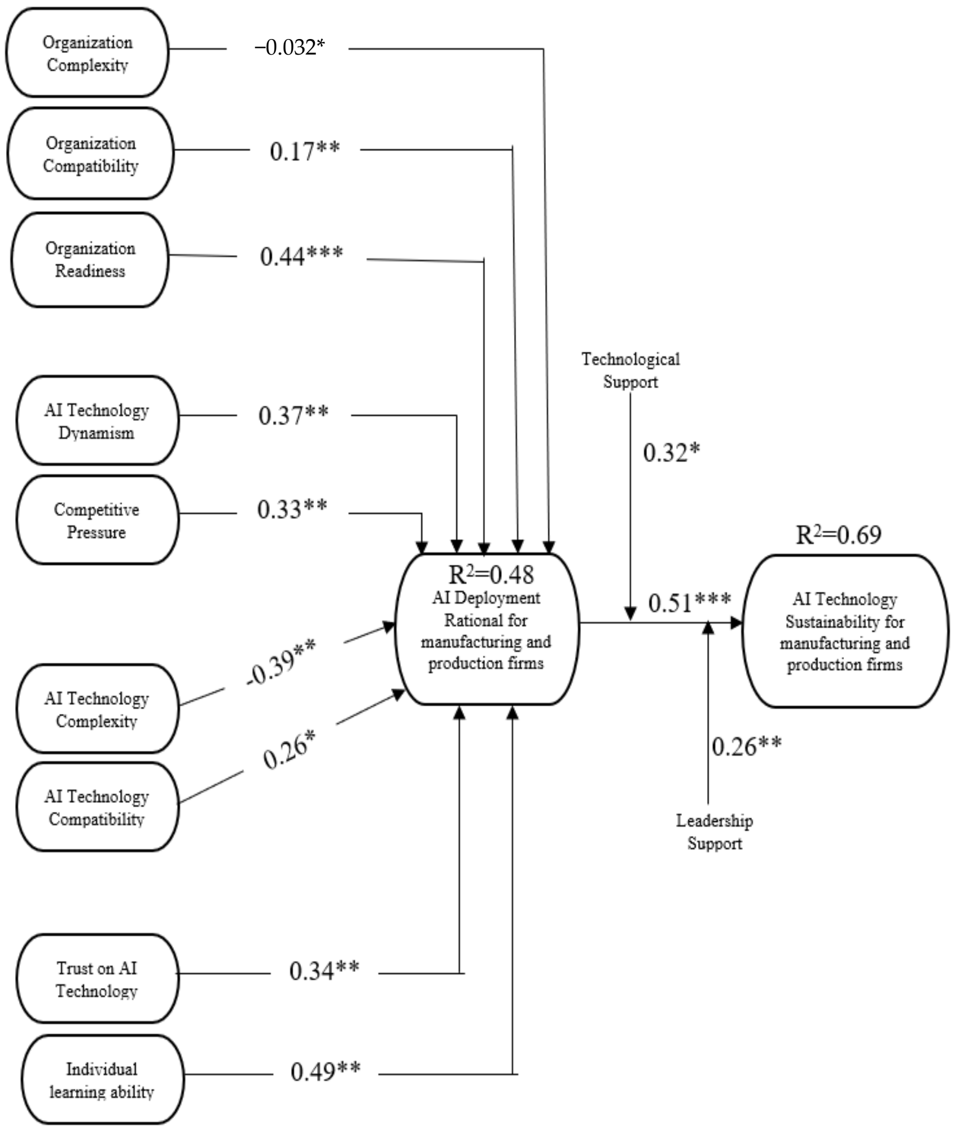

Figure 2. Validated research model. Note: $p < 0.05$ (*); $p < 0.01$ (**); and $p < 0.001$ (***).

