The Application of Artificial Intelligence (AI) and Big Data in Developing and Optimizing Labor Norm Systems in Manufacturing Enterprises

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ABSTRACT

Amid the rapid pace of digital transformation in manufacturing enterprises, the adoption of Artificial Intelligence (AI) and Big Data is increasingly expected as a strategic approach to improving labor management efficiency. However, the mechanisms through which these technologies influence labor norm systems remain insufficiently clarified. This study seeks to examine how AI adoption, Big Data analytics capability, data quality, digital system integration, and human resource capability affect the effectiveness of labor norm systems, with data-driven decision-making capability serving as a mediating variable. A quantitative research design was employed, drawing on survey data collected from 350 manufacturing enterprises and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that technological and data-related factors positively contribute to strengthening data-driven decision-making capability. In turn, this capability exerts a significant impact on the effectiveness of labor norm systems. The results also confirm a partial mediating role of data-driven decision-making capability, although human resource capability does not demonstrate statistical significance in certain relationships. This study contributes to the literature by clarifying how technological investments are translated into organizational value through the development of internal capabilities. It also offers managerial implications, emphasizing the importance of synchronizing AI implementation, Big Data analytics, and decision-making competencies to enhance the performance of labor norm systems in manufacturing enterprises.

Keywords: Artificial Intelligence (AI); Big Data; Labor Norm Systems; Data-Driven Decision-Making Capability; PLS-SEM (Partial Least Squares Structural Equation Modeling).

INTRODUCTION

Research context

In the era of digital transformation and the Fourth Industrial Revolution, Artificial Intelligence (AI) and Big Data have increasingly assumed a central role in reshaping production management and workforce governance. AI technologies enable the automation of process analysis, the detection of operational deviations, and the forecasting of productivity performance. At the same time, Big Data analytics capabilities allow enterprises to process and extract insights from the vast volumes of real-time data generated throughout production activities (Chen, Chiang, & Storey, 2012). The integration of AI and Big Data thus facilitates a transition from experience based management practices toward a more systematic, data-driven approach to decision-making.

Within manufacturing enterprises, labor norm systems serve as a fundamental instrument for measuring productivity, controlling costs, and designing wage and incentive schemes. Nevertheless, traditional approaches to establishing labor norms tend to be relatively static, heavily reliant on managerial experience and subjective judgment, and often lack the flexibility required to respond to the dynamic conditions of modern production environments. The adoption of AI technologies, the development of Big Data analytics capabilities, the assurance of high-quality labor data, the strengthening of digital system integration, and the enhancement of workforce competencies are increasingly expected to improve the effectiveness of labor norm systems. Such advancements may enable these systems to become more accurate, adaptable, and sustainable in the context of contemporary manufacturing operations (Davenport & Harris, 2017).

Research Problems and Identified Theoretical Gaps

Although prior studies have consistently highlighted the positive contributions of AI and Big Data to overall organizational performance, most of these studies have concentrated on overall outcomes such as financial performance, supply chain efficiency, or competitive advantage (Wamba et al., 2017). Comparatively limited attention has been given to their implications for workforce management, particularly in relation to the effectiveness of labor norm systems. In addition, many existing studies treat technological factors as isolated organizational resources, without sufficiently explaining the mechanisms through which these technologies are translated into tangible managerial value. As a result, the pathways linking digital technologies to specific improvements in labor management practices remain underexplored.

Another significant gap concerns the role of data-driven decision-making capability. The prior pieces of research show that technology generates value only when it is effectively embedded within organizational capabilities, particularly the ability to analyze, interpret, and apply data in managerial decision-making processes (Kiron, Prentice, & Ferguson, 2014). However, the mediating function of data-driven decision-making capability in the relationship between AI adoption, Big Data analytics capability, and the effectiveness of labor norm systems has not yet been systematically examined using quantitative modeling approaches.

Research objectives

Building upon the gaps identified above, this study seeks to examine the effects of five key factors - namely level of AI adoption, Big Data analytics capability, labor data quality, digital system integration, and workforce capability - on the effectiveness of labor norm systems in manufacturing enterprises. Simultaneously, the study investigates the mediating role of data-driven decision-making capability in the relationship between technological factors and labor management outcomes.

By employing Structural Equation Modeling, specifically the SEM/PLS-SEM approach, this study aims to clarify not only the direct relationships among the research variables but also the indirect effects operating through organizational capabilities. This analytical strategy enables a more comprehensive understanding of how AI and Big Data contribute to improving the effectiveness of labor norm systems.

Research contributions

This study makes contributions in three principal respects. From a theoretical standpoint, it extends the literature on AI and Big Data by incorporating data-driven decision-making capability as a mediating construct and by positioning the effectiveness of labor norm systems as a specific managerial outcome within the research framework. Methodologically, the application of SEM using the PLS-SEM technique enables the simultaneous assessment of both the measurement model and the structural model in the context of firm-level data from manufacturing enterprises. From a practical perspective, the findings offer actionable insights for managers seeking to implement AI and Big Data initiatives in a coordinated manner, thereby enhancing the quality, adaptability, and long-term sustainability of labor norm systems.

