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Integrating IoT Maturity and Data Driven Decision Making: A Hybrid SEM-AHP Framework for Smart Factory Performance

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Abstract

Industry 4.0 has transformed manufacturing models, and the Internet of Things (IoT) has become a central aspect of future factories to be smart and connected. However, most industries do not have an elaborate mechanism to determine the impact of IoT readiness and its implementation in the performance of the entire factory due to its transformational nature. This paper advances a cross-strategy that combines the IoT adoption indicators and Partial Least Squares Structural Equation Modeling (PLS-SEM) to estimate key enablers and results of smart factory performance. The framework also draws on the data of surveys given by manufacturing experts across multiple areas of industry, and it is based on the relationships between Digital Readiness, IoT Maturity, Production Flexibility, Data-Driven Decision-Making, and Smart Factory Performance. The research also incorporates the Analytic Hierarchy Process (AHP) to determine interdependencies of the essential adoption drivers and focus on the improvements. The results of the PLS-SEM analysis indicate that digital readiness and the level of IoT maturity have positive effects on the agility of productions and performance outcomes with a high impact. The framework can be also used to provide a realistic diagnostic to manufacturers that want to gauge their Industry 4.0 preparedness and formulate informed investments decisions on IoT-based technologies.

Keywords
IoT Maturity, Smart Factory Performance, Digital Readiness, Data-Driven Decision Making, Production Flexibility, PLS-SEM & AHP.

1. Introduction
The fourth industrial revolution or the industry 4.0 has changed the manufacturing paradigm. The core of this change is the Internet of Things (IoT) an influential technology that makes connections smooth, workflow data extracting, and automation of most of the processes, possible in real-time (Yao & Lin, 2016). Smart factories rely on IoT capabilities to handle flexible responses to changed production scenarios, operational optimization, new levels of flexibility and decisions based on data.

Although the number of organizations that adopt IoT grows across the industries, many organizations are struggling to assess the impact that it has on the general performance of a factory. A significant piece is lacking in the area of developing systematic and evidence-based frameworks aiming to measure maturity with respect to IoT and relate that level of maturity to measurable performance levels. Without these models, the manufacturers risk misallocation of resources as well as underestimating the worth of smart technologies.

And it is the effort of trying to bridge that gap proposed in this paper by proposing an integrated model of PLS-SEM and AHP (Xhafaj et al., 2022). The model confirms the substantiation of connections among such essential constructs as online preparedness, IoT maturity, flexibility in terms of production, data-driven decisions, and smart factory performance. Breaking down direct/mediated effects of the enablers along the industry 4.0 environments, the study is based on surveyed responses by manufacturing professionals in different industries.

The combination of statistical modeling and multi-criteria decision analysis proposed in the paper not only determines the impact of the key factors but also enables the ranking of these factors on a scale relative to one another. Such a two-pronged methodology provides a diagnostic and strategic perspective with which to determine the Industry 4.0 readiness and make effective IoT investment decisions (Mohapatra et al., 2024).

1.1 Research Objectives

1) To create and validate the PLS-SEM model that gauges the role of the IoT maturity and IoT readiness with the effects on smart factory performance.

2) To identify some fundamental concealed variables and observable proxies to Industry 4.0 implementation of manufacturing.

3) To find out how the flexibility of production and data-based decision-making mediate the relationship between the improvement of the results of the production.

4) To include AHP techniques to be used in ranking an IoT adoption enabler and to discover causal relationships.

5) To give a grounded outline of industrial capability that manufacturers, policymakers, and researchers can use to assess and improve Industry 4.0 to achieve.

2. Literature Review

The required insight into the organizational role of culture and its effects on AI readiness and responsiveness in fluctuating rates of disruptions is offered by the dynamic capabilities. This is especially important since the capabilities will assist a firm to adjust and redesign its resources in situations where available rapid changes are many. The organizational culture will become the most crucial aspect when building AI preparedness because it enables flexibility, innovation and resilience which is the central aspect of such adoption and implementation of AI (Murire, 2024). Technological agility and strategic goals also have to be correlated with cultural values in order to realize an Artificial intelligence responsiveness within real-time.

