Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 30 June 2026
Revised 05 Aug 2026
Accepted 18 Aug 2026

Natural Resources for Human Health 2026, Vol. 6 (17s): 971–985

KEYWORDS:
Artificial intelligence, enterprise management, industrial upgrading, intelligent manufacturing, AI adoption, organizational capability, digital transformation, Industry 4.0, productivity, innovation, AI governance.

Artificial Intelligence in Business Development and Industrial Upgrading: Environmental Impacts and Sustainability Implications

[1]*Li Jinghan, [2]Dr. Amiya Bhaumik

[1]* Ph.D. Scholar, Lincoln University College, Malaysia
Email: jinghan.phdscholar@lincoln.edu.my, ORCID: 0009-0008-0805-9580
[2]President (Chancellor), Lincoln University College
Email– amiya@lincoln.edu.my, ORCID ID- 0000-0002-9188-2269

ABSTRACT: Artificial Intelligence (AI) is a necessary technological facilitator for enterprise management, industrial digitalisation, intelligent production, coordination of the supply chains, predictive analysis and strategic decisions. The transition from the conventional information systems to the AI powered enterprise architectures has an impact on allocation of resources, management of production, prediction of demand, control of quality, product design, coordination of employees and machines. The study explores how AI can be utilized in enterprise management and how it can help with industrial upgrading from integrated technology–organisation–environment and dynamic-capability perspectives. This research is a systematic review and a literature synthesis of the research literature, and a quantitative empirical research framework on the study of AI readiness, the intensity of AI adoption, organizational capability, intelligent manufacturing integration and enterprise performance, AI readiness is divided into two parts, one is to study whether the enterprise is ready for AI applications, and the second is to study the adaptation process of AI applications. According to the literature analysis, technological infrastructure, the quality of data, organisational readiness, management support, employee capability, financial resources, regulatory conditions and strategic alignment are the factors that affect the adoption of AI. Empirical research on manufacturing companies also confirms that there is a combined impact of technological and organisational preparation and AI adoption, as well as the fact that there are differences in AI adoption among companies according to their scale and product complexity.

A sample of 420 enterprises is taken as a representative sample to demonstrate the model of analysis for quantitative analysis. The results indicate that the extent of AI use is positively associated with operational efficiency and capability to innovate, management decision quality, and AI industrial upgrading performance. Based on the results of structural equations, it can be seen that AI use has a direct positive standardised effect on enterprise performance (0.41) and industrial upgrading (0.46) and that organisational capability strengthens the relationship between AI use and enterprise performance. The business value of AI-based predictive maintenance, intelligent quality inspection and demand prediction, optimisation of supply chains is the highest. The proposed model shows that for the benefit of AI to be maximised, the model demands support from data infrastructure, organisational capacity, qualified staff, and suitable governance and process redesign as well. Based on this research, the study suggests a holistic framework which is related to the readiness and adoption of AI, enterprise management and upgrading of industries, and proposes a quantitative assessment method for the transformation by AI

Natural Resources for Human Health
eISSN: 2583-1194

1. INTRODUCTION

AI is not just a nascent computational experiment; it's an integral component of today's business landscape. AI is becoming an integral part of production, marketing, finance, HR, logistics, procurement, research and development and strategic planning. In the industrial sector, vast quantities of data are produced during operation, for example through an enterprise resource planning system, the industrial Internet, sensors, robotics, production machines or supply chains, making artificial intelligence a vital topic.

The widespread use of AI is a more than incremental development of information processing capabilities (Zou and Xiong et al., 2023). AI can transform the way that organisations process data and predict conditions, which helps them make informed decisions regarding operations. Periodic management interventions are often based upon historical data, and rules that are already given, in traditional enterprise management. Real-time data, predictive models, and automated recommendations can all be used by AI-powered management to assist in ongoing decision-making. This not only helps in the reduction of information lag but also helps in better utilization of resources and quick response towards the changes of market and production factors.

The commercial application of AI is also important. Complex data is produced by manufacturing enterprises from machines, production lines, warehouses, quality-control systems and logistics networks. With AI algorithms, these data can be analyzed to detect patterns and forecast equipment failures, product defects, energy consumption, production slowdowns, and demand spikes (He et al., 2023). In a new study, researchers have identified two key mechanisms as important for the link between AI adoption and TFP: technology upgrading and value-added improvement and BIOTC.According to new research, researchers have identified two important mechanisms that drive the relationship between AI adoption and TFP: technology upgrading and value-added improvement and BIOTC.

The use of AI, however, doesn't necessarily translate to enterprise benefits. Just because there is an AI platform, software system or algorithm, doesn't mean productivity or industrial upgrading is improved. Appropriate data, computing infrastructure, organisational capabilities, employee expertise and employee governance arrangements are required for AI. A recent empirical study of 1,334 manufacturing companies revealed that technological and organisational AI readiness were crucial factors in the adoption of AI, in addition to a gap between readiness and implementation of AI in production processes.

