How does big data influence smart manufacturing in the presence of preventive maintenance? A multi-analytical investigation

Abstract

Purpose: Smart manufacturing (SM) capitalizes on big data analytics (BDA) advancements by enhancing current capabilities such as defect identification and enabling supporting capabilities such as preventive maintenance (PM). The previous literature lacks to investigate the comprehensive associations between SM, BDA, and PM. Therefore, this study aims to investigate the relationship among SM, BDA, and PM.

Design/methodology/approach: The present research implements a multi-analytical PLS-SEM-ANN approach to investigate the relationships among BDA, PM, and SM.

Findings: This investigation indicates that BDA is an effective digital technology that positively affects the operations of SM and PM. Furthermore, the results suggest that PM has a positive influence on SM and that it also positively mediates the relationship between BDA and SM where PM cannot be treated as an auxiliary practice, and plays an important role in SM as a primary operation. Furthermore, implementing the BDA enhances the performance of SM and PM.

Originality: The role of PM in the context of BDA and SM has been ignored in past research, and this study offers novelty by examining this relationship.

Keywords: PLS-SEM; Big data analytics; Smart manufacturing; Artificial neural network; Preventive maintenance.

Quick value overview

Interesting because: Manufacturing firms are increasingly embracing big data analytics (BDA) to improve operations. This study investigates the impact of the BDA on smart manufacturing (SM) and presents the findings in a manner that highlights how the tool influences preventive maintenance (PM). This is an area whose vigor has not been explored by the scholarly literature.

Theoretical value: The research provides valuable insights into the operation of manufacturing plants by indicating that BDA is a digital tool that has a positive impact on the operations of SM and PM. The research establishes that PM is indeed a significant operation, rather than an

auxiliary operation, for the SM. Furthermore, the research establishes that PM is indeed a mediator in the BDA and SM relationship between the two operational activities.

Practical value: The study is of significant importance to the manufacturing industry practitioners. Both the effectiveness of PM and the relevance of BDA should not, therefore, be overlooked. If they are integrated and used judiciously, better operational efficiency, and maintenance practices that will result in better performance of the manufacturing firms will accrue. This study provides valuable information and is, therefore, beneficial to the firms on how they can enhance the utilization of these two important aspects in SM.

1. Introduction

During the fourth industrial revolution (Industry 4.0), manufacturing companies utilize new digital technologies that provide the opportunity to create intelligent goods and production (Demeter et al., 2024). Along this line, smart manufacturing (SM) builds the essential part of Industry 4.0 (Arcidiacono and Schupp, 2024), which has a broader scenario to be applied (Vance et al., 2023). SM is a data-driven ecosystem that promotes the flow and sharing of real-time information via ubiquitous networks to form industrial intelligence for all entities involved in production (O'Donovan et al., 2015a). SM goes beyond the digital transformation itself and carries digital technologies such as Internet of Things (IoT), Big Data analytics (BDA), Virtual Reality (VR) and Augmented reality (AR) (Krishnan, 2024). The complete manufacturing efficiency gained through these integrated systems entails real-time information exchange, visualization of the results of operations, and interconnection of machinery with other devices (Krishnan, 2024). It also enables the automation of operations, preventive maintenance (PM), and utilization optimization; moreover, it contributes to data-driven decision-making (Kusiak, 2019). This way, manufacturers who embraced digitalization were able to manage recent uncertainties substantially better than those who had not (Dutta et al., 2022).

Additionally, it is widely documented in the research on information systems that contextual variables play an important role in building BDA competence. Concerning BDA in SM, among the potential future trends in improving sustainability in a manufacturing firm and adding new value is the use of BDA across the whole manufacturing lifespan (Opresnik and Taisch, 2015). BDA can provide cost-effective storage and processing of all important supply chain information including where supplies originate, how much inventory exists at any time as well as product sales patterns (Krishnan, 2024). The results of this data allow unprecedented supply chain visibility, connectivity, and traceability to build capabilities that will design cheaper

management practices at scale. Increased transparency adds a lot of value to the supply chain operation in several other dimensions, such as optimal planning, managing transportation more effectively, and maintaining portfolio management (Oluyisola et al., 2020). For instance, Liu et al. (2019) have identified an optimal routing model for laundry sorting from different supply sources using dynamic route planning by integrating traffic big data inputs.

BDA attempts to quickly reach proper judgments in a digital organization so that the system can react to changes and uncertainty. In addition to this, Wan et al. (2017) highlighted the role of equipment maintenance in SM and asserted the importance of preventive maintenance (PM) in SM to find the problems earlier. Data collection and BDA have made active PM for SM possible (Wan et al., 2017). With BDA, manufacturers can monitor their production streams in real time and detect bottlenecks helping with identifying areas of inefficiency that need fixing[1]. For example, they can follow the performance of equipment and identify issues before they happen using data from sensors attached to machinery. This can alert to PM causing the assembly line never to come out without issue[1]. Furthermore, this continuous and instantly available data leads to improved productivity by enabling more precise as well as predictive maintenance of production systems and processes (Feng et al. 2017).

