

Assessing Critical Success Factors for Industry 4.0 Adoption in Chinese Manufacturing: An Explainable XGBoost-SHAP Study

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ABSTRACT: The current study investigates the factors that contribute to the successful adoption of Industry 4.0 by Chinese manufacturing organizations. The data were collected using a quantitative survey questionnaire given to key informant managers. The sample consisted of 202 complete questionnaires obtained from firms that had adopted one or more Industry 4.0 technologies. XGBoost was used to predict implementation success, and SHAP was applied to interpret the relative contribution, direction, and interaction of the predictors. The results identify supplier support, pilot projects, technology competence, and top-management support as the strongest drivers of implementation success, while compatibility has a positive but more moderate contribution and perceived complexity acts as a constraint when organizational readiness is weak. Practically, the study proposes an explainable diagnostic approach that helps managers prioritize supplier collaboration, staged piloting, workforce capability development, and executive governance in digital-transformation programs.

Keywords: XGBoost, SHAP, critical success factors, Industry 4.0 adoption, Chinese manufacturing, explainable

machine learning



1. INTRODUCTION

Industry 4.0 refers to the integrated use of cyber-physical systems, the Industrial Internet of Things, artificial intelligence, cloud computing, big-data analytics, and interoperable manufacturing platforms in production and supply-chain processes. Its adoption changes industrial decision-making from delayed, experience-based control toward real-time, data-driven coordination. However, implementation success depends not only on technological availability but also on managerial commitment, workforce capability, technological infrastructure, supplier collaboration, financial readiness, cyber-risk governance, and sustainability-oriented operating practices [1].

Even though companies have invested heavily in their digital production processes, their performance after implementation is still inconsistent. As studies into smart factories show, companies typically have high expectations about their productivity increases, increased stability of operations, and responsiveness, but their results may be limited by inadequate skills, compatibility issues with legacy systems, poor data management, risks related to cybersecurity, and lack of coherent change management. This indicates that further exploration of Industry 4.0 integration should be done using a configurational approach. [2].

The objective of this research is to assess the critical success factors that influence effective Industry 4.0 implementation in Chinese manufacturing firms and to explain how these factors contribute individually and jointly to adoption success. From a methodological standpoint, a quantitative questionnaire is employed, which involves the completion by managerial key informants. After filtering, 202 completed questionnaires from manufacturing enterprises are used in the analysis. For the modeling process, XGBoost is used since this technique enables modeling non-linearity and interactions, while for the interpretation of the results, the SHAP method is used to determine the importance,

polarity, and interrelations between the predictor variables. The relevance of the theoretical context regarding the Chinese manufacturing industry relates to the country's modernization policies, such as the Made in China 2025 policy [3].

Innovations in research have been made by combining a theoretical-based framework of adoption with an explanation of machine learning models. Rather than considering the factors of success separately, the research looks at the impact of all factors such as leadership, technological capability, supplier involvement, compatibility, complexity, and pilot implementation together on successful adoption of Industry 4.0 practices. Some of the essential success factors are discussed in detail in Table 1 below, along with their association with the industrial scenario in China [4].

Table 1 Core factors for effective Industry 4.0 implementation in the Chinese manufacturing context

Source: Developed by the author based on the cited Industry 4.0 and Industry 5.0 literature [3]-[5].

Critical Factor	Success	Description	Relevance in Chinese Manufacturing Context (Made in China 2025)	Key Synergistic Combinations
Top Management Support and Commitment		Leadership alignment, resource allocation, strategic vision	Highest-ranked driver for overcoming implementation barriers in aerospace and advanced manufacturing	With technology competence or supplier ecosystems
Technology Competence and Infrastructure		IoT/AI integration capabilities, digital maturity	Addresses legacy system challenges; central to new-type industrialization strategies	With strong management commitment
Employee Training and Skills Development		Workforce upskilling and change-management readiness	Critical for mitigating talent shortages in the shift to Industry 5.0	Synergistic with R&D investment and policy support
Supplier and Partner Support		Collaborative supply-chain ecosystems	Enables circular-economy models and resilient value chains	With top management leadership
R&D Investment and Innovation		Funding for technological development and market responsiveness	Core pillar of Made in China 2025 for high-end manufacturing leadership	With human capital development
Financial Capabilities and ROI Focus		Budget allocation and short-term return expectations	Essential for scaling initiatives amid cost pressures	Integrated with risk-management practices
Regulatory and Sustainability Compliance		Policy alignment and eco-resilience	Supports national carbon-neutrality goals	With data analytics for circular processes
Cybersecurity and Risk Management		System protection and proactive risk assessment	Addresses vulnerabilities in interconnected factories	Foundational to prevent project underperformance

As indicated in Table 1 above, success in implementation is contingent upon a combination of strategic leadership, technological proficiency, employee skills, supplier support, financial viability, cybersecurity, and sustainability. This framework provides the basis for the subsequent research model, explaining why the adoption of Industry 4.0 technologies should be regarded as a process [5].