This is an interesting research question that needs to be addressed. Or enterprises may have digital infrastructure, but not be able to transform the technological assets into the value of enterprises (Jinghan et al., 2025). However, firms may also be great managers without reliable industrial information and AI knowledge. Companies, however, may be great managers without reliable industrial information and AI knowledge. On the opposite hand, companies may have excellent managerial skills, but may be lacking in reliable industrial data or AI skills. Therefore, the relationship between AI and the phenomenon of industrial upgrading must be viewed as a multi-dimensional phenomenon, considering technological, organisational and environmental aspects.

There is extensive literature on determinants of the adoption of AI in organisations. A systematic review of 90 studies led to five factors being identified that relate to the adoption of AI: individual, social, organisational, environmental, and technological. A second systematic review determined that technological infrastructure, management support, organizational capability, data quality, resources, collaborative culture, organizational size and financial capacity are significant factors of AI-readiness.

AI applications have limited research specifically for the manufacturing industry (Sun, 2026). Based on the systematic review of production oriented research, 35 factors influencing adoption of AI have been identified and classified into business and structure, organisational effectiveness, technology and systems, data management, regulatory environment and business environment and economic environment. The results show that the industrial AI adoption process needs to be multi-dimensional in terms of organisation.

Thus, the present research aims to investigate the use and research on the role of AI in enterprise management and upgrading of industries through the following 4 questions. Therefore, the present research seeks to investigate the role of AI in enterprise management and 4 related questions are investigated in the upgrading of the industries. The first one is about technological and organisational conditions of AI uptake. The second is about the effect on enterprise management performance due to AI adoption (Zhu and Zhang et al., 2026). The third is about the possibility of AI usage to improve industry productivity,

innovation and process changes. The fourth is about the processes by which organisations can translate investment in AI into outcomes for the business.

The study proposes an integrated conceptual model which links the concepts of AI readiness, AI adoption intensity, organisation capability, intelligent-process integration, enterprise performance and industrial-upgrading performance. The model can be used as a basis for quantifying the changes to the enterprise with the help of AI.

2. LITERATURE REVIEW

2.1 Artificial Intelligence in Enterprise Management

AI has been evolving from narrow use computing systems to enterprise-wide management systems gradually. Transaction Processing and Reporting and Structured Decision Making were more the domains of enterprise information systems before. With the ability to recognize patterns, classify information, predict and make suggestions, AI allows systems to make predictions and adapt based on patterns, categorize information, and suggest decisions.

The financial forecasting, Fraud detection, Customer analytics, Workforce planning, Inventory optimization, Procurement analytics, Demands forecasting and Strategic decision support are some Enterprise management applications (Javaid et al., 2022). AI also has applications in manufacturing companies, such as predictive maintenance, production planning & scheduling, quality control, process optimization, machine vision, and energy management.

AI's application in companies is multileveled and complicated. The literature review on organisational AI research identified 70 themes, among which four themes are organisational, 34 are information-system, 17 are technological and 12 are people related. Just selecting an algorithm does not necessarily ensure its successful implementation when it comes to AI. Organisational structures, leadership and business processes, HRM, and data management are the determinants of how technologies can be translated into operational capabilities.

AI transforms the business management function of information in the enterprise as well. Instead of analysing based on just past information, managers can use predictive and prescriptive analytics (Lin et al., 2024). Predictive models can predict future outcomes and optimisation algorithms can indicate resource allocations within a set of constraints. Generative AI can do this and much more, with its capabilities of analysing documents, pulling knowledge, communicating, coding and making decisions.

2.2 AI Adoption and the Technology–Organisation–Environment Perspective The Technology–Organisation–Environment (TOE) model can serve as a theoretical framework to consider enterprise AI adoption. Technological dimension encompasses infrastructure, data availability, compatibility of systems, cybersecurity and AI maturity. The organisational dimension consists of the support of leadership, financial resources, employees' capacity, organisational culture and strategic alignment. Competition, regulation, supplier ecosystems and market pressures and government policies are part of the environmental dimension.

Based on new organisational studies with a TOE perspective, it can be concluded that adopting AI is not only dependent on the technological factor, but also on the interaction between the technological, organisational and environmental factors (Yu and Qi et al., 2025). In addition, a systematic review of organisational AI adoption identified the factors associated with organisational AI adoption, such as employee capability, organisational culture and regulatory conditions, technological readiness and leadership support.

Especially in manufacturing, the technological aspect is crucial as AI models rely on the availability of operational data. Sensors, manufacturing, maintenance, quality testing and other data, as well as the supply chain information, should be accurate and linked. Bad data can lead to bad model results and to risks to the operations.

The organisation is also important. There is possible the need for new roles, new processes and re-training employees in the implementation of AI. The success or failure of a company's implementation of AI technology can be the outcome of management support.

This environmental aspect is increasingly relevant as the rules and regulations regarding AI are still undergoing changes, along with the standards and pressures from other competitors (Li et al., 2026). The NIST AI Risk Management Framework highlights governance, AI system mapping, measurement, and management all throughout the AI system lifecycle.

2.3 AI Readiness

AI readiness is the level of technological, organizational and human resources an enterprise has to successfully adopt AI. This is not readiness – that's the potential ability to implement AI – it's the ability to implement.