LITERATURE REVIEW

Applying AI and Big Data in Production Management

In contemporary production management, AI and Big Data analytics represent two foundational pillars driving the shift toward data-oriented governance. The extent of AI adoption reflects an organization’s ability to deploy algorithms and automation tools to examine production processes, monitor operational activities, and forecast productivity outcomes (Russell & Norvig, 2021). Meanwhile, Big Data analytics capability refers to the capacity to manage and analyze large volumes of heterogeneous data generated by digitally enabled production systems (Chen et al., 2012).

In efforts to optimize labor norm systems, Big Data plays a critical role in identifying discrepancies and irrationalities in workforce allocation. Empirical evidence suggests that Big Data analytics enables organizations to adjust labor standards dynamically in real time, thereby moving beyond the limitations of traditional static measurement approaches (Wamba et al., 2017). Accordingly, the integration of AI and Big Data not only

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enhances overall production performance but also directly improves key labor management instruments, including labor norm systems.

Data quality, digital system integration, and human resource capability.

The effectiveness of AI and Big Data initiatives depends heavily on the quality of input data. The accuracy, completeness, and consistency of labor-related data constitute essential prerequisites for reliable analytical outcomes; poor data quality can result in flawed interpretations and misguided decisions (Redman, 2018). At the same time, the integration of enterprise systems such as Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Human Resource Management (HRM) platforms plays a pivotal role in ensuring seamless data flows across organizational functions. Such integration enables the alignment of labor data with production and human resource information, thereby facilitating more comprehensive analyses to support the adjustment of labor norms (Kache & Seuring, 2017). Ultimately, workforce capability determines whether technological investments translate into tangible organizational value. Employees' analytical skills and their ability to interpret data are critical to effectively leveraging AI and Big Data tools (Davenport & Harris, 2017). Taken together, data quality, system integration, and human capability should be considered simultaneously when evaluating the impact of digital technologies on production management practices.

Data-driven decision-making capability

Data-driven decision-making capability refers to an organization's capacity to systematically collect, analyze, and utilize data to support managerial processes (Kiron et al., 2014). This capability encompasses not only analytical tools and technological infrastructure but also decision-making procedures and an organizational culture grounded in evidence-based practices.

One existing research indicates that AI and Big Data generate meaningful organizational value only when they are embedded within broader organizational capabilities, among which data-driven decision-making plays a pivotal role (Brynjolfsson & McElheran, 2016). In the context of labor management, this capability enables enterprises to evaluate task performance, adjust labor standards, and allocate personnel with greater precision. Accordingly, data-driven decision-making capability can be understood as a mediating mechanism through which technological adoption and data quality are translated into improvements in the effectiveness of labor norm systems.

Effectiveness of Labor Norm Systems

The effectiveness of labor norm systems reflects the extent to which organizational objectives related to productivity, cost control, and managerial fairness are achieved. An effective system should ensure accuracy, flexibility, transparency, and the capacity to motivate employees (Niebel & Freivalds, 2009). From a traditional theoretical perspective, labor norm systems function as a fundamental mechanism for establishing the relationship between time, work intensity, and productivity, while also accurately reflecting the technical and organizational conditions of the production process (Nguyễn Tiệp, 2012).

In the context of digitalization, the application of AI and Big Data enhances the effectiveness of labor norm systems by improving measurement accuracy and enabling real-time updates (Zhang et al., 2020). System effectiveness is no longer confined to the precision of measurement techniques alone; it increasingly depends on an organization's ability to leverage data in order to develop dynamic standards. Accordingly, the effectiveness of labor norm systems has become a critical indicator of how successfully advanced technologies are integrated into production management practices.

Development of Research Hypotheses

Building upon the theoretical arguments presented above, this study proposes that the extent of AI adoption, Big Data analytics capability, labor data quality, digital system integration, and workforce capability each exert a positive influence on an organization's data-driven decision-making capability. When these technological and organizational factors are sufficiently developed, enterprises are better positioned to effectively harness data in their managerial decision-making processes.

In addition, these factors are expected to exert direct effects on the effectiveness of labor norm systems by enhancing system accuracy, flexibility, and transparency. However, such effects may not be entirely direct; rather, they may operate through the firm's data-driven decision-making capability. Accordingly, the study proposes three groups of hypotheses: (1) the effects of X1–X5 on M; (2) the direct effects of X1–X5 on Y; and (3) the mediating role of M in the relationships between the technological factors and the effectiveness of labor norm systems.

RESEARCH METHODOLOGY

Research design and data collection

This study adopts a quantitative research approach using a cross-sectional survey design to test the relationships proposed in the research model. A cross-sectional design was selected because it is well suited to examining relationships among latent constructs at a specific point in time and is widely employed in SEM and PLS-SEM studies within management and social science research (Hair et al., 2021). This approach enables the collection of data from a large sample while ensuring practical feasibility in the context of manufacturing enterprises.