The earlier research reveals an important void in the scholarly work covering BDA influencing SM (Ren et al., 2019). Although each of these domains has been extensively studied individually, the integration of BDA with SM practices continues to be under-researched. This gap is especially important in the framework of Industry 4.0, which has changed how manufacturing firms used to be done because digital technologies are evolving quickly (Arcidiacono and Schupp, 2024). Also, empirical studies specifically exploring the interaction and mutual reinforcement between these two domains are surprisingly absent. In addition, previous research has identified the influence of contextual variables on BDA competence. However, there is a lack of evidence regarding the precise interactions between these contextual variables (BDA and SM), which hinders our comprehension of the real-world consequences for manufacturing companies. Furthermore, the increasing complexity of industrial practices makes BDA more complicated as it includes challenges such as data collection, process monitoring, and anomaly detection (Windmann et al., 2015). As a result, the demand trends are changing faster than ever, and so is the data volume. This evidence shows that there is a gap in frameworks that successfully move cutting-edge technologies from

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[1] https://metrology.news/growing-role-of-big-data-usage-in-smart-manufacturing/ (Accessed on 24th October 2024).

ideas to operational realities that are productive, and sustainable. An important window of opportunity for additional research exists because of the haziness around the incorporation of cutting-edge technology into SM systems, such as BDA and PM. Therefore, with this research gap, we have formulated the following research question which is unanswered in the previous literature:

RQ: How do the associations of BDA and PM in SM systems affect manufacturing performance, sustainability, and resiliency?

Hence, to address the above research question, within the context of Industry 4.0 settings — where BDA and PM are important components determining optimization in SM systems, this study explores the under-investigated BDA, PM, and SM associations from a task-technology-fit (TTF) theory point-of-view. TTF is described as "the degree to which a technology assists an individual in performing his or her portfolio of tasks" (Goodhue and Thompson, 1995). The TTF theory is founded on the notion that technology will improve performance if there is a fit between the task's requirements and the technology's capabilities, which forms the basis of users' reactions and adoption of new technology (Cagliano et al., 2019). Grounded in TTF theory, the purpose of this study is to investigate how BDA, PM, and SM interact. The examination of prior research is followed by the formulation of the conceptual model and the study's hypotheses in the subsequent sections. The analysis of the data and the results are then reported. The results and an assessment of the management and practical significance of the findings are covered in this work's concluding sections.

2. Literature review, hypothesis proposition, and conceptual model development

2.1 Task Technology Fit (TTF) Theory

TTF is defined as "the matching of the capabilities of the technology to the demands of the task" (Dishaw and Strong, 1999). The TTF focuses on the task requirements and technological capabilities used to complete it, as well as on the individual characteristics of an employee who does the work (Goodhue et al., 2000). This theory explains how and to what extent technology assists an individual with performing a task. The concept also explains the functioning of humans, tasks, and technology in the process of performing (Goodhue et al., 2000). The concept of information technology appropriateness is wide and stable one to understand the components of organizational technology fit which are keys for determining success within

organizations (Khazanchi, 2005). TTF model model views information system value creation as a function of the support they provide for various activities, and users' evaluations of these systems are thus indicators of such values (Goodhue 1998).

The core element of TTF is the notion that to increase a person's adoption of technology, there must be a suitable arrangement between an information system's capabilities and job descriptions (Hidayat et al., 2021). Existing research has used the TTF theory to demonstrate intriguing connections between users' perceptions of the TTF and users' responses to the technology. Lin and Huang (2008) identified the critical variables influencing the use of knowledge management systems using the TTF hypothesis. According to the research of Lin and Huang (2008), perceived task-technology fit is significantly and favorably connected with knowledge management system self-efficacy. Therefore, using the task-technology fit hypothesis, they discovered that since the capabilities of MTS technology match usage requirements, customers may utilize their mobile devices to buy tourism-related goods. Rodger and George (2010) showed that end-user perceptions can be assessed and that a conceptual evaluation of the system can be adequately documented using the TTF model and a smart data strategy called the "Voice Activated Medical Tracking Application (VAMTA)". Cagliano et al. (2019) used TTF theory to present data on the effects of SM on job structure at the macro and micro levels.

2.2. BDA and SM

BDA plays an important role in the successful adoption and implementation of SM by analyzing multiple machine parameters in real time (Bag et al., 2021). Furthermore, BDA enables the detection of potential out-of-control situations before any non-conforming part is produced, thereby reducing the generation of scrap in SM (Calis Duman and Akdemir, 2021). BDA enables the efficient storage and management of critical supply chain information e.g. inventory levels, demand patterns, and supplier sources, which allows the usage of cost-effective management practices as data will add visibility, connectivity, and traceability across the supply chain (Krishnan, 2024). In addition, the usage of BDA in SM can help in vendor collaboration, and better procurement processes aid transport with lower transit time and reduced cost while helping optimization of planning (Oluyisola et al., 2020). BDA may also benefit SM by generating knowledge, optimizing KPIs, forecasting, and providing feedback on the design of products and processes (Nagorny et al., 2017). Ren et al. (2019) reported that the BDA is considered to be one of the most vital technologies among a wide range of essential

SM technologies because of its capacity to focus on large, varied datasets to uncover hidden information and patterns as well as other beneficial data. Although the previous research indicates the positive impact of BDA on SM. Still, the prior studies failed to investigate the relationship empirically. Therefore, this research contributes in this direction and offers novelty by investigating the relationship empirically, leading to the proposition of the following hypothesis:

H1: BDA has a positive influence on SM.