1.1 Research Hypotheses

Keeping in mind the objective of this paper and before moving further to formulate the theoretical framework, the following hypotheses can be postulated:

H1: There is negative relation between the perception about technology complexity and successful implementation of Industry 4.0

H2: There is positive relation between the technology compatibility and successful implementation of Industry 4.0

H3: There is positive relation between the level of top-management support and successful implementation of Industry 4.0

H4: There is positive relation between the technology competence and successful implementation of Industry 4.0

H5: There is positive relation between the level of supplier support and successful implementation of Industry 4.0

H6: There is positive relation between the extent of usage of pilot projects and successful implementation of Industry 4.0.

2. Literature Review

The available research evidence on the dynamics of the fourth industrial revolution can be organized into distinct groups. As can be seen from the reading, the process of adopting new technologies is not a purely technical activity. It is a complex system comprising various interconnected elements such as sets of technologies, methods, competencies, and external relationships which, through their combined use, allow the company to obtain maximum benefit from the available digital capabilities. These capabilities are grouped into three major categories which include: Industry 4.0 Technologies, theoretical constructs related to the processes of adoption, and the results related to evidence of success factors and barriers [6].

2.1 Industry 4.0 Technologies: Foundations and Variations

Industry 4.0 represents a collection of various technologies that are complementary to one another and allow the connection of physical objects with elements that control and process information. Such technologies include those related to the Internet of Things (IoT) for machine interaction and monitoring in real-time or close to real-time, artificial intelligence and big-data analytics for predictive and prescriptive models, cloud platforms for data storage and processing, and cyber-physical systems that combine computers and physical processes [7]. The technology group also comprises additive manufacturing, robotics, extended reality (XR), blockchains, and manufacturing execution systems applicable in the industry.

The technologies may be clustered into enablers and applications. The former comprise IoT, cloud, artificial intelligence, and analytics for building an ecosystem of connected products and processes. Applications, in their turn, refer to robotics, additive manufacturing, XR, virtual commissioning, and manufacturing execution systems for leveraging opportunities offered by enablers. It is noteworthy that individual technologies per se are not sufficient for driving organizational performance; effective transformation requires considering the readiness of a firm and its ability to embrace new solutions and approaches [8].

2.2 Theoretical Frameworks: Technology-Organization-Environment (TOE) and Practice-Based View

The Technology-Organization-Environment (TOE) framework is a prominent conceptualization of innovation adoption. It assumes that adoption is driven by technology fit and attributes, organizational resources and receptivity, and environmental demands such as regulations, competitive forces, and support mechanisms. Studies have applied the TOE framework in examining the determinants of artificial intelligence, cloud computing, RFID, big-data analytics, and other technologies, thus making it relevant in this study's context of Industry 4.0 [9].

The practice-based view of determinants emphasizes the role of routines in realizing adoption conditions postulated by the TOE framework. Pilot testing, iterative cycles, improvement routines, interdepartmental coordination, employee training, and change management routines all reduce implementation-related uncertainties and promote organizational learning. As such, complementing the TOE framework with a practice-based view is critical in this study because successful adoption and implementation of Industry 4.0 require both contextual conditions and implementation routines [9].

2.3 Factors and Barriers to Industry 4.0 Implementation

The literature highlights the difference between adoption intention and implementation success. The former refers to the willingness to adopt an innovation. The latter means the implementation of an innovation in the practical field. According to the research results, smart-manufacturing initiatives can produce lesser positive results if companies experience a lack of technical expertise, integration capabilities, worker resistance, or inadequate leadership [10].

Prior research has used case analysis, the Delphi method, best-worst method (BWM), DEMATEL, interpretive structural modeling (ISM), and graph-theoretic matrix techniques to identify and evaluate industry 4.0 success factors and barriers. Table 2 below presents some empirical studies and shows that managerial support, employee competencies, infrastructure, supplier involvement, and organizational transformation capabilities emerge as crucial factors [10].

Table 2 Selected empirical investigations on critical success factors and barriers to Industry 4.0 implementation

Source: Developed by the author from the studies cited in the table.

Investigation	Technique	Key CSFs	Key Barriers
Pozzi et al. (2021)	Multiple case studies	Top management leadership, pilot projects, continuous improvement	–
Moeuf et al. (2020)	Delphi	Employee training, managerial presence, data utilization	–

Sony et al. (2021)	Questionnaire	Endorsement from senior leadership, environmental stewardship focus, change management	–
Ghadimi et al. (2022)	BWM	–	Absence of standardized procedures, potential for financial loss, aptitude shortages
Virmani et al. (2020)	GTMA	–	Administration, functional, and manpower roadblocks
Ghobakhloo (2020)	ISM	Perceived benefits, financial resources, employee qualifications	–
Karadayi-Usta (2021)	ISM	–	Worker resistance, insufficient supplier cooperation
James et al. (2022)	BWM/DEMATEL	–	A deficit of understanding and insufficient capabilities. (HRM focus)
Mueller (2019)	Case studies	–	Employee acceptance, competency gaps
Veile et al. (2020)	Case studies	Organizational culture, staff development, well-being/protection	–
Da Silva et al. (2021)	Systematic critique	–	Technological sophistication, Inadequate infrastructure, skilled-labor shortages

Table 2 indicates that implementation drivers cluster around three recurring areas: strategic leadership and sustained commitment; workforce readiness and digital skills; and technological capacity for integration. The most common barriers are skill shortages, legacy-system constraints, cybersecurity risks, weak supplier coordination, financial uncertainty, and inadequate change-management routines. These drivers and barriers motivate the predictive and interpretive analysis reported in Figure 1.