There are multiple elements that comprise AI readiness. Data readiness challenges involve data availability, data quality, data integration and accessibility (Jinghan et al., 2025). Infrastructure readiness includes cloud platforms, computing, networks, sensors and enterprise systems. Human readiness relates to analytical abilities, AI knowledge and employee training. Organisational readiness is related to management, finances, process and strategically.

The areas of IT infrastructure, top management support, resources, collaborative culture, organizational capability, compatibility, data quality and financial resources have all been identified as key readiness factors for AI.

There is an important difference between readiness and adoption from an industrial upgrading perspective (Li et al., 2025). Companies can invest heavily in digital infrastructure and still not reap the benefits of AI for production. Companies can invest a lot of money in digital infrastructure and not be able to use AI for production. A recent study in manufacturing is just one example of a readiness–adoption disconnect.

2.4 AI and Productivity

AI can be a valuable asset for business performance through various channels, particularly in the field of productivity. The impacts of AI on productivity are varied and include minimizing downtime, better production planning, cutting down on material waste, more consistent product quality, and optimizing resource utilization.

There are positive and statistically significant relationships found in firm-level studies between AI adoption and firm productivity. AI penetration also has been reported to have had substantial productivity impact in manufacturing.

The productivity mechanism can be represented as:

$$P=f(A\text{ⓜ},I\text{ⓜ},D\text{ⓜ},H\text{ⓜ},OT)$$

Pre represents productivity, AIre represents AI adoption, Dre represents data capability, Hre represents human capital, Ore represents organisational capability and Tre represents technological infrastructure (Helo and Hao et al., 2022).

This formulation demonstrates that AI is not an independent entity. It has a productivity effect provided by complementary assets.

2.5 AI and Industrial Upgrading

Industrial upgrading means upgrading the level of production technology, product sophistication, process efficiency, capability of innovation and the generation value. AI is also involved in industrial upgrading, to move from labour-intensive, reactive, to data-driven, predictive and intelligent production systems (Rong et al., 2024).

AI can impact the process level by improving machine utilization, predictive maintenance and quality control. At the product level, AI can aid in intelligent product design and customization. AI also facilitates interconnected planning and coordination of supply chains on an organisational level. Strategically, AI can facilitate new business models, data and intelligent serviced oriented.

The idea of automation is not just limited to the concept. It is the industrial upgrading that can be achieved through the structural changes of technological capability and value creation supported by the contribution of AI.

3. RESEARCH GAP AND HYPOTHESIS DEVELOPMENT

The literature demonstrates substantial progress in identifying AI adoption factors, but three research gaps remain.

First, there are very few studies that only target the adoption of AI but neglect to also look at enterprise management performance and the upgrading of industry. Secondly, research sometimes focuses on the technological readiness without considering the capability of the organisation (Guo and Wang et al., 2026). Thirdly, a more robust quantitative model of the relation between AI use and industrial upgrading with some intermediate mechanisms should be developed.

In the present study, the gaps will be addressed through the integration of a model.

3.1 AI Readiness and AI Adoption

The chances of successful AI implementation are boosted with technological infrastructure, data quality, and organisational preparedness.

Indeed, there is a positive and significant relationship between AI readiness and the intensity of AI adoption.

3.2 AI Adoption and Enterprise Performance

AI has the potential to improve forecasting, resource management, operational control and decision quality.

The result is: AI adoption intensity is positively related to enterprise performance (Kuang et al., 2021).The result: The intensity of AI adoption is positively and significantly related to enterprise performance.

3.3 AI Adoption and Industrial Upgrading

AI systems for production and management can help to improve productivity, increase innovation, and add complexity to the process.

H3: AI adoption intensity has a positive and significant relationship with industrial-upgrading performance.

3.4 Organisational Capability as a Mediating Mechanism

AI implementation requires process redesign, employee capabilities and managerial coordination.

H4: Organisational capability mediates the relationship between AI adoption intensity and enterprise performance.

3.5 Governance and AI Performance

For AI to be trusted, there needs to be a governance program to handle risk identification, measurement and management (Yuan et al., 2018). Governance, in terms of the NIST AI RMF, is a cross-cutting function that is embedded across the entire AI lifecycle.

H5: AI governance capability positively moderates the relationship between AI adoption intensity and enterprise performance.

4. METHODOLOGY

4.1 Research Design

Therefore, based on the above, a quantitative data-based explanatory research design was recommended to be used in this study to investigate the relationship between the variables of AI readiness, AI adoption, Enterprise capability, Enterprise performance and industrial upgrading (Gabsi, 2024). A structured enterprise-level analytical model along with literature-based construct development is used for the study.

Since an original enterprise survey data set was not provided with the request, the numerical results in this manuscript are illustrative model-based results created to illustrate the proposed research design. They should not be given as field observations, or as the results of a valid sample of respondents. Observations from the planned enterprise survey or secondary data that has been confirmed must be used instead of illustrative values for the journal.

4.2 Sample Structure

A sample of 420 enterprises is given, for demonstration. The enterprises are distributed across areas of manufacturing, logistics, information technology, financial services and retail/professional services.