2.3. BDA and PM

Preventive maintenance "seeks to prevent equipment failures by using a predetermined schedule of planned maintenance actions based on time passed or meter triggers" (Su and Huang, 2018). Maktoubian and Ansari (2019) researched the problem of sustaining medical devices and revealed that BDA, self-integrity monitoring, and PM could be the best strategies for predicting equipment failure early on before it negatively affects the delivery of any healthcare services. With big data, PM can optimize maintenance planning while minimizing consequential costs associated with faulty equipment (Munirathinam and Ramadoss, 2014). Concerning the development of smart factories and digital production, Wan et al. (2017) focused on active preventive maintenance using industrial big data. By combining Hadoop with Storm, a rather all-encompassing maintenance solution is proposed that takes into account both offline and online conditions. Mahmood and Munir (2020) used the IoT and big data to construct a predictive and preventive maintenance framework for the telecom business. It was found that this framework was supportive of PM in the telecom sector. Similarly, Tao et al. (2018) emphasized the effective application of BDA to support SM and PM. For instance, by creating prediction models, an examination of previous data can be utilized to predict the incidence of faults (Kusiak and Verma, 2012). In contrast to the studies mentioned above, this study extends the application of BDA-enabled preventive maintenance to the broader context of SM. While previous research has focused on early fault detection and operational efficiency, this study focuses on optimizing industrial equipment performance and increasing productivity across manufacturing processes. The transition from healthcare and telecom to industrial settings highlights BDA's versatility and potential to drive sustainability and efficiency across diverse sectors. Therefore, the following hypothesis is proposed:

H2: BDA has a positive influence on PM.

2.4. PM and SM

In SM, ensuring continuous production requires equipment maintenance, which can have an impact on both production efficiency and equipment deployment (Wan et al., 2017). Given the close relationship between the goals of PM and SM, this topic is relevant. PM is an essential tool for SM. Given the potential for large cost savings, it is crucial to create SM policies and systems by integrating manufacturing elements, especially those that decrease losses, process upset, and downtime, such as PM programs (Lao et al., 2014). Chien and Chen (2020) established a data-driven framework for strategic maintenance in SM and provided an approach for the early detection of faulty equipment, increasing the maintenance cycle and reducing costs. Their study was focused on the healthcare sector to propose a framework for health monitoring and maintenance for SM and they found the practical implication of the proposed approach in early recognition of faulty tool status. Our study also follows this approach in the manufacturing sector to identify the early defects and prolong cycles to enhance productivity. Chen et al. (2020) presented an equipment electrocardiogram system oriented on fine-grained data collected throughout the manufacturing equipment's operational length to reveal the equipment's performance decline in SM. Their study revealed that this mechanism would improve the efficiency of production lines. Wan et al. (2017) suggested for an active PM in SM a manufacturing big data solution by providing a system architecture that is used for active PM. Lao et al. (2014) also proposed a predictive control model that effectively integrates scheduled PM in SM to increase dynamic economic performance. Likewise, O'Donovan et al. (2015a) asserted that the propensity for maximizing machine uptime and availability, which are policies that adopt a preventive and predictive approach to maintenance, are suitable for SM. Moreover, some studies have validated the mediating role of PM (Ahmad et al., 2019). In contrast to the above studies, this study focuses on the requirements of the current manufacturing setup in the context of providing solutions through BDA and PM in the smart manufacturing sector. Moreover, providing evidence for the mediating role of PM in improving SM through the application of BDA. Therefore, the following hypotheses are formulated:

H3: PM has a positive influence on SM.

H4: PM positively mediates the relationship between BDA and SM.

As per the discussion above and the hypotheses, a conceptual model has been developed, as shown in Figure 1.
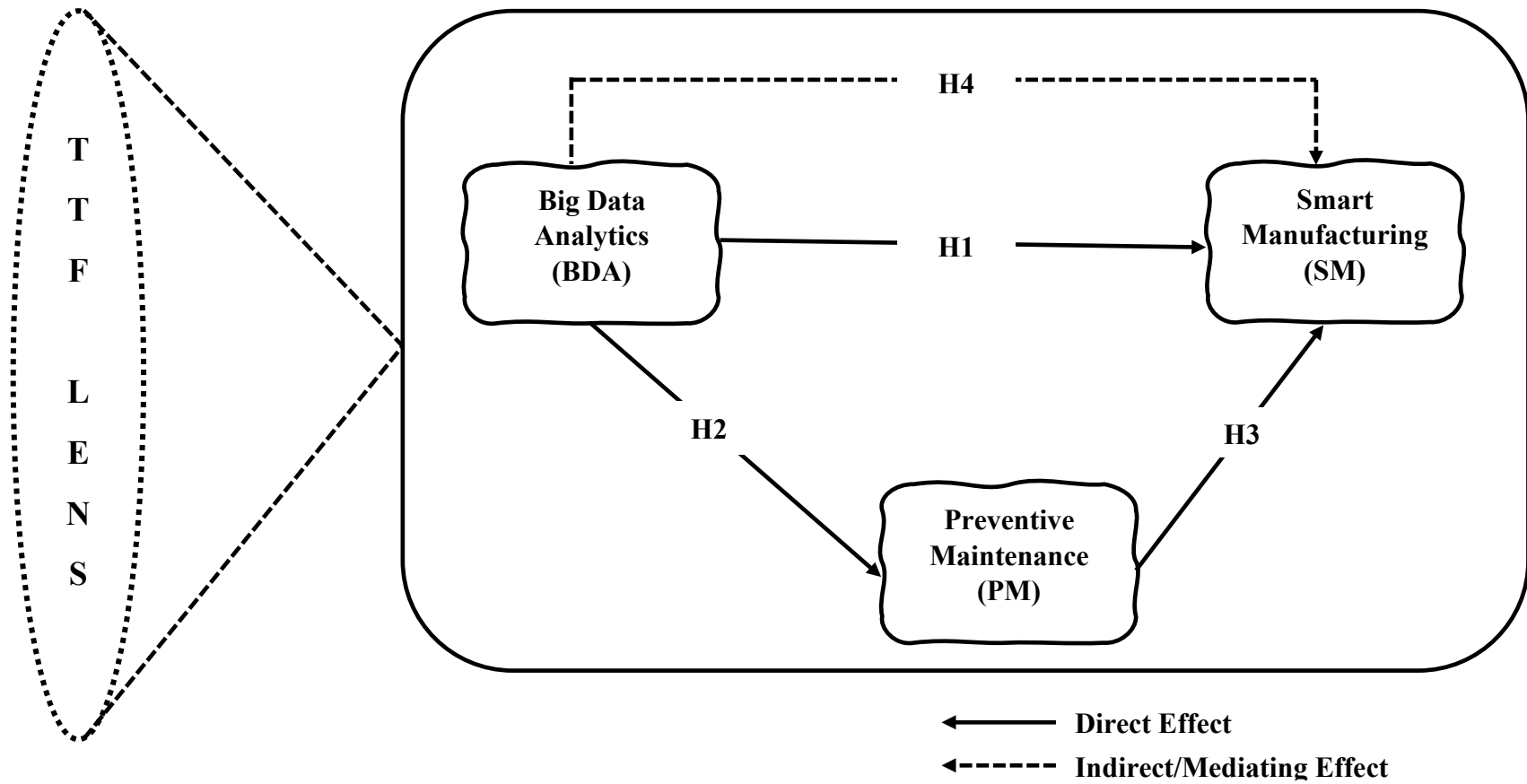
Figure 1: Conceptual model