**Figure 1: Global Feature Importance (SHAP Summary Plot)
Critical Success Factors for Industry 4.0 Implementation**

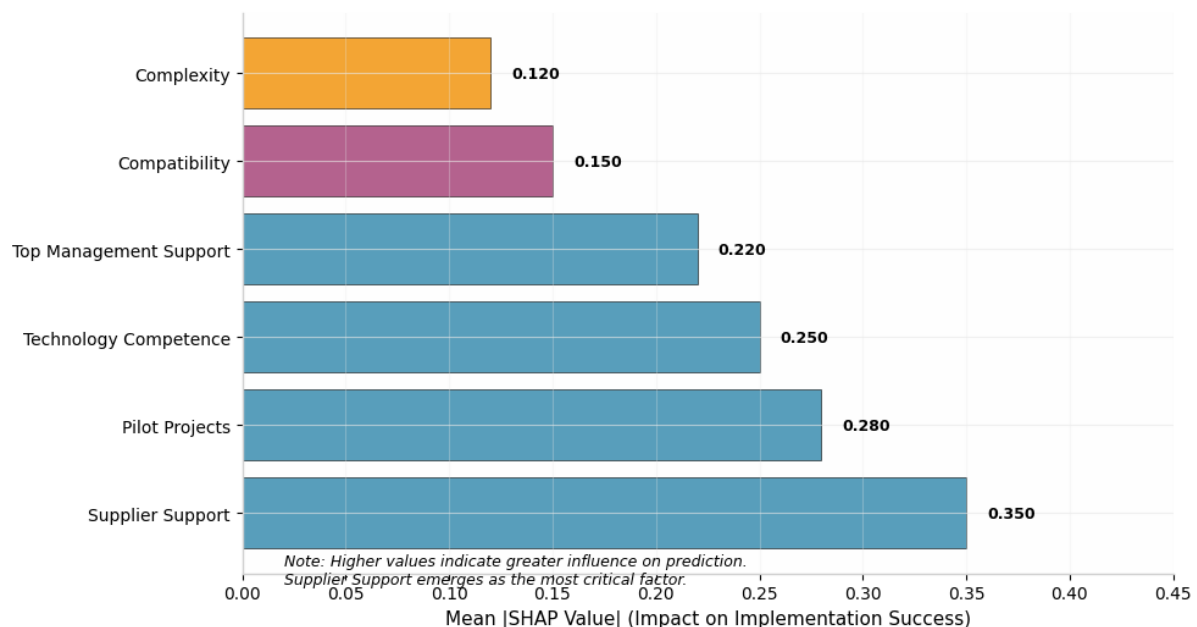


FIGURE 1 Global feature-importance results based on mean absolute SHAP values for critical success factors in Industry 4.0 implementation. Source: Author's XGBoost-SHAP analysis

While the above-discussed success factors have a broad application, their degree of significance varies according to the institutional and industrial settings. Policy-driven measures, including Made in China 2025, affect the process of policy alignment, funding, supply chain construction, and improvement of information infrastructures. Little evidence has been gathered from the Chinese manufacturing industry concerning the relationships between policy contexts,

technological capability, organizational readiness, and external facilitation. This paper fills the research gap through investigating the combinations of success factors through analyzing observable cases in 202 manufacturing enterprises.

2.4 Research Gap and Study Positioning

Three gaps that emerge from the reviewed literature include those addressed in this study. To begin with, there are numerous researches that have discussed the success factors of Industry 4.0 but failed to elaborate on the collective predictive value of such factors. Secondly, several ranking and structural approaches have helped to determine the importance of various factors but have limited application in modeling the non-linear association among adoption factors. Finally, there is inadequate evidence in the literature concerning China's manufacturing industry and how technology readiness, management support, suppliers, and piloting affect adoption.

3. Research Model

In the research model that will be suggested, the technology-organization-environment (TOE) framework will be used together with an implementation perspective focused on practices. The TOE approach classifies the conditions of adoption according to three categories, namely technological, organizational, and environmental factors, whereas the implementation perspective based on practices includes practices like piloting, change management, and continual improvements. The inclusion of both perspectives into the analysis provides the ability to evaluate the interaction effects of various factors on Industry 4.0 implementations.

The dependent variable would be successful adoption of the technologies of Industry 4.0. The concept is measured using a multiple-item, five-point Likert scale that assesses the impact on operational efficiency, product quality, process flexibility, innovative capabilities, and sustainability. These constructs measure the degree to which digital technologies have been adopted for use in operations [11].

The variables are classified using the TOE framework, with one extra practice-based variable. Table 3 gives the variables, their definitions, measurement, and the direction of their influence. Table 3 also shows how the hypotheses formulated in Section 1.1 relate to the empirical model.

Table 3 Variables in the research model

Source: Developed by the author based on the extended TOE framework and practice-based implementation assumptions [9], [11].