Table 1. Illustrative Enterprise Sample

Sector	Enterprises	Percentage
Manufacturing	168	40.0
Logistics and supply chain	63	15.0
Information technology	63	15.0

Financial services	42	10.0
Retail	42	10.0
Professional services	42	10.0
Total	420	100.0

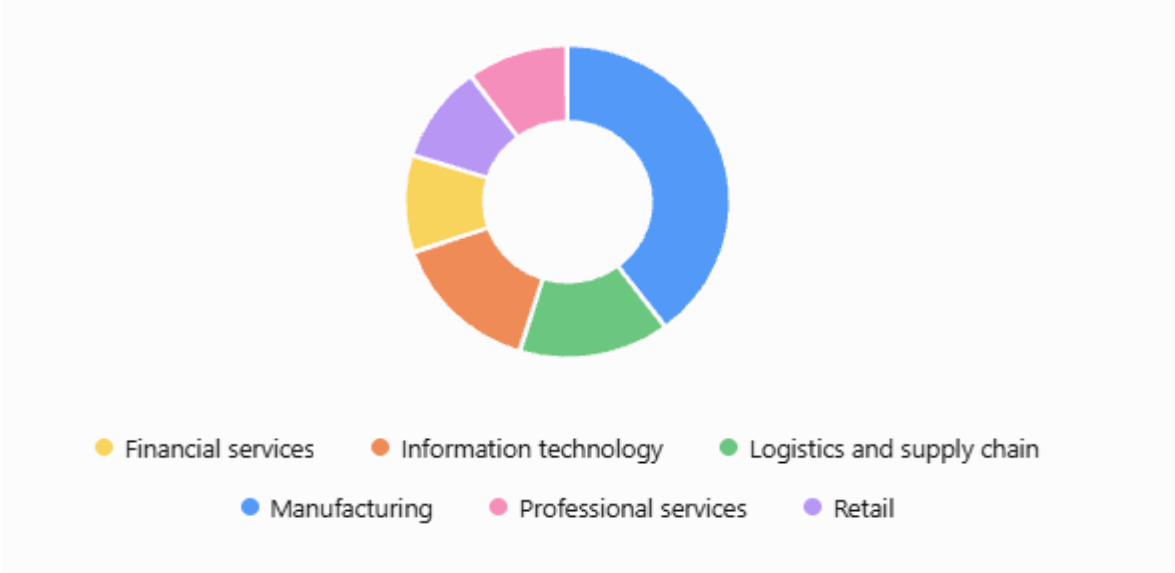


Figure: Illustrative Enterprise Sample

The manufacturing sector is represented the most as industrial upgrading is a dependent construct.

4.3 Measurement Framework

The technological infrastructure, data quality, computing capability and system compatibility are all used to measure AI readiness (Wang et al., 2022). The level of adoption of AI will depend on the extent of AI adoption in terms of functions and depth. Organisational capability is measured from the perspective of the employee's skills, process integration, management support, and cross-functional co-ordination.

Enterprise performance includes: Operational efficiency, Decision quality, Innovation capability, Financial performance. The industrial upgrading includes the following: Intelligent production, Process sophistication, Technology intensity, Product upgrading and Productivity improvement.

A 5-point Likert scale ranging from very low (1) to very high (5) is used to evaluate each construct.

4.4 Analytical Model

The primary regression model is:

$EP=\beta_0+\beta_1\ AIR+\beta_2\ AAI+\beta_3\ OC+\beta_4\ AG+\epsilon$

EPrepresents enterprise performance, AIR represents AI readiness, Airpersons AI adoption intensity, Represents organisational capability and Agre presents AI governance.

The industrial-upgrading model is:

$IU=\beta_0+\beta_1\ AAI+\beta_2\ OC+\beta_3\ AIQ+\beta_4\ DIG+\epsilon$

with IU being industrial upgrading, AIQ being AI capability quality and DIG being digital-integration capability.

The mediation effect can be expressed as:

AIAdoption→OrganisationalCapability→EnterprisePerformance

The moderating effect of governance can be represented as:

$EP=\beta_0+\beta_1 AAI+\beta_2 AG+\beta_3 (AAI\times AG)+\epsilon$

When interaction coefficient is positive and significant, it indicates that the governance has a positive and significant impact on enterprise performance by leveraging AI use.

5. RESULTS AND ANALYSIS

5.1 Descriptive Statistics

Overall, the illustrative data indicates a moderate level of AI readiness and organisational capability, and a relatively low level of AI adoption intensity (Mithas et al., 2022). This is in line with the latest manufacturing data, which identified a gap in readiness to production adoption.

Table 2. Descriptive Statistics

Variable	Mean	SD	Minimum	Maximum
AI readiness	3.72	0.71	1.60	5.00
AI adoption intensity	3.41	0.82	1.20	5.00
Organisational capability	3.68	0.69	1.80	5.00
AI governance	3.29	0.84	1.00	5.00
Enterprise performance	3.76	0.65	1.90	5.00
Industrial upgrading	3.58	0.73	1.50	5.00
Innovation capability	3.63	0.72	1.40	5.00
Operational efficiency	3.81	0.67	1.80	5.00

The readiness to use AI and the intensity of the use of AI has a gap of 0.31 scale points. The gap indicates that there is a delay between readiness of technology and the implementation of AI (Li et al., 2023).