3. Method

3.1. Collecting the data and sampling

We selected the organization listed in the "Centre for Monitoring Indian Economy (CMIE)" Pvt. Ltd. directory through process IQ software. We circulated the questionnaire and received a total of 287 responses. However, after removing invalid responses and discarding incomplete data, the analysis was conducted using only 276 of the questionnaires that were considered legitimate. This equates to a response rate of 39.83%. The survey questionnaire was also reviewed for content and face validity with 15 industry professionals in BDA and maintenance management before the data were distributed. In response to the comments and suggestions provided, the questionnaire was updated to include some changes, such as eliminating jargon and trendy remarks. We subsequently tested the questionnaire through its paces by pilot-testing it on a representative sample of 25 participants. The construct reliability and validity were tested to determine whether the items represented the constructs. After completing the questionnaire, each responder discussed his or her thoughts on the survey with the authors and noted any ambiguities that may have been present. The final draft of the questionnaire was crafted after additional changes and adjustments were made. Finally, the questionnaire was distributed to Indian manufacturing firms. Furthermore, this sample size is larger than the bare minimum recommended by the 50-fold rule for analyzing artificial neural networks, which specifies that the sample size must be at least 50 times the size of the parameter that may be adjusted in the network (Alwosheel et al., 2018). Since the neural network has only three parameters, the smallest sample size is 150. Thus, 276 participants provided an adequate sample size for ANN evaluation.

3.2. Measures

The items for measurement were modified somewhat in terms of their language to make them more appropriate for the setting of the research, which was based on previously existing scales that had been constructed (see Appendix 1). We utilized 5-point Likert scales since they are too lengthy and might confuse the respondents. This approach allowed us to reduce the respondents' annoyance and increase the number of people who responded to the survey (Pai and Huang, 2011). The details of the respondents are given in Table 1.

Table 1: Respondents' summary

	Attributes	Numbers	Percent
Age (years)	25 to 30	32	11.6
	31 to 45	153	55.4
	46 and above	91	33
Association with the organization (in years)	1 to 2	21	7.6
	3 to 10	137	49.6
	Above 10	118	42.8
Employee designation	Engineer, Management trainee, Executives Assistant Manager, etc.	146	52.9
	The shop floor manager, Total Productive Maintenance (TPM) experts, Data analytics, etc.	77	27.9
	General Manager, Vice President, Director, etc.	53	19.2
Firm type (product wise)	Industrial machinery	97	35.1
	Agricultural products	36	13
	Process control equipment	49	17.7
	Medical equipment	31	11.2
	Alloy & stainless steel	63	23

4. Analysis and findings

4.1. Common method bias (CMB)

To begin addressing the issue of nonresponse bias, we first evaluated the characteristics of the individuals who participated in the survey. This approach allowed us to validate the representativeness of the sample parts drawn from a diverse range of sample units, such as the types of companies. The data derived from surveys reveal the potential for CMB because findings may emerge from a wide variety of causes, one of which is the implicit social desirability associated with responding to questions in a certain manner (Chatterjee et al., 2022). It has an impact on the indicators that are used to demonstrate a specific degree of variance (Podsakoff et al., 2003). The survey's pretest questions were reorganized, and their wording was modified to make them more comprehensible to the respondents. In addition, throughout the survey phase, the potential respondents were assured that their identity, as well as the confidentiality of their responses, would be rigorously maintained. These procedures were followed to eliminate or at least reduce the possibility of bias in the results. Nonetheless, a statistical study was carried out to determine the extent of CMB. The single-factor test developed by Harman was carried out (Hossain et al., 2020). The first component was shown to have a value of 44.91%, which is lower than the maximum suggested threshold value of 50% (Podsakoff et al., 2003).

4.2. Statistical analysis

PLS-SEM was used to predict a multilevel and reflective construct. This was done to circumvent the constraints that covariance-based structural equation modeling (CB-SEM) has in empirical research of this kind (Akter et al., 2017). The use of PLS-SEM is effective at preventing favorably biased model fit indices for large, sophisticated models as a consequence of the model's lax modeling assumptions (Akter et al., 2017). Moreover, we used PLS-SEM because it is descriptive and predicts the most important outcome variables while requiring smaller sample sizes, i.e., $n = 276$ in our instance, for complicated associations (Henseler et al., 2014).