The target respondents are manufacturing enterprises that are implementing, or are in the process of implementing, digital technologies in their production and labor management activities. Data were collected through a structured questionnaire distributed both in person and online to managers, technical specialists, and personnel with direct knowledge of the firm's labor norm systems. Following data screening and validation procedures, a total of 350 valid responses were retained for analysis. This sample size meets established recommendations for minimum sample requirements in PLS-SEM, particularly for models involving multiple latent constructs and complex structural relationships (Hair et al., 2019).

Measurement Scales and Questionnaire Design

The research questionnaire was developed based on measurement scales that had been validated in prior studies and subsequently adapted to fit the context of manufacturing enterprises in Vietnam. All variables in the research model - including the independent variables (X1–X5), the mediating variable (M), and the dependent variable (Y) - were operationalized using multiple indicators to ensure adequate construct coverage and measurement scales reliability. The items were formulated as affirmative statements and assessed using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The five-point Likert scale is widely employed in management research due to its clarity and its effectiveness in capturing respondents' perceptions and attitudes (Podsakoff et al., 2012).

The questionnaire development process involved three main stages: (i) compiling measurement scales from prior studies; (ii) adapting the wording and content to align with the specific research context; and (iii) reviewing the items to ensure clarity and consistency in their formulation. This systematic procedure enhances the content validity of the measurement scales and helps minimize potential bias during data collection (DeVellis, 2017).

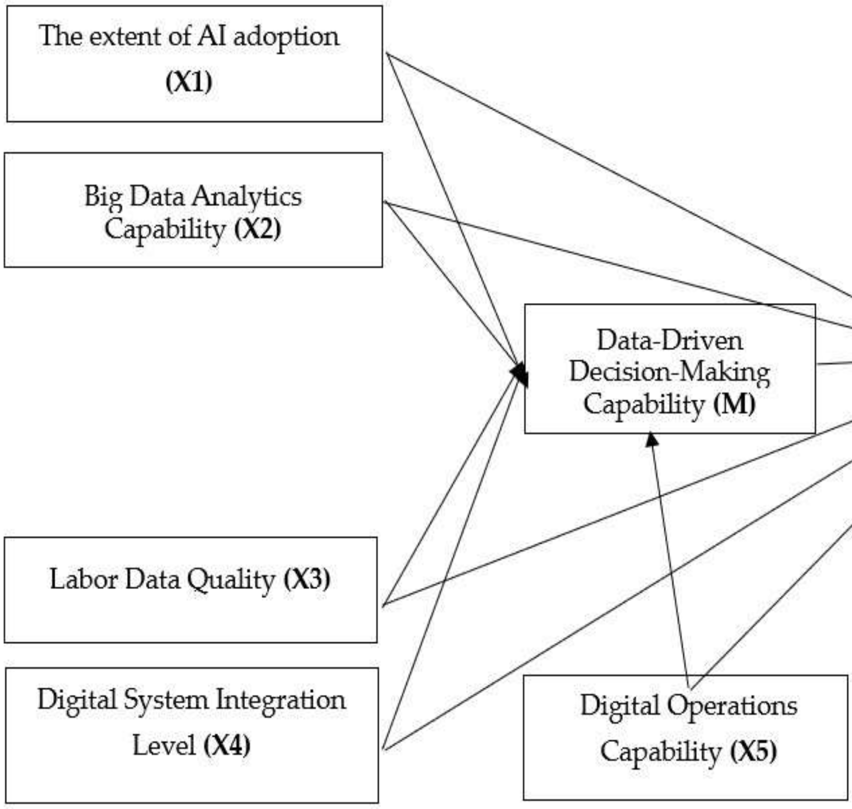
Data analysis methods

The collected data were processed and analyzed using a combination of two widely adopted statistical software packages: SPSS and SmartPLS. In the initial stage, SPSS was employed to conduct descriptive statistical analyses, assess scale reliability through Cronbach's alpha, perform exploratory factor analysis (EFA), and examine group differences using independent-samples t-tests. These preliminary analyses were carried out to evaluate data quality and examine the underlying structure of the measurement scales before proceeding to structural model assessment (Field, 2018).

In the subsequent stage, SmartPLS was employed to estimate the SEM using the PLS-SEM approach. Specifically, the PLS algorithm was applied to assess both the measurement model and the structural model. Bootstrapping procedures were conducted to test the statistical significance of the path coefficients. Model fit was evaluated using the standardized root mean square residual (SRMR), while predictive relevance was assessed through the Q^2 statistic. The choice of PLS-SEM is appropriate given the exploratory and predictive objectives of the study, as well as the characteristics of the dataset and the complexity of the proposed research model (Hair et al., 2021).