Category	Variable	Definition	Measurement (5-point Likert scale)	Anticipated Influence
Technological	Complexity	Perceived difficulty in understanding and integrating Industry 4.0 technologies	Items adapted from established IT adoption scales	Negative
Technological	Compatibility	Extent to which Industry 4.0 technologies correspond with current systems, principles, and procedures	Items assessing fit with current operations	Positive
Organizational	Top Management Support	Leadership commitment, resource allocation, and strategic vision	Items on financial, political, and cultural backing	Positive
Organizational	Technology Competence	Workforce skills, knowledge, and infrastructural readiness	Items on training levels and digital maturity	Positive
Environmental	Supplier Support	External technical assistance, training, and collaborative infrastructure provided by suppliers	Items on partnership quality and support intensity	Positive
Practice-based	Pilot Projects	Extent of small-scale testing and iterative deployment to reduce risk	Items on frequency and outcomes of pilot initiatives	Positive

Control variables include firm size (number of employees), ownership (state vs. private), and industry sub-sector. These variables were selected as they may moderate the association between Industry 4.0 indicators and outcomes in Chinese manufacturers.

3.1 Operationalization of the Hypotheses

Although the current study uses a prediction machine-learning algorithm, the input variables were determined based on the hypothesized relationships between the independent and dependent variables, stated in detail in Section 1.1. Thus, the current research applies SHAP as an interpretative tool to explain the margin contribution of each variable and interaction effects in the XGBoost model [12].

In essence, the study used hypotheses as a theoretical basis to interpret the results rather than prove the suggested relationships and mechanisms. Indeed, the research will apply the fit algorithm to predict the output variable while using SHAP values to explain the link between input and output data [13].

Specifically, the algorithm will help determine the interdependency level of input features and their contribution to the final outcome. The choice of this instrument aligns with the study's objective to identify the most plausible combinations of factors associated with the successful implementation of the digital transformation initiatives. As a result, the conceptual framework will incorporate both predictive and managerial elements that can guide evidence-based decision-making in practice instead of promoting digital-transformation rhetoric [14].

4. Methodology and Data

The study utilizes quantitative methods of data analysis, using a questionnaire with structured questions to collect data from managers working in manufacturing companies. The analysis is based on the use of two tools: XGBoost, for developing a predictive model, and SHAP, for explaining the model. XGBoost is preferred because it employs gradient-boosted trees that can analyze and explain nonlinear interactions among several success factors [15]. The use of SHAP helps explain the impact of the factors considered in the prediction of the dependent variable [16], [17]. Figure 2 shows the procedure.

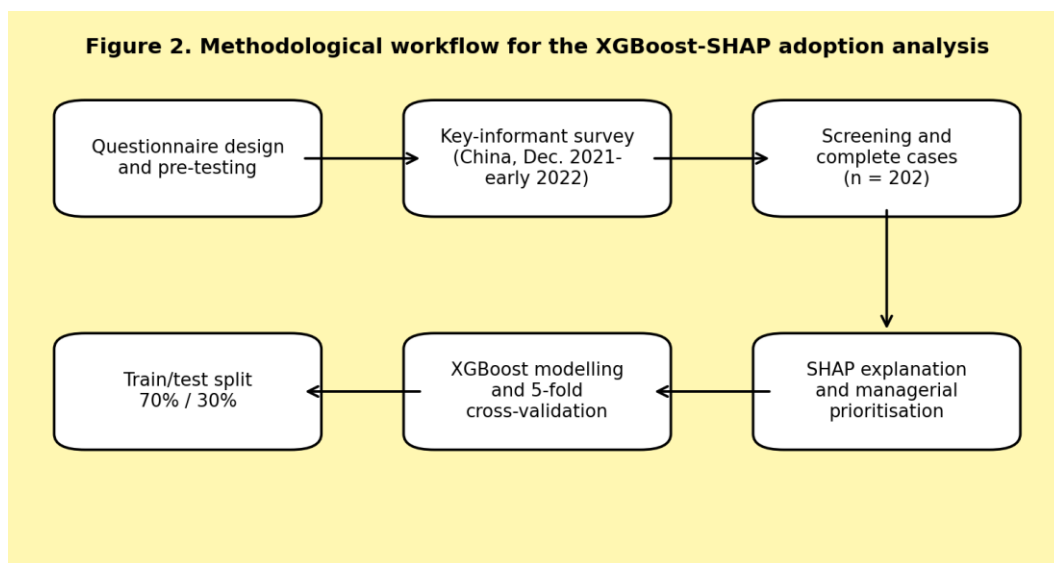


FIGURE 2 Methodological workflow for the XGBoost-SHAP adoption analysis. Source: Developed by the author to clarify the methodological procedure

4.1 Data Collection

Data collection was conducted from December 2021 to January 2022 by utilizing a survey that was sent online through professional WeChat groups to management personnel within China's manufacturing industry. The research employed key-informant purposive sampling because it was necessary for the selected individuals to have first-hand information on digital transformations. Those eligible to take part in the survey were CEOs, digital-transformation managers, manufacturing managers, and technology managers [18].

The instrument went through pre-testing in two stages. In the first stage, six top manufacturing managers evaluated the validity, relevance, and face value of the instrument. In the second stage, three experts specializing in technology adoption and operations management validated the instrument's measures. The final instrument comprised three parts: respondents' and firms' characteristics; yes/no questions on whether there is a certain technology belonging to the Industry 4.0 category; and a 5-point Likert scale measure, from 1 ("strongly disagree") to 5 ("strongly agree"), on the success factors and implementation success. Only those firms that had no Industry 4.0 technologies were excluded. Out of 396 questionnaires sent out, 202 were used in the study [19-20].