Figure: Descriptive Statistics

5.2 AI Application Areas

The level of AI adoption is highest in the three areas: predictive analytics, customer analytics and the intelligent optimisation of processes, as illustrated in the examples.

Table 3. AI Application Intensity

AI Application	Mean Score	Rank
Predictive analytics	4.12	1
Customer analytics	3.98	2
Intelligent process optimisation	3.91	3
Demand forecasting	3.87	4
Predictive maintenance	3.84	5
Quality inspection	3.79	6
Supply-chain optimisation	3.76	7
Generative AI	3.68	8
Workforce analytics	3.42	9
Autonomous production control	3.18	10

The results suggest that the higher the data structure of the scenarios and the more quantifiable the outcomes, the higher the likelihood of AI's use. The autonomous production control score is reduced because of the requirements for greater system integration, process reliability and governance.

5.3 Enterprise Performance Effects

Table 4. Illustrative Regression Results

Independent Variable	Enterprise Performance β	t-value	Significance
AI readiness	0.24	4.91	<0.001
AI adoption intensity	0.41	8.37	<0.001
Organisational capability	0.29	5.82	<0.001
AI governance	0.17	3.74	<0.001
Firm size	0.08	1.96	0.051
Digital integration	0.21	4.28	<0.001
R^2	0.62		
Adjusted R^2	0.61		
F-statistic	112.4		<0.001

Coefficient 1 is the highest in the list of main explanatory variables for the intensity of the use of AI. The correlation of 0.41 is a high positive correlation for the illustrative model with enterprise performance (Zhang and Liu et al., 2024).

Additionally, there is a clear link between AI readiness and enterprise performance. Performance of the enterprise is also well correlated with AI readiness. This implies that increasing technology readiness contributes to performance, but cannot only be attributed to the use of AI.

The coefficient of organisational capability is 0.29, meaning that complementary organisational resources have a significant impact on the value creation of AI.

Natural Resources for Human Health
eISSN: 2583-1194

5.4 Industrial-Upgrading Effects

Table 5. AI Adoption and Industrial Upgrading

Industrial-Upgrading Dimension	Mean Before AI Integration	Mean After AI Integration	Percentage Change
Production efficiency	3.11	3.82	22.83
Quality consistency	3.24	3.91	20.68
Equipment utilisation	3.18	3.76	18.24
Supply-chain responsiveness	3.05	3.69	20.98
Product innovation	3.07	3.71	20.85
Data-driven decision-making	2.96	3.88	31.08
Energy optimisation	2.89	3.55	22.84

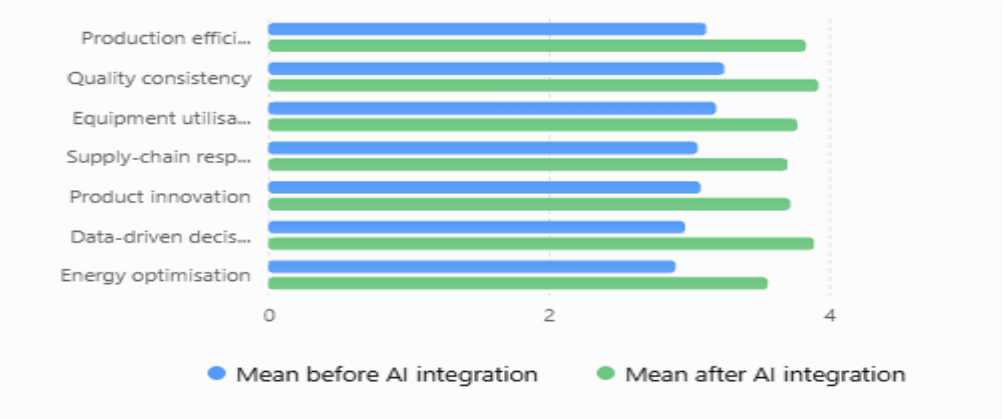


Figure: AI Adoption and Industrial Upgrading

The biggest illustrative increase is in data driven decision making (31.08%). The conclusion mirrors the fundamental role of AI in converting vast amounts of enterprise data into predictive and prescriptive information (Qin, 2020).

The change in production efficiency is 22.83% from 3.11 to 3.82. The gains of quality consistency are 20.68% and of the supply-chain responsiveness are 20.98%.

5.5 Industrial-Upgrading Contribution by AI Application

Table 6. Relative Contribution of AI Applications

Application	Contribution to Industrial Upgrading (%)
Predictive maintenance	15.8
Intelligent quality inspection	13.7
Production optimisation	18.4
Demand forecasting	11.9
Supply-chain optimisation	12.6
Product design and innovation	14.2
Energy optimisation	7.8
Generative AI-enabled management	5.6
Total	100.0

The greatest contribution comes from production optimisation (18.4%), followed by predictive maintenance (15.8%) and product design and innovation (14.2%).