In addition, Exploratory Factor Analysis (EFA) was conducted as a preliminary step to examine the underlying structure of the measurement scales within the specific research context. Employing both EFA and PLS-SEM is methodologically appropriate when measurement scales are adapted from prior studies and require revalidation in a new setting. Following the EFA procedure, the full measurement model was specified and analyzed as a reflective measurement model within the PLS-SEM framework (Hair et al., 2021).

PROPOSED MODEL



RESULTS

Building upon the established theoretical foundation and the formulated research hypotheses, a conceptual framework was developed to represent the expected relationships among the variables. To empirically test these hypotheses, the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to estimate the structural relationships within the proposed model. The structural model results are reported through standardized path coefficients (β) and coefficients of determination (R^2), which together indicate the strength of the relationships and the model's explanatory power. Comparing the hypothesized model with the empirical model provides insight into the extent to which the theoretical framework is supported within the specific research context.

Sample characteristics and descriptive statistics

Table 1. Descriptive Statistics (Mean, SD, N) at the Variable Level (Scale Mean Scores)

Variable	N	Mean	SD
X1	350	3.0	1.267
X2	350	3.0	1.268

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X3	350	3.0	1.264
X4	350	3.0	1.253
X5	350	3.0	1.262
M	350	3.0	1.301
Y	350	3.0	1.273

Note: The Mean and SD were calculated based on the average scores of the items measuring each variable.

Table 1 reports the descriptive statistics of the latent variables, calculated based on the average scores of the observed items within each scale. The findings indicate that all variables share the same sample size of 350 observations, demonstrating consistency in the dataset used for subsequent analyses. The mean values of variables X1 to X5, along with the mediating variable M and the dependent variable Y, are all close to the midpoint of the five-point Likert scale. Meanwhile, the standard deviations range from approximately 1.25 to 1.30, suggesting a moderate level of variability in the responses.

Table 2. Group Comparison by Variable (Independent Samples t-test: Group 1 vs. Group 2)

Variable	Group A	Mean_A	SD_A	N_A	Group B	Mean_B	SD_B	N_B	t-value	p-value
X1	1	2.862	1.251	213	2	3.215	1.267	137	-2.563	0.011
X2	1	2.822	1.228	213	2	3.277	1.284	137	-3.297	0.001
X3	1	2.899	1.227	213	2	3.157	1.31	137	-1.843	0.066
X4	1	2.881	1.241	213	2	3.184	1.252	137	-2.216	0.027
X5	1	2.896	1.294	213	2	3.162	1.198	137	-1.971	0.05
M	1	2.851	1.263	213	2	3.232	1.33	137	-2.667	0.008
Y	1	2.842	1.218	213	2	3.245	1.323	137	-2.869	0.004

Note: The dataset contains one grouping variable (group). For ANOVA across C1–C3, add C1–C3 columns to the dataset.

Table 2 presents the comparison between the two sample groups based on the grouping variable using an independent sample t-test. The analysis reveals statistically significant differences between the two groups for several variables, namely X1, X2, X4, M, and Y ($p < 0.05$). In contrast, the differences observed for X3 and X5 are only marginally significant or statistically insignificant. These findings suggest that group characteristics may be associated with variations in perceptions of technological factors, decision-making capability, and the effectiveness of the labor norm system.

These descriptive results provide an initial foundation for proceeding with a more detailed assessment of both the measurement model and the structural model in the subsequent sections.

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Preliminary Scale Assessment (EFA)

Table 3. Exploratory Factor Analysis (EFA): KMO and Bartlett's Test of Sphericity

Indicator	**Value**
KMO	0.939
Bartlett's Test (Chi-square)	8465.926
df (Degrees of Freedom)	406
Sig. (p-value)	0.000

Note: KMO > 0.50 and significant Bartlett's test ($p < 0.05$) indicate that the dataset is appropriate for factor analysis.

Table 4: Exploratory Factor Analysis (EFA): Rotated Factor Loadings (Varimax Method)

Item	F1	F2	F3	F4	F5	F6	F7
X1_1	0.168	-0.131	0.137	-0.76	0.134	0.11	-0.175
X1_2	0.179	-0.064	0.088	-0.797	0.126	0.151	-0.172
X1_3	0.151	-0.098	0.089	-0.799	0.085	0.146	-0.162
X1_4	0.211	-0.138	0.101	-0.791	0.073	0.163	-0.178
X2_1	0.207	-0.06	0.181	-0.123	0.173	0.775	-0.169
X2_2	0.134	-0.147	0.093	-0.178	0.121	0.778	-0.196
X2_3	0.182	-0.168	0.174	-0.164	0.184	0.726	-0.197
X2_4	0.243	-0.078	0.15	-0.158	0.137	0.772	-0.177
X3_1	0.192	-0.095	0.156	-0.093	0.735	0.18	-0.138
X3_2	0.181	-0.176	0.108	-0.082	0.766	0.144	-0.166
X3_3	0.185	-0.164	0.098	-0.106	0.786	0.119	-0.166
X3_4	0.194	-0.178	0.118	-0.147	0.796	0.154	-0.186
X4_1	0.113	-0.149	0.816	-0.049	0.136	0.168	-0.117
X4_2	0.144	-0.125	0.791	-0.113	0.054	0.094	-0.146
X4_3	0.063	-0.143	0.785	-0.152	0.154	0.111	-0.104