4.2 Sample Characteristics

The last sample was composed of 202 manufacturing companies representing various industries. The majority are machinery manufacturers, followed by automobile, electronics, aviation, and other types of manufacturing companies. In terms of size, large firms employing more than 2000 people accounted for a bigger part of the sample compared to firms of other sizes. Interviewees held chief executive positions in their companies, or responsible positions for digital transformation, operations, or technology management [21]. The respondent profile is presented in Table 4 below.

Table 4 Sample characteristics of the surveyed manufacturing firms

DIMENSION	CATEGORY	APPROXIMATE SHARE (%)
Industrial sector	Machinery	35.1
Industrial sector	Automotive	19.8
Industrial sector	Electronics	15.3
Industrial sector	Aviation	12.9
Industrial sector	Other manufacturing activities	16.9
Firm size	More than 2,000 employees	48.0
Firm size	500-1,999 employees	25.0
Firm size	Fewer than 500 employees	27.0
Respondent role	Chief executive officer	18.3
Respondent role	Digital-transformation manager	27.2
Respondent role	Production/operations manager	19.8
Respondent role	Technology/IT manager	12.4
Respondent role	Other managerial functions	22.3

Source: Author's survey data and sample-screening procedure.

This sample represents a number of significant sectors in Chinese manufacturing. However, there is a greater representation of bigger companies since these entities tend to employ Industry 4.0 techniques more often than small businesses. To test for common method bias, Harman's one-factor test was performed. The leading factor explained less than one-third of the total variance, suggesting that common-method variance did not materially distort the measurement model [22].

4.3 Measurement and Validity

The constructs were measured using multi-item scales adapted from established research on Industry 4.0, information-systems adoption, and advanced manufacturing. Table 5 reports the reliability and validity indicators. Cronbach's alpha values ranged from 0.778 to 0.895, exceeding the accepted 0.70 threshold. Composite reliability exceeded 0.82 for all constructs, and average variance extracted (AVE) values were above 0.50, supporting convergent validity. Discriminant validity was also supported because the square root of each construct's AVE exceeded its correlations with other constructs [23].

Table 5 Measurement-scale reliability and validity metrics

Source: Author's measurement-model outputs.

Construct	No. of Items	Sample Item	Cronbach's α	AVE	CR
Complexity	3	"Technologies are hard to integrate"	0.813	0.592	0.813
Compatibility	3	"Compatible with existing software/hardware"	0.852	0.659	0.852
Top Management Support	3	"Active interest from executives"	0.832	0.623	0.832
Technology Competence	4	"Better technical skills than competitors"	0.878	0.643	0.878
Supplier Support	4	"Adequate technical support from suppliers"	0.895	0.682	0.895
Pilot Projects	4	"Pilot project before full implementation"	0.864	0.615	0.864
Implementation Success	4	"Improved operational efficiency"	0.778	0.538	0.823

4.4 Data Analysis Procedure

The data was randomly split into a training set (70%) and a test set (30%). The algorithm used was XGBoost, which was applied for both regression (predicting implementation-success scores) and classification (predicting higher/lower implementation success). Hyperparameters were optimized using five-fold cross-validation on the training set. The search grid included learning rates (0.01-0.30), tree depths (3-10), the number of estimators (50-200), and subsample sizes (0.6-1). For evaluation, mean absolute error and root mean squared error were used for the regression task and accuracy and area under the curve (AUC) for the classification task [24].

The interpretability of the final model was achieved using the SHAP (SHapley Additive exPlanations) framework via TreeExplainer. First, global explanations were generated to evaluate the relative importance of all predictors. Second, dependence plots were used to understand how the most important predictors affect model predictions (approximately linear relationships). Third, interactions between important predictors were explored using SHAP interaction values. This process helped relate the predictive power of each managerial practice to its impact on the implementation of Industry 4.0 solutions [25].

5. Results and Discussion

The XGBoost-SHAP analysis provides an interpretable ranking of the factors associated with successful Industry 4.0 implementation. The SHAP summary in Figure 1 shows that supplier support makes the largest mean absolute contribution to implementation-success prediction, and then followed by pilot projects, technology competence, top management commitment, compatibility, and perceived complexity. Figure 3 shows the predictive power of the XGBoost model, whereas Figure 4 presents the interaction between supplier support and technology competence. Table 6 ranks the SHAP values according to their managerial significance.