5.4. Results

After statistical validation, the results show that all twelve hypotheses are supported, as are the two moderators, TS and LS. Hypotheses H1a and H3a are found to possess negative relationships, as the path coefficients concerned are −0.32 and −0.39. Between these two, the effect of ATCX on ARMP is greater, as the path coefficient of the linkage has greater magnitude. The remaining hypotheses have positive relationships. Our analysis revealed that among the effects of OCO, ORE, ATD, COP, AICO, TAT, and ILA on ARMP, the effect of ILA on ARMP (H4b) is the highest, as the concerned path coefficient is the largest (0.49 with significance level $p < 0.01$) in this context. The impact of ARMP on ASMP (H5) is appreciable, as the concerned path coefficient is 0.51 with significance level $p < 0.001$. The effect of the moderators TS and LS on the linkage H5 are considerable, as the path coefficients are 0.32 ($p < 0.05$) and 0.26 ($p < 0.01$), respectively.

As for the estimates of the coefficients of determinant, the nine exogenous variables (OCX, OCO, ORE, ATD, COP, ATCX, AICO, TAT, and ILA) can explain the mediating variable ARMP to the extent of 48%, whereas ARMP can interpret ASMP to the extent of 69%, which is the explanatory power of the model.

6. Discussion

Validation shows that H1a is supported. As the complexity of an organization increases, deployment of technology is negatively impacted. This supplements the findings of Parveen and Alsheibani [70], who observed that, in Malaysia, complexity impedes users from using wireless mobile devices to access the internet. H1b was supported by validation, which shows that compatibility helps in technology deployment. This idea has received support from other studies [69] that have noted that entrepreneurial competencies help to develop deployment attitude.

In addition, H3a is statistically validated. This hypothesis states that unless an organization is ready to accept an innovation, its deployment will be hampered. This idea has been supported by another study [8] that observed that organizational readiness of SMEs in Nigeria yielded better results when modern technology was adopted.

Hypothesis H2a is supported statistically as well. Technological dynamism (rapid change of technology) is a crucial factor for industrial adoption. This concept receives support from Dean and Sharfman [78], where the authors cautioned that in adoption of any new technology, the slightest mistake in realizing a dynamic environment can be disastrous. Similarly, H2b receives support from the previous study of Tabatabaei [79].

Hypothesis H3a is supported by Cagliano et al. [83], who inferred that technological complexity might disturb the relation between smart manufacturing technologies and work organizations. The authority of an organization needs to foster trust among its employees to help deploy AI in manufacturing and production firms. This is the essence of Hypothesis H4a, and conforms with expectation disconfirmation theory [17]. Hypothesis H4b receives support from a study by Simons et al. [55], who found that individual learning is necessary for organizational success. This study is able to explain how different organizational characteristics and employee competencies can help organizations to appropriately apply AI-embedded technologies under different contextual moderating factors which could eventually help them to achieve sustainability.

The effects of the moderators on linkage H5 are significant, which is supported by Cheung et al. [99], who observed that leadership support occupies a vital role in an organization's achieving success. The effects of the moderators TS and LS on H5 receive support from multigroup analysis as well. We now discuss these effects using graphs. A graphical representation of the effects of High TS and Low TS on linkage H5 are shown in the graph below (Figure 3).

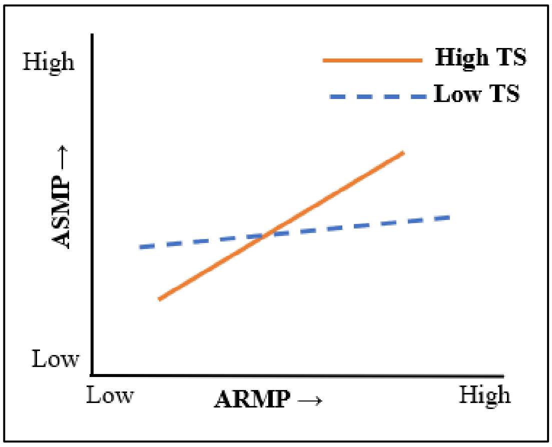

Figure 3. Effects of TS on H5.

Figure 3 shows that with an increase in ARMP, the rate of increase of ASMP is greater due to the effects of high TS as compared to the effects of low TS; the gradient of the continuous line representing high TS is more than the gradient of the dotted line that represents low TS.