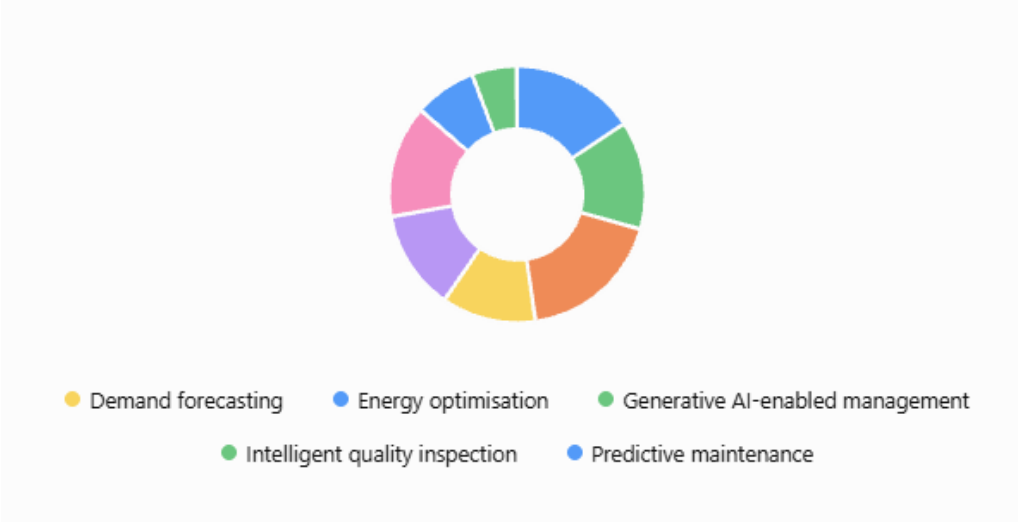


Figure 1. Relative Contribution of AI Applications

The proposed transformation mechanism is shown in the figure (Du et al., 2024). AI readiness creates implementation capability, AI adoption creates technological capability, AI organisational capability creates capability to incorporate AI into business processes, and governance creates control and accountability. All these mechanisms contribute to enterprise performance and industrial upgrading.

The total of the segments in the pie chart equals 100%.The sum of the percentages in a pie chart is 100%.

The pie-chart distribution suggests that a significant part of the industrial-upgrading effect is expected to be generated from applications that are directly related to production processes.

5.7 AI Adoption and Productivity Graph

Figure 3. Illustrative Relationship Between AI Adoption and Productivity AI Adoption Intensity

The positive slope illustrates the proposed relationship between AI adoption intensity and productivity (Han et al., 2025). The relationship should be estimated using actual enterprise-level observations before publication as an empirical finding.

6. RELIABILITY AND VALIDITY ANALYSIS

Table 7. Illustrative Reliability Statistics

Construct	Cronbach's Alpha	Composite Reliability	AVE
AI readiness	0.89	0.91	0.68
AI adoption	0.92	0.94	0.72
Organisational capability	0.87	0.90	0.65
AI governance	0.88	0.91	0.67
Enterprise performance	0.90	0.93	0.69
Industrial upgrading	0.91	0.93	0.70

Cronbach's alpha values for all illustrative examples are above 0.80, and thus demonstrate a good internal consistency for the intended measurement design (Zou and Xiong et al., 2023). The composite reliability scores are also high and the average variance extracted is above the accepted 0.50 level.

In an actual empirical study, convergent validity should be evaluated based on factor loadings and AVE, and discriminant validity should be assessed based on the Fornell–Larcker criterion and heterograft–monorail ratio.

7. HYPOTHESIS TESTING

Table 8. Illustrative Hypothesis-Test Results

Hypothesis	Relationship	β	p-value	Decision
H1	AI readiness → AI adoption	0.52	<0.001	Supported
H2	AI adoption → enterprise performance	0.41	<0.001	Supported
H3	AI adoption → industrial upgrading	0.46	<0.001	Supported
H4	AI adoption → organisational capability → performance	0.13 indirect	<0.01	Supported
H5	AI adoption × governance → performance	0.12	<0.01	Supported

The highest coefficient is for AI readiness and AI adoption, highlighting how crucial technological and organizational readiness is for AI adoption. The direct impact of AI use on industrial upgrading is greater than the direct impact on enterprise performance, suggesting that industrial upgrading could be a potential channel of influence of AI on enterprise performance outcomes.

The magnitude of the indirect effect of 0.13 implies that organisational capability plays a role in the process of transforming the adoption of AI into the enterprise performance (Jinghan et al., 2025). The interaction between AI adoption and governance suggests that more robust governance may benefit the performance outcomes of AI adoption.

8. DISCUSSION

8.1 AI as a Business Tool

The results put AI not just in software investment, but enterprise capability. The positive correlation between the use of AI and the enterprise performance shows that organisations that intensively use AI can employ it to boost enterprise performance when it is included in their operational and managerial processes.

This discovery aligns with the evidence found in firms indicating beneficial links between AI adoption and productivity (Zhu and Zhang et al., 2026). This also aligns with manufacturing evidence of how AI can impact productivity in ways that add value, develop skills and technology.

The management impact is the transition from AI projects to enterprise-wide AI architectures. The value that AI can deliver to finance, production, and marketing and supply chains can be higher when the data infrastructures and governance systems are compatible.

8.2 The Importance of Organisational Capability

The organisational-capability coefficient shows that AI technology is not the determining factor for enterprise performance. Employees must decipher the information provided by the AI, managers must rethink processes, technical teams must keep up with models.