However, disruption is not always rapid and can therefore keep pace with this responsiveness and this has been especially seen in high impact crises such as global pandemics that have demonstrated the inadequacy in the established mode of operations. However, whereas the related literature covers the cultural dimensions of collaboration and innovation in relations with AI, the deficiency in the studies literature on the subject is focused on investigating the work without extreme disruptions of the conditions atmosphere (Amankwah-Amoah et al., 2024). This gap should be filled to enhance theoretical and practical understanding in the area of organizational resilience in the increasing magnitude of uncertainty.

2.1 IoT and Industry 4.0

The adoption of IoT in manufacturing systems has become a keystone of Industry 4.0 because it provides real-time observation issues and automates processes and makes smart decisions (Ashima et al., 2021). It has been cited that there is a direct connection between IoT maturity and the enhancement of operational efficiency, flexibility of production, and quality of products produced. Nevertheless, the formalized way of the evaluation of the IoT preparedness of an organization and its consequences to the performance of the factories remains a weakness of many organizations. The current models tend to pay more attention to technical adoption and are silent on the synergistic effect that digital readiness, organizational culture, and the ability to use data have.

2.2 Smart Factory Performance Readiness and Measurements Model

Smart factory performance is not just about adoption of the technology; it needs the ecosystem of interdependencies i.e. digital infrastructure, human- technology interaction, responsive decision systems (Won & Park, 2020). Some researchers have gone ahead to investigate such multidimensional constructs using Structural Equation Modeling (SEM) but have not incorporated variables that are specific to IoT into performance measurement systems. The gap of research that is yet to be researched is on the inexistence of verily detailed models that are modified into the industry 4.0 environments.

2.3 Priority role of AHP in technology

Analytic Hierarchy Process (AHP) has also been used largely in determination of priorities and ranking critical success factors during adoption of technology (Lee et al., 2012). AHP can be utilized in an Industry 4.0 setting to determine the relative estimated priority of the enablers of IIoT and place them in order of strategic goals. The integration of AHP and SEM offers a blend of the two methods through which one both gets to validate relationships at a structural level and also get a structural validation of relationship hierarchy of key items in the decision-making process (Jakhar & Barua, 2014).

3. Methodology

3.1 Data Collection and Sampling Design

The research was carried out using a structured questionnaire which was administered to professionals in the manufacturing industries who are involved in implementation of Industry 4.0 (Motyl et al., 2017). The purposive form of sampling was adopted where respondents who had relevant experience, i.e. production managers, engineers as well as IT specialists, were targeted. A well-laid out questionnaire was composed containing 8 items in an attempt to capture these constructs. In order to make the data as reliable as possible, all questions will be placed on a 1-5 likert scale of disagree (1) to agree (5) (Croasmun & Ostrom, 2011). The necessary 100 valid responses became obtained, hence adequate to conduct PLS-SEM analysis. Pre-final distribution was also done with a pilot test Smart-PLS has been used to analyze the items attained to obtain the level of reliability and the structural interrelationships of the model.

3.2 Measurement properties of constructs

The measurement model comprises of five overarching constructs that are defined by validated pointers based on existing literature and a synopsis of which is table 1.

Digital Readiness is theorized based on two indicators ICT Infrastructure (DR1) and Technical Skill Availability (DR2). Such characteristics are based on the underlying technological infrastructure and access to digitally-proficient workforce in an organization.

IoT Maturity occurs by the use of Cybersecurity Readiness (IoTM1) and Interoperability Standards (IoTM2). The two are a whole that demonstrates the preparedness of the organization regarding secure IoT deployment and the capability of systems to communicate across platforms without problem.

Smart Factory Performance encompasses two indicators, that is, Financial Investment (SFP1) and Government Policy Support (SFP2). These indicators represent the resource commitment of the firm and the external institutional environment that promotes smart manufacturing efforts.

Top Management Support (DDDM1) is defined as Data-Driven Decision Making and highlights the strategic management and managerial dedication that should be applied in incorporating data analytics within the decision-making processes.