Along with PLS-SEM, the research supplements the analysis by using Artificial Neural Network (ANN) to enhance the depth and robustness of the analysis. There are several advantages of supplementing ANN with PLS-SEM, such as improving the quality of the PLS-SEM results. ANN can be used to impute the missing data in the dataset, as to obtain reliable results, proper handling of missing data is very crucial. ANNs can capture complicated, non-linear interactions between variables that PLS-SEM may struggle to accurately predict. This can be especially useful when the relationships aren't perfectly linear. ANN can capture linear and nonlinear correlations between variables, yielding more accurate findings. This feature influences each variable in the model, overcoming the limitations of multiple regression, SEM, and logistic analysis (Albahri et al., 2022). SEM and ANN studies were coupled to overcome the limitations of SEM in capturing linear, testing hypothesis, and nonlinear interactions among components (Raut et al., 2018). ANN shows higher accuracy and can potentially provide better predictive accuracy than PLS-SEM. In addition, when the dataset is large and complex, then ANN provides better precision than PLS-SEM. Which can further help in improving the predictive validity. Alnoor et al. (2022) in their book chapter "Artificial Neural Networks and Structural Equation Modeling" mentioned that various statistical techniques have arisen to augment the SEM approach by capturing nonlinear and non-compensated relationships between variables. The Artificial Neural Network (ANN) technique is essential for confirming SEM results and understanding nonlinear interactions between components (Alnoor et al., 2022).

4.2.1. Measurement model assessment

Since we employed a reflective model, we adhered to the four phases suggested by the relevant research (Hair et al., 2019). The scores of the most important reliability measures are shown in

Table 2. First, we determined the reliability of the items by calculating their respective loadings and then comparing those values. Loadings larger than 0.708 are the suggested cut-off, which indicates that the construct explains at least 50% of the variation in the item and, as a result, assures the reliability of the item. The cut-off value is determined by the correlation between the indicator and the construct (Hair et al., 2019). In this respect, all loadings surpassed the cut-off value (Table 2). Composite reliability (CR) and rho_A were used to measure internal reliability. In Table 2, all of the rho_A, Cronbach's alpha (CA), and CR scores for the first-order constructs were greater than the threshold of 0.70 (Hair et al., 2019), which demonstrates that there is a high degree of internal reliability. This indicated that the measurement model constructs had a satisfactory level of convergent validity (CV). CV was shown for each of the constructs when the "average variance extracted" (AVE) was erect to be at or above the suggested threshold value of 0.50 (Hair et al., 2019).

Table 2: Measures of reliability and validity

Construct	Item code	Loadings	CA	(rho_A)	CR	(AVE)
			$SRMR = 0.046$			
	BDA 1	0.878	**0.917**	**0.918**	**0.938**	**0.751**
Big Data Analytics (BDA)	BDA 2	0.846				
	BDA 3	0.881				
	BDA 4	0.857				
	BDA 5	0.869				
Preventive Maintenance (PM)	PM 1	0.880	**0.904**	**0.907**	**0.933**	**0.777**
	PM 2	0.866				
	PM 3	0.880	$R^2 = 0.206$		$Q^2 = 0.197$	
	PM 4	0.899				
Smart Manufacturing (SM)	SM 1	0.794	**0.890**	**0.891**	**0.919**	**0.694**
	SM 2	0.832				
	SM 3	0.839				
	SM 4	0.845	$R^2 = 0.356$		$Q^2 = 0.291$	
	SM 5	0.853				
	Heterotrait-monotrait ratio (HTMT)					
PM → BDA	0.496					
SM → BDA	0.608					
SM → PM	0.503					

Finally, we checked that each concept was distinguishable from the rest of the models by measuring their discriminant validity, as shown in Table 2. Since the Fornell–Larcker criteria have been subjected to some critiques (Queiroz et al., 2022), an examination of discriminant

validity based on heterotrait–monotrait (HTMT) was carried out. The HTMT provides a summary of the average correlation that exists between items that measure the same construct and the average correlation that exists between all items that measure that construct (Henseler et al., 2015). The threshold for HTMT is set at levels lower than 0.85. In this respect, all of the values given in Table 2 are in agreement with scholarly suggestions (Henseler et al., 2015), confirming that the constructs are separate from one another.

4.2.2 Structural Model Assessment

By examining the model results, one may determine whether the structural model can predict several anticipated constructs. The inquiry used a method called nonparametric bootstrapping using 5000 subsets of samples to assess the accuracy of the estimate. A standardized root mean square (SRMR) score, which must be smaller than 0.08 to indicate that a model is suitable for its purpose, was used in the validation process (Cho et al., 2020) for a sample size greater than 100 (276). The SRMR score for the present research is 0.046 (see Table 2), which indicates the good fitness of the model. Stone-Geisser's Q^2 test allowed us to evaluate the predictive significance of our model (Mitrega et al., 2017). This test is computed through blindfolding, which involves a predetermined number of resamples. It is necessary to prove the predictive capability of the model with values higher than zero (Hair et al., 2019). The Q^2 values for the present study (see Table 2) are 0.197 and 0.291, which surpassed the threshold value and indicate the significant predictive capability of the model (Hair et al., 2017). The R^2 value is also presented in Table 2 to indicate the robustness of the model. The threshold R^2 value for a good model is 0.1 (Hair et al., 2016). In addition, the f^2 effect size was computed for each independent variable to evaluate the importance of the independent factors in predicting the dependent variable. These impacts are considered small to medium in size according to the criteria of Hair et al. (2017). To demonstrate the statistical significance of the pathways and the validity of the hypothesis, the values of the various standard coefficients, such as β, must be more than zero, and the *p-value* should be lower than 0.05. All of the assumptions presented in this research were confirmed to be correct by the findings shown in Table 3.