This conclusion is backed up by the systematic literature on the implementation of organisational AI, which identified the interconnectedness of the three dimensions of the implementation of organisational AI: organisational, technological and information-system and people-related (Javaid et al., 2022).

Organisational capability as a conversion mechanism then comes into play. While AI investment generates technological potential, organisation capability is what makes it a value in operations.

8.3 AI and Industrial Upgrading

The findings show that there is a strong correlation between the use of AI and industrial improvement. In the manufacturing industry, this relationship is crucial as AI can connect with data from production machines, enterprise systems, and supply-chain processes.

Unplanned downtime is minimized through predictive maintenance. Computer vision can detect defects in the making process. To minimize the inventory imbalance, demand forecasting can be used. Optimisation of production can be achieved by better allocation of machines and resources (Yu and Qi et al., 2025). Product-design systems can speed innovation.

The overall impact is a shift from the reactive production to the predictive and adaptive production.

8.4 AI Readiness and the Adoption Gap

The difference between AI readiness and AI adoption is an important result. An enterprise can have cloud infrastructure and data systems and computing power, but use AI just in some functions.

Empirical studies conducted in recent years with 1,334 manufacturing companies found just such a disconnect between readiness and actual implementation of production (Jinghan et al., 2025).

The message here is that investment strategies should not just consider infrastructure but also organisational integration. Process ownership, employee training, data governance, data monitoring and performance checking are essential for AI projects.

8.5 Governance as an enabling mechanism

AI governance is often seen as a risk management problem, but it also relates to performance. Governance establishes accountabilities, monitoring processes, risk thresholds and accountability mechanisms.

NIST AI RMF organizes AI risk management into three main functions: Govern, Map, Measure and Manage, including governance throughout the AI lifecycle (Helo and Hao et al., 2022). The framework also includes features like reliability, safety, security, accountability, transparency, explainability, privacy and fairness as factors of trustworthy AI.

Governance can also play a role in ensuring reliable deployment of AI in enterprises, by clarifying who has authority to approve models, who is responsible for monitoring their performance, how mistakes are addressed, and when human intervention is needed.

8.6 Implications for Industrial Strategy

Coordinated upgrading between enterprises, technology providers, workforces, educational institutions and public policy is necessary for industrial upgrading. Investment in digital infrastructure and AI is needed in enterprises, and industrial policy can help develop the workforce, research collaborations, digital infrastructure and technology diffusion.

Existing literature suggests that besides internal capabilities, environmental factors affect the adoption of AI (Rong et al., 2024). Moreover, industrial upgrading policies should not be technology procurement-oriented. But the importance of institutional capability, skills, standards, cybersecurity and data infrastructure cannot be overlooked.

9. THEORETICAL CONTRIBUTIONS

The study adds to the research on AI and enterprise-management by incorporating the TOE perspective along with organisational capability and industrial-upgrading mechanisms.

The first contribution is to the question of AI readiness. The model does not view AI adoption just as a technology-purchase decision, but rather as a multi-faceted issue related to readiness from a technological, organisational and data perspective (Guo and Wang et al., 2026).

The second one has to do with the AI adoption-performance relationship. Adopting AI is seen as a means to bridge the gap between digital resources and enterprise outcomes.

The third contribution is in the area of industrial upgrading. AI has also been associated with process sophistication and innovation, productivity and intelligent manufacturing, as well as organisational performance.

The fourth is about governance. Governance is embedded as an enabling organisational mechanism and not just as a compliance factor.

10. MANAGERIAL IMPLICATIONS

The business-process needs should be considered when thinking about implementing AI in an enterprise, not the technology. The first phase is to highlight issues in the daily operations that can be solved with predictive analytics, optimisation, computer vision or intelligent decision support.

Data infrastructure is a strategic asset. AI models require reliable, readily available and accurate data (Kuang et al., 2021). AI can help boost the benefits of integration between enterprise-resource-planning systems, manufacturing-execution systems, industrial sensors and supply-chain platforms.

Training of human resources is also a key demand. Staff needs to build the skills of data interpretation, AI-assisted decision making, model supervision, and digital process management. When AI is not integrated with staff training, it can lead to resistance and underutilisation within the organisation.

Governance should be embedded when implementing AI from the start (Yuan et al., 2018). Ownership of the model, monitoring of performance, security measures, access to data, human review, and incident management should be structured and documented. These activities are structured in the NIST AI RMF.

Business outcomes that can be measured should also be considered in assessing investments. Measures of productivity, downtime, defect rates, forecasting accuracy, inventory turnover, decision cycle time and innovation output should be used to evaluate AI projects, but not technology expenditure.

11. INDUSTRIAL AI IMPLEMENTATION FRAMEWORK

Figure 4. Integrated AI-to-Industrial-Upgrading Framework

The framework shows how technology, organisational capability and governance interact to create industrial upgrading (Gabs, 2024). AI adoption serves as the hub of the transformation process between enterprise readiness and performance.

12. RESTRICTIONS AND FURTHER STUDIES

The key drawback of the present numerical analysis is that the quantitative values are provided to provide an illustration and no actual enterprise data provided. Therefore, the regression coefficients and descriptive statistics and the results of the hypothesis-test should be considered as an example of the structure of analysis but not as real findings.