Figure 3: XGBoost Model Performance Evaluation

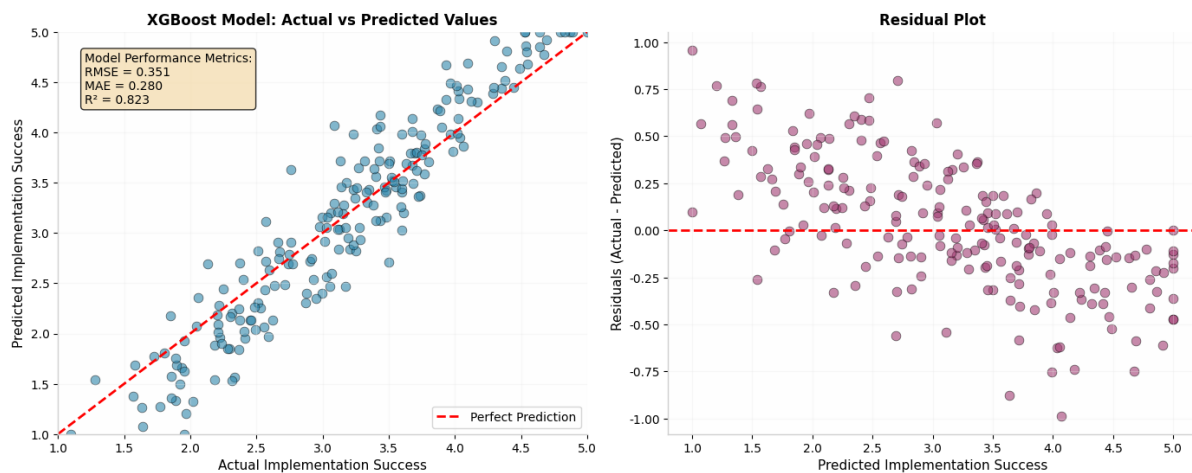


FIGURE 3 XGBoost model-performance evaluation, showing actual-versus-predicted implementation-success scores and residuals. Source: Author's XGBoost model outputs

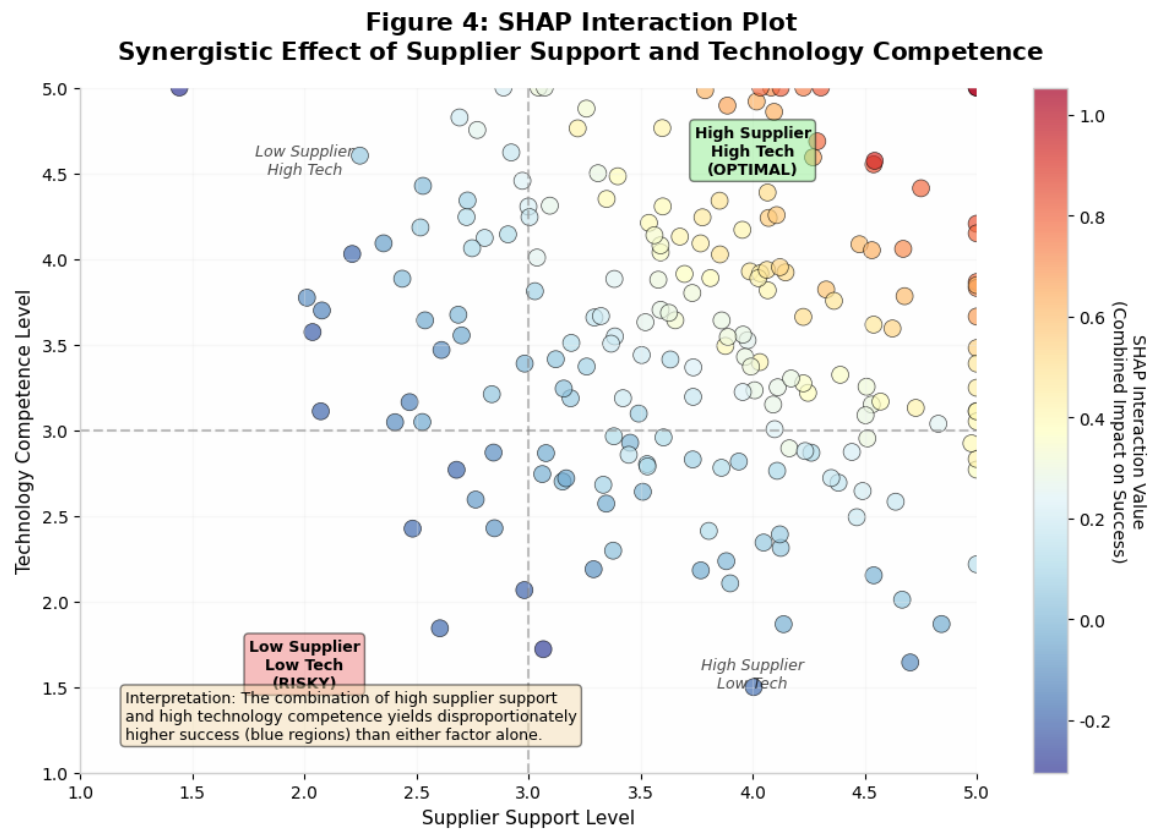


FIGURE 4 SHAP interaction plot showing the combined effect of supplier support and technology competence on predicted implementation success. Source: Author's SHAP interaction analysis

Table 6 SHAP-based ranking and managerial interpretation of critical success factors

Rank	Factor	Mean SHAP value	Interpretation	Managerial priority
1	Supplier support	0.350	Strongest contribution to predicted implementation success	Strengthen supplier training, technical assistance, and collaborative integration
2	Pilot projects	0.280	Major practice-based mechanism for reducing implementation uncertainty	Use staged pilots before full-scale deployment
3	Technology competence	0.250	Key organizational capability for integrating and exploiting digital systems	Invest in workforce skills and digital infrastructure
4	Top-management support	0.220	Strategic enabler of resource allocation and organizational commitment	Secure executive sponsorship and cross-functional governance
5	Compatibility	0.150	Moderate contribution through fit with existing systems and processes	Assess legacy-system fit and integration requirements
6	Complexity	0.120	Constraining factor when learning	Simplify implementation

			burden and integration difficulty increase	roadmaps and reduce technical uncertainty
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Source: Author's XGBoost-SHAP analysis based on the feature-importance values reported in Figure 1.