Table 3: Hypothesis testing

Path	β	*T*-Statistics	*p* Value	Hypotheses	Result
Direct effect					
BDA→SM	0.551	9.198	0.000	H1	Accepted
BDA→PM	0.453	7.452	0.000	H2	Accepted
PM→SM	0.257	4.261	0.000	H3	Accepted
Indirect or mediating effect					

BDA→PM→SM	0.117	3.309	0.001	H4	Accepted

A "bias-corrected and accelerated (BCa)" bootstrap approach with 5000 subsamples was used to assess the assumptions included within the structural model. The outcomes from Table 3 suggest that all the hypotheses (H1-H4) are supported by the present study.

4.2.3 Artificial neural network analysis

Considering that PLS-SEM is limited in its ability to detect linear and compensatory effects (Lim et al. 2021), this research adopts artificial neural network (ANN) analysis to supplement PLS-SEM analysis, as ANNs can acquire nonlinear associations in this research and hence are beneficial for decision-making (Wan et al., 2021). The BDA and the PM each had their own separate ANN models. The root mean squared error (RMSE) is calculated for each of the 10 neural networks to evaluate how well models 1 and 2 predict future outcomes (Wang et al., 2022). The next step that we performed, which was analogous to what Liébana-Cabanillas et al. (2017) performed, was to use the relevant features that the PLS-SEM path analysis revealed as the feed neurons for the ANN models. A nonnormal data dispersion and the presence of nonlinear correlations between the independent variables and the dependent variables are two of the grounds for using the ANN. The presence of nonlinear interactions between the independent and dependent variables, as well as the fact that the data dispersion is not normally distributed, are two of the main arguments in favor of using ANNs (Leong et al., 2020). According to Taneja and Arora (2019), the "feed-forward-backward-propagation" (FFBP) technique may be used to train the system to predict the study's outcomes by feeding in data in one path and sending the estimated errors in the other. The input and hidden layers were constructed using multilayer perceptrons with sigmoid activation parameters (Sharma and Sharma, 2019). We used 90% of the samples during training and 10% during testing, as suggested by Leong et al. (2018). The prediction efficacy of both ANN models is compared in Table 4. All the ANN models demonstrate a good level of prediction accuracy with the given RMSE values (Lee et al., 2020).

Table 4: RMSE scores for the BDA and PM

	Model 1 Inputs: BDA & PM Output: SM				Model 2 Input: BDA Output: PM			
	Trained sample		Tested sample		Trained sample		Tested sample	
ANN	RMSE	Percentage	RMSE	Percentage	RMSE	Percentage	RMSE	Percentage

1	0.858	89.1	0.840	10.9	1.056	90.2	0.875	9.8
2	0.890	91.3	0.763	8.7	1.054	87.3	0.873	12.7
3	0.891	90.6	0.722	9.4	1.052	89.5	1.049	10.5
4	0.893	88.8	0.874	11.2	1.060	85.5	1.045	14.5
5	0.855	87.3	0.586	12.7	1.052	91.3	0.833	8.7
6	0.927	89.5	0.562	10.5	1.036	88.4	0.942	11.6
7	0.873	88	0.878	12	1.039	88	1.080	12
8	0.916	90.9	0.762	9.1	1.049	92.8	1.377	7.2
9	0.930	89.9	0.861	10.1	1.094	87.7	0.912	12.3
10	0.871	90.2	0.643	9.8	1.043	88.8	1.068	11.2

The independent variables are also ranked in terms of their normalized relative relevance to the dependent variables in Table 5 (Lim et al., 2021). In ANN Model 1, the BDA is the best driver of SM (with a 100% normalized relative value), while the PM is the second-best driver of SM (with a 54.12% normalized relative value). Despite ANN Model 2 consisting of a single neuron, the sensitivity analysis revealed a normalized significance of 100%. The PLS-SEM and ANN results were assessed using the patch coefficient and the normalized relative significance (Ng et al., 2022). As shown in Table 6, the findings for ANN models 1 and 2 are consistent.

Table 5: Sensitivity analysis

	Model 1 Output: SM		Model 2 Output: PM
ANN	**BDA**	**PM**	**BDA**
1	0.688	0.312	1.000
2	0.724	0.276	1.000
3	0.665	0.335	1.000
4	0.568	0.432	1.000
5	0.731	0.269	1.000
6	0.705	0.295	1.000
7	0.662	0.338	1.000
8	0.505	0.495	1.000
9	0.660	0.34	1.000
10	0.658	0.342	1.000
Average relative importance	**0.656**	**0.343**	**1.000**
Normalized relative importance (%)	**100**	**54.12**	**100**

Table 6: PLS-SEM and ANN comparative analysis

PLS-Path	T Statistics	ANN results: Normalised	PLS-SEM-based ranking of	ANN-based ranking of	Concluding remark

		relative importance (%)	independent variables	independent variables	
Model 1: SM as an output					
BDA→SM	9.198	100	1	1	Consistent
PM→SM	7.452	54.12	2	2	Consistent
Model 2: PM as an output					
BDA→PM	4.261	100	1	1	Consistent

5. Discussion and implications

The research aims to investigate the impact of BDA on SM and PM, and PM on SM, and overall improvements in task performance; thus, using TTF theory to bring clarity into these interactions. The TTF theory also suggests that the benefits of technology are optimized when there is a synergistic alignment between technological characteristics/capabilities and specific applied tasks. This is where BDA helps SM and PM to a great extent because of its fit with data-centric modern manufacturing processes. The findings of the research indicate that BDA is a strong predictor of SM and PM. This conclusion lends credence to the previous research on the possible advantages of BDA for SM (H1) (Krishnan, 2024; Bag et al., 2021; Majeed et al., 2021; He and Wang, 2018) and PM (H2) (Wan et al., 2017; Crespo Márquez et al., 2020). Furthermore, the results also suggest that the implementation of PM helps in the adoption of SM (H3). These findings could be associated with the findings of Koon (2021) and O'Donovan et al. (2015a).