Production Flexibility is established in terms of Organizational Culture (PF1) which focuses on the contribution of adaptive, collaborative, and innovator workplace environments in facilitating flexible production systems.

The conceptual basis of studying the relationships outlined in the structural model is made up of these constructs and their respective indicators.

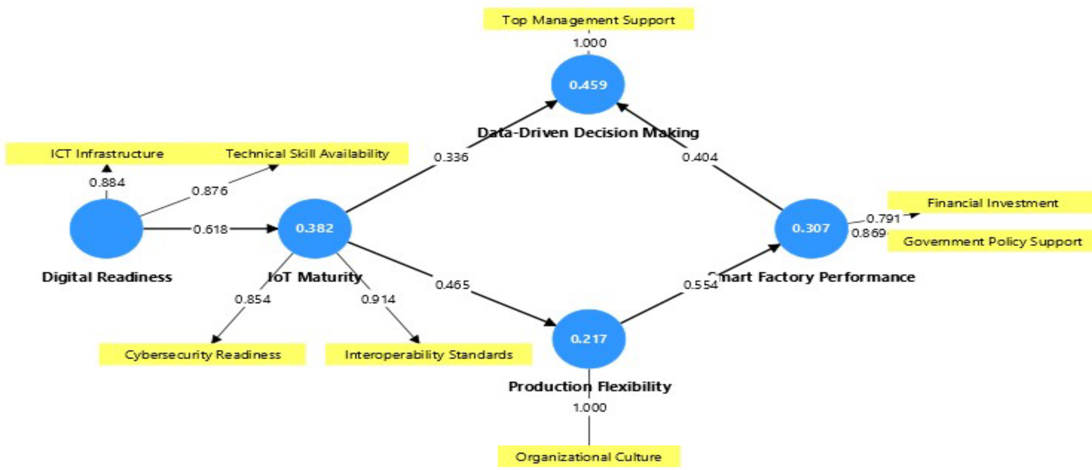

Fig. 1. The Structural Model

Table 1. Measures

Constructs	Measures	Sources
Digital Readiness	ICT Infrastructure (DR1)	(ALZHANOVA et al., 2020; Cucor et al., 2022)
	Technical Skill Availability(DR2)	
IoT Maturity	Cybersecurity Readiness (IoTM1)	(AlEnezi, 2019)
	Interoperability Standards (IoTM2)	
Smart Factory Performance	Financial Investment (SFP1)	(Arcidiacono & Schupp, 2024)
	Government Policy Support (SFP2)	
Data-Driven Decision Making	Top Management Support (DDDM1)	(Szukits & Móricz, 2024)
Production Flexibility	Organizational Culture (PF1)	(Naranjo Valencia et al., 2010)

In table 2, this was measured by using measurement model and composite reliability (CR) to determine the indicator loadings and average variance extracted (AVE) (Hair Jr et al., 2020). It displays how each of the constructs uses the variance, regarding the variables within their groups. AVE > 0. 50 will indicate that it explains more than 50 percent variance of the specific indicators of the respective construct. Also, the Cronbachs α (CA) are around 0.7 and the composite reliability (CR) are around 0.8. CA above 0.60 and 0.70 is good and CR 0.70 to 0.90 is good. Such results demonstrate that the indicators of this construct, which were adopted in the survey instrument, are correct and yield reliable outcomes.

Table 2. Construct, measurement items and their loadings

Construct	Measurement Items	Factor Loadings	Cronbach's α (CA)	Composite reliability (CR)	Average variance extracted (AVE)
Digital Readiness	DR1	0.884	0.708	0.872	0.774
	DR2	0.876			
IoT Maturity	IoTM1	0.854	0.726	0.878	0.783
	IoTM2	0.914			

Smart Factory Performance	SFP1	0.791	0.556	0.817	0.690
	SFP2	0.869			

3.2 Hypothesis Development

H1: Data-Driven Decision making has a direct impact on the performance of Smart factory.

H2: Digital Readiness affects the IoT Maturity positively.

H3: The presence of IoT Maturity was beneficial with regard to the Data-Driven Decision making.

H4: Production Flexibility is affected positively by the level of the IoT Maturity.