A graphical representation of the effects of Strong LS and weak LS on linkage H5 are shown in Figure 4.

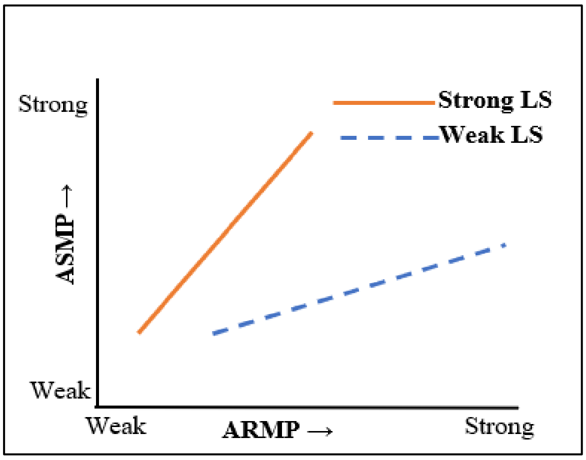

Figure 4. Effects of LS on H5.

In Figure 4, it can be seen that with increasing ARMP, the rate of increase of ASMP is less for the effects of weak LS compared to the effects of Strong LS on H5, as the gradient of the dotted line representing weak LS is less than the gradient of the continuous line that represents strong LS.

6.1. Theoretical Contributions

This study theorizes as to how the sustainability of production and manufacturing firms can be improved by the adoption of AI. The study has attracted different stakeholders to project that the rational multidisciplinary application of AI can improve the dynamic ability of a firm. These multidisciplinary applications can be used in a wide range of organizational operations. In this respect, this study provides effective inputs to the research community through our theoretical model on how other organizations can benefit by choosing other AI applications that have related multidisciplinary capabilities.

Moreover, this study has elucidated a new perspective on using AI technology by considering new determinants, such as AI technology dynamism, which helps an organization to adopt AI-embedded technology. This is claimed as a theoretical contribution of this study.

From the literature, we identified the antecedents of the rational deployment of AI in manufacturing and production firms. These antecedents have been explained using various theories. For example, the identification of organizational and AI technological compatibility are supplemented by TTF theory. Organizational and technological complexity were identified from our literature review of contingency theory.

The concepts of readiness and trust have been explained in terms of both the theory of organizational readiness and expectation disconfirmation theory. Moreover, this study has effectively introduced ideas from the literature. For example, the concept of readiness was obtained from Aboelmaged [48], Idris [8], and Alsheibani et al. [105]. The concept of complexity (organizational and technological) was obtained from Parveen and Sulaiman [70] and Veliu and Manxhari [106]. The concept of compatibility in reference to organizational and technological aspects was inherited from the study of Halabi et al. [69]. The concept of learning ability was borrowed from Simons [55], and leadership support was conceptualized from the study of Cheung et al. [99].

Precisely how this literature can help to theorize the model had not been comprehensively explained in previous studies. This could be claimed as one of the theoretical contributions of this study as well. This study effectively deals with the identification of factors that prompt adoption of AI in organizations. To do this, a standard adoption model could have been used, however, that is not the approach carried out in this paper. Several relevant and better-suited antecedents have been considered instead, resulting in a successful model. It is pertinent to mention here that Industry 4.0 has many components, including AI, Blockchain, Big Data Analytics, Cyber Physical Systems, and more [107]. In our study, the prospect of deploying AI applications and sustainability in manufacturing and production firms have been analyzed by developing a theoretical model. It is expected that our theoretical model can provide inputs for developing other models regarding the adoption of components of Industry 4.0 such as Blockchain by firms. Our theoretical model may be helpful in developing similar models of applying AI technology in other sectors, such as the service sector.

6.2. Managerial Implications

This study has provided several managerial implications as well. In keeping pace with the rapid development of intelligent manufacturing and production systems [108], organizations need to migrate the operational process from a human physical system to a cyber–physical system to ensure more automation. The management of the organization must ensure that, through automation, the organization can attain a high level of productivity and accuracy. This level should be such that it is even beyond a human's ability [109].