In reality, manufacturing operations evolve continuously over time, and they are subject to a wide variety of unpredictable disruptions, including those linked to resources and personnel (Ouelhadj and Petrovic, 2009). The scheduling system should be able to detect disruptions and adjust accordingly. Static and dynamic scheduling are the two most commonly used methods. However, these methods have limitations and cannot address unexpected situations. Production scheduling is currently available for making use of emerging technologies such as big data in the SM era (Al-Gumaei et al., 2018). For the system to adapt to the dynamic nature of the manufacturing sector, it is essential to integrate big data-oriented optimization into the scheduling process. SM uses BDA to enhance current analytical capabilities and develop new capabilities, such as predictive analytics, in tandem with a manufacturing trend toward increased data "volume, velocity, and variety" (Moyne et al., 2016). In addition, BDA in the SM makes it possible for machines or equipment to adapt their behavior following various circumstances and needs by drawing on their previous observations and their learning capacity (Zhong et al., 2017).

More concretely, Sim (2019) demonstrates this convergence by implementing a Smart Equipment Engineering System (SEES), which aligns failure reasons to machinery while the equipment is running and restores real-time stability state besides it reduces downtime following predictive monitoring with machine observable states as early planning in place of dealing a time when will preventively fail. In a capital-intensive operation, such as manufacturing where machinery costs account for a substantial proportion of total production expenses (Toth and Mokuya 2002) taking this approach to maximize usage time is important. Other manufacturing areas have had positive experiences such as production, distribution and maintenance, diagnostics, and energy management (O'Donovan et al., 2015b); illustrating the wide array of uses for BDA in SM. The PM role becomes even more essential in SM as it maximizes the equipment utilization rate, thus since total ownership cost can tend to be ~ 60–75% of an asset lifecycle expense (Dhillon, 2006). Equipment utilization and efficiency affecting supply chains: A demand-driven, customer-centric supply chain, which is an SM characteristic (O'Donovan et al., 2015a) relies heavily on equipment uptime. Effective SM requires critical uptime and availability, which is the promise of BDA — providing real-time data-driven insights that allow for smarter timing in maintenance events as well as predicting incoming equipment failures.

In addition, the eco-friendly orientation of SM with focused PM driven by BDA reduces energy consumption and ensures equipment utilization efficiency. SM initiatives, by identifying and correcting inefficiencies, accomplish more with less energy output thus also having lower environmental impact (O'Donovan et al., 2015a). Routine maintenance not only sustains energy efficiency but also ensures maximum performance and a machine operating at its full capacity adds direct value to higher productivity. PM practices performed with BDA result in more reliable equipment and reduced failure rates which further comes to produce lower operational costs as well as longer asset life (O'Donovan et al., 2015a). As a result, the U.S. Department of Energy reports that PM can prevent up to an 18% reduction in energy use (Koon, 2021), further emphasizing how important a part PM plays in cost and energy savings. In this way, the discussion indicates how the interaction between BDA, PM, and SM can be seen in the industry settings, and offers the possible reason for accepting all the hypotheses.

5.1 Theoretical implications

The usefulness of the TTF has been questioned because of its lack of theoretical underpinning, as indicated previously. This paper contributes to the advancement of TTF theory. According

to the research findings, BDA may increase the "volume, velocity, and variety" of data, which in turn leads to an increased rate of SM acceptance and implementation (Moyne et al., 2016). The incorporation of BDA, which is characterized by the use of analyzing real-time data, necessarily provides a means of gauging the efficacy of BDA as a technology in an SM system (Krishnan, 2024). This is accomplished by evaluating the connection between the technology and the tasks (improving the performance of the SM system) that the technology intends to endorse. In addition, BDA technology helps enhance the performance of PMs by providing real-time machine monitoring and preventing machine failure by precisely analyzing real-time data (Crespo Márquez et al., 2020). This helps keep the machines running smoothly. This work contributes to the growing body of research on the use of BDA and its implications for SM and PM. While the use of BDA in different industries has been extensively studied, specific applications in SM are still relatively unexplored. Current studies frequently focus on broad overviews of BDA or specific areas like finance or healthcare but may not go extensively into the manufacturing sector.

This study conducts a specialized analysis of how BDA can be specifically implemented in the SM context, providing industry-specific insights. This adds to the current literature by broadening its scope to address industry-specific difficulties and opportunities in SM. In addition, the PM concentration has been observed to be an important indicator of SM facilitation. PM is also an effective method for increasing machine life, decreasing energy consumption, and enhancing SM adoption and practice. In this regard, this study advances the theoretical knowledge of PM by demonstrating how BDA, when combined with smart manufacturing systems, provides more accurate, real-time, and proactive maintenance procedures. This goes beyond traditional approaches and presents a data-driven paradigm for PM, bridging a significant gap in the literature where the role of BDA in PM is currently unclear. The present research can help organizations comprehend the influence of BDA and PM in SM adoption and proceed toward the effective execution of the strategy. Nevertheless, the importance of sustainability in manufacturing is growing, and the precise role of BDA in achieving sustainable manufacturing outcomes (such as energy efficiency and waste reduction) remains unexplored. This study closes the gap by investigating how BDA in smart manufacturing contributes to sustainability goals. It broadens the theoretical discourse by demonstrating that the integration of BDA not only improves operational efficiency but also increases sustainability, which aligns with growing concerns about eco-efficiency in manufacturing.