H5: The effect that Production Flexibility has on the Smart Factory Performance is positive.

H6: Data-Driven Decision making mediates the relationship between IoT Maturity and Smart Factory Performance.

H7: Production Flexibility mediates the relationship between IoT Maturity and Smart Factory Performance.

Table 3. Results of Direct Hypotheses

Hypothesis	**Path**	**Coefficient**	**t-Statistic**	**p-Value**	**Outcomes of assessment**
H1	Data-Driven Decision Making -> Smart Factory Performance	0.481	6.216	0.000	Accepted
H2	Digital Readiness -> IoT Maturity	0.618	10.298	0.000	Accepted
H3	IoT Maturity -> Data-Driven Decision Making	0.608	8.186	0.000	Accepted
H4	IoT Maturity -> Production Flexibility	0.465	4.647	0.000	Accepted
H5	Production Flexibility -> Smart Factory Performance	0.349	4.447	0.000	Accepted

In table 3, there are five hypotheses of direct effect and all of them are accepted as all the p-values of the hypotheses are less than 0.001 (Biau et al., 2010).

Table 4. Indirect hypotheses' result

Hypothesis	**Path**	**Coefficient**	**t-Statistic**	**p-Value**	**Conclusion**
H6	IoT Maturity -> Data-Driven Decision Making -> Smart Factory Performance	0.292	4.572	0.000	Accepted
H7	IoT Maturity -> Production Flexibility -> Smart Factory Performance	0.162	6.190	0.000	Accepted

In table 4, two indirect hypotheses are shown. Data-Driven Decision making and production flexibility both mediate the relationship between IoT Maturity and Smart Factory Performance. Both hypotheses's p values are <0.001. So, both are accepted (Di Leo & Sardanelli, 2020).

The scale of applying the intensity used in the AHP is displayed in Table V where linguistic directions which are used to express relative measure of significance of one weight against the other is given a number (1-9) (Wang & Chen, 2008). Odd numbers are used to denote more and more intensity of preference, whereas even numbers are used to compromise or yield some shades of judgments.

Table 5. Scale for AHP

Intensity scale	Linguistic terms	Explanation
1	Equal importance	Both factors contribute equally
3	Moderate importance	moderately favored one factor over another
5	Strong importance	strongly favor one factor over another
7	Very strong importance	strongly favored
9	Extreme importance	favoring one factor over another is of the highest possible order of affirmation
2,4,6,8	Intermediate importance	When compromise is needed

Table 6 indicates the pair wise comparison matrix that was included in determining the relative importance of eight factors (e.g., DDM1, DR2, etc.) by means of the AHP method. The resulting weights indicate that DDM1 (0.34) and DR2 (0.29) are the most influential and those which are the least significant are SFP2 (0.02) and IoTM1 (0.02). This is a matrix that indicates views of experts in prioritization of factors according to the intensity scale of AHP (Chang et al., 2009). Results in the weights guide priorities that should be taken into consideration in decision-making since they define what factors are most influential in the evaluation.

Table 6. Pairwise Comparison Matrix and Resulting Weights Using AHP

	DDM1	DR2	DR1	PF1	SFP1	IoTM2	IoTM1	SFP2	Weight
DDM1	1	2	5	7	3	9	7	9	0.34
DR2	0.5	1	4	5	9	7	9	5	0.29
DR1	0.2	0.25	1	5	5	4	6	9	0.15
PF1	0.14	0.2	0.2	1	1	1	3	3	0.05
SFP1	0.33	0.11	0.2	1	1	2	3	7	0.06
IoTM2	0.11	0.14	0.25	1	0.5	1	4	2	0.04
IoTM1	0.14	0.11	0.16	0.33	0.33	0.25	1	2	0.02
SFP2	0.11	0.2	0.11	0.33	0.14	0.5	0.5	1	0.02

The results of the AHP consistency check appear in Table 7 indicating the Consistency Ratio (CR) is 0.0958 and is lower than 0.1 which is the acceptable value (Lukinskiy et al., 2021). This means that the pair-wise comparisons make logical sense, and this confirms the soundness of the obtained weights.