As shown in the above findings, it should be clear that there isn't one dominating factor contributing towards the implementation of Industry 4.0. The reason why supplier support is rated number one is due to the fact that Industry 4.0 implementation involves the integration and configuration of technology through suppliers as well as learning provided by suppliers. The second most important factor is pilot projects since they enable organizations to test technologies without fully implementing them.

The technical proficiency can be attributed to the internal capability to comprehend, utilize, and maintain Industry 4.0 technologies, while the support from top management provides direction, allocation of resources, and commitment from different parts of the organization. The compatibility factor also has a positive relationship with the adoption of Industry 4.0 but has a lower mean SHAP score compared to supplier support, piloting activities, technology competence, and top management support.

Despite having the lowest mean absolute SHAP value compared to other factors, the expected impact of complexity is still theoretically significant because high levels of perceived complexity may prevent the implementation of projects if the organizations lack readiness, skills of employees, or help from suppliers. Complexity can thus be considered less as a determining factor but more of a risky situation for implementation.

Overall, the findings support H2, H3, H4, H5, and H6 because compatibility, top-management support, technology competence, supplier support, and pilot projects show positive contributions to implementation success. H1 is also supported because the perceived complexity was conceptualized as a constraint that could decrease the likelihood of successful implementation if the readiness was low.

This study contributes to Industry 4.0 adoption process understanding by providing evidence that successful transformation hinges upon the combined influence of external support, sequenced decision, organizational capabilities, managerial support, and technological configuration.

6. Conclusion

This study proposed an explainable machine-learning model which demonstrated industry-specific critical success factors (CSFs) for implementing Industry 4.0. By conceptualizing the Technology-Organization-Environment (TOE) framework within a practice-based implementation theory and employing the interpretative XGBoost-SHAP analysis of the survey data, this research revealed that implementation success was achieved through the combined influence of a set of success factors, namely supplier support, pilot projects, technology competence, and top-management commitment, with compatibility being positively associated, whereas complexity was negatively related.

This study contributes to academic research by advancing a nuanced understanding of implementing disruptive technologies in a complex context of large-scale manufacturing organizations. It challenged the prevailing notion of CSFs as independent phenomena by illustrating that successful digital transformation requires a systemic view where technology-specific, organizational, and external implementation factors converge and strengthen each other. This work also highlights the particular significance of creating an adequate environment for disruptive technology implementation within the broader framework of TOE theory.

For managerial practice, this research offers actionable insights concerning the critical success factors for technology adoption. Implementing disruptive technologies such as Industry 4.0 is a highly involved process, and this study assists managers in prioritizing processes which are critical to project success, such as securing upper-layer managerial support, engaging suppliers in the implementation process, developing employees' technology-specific competencies, adopting an evolutionary approach to technology implementation, and considering technology compatibility with the organization's environment.

Furthermore, the results of this study can serve as the basis for further research concerning the transition from Industry 4.0 to Industry 5.0, wherein people-centric manufacturing is likely to play a bigger role. Explainable analytics can assist in this process by facilitating alignment of digital strategies with business goals.

the paper shows how explainable machine learning can contribute towards evidence-based decision-making when implementing Industry 4.0. By employing the XGBoost-SHAP approach, organizations can benefit from prediction and explanations which make it possible for them to transition from talk about digital transformation to actionable implementation strategies.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