The managers need to be sincere to ensure that organizational characteristics, in the context of compatibility and readiness, are conducive. The manager should focus attention so that organizational contextualization is not too complex to inhibit automation. From the perspective of situational characteristics, managers need to be vigilant to keep pace with the dynamism of AI technology and need to stay aware of and assimilate the processes followed by their competitors in using AI to ensure accelerated automation.

With management support, the workforce needs proper training on AI technology so that it can address any technological complexity and the employees accept to smoothly adopt automation and apply it for smart maintenance. It is the duty of the senior management to acquaint the employees with knowledge regarding AI technology. Nevertheless, the management of the organization needs to train the employees so they are conversant about predictive intelligent maintenance in order to achieve sustainability by reducing expensive unplanned downtime.

This study highlights that technical support for AI technology plays a crucial role in sustaining continuous maintenance of the intelligent system without any unexpected interruption. In this context, management is required to focus on a supply line of labor in order to constantly maintain intelligent machines. The leadership of the organization must be vigilant to ensure that an adequate budget is allocated to training employees in more sophisticated system deployment. Thus, in brief, the management should be smart and intelligent in addressing dynamic situations.

6.3. Limitations and Directions for Further Research

Our conceptual model was validated by a survey involving only 343 respondents. This meagre representation can hardly project a generic view. Moreover, the responses were all from the employees of Indian firms, and the model was validated by analyzing those responses. In this sense, the model, cannot be construed as projecting a generalized picture. The adoption of AI in Indian organizations is in the nascent stage; hence, responses were taken from non-adopters. The model needs to be modified as and when manufacturing and production firms fully adopt AI. Further, by considering other suitable factors, the explanatory power of the model could have been improved. Future researchers may take up all these unaddressed issues to explore whether the model in this paper can be improved upon. In identifying the predictors for automation in firms, this study did not consider factors such as privacy and security concerns. Those could impact employees' level of trust. Future research could add additional factors such as these in order to improve the research model.

7. Conclusions

This study has identified the characteristics impacting the AI deployment rationale of manufacturing and production firms. The characteristics have been segmented into four categories: organizational characteristics, situational characteristics, technological characteristics, and individual-centric characteristics. On analysis, the study was able to infer that the organizational characteristic of readiness has the highest impact on AI deployment in manufacturing and production firms. This leads us to suggest that organizational top management needs to place emphasis on training employees to be compatible with all eventualities as they engage in the use of AI-related applications in their firms.

This study highlights a negative relationship that persists between organizational complexity (under the organizational characteristics category) and AI deployment, as well as between AI technology complexity (under the technological characteristics category) and AI deployment. This result provides effective inputs to firm management. They are to be vigilant so that these complexities cannot impede the process of AI deployment in their firms. For this, management needs to take the appropriate steps to mitigate these complexities.

This study found that both leadership support and technological support effectively moderate AI deployment for ensuring sustainability in firms. In this respect, the concerned management teams of such firms should see that their employees do not encounter constraints in their use of new AI-based systems. Moreover, leadership support should be offered to all levels of employees. Our theoretical model was made more robust by integrating the concept of organizational and technological compatibility and complexity issues, which have often been incompletely dealt with in earlier literature; thus, this study has opened an avenue to other researchers to explore more insights in sustainability management.

In brief, the following are the key outcomes of our research study. First, this study was able to identify different antecedents that impact AI deployment in manufacturing and production firms. Second, we were able to show the significance of technological support and leadership support in overcoming unexpected roadblocks in the use of AI for sustainability in manufacturing and production firms. Third, through our study we were able to ascertain that AI technology can support sustainable automation for manufacturing and production firms when supplemented with the support of the leadership team. Finally, our study shows that organizational readiness towards deployment of AI in manufacturing and production firms has the highest potential to impact AI deployment, whereas organizational and technological complexity both negatively impact AI deployment in manufacturing and production firms.

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