Table 7. Result of Consistency

Consistency Factor	Results
λmax	8.939673
CI	0.134239
RI	1.41
CR	0.095808

4. Discussion

It is indicated in this discussion that the nature and extent of IoT Maturity and Digital Readiness render the Smart Factory Performance convenient and effective in Industry 4.0 situations (Lin et al., 2020). In particular, digital readiness is an influential factor in IoT maturity, which in turn leads to Data-Driven Decision Making and Production Flexibility two factors with highly considerable direct effects on performance outcomes. The results reinforce the primacy of IoT functions and structure focusing on cyber-based infrastructure in developing the malleability and efficacy of operations in intelligent production systems.

Noteworthy, the mediating effects of data-driven decision making with production flexibility imply that the contribution of IoT maturity is not only direct, but also via the effective decision process and flexibility of production capacities (Szukits, 2022). The second-order effect can help illustrate the strategic significance of the investment of technological and organizational preparedness to achieve the full extent of performance improvements.

These understanding are further supplemented by the AHP analysis which indicates that Top Management Support and Technical Skill Availability are the enablers that are considered most vital to effective IoT adoption and smart factory to undergo transformation. Such human and management aspects overshadowed more technological ones such as cybersecurity, policy support or the need to encourage committed leadership and skilled workforce creation to lead to the success of the Industry 4.0 (Behie et al., 2023).

Expert evaluations were consistent, and confirmed by CR value smaller than 0.1 value, which ensures the reliability of the prioritization results. Comprehensively, the combination of PLS-SEM and AHP offers a robust method to perform an integrated assessment of preparation that can help the manufactures to determine the core performance drivers and place priority on strategic investments (Qureshi et al., 2023).

5. Conclusion

It is in this context that the hybrid framework, the combination of metrics related to IoT adoption and PLS-SEM, and the AHP are introduced into the study to test the operational effectiveness of smart factories under Industry 4.0 (Kumar et al., 2024). The results reveal that production agility and performance are enriched enormously due to digital readiness and IoT maturity due to engendering data-driven decision making. The model can be used as a practical assessment practice by manufacturers to determine their readiness with regard to Industry 4.0 and prioritizing various technological and organizational enablers (Sony & Naik, 2020). The incorporation of AHP is the feature of the framework that provides more insightful strategic implications due to a deeper understanding of how different critical factors relate to one another. This study can address this gap by correlating the variables specific to IoT with the measurable performance indicators and giving a methodological framework in assessing smart factory (Sony & Naik, 2020). The model can be further enhanced in the future with new technologies or sectors, including AI and blockchain, or to other regions, in order to guarantee its high applicability level.

5.1 Implications

Theoretical contribution of the research is the usage of IoT-related constructs into the tested PLS-SEM model with the help of AHP (Sneesl et al., 2023). It further elaborates on how the digital readiness and IoT maturity relate to the performance of a smart factory specifically using mediating factors such as flexibility within production and induction of breakthroughs within data-driven decision-making. The performed research is a contribution to the current gray literature on how to assess Industry 4.0 performance and provides the basis of future empirical research on digitalization in the production sector.

The model is a decision-support tool when viewed as a managerial tool. It guides manufacturing leaders to evaluate their strategic and statistical readiness to be ready with Industry 4.0 as the manufacturing executives need to prioritize the investments between various enabling technologies. The AHP integration also assists the practitioners to know the relative importance of the factors of adoption so that a more targeted planning, resources allocation and performance optimization could be undertaken (Ho, 2008).

5.2 Limitations

The research has its limitations in spite of the variable contributions. The study is founded on cross-sectional survey data therefore lacking the capability to determine correspondences with time (Rindfleisch et al., 2008). The results are based on self-reported perceptions of manufacturing experts, and this can be full of biasness. Moreover, the model currently has only a few constructs and fails to consider other technologies that are on the rise. Lastly, the sampling is localized and this aspect can influence or compromise the standardization of the findings in another industrial setting and geography (Reynolds et al., 2003). The model must be used in future to cover a wide range of areas and longitudinal data must be included to make the model more applicable and predictive.

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