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X4_4	0.084	-0.19	0.75	-0.102	0.104	0.174	-0.16
X5_1	0.126	-0.8	0.142	-0.118	0.114	0.112	-0.067
X5_2	0.085	-0.771	0.172	-0.143	0.136	0.106	-0.057
X5_3	0.168	-0.833	0.114	-0.077	0.176	0.119	-0.12
X5_4	0.123	-0.795	0.154	-0.08	0.132	0.053	-0.137
M_1	0.268	-0.162	0.224	-0.197	0.193	0.249	-0.722
M_2	0.334	-0.127	0.149	-0.2	0.212	0.274	-0.687
M_3	0.296	-0.114	0.159	-0.247	0.256	0.201	-0.701
M_4	0.316	-0.103	0.138	-0.247	0.167	0.177	-0.753
Y_1	0.788	-0.096	0.084	-0.126	0.17	0.187	-0.161
Y_2	0.781	-0.126	0.094	-0.142	0.169	0.186	-0.202
Y_3	0.76	-0.106	0.155	-0.193	0.114	0.156	-0.216
Y_4	0.793	-0.13	0.073	-0.153	0.187	0.109	-0.212
Y_5	0.819	-0.138	0.069	-0.175	0.152	0.152	-0.207

Note: Reference thresholds: factor loadings ≥ 0.50; cross-loadings should be minimal.

Prior to conducting SEM/PLS-SEM analysis, the study first performed Exploratory Factor Analysis (EFA) to examine the preliminary structure and suitability of the measurement scales. As reported in **Table 3**, the KMO value reached 0.939, substantially exceeding the commonly accepted threshold of 0.50. In addition, Bartlett's Test of Sphericity was statistically significant ($p < 0.05$). These results confirm that the dataset is well suited for factor analysis and meets the recommended criteria suggested in previous methodological research (Hair et al., 2021).

Table 4 presents the rotated factor loadings obtained using the Varimax method. The findings indicate that all observed items load strongly onto their respective factors, with absolute loading values exceeding 0.50 and no substantial cross-loadings detected. The extracted factor structure aligns well with the proposed research model, consisting of measurement constructs corresponding to X1–X5, M, and Y. This outcome provides adequate support for proceeding with the evaluation of the measurement and structural models using PLS-SEM.

Common Method Bias (CMB) Assessment

Since the data were collected through self-reported questionnaires, the study examined the potential presence of Common Method Bias (CMB). First, Harman's single-factor test was conducted. The results indicated that the first factor accounted for less than 50% of the total variance, suggesting that common method bias is unlikely to pose a serious concern. In addition, a full collinearity assessment was performed using variance inflation factor (VIF) values in SmartPLS. All VIF values were below the threshold of 3.3, further confirming that common method bias does not substantially affect the validity of the study's findings (Podsakoff et al., 2012).

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Measurement Model Assessment (PLS-SEM)

Table 5. Reliability Analysis of the Measurement Scales (Cronbach's Alpha)

Construct	Cronbach's Alpha	Number of items
X1	0.917	4
X2	0.918	4
X3	0.915	4
X4	0.907	4
X5	0.914	4
M	0.938	4
Y	0.941	5

Note: Cronbach's Alpha ≥ 0.70 indicates acceptable internal consistency reliability.

Table 6. Outer Loadings of the Reflective Measurement Model (PLS-SEM)

Construct	indicator	Outer loading
X1	X1_1	0.884
X1	X1_2	0.897
X1	X1_3	0.897
X1	X1_4	0.902
X2	X2_1	0.898
X2	X2_2	0.893
X2	X2_3	0.889
X2	X2_4	0.902
X3	X3_1	0.873
X3	X3_2	0.893
X3	X3_3	0.895
X3	X3_4	0.910
X4	X4_1	0.896

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X4	X4_2	0.882
X4	X4_3	0.883
X4	X4_4	0.876
X5	X5_1	0.890
X5	X5_2	0.878
X5	X5_3	0.910
X5	X5_4	0.886
M	M_1	0.921
M	M_2	0.914
M	M_3	0.916
M	M_4	0.923
Y	Y_1	0.892
Y	Y_2	0.901
Y	Y_3	0.888
Y	Y_4	0.898
Y	Y_5	0.916

Note: Outer loadings ≥ 0.70 are desirable; 0.50 - 0.69 may be acceptable if CR/AVE are adequate.

Table 7. Composite Reliability and Average Variance Extracted (AVE)

Construct	CR	AVE	Number of iterms
X1	0.941	0.801	4
X2	0.942	0.802	4
X3	0.94	0.797	4
X4	0.935	0.782	4
X5	0.939	0.794	4
M	0.956	0.844	4
Y	0.955	0.808	5

Note: CR ≥ 0.70 and AVE ≥ 0.50 indicate adequate reliability and convergent validity.