5.2 Managerial implications

Looking into the managerial implications of the present research, the first relationship establishes an association between BDA and SM. Several checkpoints and monitors are set up in the SM setting throughout the production process, from the arrival of raw materials to the shop floor to the shipment and packing of finished goods (Ren et al., 2019). A substantial quantity of data about the manufacturing process is generated and compiled inside the SM. To boost the efficiency of production and management of entire manufacturing operations for complicated goods, manufacturers can examine this information by incorporating BDA. This approach can help them optimize process parameters, reduce process flaws, improve item quality and efficiency, etc. (Majeed et al., 2021). BDA enables real-time monitoring and prediction capabilities, assisting manufacturers in optimizing equipment usage, reducing downtime, and minimizing waste, all of which lead to more sustainable production methods. These kinds of managerial implications might substantially contribute to reducing energy usage, wasting materials, and having a carbon footprint and an overall negative influence on the environment. For instance, to accomplish a high level of integration between production and logistics on shop floors, Guo et al. (2021) developed a cyber-physical system (CPS)-based self-adaptive collaborative control (SCC) mode for smart production-logistics systems. In addition, a demonstration of notion simulation premised on a factory situation was created to illustrate the suggested approach. The outcomes demonstrate that the proposed SCC method surpasses the traditional method without SCC in terms of lowering the waiting period, makespan, and energy usage, all while preserving an appropriate level of computational time. This reduction in resource use and energy usage not only lowers operational costs but also minimizes manufacturing processes' environmental impact.

The second association (BDA to PM) suggests that real-time data should make supervising manufacturing easier, allowing manufacturers to stay current on production irregularities and develop the most effective operational control strategies possible. This would allow manufacturers to produce goods of the highest quality (Bai et al., 2017). Big data allows for the storage and analysis of data for continuous PM, which enables fault identification and the improvement of operating processes (Hinojosa-Palafox et al., 2021). For instance, reliance on BDA by senior facilities manager Matthew Graham and his PM department to detect emerging motor bearing wear of a start unit is demonstrated where data analysis enables the team to replace those sets of bearings for $3,000 with minimal disruption to the building's tenants (Aliento, 2017). In this way, implementing BDA improved PM performance and prevented

costs of up to $20,000 for a new motor and severe discomfort because the motor was responsible for almost 25% of the ventilation (Aliento, 2017).

Furthermore, the last association (PM and SM) suggests that a system's digital health may be monitored and communicated to an operator, who can then assess the situation and take appropriate action based on the information gleaned (Assad et al., 2021). For instance, Maw (2022) suggested that implementing PM with digitalization can improve transparency through improved decisions, simplicity through easy access, efficiency through enhancing equipment performance, and optimization through deploying the right tool at the right place. Therefore, in this way, the BDA not only facilitates the direct adaptation of SM but also improves the effectiveness of SM by boosting PM performance.

Nevertheless, the integration of SM technology opens up new job prospects, particularly in highly skilled areas such as data analysis and machine learning. While traditional manufacturing employment may evolve, there is an increasing demand for a workforce competent in digital technology, prompting the creation of new educational and training programs. On an economic basis, these developments increase productivity and competitiveness, allowing businesses to innovate and scale more effectively, supporting overall economic growth. Thus, the integration of BDA with SM promotes a more sustainable, growing, and dynamic industrial landscape, with positive implications throughout society.

6. Conclusion

This research examined the use of BDA to improve SM and PM concentrations. It has been shown that BDA has a positive influence on PM and SM and that PM also has a positive effect on SM. Furthermore, it has been shown that PM has a mediating effect on BDA and SM. Therefore, using BDA is beneficial for the effective implementation and practice of SM. Additionally, this study contributes to improving the results of PM implementation. Finally, PM extends the life of equipment while also lowering the energy used and the expenses associated with it. This makes it possible for SM to be carried out more easily. The incorporation of BDA into PM data improves SM performance by carrying out actual-time data analysis and, as a result, optimum forecasting. However, there are still certain limitations. This research used BDA in selected SMs located within a certain area. Although there is considerable support for the concept in the research literature, universal applicability may be difficult to achieve because of this, as in prior sections. The findings of the model's testing presented in this research are likewise quite favorable. On the other hand, this presents a

possibility for future research to consider a more diverse pool of participants. In addition, the model did not consider other factors that might impact the adoption of new technologies, such as cultural norms, firm policy, or management and workforce mindsets. When trying to understand why BDA is being used in modern industrial settings, we believe that future research should consider the aspects mentioned earlier. The increasing application of newly developed technologies necessitates ongoing ideation and validation of the latest research effort for this topic to be relevant. In addition, prospective research may also take into consideration the possibility of including the moderating impacts of PM results in the study. In the future, researchers may look at the possibility of combining components of policy and governance to assist organizations in making decisions about the implementation of appropriate BDA algorithms and applications. Despite these drawbacks, BDA-enabled platforms are very powerful and provide organizations with the opportunity to make better use of their data, improve existing operations, and invent new enterprises.

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