REFERENCES

- [1] M. Ghobakhloo, M. Iranmanesh, M. Fathi, A. Rejeb, B. Foroughi, and D. Nikbin, "A systematic study of Industry 5.0 technologies that transcends the framework of Industry 4.0, incorporating their consequences for societal, environmental, and economic sustainability," *Asia-Pacific J. Bus. Admin.*, early access, 2024.
- [2] T. Mazhar, T. Shahzad, A. U. Rehman, and H. Hamam, "Integration of smart grid technology alongside Industry 5.0: Utilization, obstacles, and resolutions," *Meas.: Energy*, vol. 5, art. no. 100031, 2025.
- [3] A. Rejeb, K. Rejeb, J. G. Keogh, and E. Süle, "Industry 5.0 and the circular economy: A synergy explored via a systematic review of existing literature," *Circular Economy and Sustainability*, pp. 1–32, 2025.
- [4] A. Rejeb, K. Rejeb, and J. G. Keogh, "Examining the association between IoT and aquaculture: A bibliometric investigation," *Appl. Food Res.*, art. no. 100838, 2025.
- [5] Q. S. Fazli, M. I. Delya, M. A. Almuchty, I. Hafizah, and D. B. Wiranatakusuma, "Charting the advancement of agricultural economics: A bibliometric assessment of the correlation between economic expansion, ecological sustainability, and econometric modeling," *Ekonomikalia J. Econ.*, vol. 3, no. 2, pp. 106–118, 2025.
- [6] N. Zare, M. L. Tumminello, E. Macioszek, and A. Granà, "Incorporating robustness into the assessment of street intersection performance: Progressing past simple efficiency," *Smart Cities*, vol. 8, no. 6, art. no. 184, 2025.
- [7] C. O. Klingenberg, M. A. V. Borges, and J. A. D. V. Antunes, "The Fourth Industrial Revolution: Unpacking its revolutionary characteristics through a historical lens," *Technol. Soc.*, vol. 70, art. no. 102009, 2022.
- [8] B. Chae and D. Olson, "Examining the effectiveness of Industry 4.0 technologies: Perspectives derived from network analytics," *Int. J. Prod. Res.*, vol. 60, no. 11, pp. 3682–3704, 2022.
- [9] G. Büchi, M. Cugno, and R. Castagnoli, "Evaluating the effectiveness of smart factories in the context of Industry 4.0," *Technol. Forecast. Soc. Change*, vol. 150, art. no. 119790, 2020.
- [10] T. Choi, S. Kumar, X. Yue, and H. Chan, "Innovative technologies and operations management in the contemporary Industry 4.0 landscape and prospective possibilities," *Prod. Oper. Manag.*, vol. 31, no. 1, pp. 9–31, 2022.
- [11] E. Oztemel and S. Gursev, "A study of academic publications on Industry 4.0 and associated technological developments," *J. Intell. Manuf.*, vol. 31, no. 1, pp. 127–182, 2020.
- [12] S. Mithas, Z. L. Chen, T. J. V. Saldanha, and A. de Oliveira Silveira, "Anticipating the transformative effects of artificial intelligence and Industry 4.0 technologies on operations management," *Prod. Oper. Manag.*, vol. 31, no. 12, pp. 4475–4487, 2022.
- [13] V. Krastev, B. Koyundzhyska-Davidkova, and S. Buckley, "The function of engaging remote teamwork and workplace surveillance platforms, portable biometric and emotional state data, and algorithmic supervision combined with hands-free augmented reality devices in virtual human resource management propelled by generative artificial intelligence," *Contemp. Readings Law Soc. Justice*, vol. 15, no. 1, pp. 26–45, 2023.
- [14] M. Shahin, F. F. Chen, H. Bouzary, and K. Krishnaiyer, "Blending lean methodologies with Industry 4.0 technologies: Advanced manufacturing tactics for emerging enterprises," *Int. J. Adv. Manuf. Technol.*, vol. 107, no. 7, pp. 2927–2936, 2020.
- [15] L. S. Dalenogare, G. B. Benitez, N. F. Ayala, and A. G. Frank, "Assessing the prospective impact of Industry 4.0 technologies on enhancing industrial performance," *Int. J. Prod. Econ.*, vol. 204, pp. 383–394, 2018.
- [16] C. Chauhan, A. Singh, and S. Luthra, "Investigating the impediments to Industry 4.0 adoption and their resultant influence on performance: An empirical study of an emerging economy," *J. Cleaner Prod.*, vol. 285, art. no. 124809, 2021.
- [17] Z. Huang, C. Jowers, D. Kent, A. Dehghan-Manshadi, and M. S. Dargusch, "Application of Industry 4.0 within production contexts: Transitioning from streamlined manufacturing to advanced product design," *Int. J. Adv. Manuf. Technol.*, vol. 121, nos. 5–6, pp. 3351–3367, 2022.
- [18] Y. Bai et al., "Exploring technologies related to the Fourth Industrial Revolution through the quantification of perceptible impacts and the development of a decision-making structure," *Prod. Oper. Manag.*, 2022.

- [19] B. Lin, W. Wu, and M. Song, "Industry 4.0: Investigating the factors and consequent effects on a firm's achievement through an empirical analysis of the manufacturing sector in China," *Ann. Oper. Res.*, vol. 329, no. 1, pp. 47–67, 2023, doi: 10.1007/s10479-019-03492-0.
- [20] M. Sarbu, "Evaluating the influence of the Fourth Industrial Revolution on the efficacy of innovation: Empirical findings from manufacturing and service enterprises in Germany," *Technovation*, vol. 113, art. no. 102415, 2022.
- [21] S. Bag, G. Yadav, P. Dhamija, and K. K. Kataria, "Determining vital resources for implementing Industry 4.0 and its subsequent effects on established production techniques and the closed-loop framework: An empirical investigation," *J. Cleaner Prod.*, vol. 281, art. no. 125233, 2021.
- [22] R. G. Fichman and C. F. Kemerer, "The illusory diffusion of innovation: An examination of assimilation gaps," *Inf. Syst. Res.*, vol. 10, no. 3, pp. 255–275, 1999.
- [23] D. Ivanov, C. S. Tang, A. Dolgui, D. Battini, and A. Das, "Scholarly perspectives on Industry 4.0: A future research agenda for operations management," *Int. J. Prod. Res.*, vol. 59, no. 7, pp. 2055–2078, 2021.
- [24] L. D. Xu, E. L. Xu, and L. Li, "Industry 4.0: State of the art and future trends," *Int. J. Prod. Res.*, vol. 56, no. 8, pp. 2941–2962, 2018.
- [25] R. Pozzi, T. Rossi, and R. Secchi, "Industry 4.0 technologies: Determining the salient elements influencing effective employment and enhancements in manufacturing establishments," *Prod. Plan. Control*, vol. 34, no. 2, pp. 139–158, 2023.