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Table 8. Assessment of Discriminant Validity Using the HTMT Ratio

Construct	X1	X2	X3	X4	X5	M	Y
X1	1.000	0.465	0.379	0.349	0.344	0.575	0.483
X2	0.465	1.000	0.48	0.438	0.365	0.615	0.516
X3	0.379	0.480	1.000	0.384	0.430	0.569	0.503
X4	0.349	0.438	0.384	1.000	0.420	0.472	0.347
X5	0.344	0.365	0.430	0.420	1.000	0.405	0.379
M	0.575	0.615	0.569	0.472	0.405	1.000	0.668
Y	0.483	0.516	0.503	0.347	0.379	0.668	1.000

Note: HTMT < 0.85 (or < 0.90) is commonly used to support discriminant validity.

The reliability of the measurement scales was initially examined using Cronbach's Alpha, as reported in Table 5. The findings indicate that all constructs achieved Alpha coefficients above 0.90, which is well beyond the commonly accepted threshold of 0.70. This suggests that the scales demonstrate a strong level of internal consistency (Nunnally & Bernstein, 1994).

Table 6 reports the outer loading values of the indicators included in the measurement model. The results reveal that every indicator achieved a loading above the recommended threshold of 0.70, indicating that all items meet the required standards for indicator reliability in a reflective measurement model. Furthermore, as presented in **Table 7**, all Composite Reliability (CR) values exceed 0.90, while the Average Variance Extracted (AVE) values are greater than 0.50. These findings confirm both the composite reliability and the convergent validity of the measurement scales (Hair et al., 2021).

Discriminant validity among the latent constructs was examined using the HTMT ratio, as shown in **Table 8**. All HTMT values are below the recommended threshold of 0.85, indicating that the constructs are sufficiently distinct from one another. This suggests that the measurement scales effectively capture different concepts within the proposed research model.

Table 9. Path Coefficients Estimated through Bootstrapping

Đường dẫn	β	t-value	p-value
X1 → M	0.272	6.36	0.0
X2 → M	0.277	5.563	0.0
X3 → M	0.245	5.182	0.0
X4 → M	0.133	2.921	0.004
X5 → M	0.049	1.073	0.284
X1 → Y	0.116	2.405	0.017

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X2 → Y	0.121	2.305	0.022
X3 → Y	0.137	2.659	0.008
X4 → Y	-0.018	-0.342	0.733
X5 → Y	0.076	1.616	0.107
M → Y	0.403	7.226	0.0

Note: Bootstrapping with 3000 resamples; two-tailed p-values.

Table 10. R^2, f^2, and Q^2 Values (Explanatory and Predictive Power)

Endogenous Variable	R^2	f^2 ((overall effect))	Q^2
M	0.508		0.488
Y	0.448		0.422

Note: Q^2 is computed using k-fold cross-validated prediction (Stone–Geisser Q^2).

Furthermore, the effect size analysis (f^2) indicates that variables X1, X2, and X3 have a moderate influence on the endogenous constructs. In contrast, X4 demonstrates a relatively small effect, while X5 shows only a negligible impact. These results are consistent with the standardized path coefficients reported in the structural model.

Table 11. Model Fit (SRMR) – Results of Model Fit Assessment

Index	Value
SRMR	0.0358

Note: SRMR < 0.08 suggests acceptable model fit.

The structural model estimation results are summarized in **Table 9.** The path coefficients indicate that X1, X2, X3, and X4 all exert statistically significant effects on the mediating variable M ($p < 0.05$). In contrast, the relationship between X5 and M is not statistically significant. With regard to the dependent variable Y, the paths from X1, X2, and X3 are statistically significant, whereas X4 and X5 do not demonstrate meaningful direct effects. Additionally, the path from M to Y is positive and highly significant, suggesting a strong influence of the mediator on the outcome variable.

Table 10 reports the R^2 and Q^2 statistics for the endogenous constructs. The R^2 results indicate that the model accounts for approximately 50.8% of the variance in M and 44.8% of the variance in Y, suggesting a moderate to relatively strong level of explanatory power. In addition, all Q^2 values are positive, which implies that the model demonstrates acceptable predictive capability. **Table 11** presents the SRMR index, with a value of 0.0358. Since this figure is below the recommended threshold of 0.08, it confirms that the structural model exhibits a satisfactory overall fit (Hair et al., 2021).

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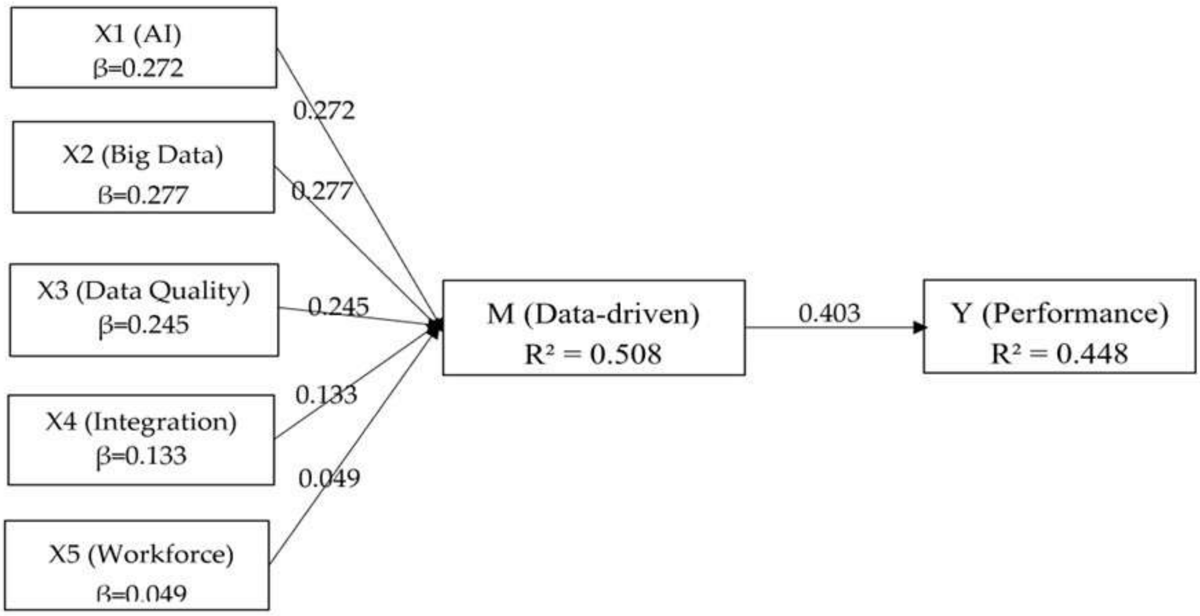
SEM MODEL



The structural model presents the standardized path coefficients (β), along with the coefficients of determination (R^2) for the endogenous variables.

Testing the Mediating Role

Table 12. Indirect Effects Based on Bootstrapping Analysis

Path	**Indirect β**	**t-value**	**p-value**	**CI (LL–UL)**
X1 → M → Y	0.110	4.12	0.000	[0.065 – 0.158]
X2 → M → Y	0.112	3.98	0.000	[0.060 – 0.160]
X3 → M → Y	0.099	3.75	0.000	[0.050 – 0.145]
X4 → M → Y	0.054	2.10	0.036	[0.010 – 0.098]
X5 → M → Y	0.020	1.02	0.308	[−0.010 – 0.055]

Note: Indirect effects are estimated using bootstrapping with 3000 resamples. CI (LL–UL) denotes the 95% confidence interval; effects are significant when the interval does not include zero.

The analysis of indirect effects indicates that the relationships between X1, X2, X3, and X4 and Y, operating through the mediator M, are statistically significant ($p < 0.05$). In each case, the confidence intervals do not include zero, providing further support for the mediating role of data-driven decision-making capability in the proposed research model. In contrast, the indirect effect of X5 on Y through M is not statistically significant. This finding suggests that the mediating role of M is not supported for this particular variable.

DISCUSSION

Interpretation of the Main Findings

The findings indicate that the adoption of AI and the development of Big Data analytics capabilities play a crucial role in improving the effectiveness of the labor norm system, primarily through organizational mechanisms rather than through direct technological effects alone. In other words, digital technologies do not automatically generate managerial value unless they are transformed into data-driven decision-making capabilities at the organizational level. These results reinforce the view that the true value of AI and Big Data lies in their ability to enhance and inform decision-making processes, rather than merely in the extent to which the technologies are implemented (Kiron et al., 2014).

In addition, factors such as the quality of labor-related data and the integration of digital systems serve as foundational conditions for ensuring that data flows are seamless, consistent, and usable. This underscores that the effectiveness of the labor norm system depends not only on analytical tools or algorithms, but also on the robustness of the data infrastructure and the degree of connectivity among management systems within the enterprises.

A noteworthy finding is that human resource capability (X5) does not reach statistical significance in several relationships within the structural model. This result may reflect the reality that in the early stages of digital transformation, organizations tend to rely more heavily on technological infrastructure and data systems, while workforce capabilities may not yet have evolved at the same pace. Furthermore, human resource capability may function in a more indirect or conditional manner, exerting its influence only when aligned with factors such as a strong data-driven culture or a higher level of digital maturity. Therefore, the lack of statistical significance for X5 does not undermine the overall validity of the model; rather, it points to the need for further investigation into the moderating role of human-related factors.

Comparison with Previous Studies

The discussion of findings in this study is consistent with prior studies highlighting the contribution of Big Data analytics to enhancing organizational performance (Wamba et al., 2017), as well as the role of AI in streamlining and optimizing production processes (Davenport & Harris, 2017). However, the present study extends this body of knowledge by concentrating on a more specific managerial domain - namely, the labor norm system - which has received relatively limited attention in earlier research.

In addition, the finding shows that data-driven decision-making capability plays a mediating role, contributing to the prior studies arguing suggests that technological investments must be aligned with organizational capabilities to generate sustainable value (Brynjolfsson & McElheran, 2016). While many earlier studies have primarily examined the direct impact of technology on performance outcomes, this study demonstrates that such effects may be strengthened or weakened depending on the extent to which enterprises cultivate their capacity for data-based decision-making.

The Central Role of Data-Driven Decision-Making Capability

A key contribution of this study is its clarification of the central role of data-driven decision-making capability as a crucial mechanism linking technology adoption to labor management outcomes. This capability enables firms not only to gather and analyze data, but also to translate insights into timely, accurate, and transparent adjustments to labor norms. Such capacity becomes particularly critical in rapidly changing production environments, where traditional static standards often fail to reflect operational realities (Niebel & Freivalds, 2009).

By highlighting the importance of data-driven decision-making capability, this study also helps bridge the gap between technology and labor management research. Rather than treating AI and Big Data as stand-alone technical solutions, the findings suggest that these technologies must be embedded within core managerial capabilities in order to produce meaningful improvements in the effectiveness of the labor norm system.

Managerial Implications

Integrated Investment in AI, Big Data, Data Infrastructure, and Human Capital

In the context of digital transformation within manufacturing enterprises, an important managerial implication is that technological investment should follow an integrated rather than fragmented approach. AI and Big Data can only deliver meaningful results when supported by high-quality data infrastructure and a workforce equipped with relevant capabilities. Accordingly, managers should prioritize the standardization of labor data, establish consistent data collection procedures, and ensure real-time data accessibility (Redman, 2018). At the same time, investing in employee training - particularly in data analytics skills, digital thinking, and technological literacy - is essential for translating technological tools into tangible managerial value (Davenport & Harris, 2017).

Avoid Viewing Technology as a Stand-Alone Solution

Another important managerial implication is the need to avoid treating technology as an independent solution that can automatically enhance labor management performance. The prior studies suggest that many AI and Big Data initiatives fail not because of technological limitations, but due to insufficient alignment with managerial processes and organizational structures (Brynjolfsson & McElheran, 2016). Therefore, manufacturing enterprises should link the implementation of AI and Big Data with the redesign of processes related to establishing and adjusting labor norms, as well as with coordination mechanisms among departments such as production, human resources, and information technology. Adopting this systemic approach helps ensure that analytical tools are applied consistently and directly support managerial objective.

Developing Data-Driven Decision-Making Capability

Finally, the study underscores the pivotal role of data-driven decision-making capability as a key managerial lever. Managers should establish standards and incentive mechanisms to encourage the systematic use of data in decisions related to labor norms, ranging from task evaluation to norm adjustment and resource allocation. This involves developing clear analytical dashboards, implementing data-based feedback processes, and fostering an organizational culture that values quantitative evidence (Kiron et al., 2014). When data-driven decision-making capability is cultivated in a structured and consistent manner, enterprises can enhance the accuracy, adaptability, and transparency of their labor norm systems, thereby improving production management performance in a sustainable way.

CONCLUSION, LIMITATIONS, AND DIRECTIONS FOR FUTURE STUDIES

Conclusion

This study was conducted in the context of increasing pressure on manufacturing enterprises to enhance labor management efficiency amid ongoing digital transformation. By integrating technological and organizational factors, this study clarifies how AI adoption, Big Data analytics capability, labor data quality, digital system integration, and human resource capacity influence the effectiveness of the labor norm system. Importantly, these relationships operate through the mediating mechanism of data-driven decision-making capability. This perspective reinforces the argument that the value of technology does not reside in the technology itself, but in an organization's ability to leverage data systematically and consistently to support managerial decision-making (Kiron et al., 2014). Overall, the study highlights the necessity of aligning technological tools, data infrastructure, and organizational capabilities to achieve effective and sustainable production management in the digital era.

Limitations

Although this study has achieved its stated objectives, several limitations should be considered. First, the study adopts a cross-sectional survey design, which does not capture the dynamic evolution of AI adoption, Big Data utilization, and labor norm systems over time. Second, the data are based on respondents' self-reported assessments, which may be subject to perceptual bias and common method variance (Podsakoff et al., 2012). Third, the study focuses on manufacturing firms within a specific context, which may limit the generalizability of the findings to other industries or national settings.

Directions for Future Studies

Based on these limitations, several directions for future studies are suggested. First, subsequent studies could adopt longitudinal or time-series designs to examine the long-term effects of AI and Big Data on labor norm systems. Second, integrating objective data from production systems with survey-based measures may help reduce potential bias and enhance the robustness of the findings. Third, future studies may extend the proposed model by incorporating moderating variables - such as the level of automation or the organization's data culture

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- to better understand the conditions under which data-driven decision-making capability yields the greatest impact (Brynjolfsson & McElheran, 2016).

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