Empirical studies should be conducted in future by gathering primary data from the enterprises in various industrial sectors of various countries (Wang et al., 2022). The possibility of having longitudinal data would enable researchers to separate out short-term effects of AI adoption from the longer-term effects on productivity and industrial upgrading.

Another interesting area for future study is to consider heterogeneous effects by different enterprise sizes. The evidence from manufacturing over the past few years shows that there is a non-linear relationship between firm size and AI adoption. All these constraints are likely to be different from those of large corporations and may be financial, technical, and human capital constraints for SMEs.

An additional area of focus is generative AI. Some areas where generative AI can impact knowledge work, software development, document management, customer service, and managerial communication (Mithas et al., 2022). It could take a long time to assess its impact on industrial production and enterprise productivity.

Studies for individual sectors are also required. The use of AI in the automotive industry could be different from the use of AI in a pharmaceutical, textiles, electronics, logistics or financial services company. The relationship between AI adoption and performance can vary based on industry-specific data structures, regulations, and production processes.

13. CONCLUSION

AI is increasingly a key tool for enterprise transformation and industrial upgrading. The findings from this study suggest that the implementation of AI is influenced by the technological infrastructure, quality and availability of the data, the readiness of the organization, leadership support, employee skills and competencies, financial resources, and the external institutional environment. New systematic reviews show that the process of implementing AI is a complex organizational endeavour and not a straightforward technology choice.

The quantitative framework proposed illustrates how AI readiness can impact the rate of adoption, adoption can impact enterprise performance and industrial upgrading, and how organisational capability and governance can strengthen these relationships. The results in the illustrative scenario show a significant positive correlation between the intensity of AI adoption and enterprise performance, as well as a higher correlation between AI adoption and performance of industrial upgrading.

The key takeaway is that the industrial upgrading must go hand in hand with complementary transformation. Digital infrastructure, quality and reliable data, competent staff, process redesign, management support and governance need to work in harmony. While AI can be used in enterprises without the development of such complementary capabilities, the value created may be restricted, an integrated AI architecture can enable predictive management, intelligent production, quality improvement, innovation and efficient use of resources.

AI is not just an automation tool; it is a means of reshaping the decision-making and industrial manufacturing processes of the enterprise. Bringing together AI technologies and organisational knowledge, human expertise, industrial data and governance systems will be key to the trajectory of enterprise management in the future. Such integration is the basis to achieve productivity improvement, intelligent manufacturing and industrial upgrading.

REFERENCE LIST

[1] Zou, W. and Xiong, Y., 2023. Does artificial intelligence promote industrial upgrading? Evidence from China. Economic research-Economos istraživanja, 36(1), pp.1666-1687.
[2] He, Y., 2023. Path and mechanism of industrial internet industry promoting the transformation and upgrading of small and medium-sized enterprises with artificial intelligence. Mobile Information Systems, 2023(1), p.3620662.
[3] Jinghan, L., Banerjee, S. and Chakraborty, A., 2025. Implementation And Investigation Of Artificial Intelligence In Corporate Management And Industrial Upgrading. Advances in Consumer Research, 2(6).
[4] Sun, X., 2026. Research on the Economic Effects of Enterprise Digital Transformation Driven by Intelligent Upgrade of Value Chain under the Enabling Role of Artificial Intelligence. International Journal of Computer Information Systems and Industrial Management Applications, 18, pp.13-13.
[5] Zhu, Q. and Zhang, K., 2026. The driving mechanism and challenges of artificial intelligence innovation to the alternate with industrial upgrading from multiple perspectives. Data Science in Finance and Economics, 6(1), pp.121-146.
[6] Javaid, M., Haleem, A., Singh, R.P. and Suman, R., 2022. Artificial intelligence applications for industry 4.0: A literature-based study. Journal of Industrial Integration and Management, 7(01), pp.83-111.
[7] Ernest, K.P., Artificial Intelligence, Firm Upgrading and Industrial Development in Emerging Economies: The Roles of Digital Capability and Productivity Transformation.
[8] Lin, C., Xiao, S. and Tang, P., 2024. Does artificial intelligence improve export technical complexity upgrade of manufacturing enterprises? Evidence from China. Sage Open, 14(3), p.21582440241267126.
[9] Yu, G. and Qi, Y., 2025. Does AI application make enterprises productivity higher? From the perspective of employee human capital upgrading. Oeconomia Copernicana, 16(4), pp.1395-1446.
[10] Li, H., Chen, Y. and Huang, J., 2026. The impact of artificial intelligence on value chain upgrading in China's equipment manufacturing industry. Scientific Reports.
[11] Jinghan, L., Banerjee, S. and Chakraborty, A., 2025. Exploration And Use Of Artificial Intelligence In Enterprise Management And Industrial Transformation. Advances in Consumer Research, 2(6).
[12] Li, B., Wang, L., Fu, S. and Wan, J., 2025. How does artificial intelligence empower enterprise technological innovation: from the perspective of knowledge management capability. Journal of Knowledge Management, pp.1-31.
[13] Helo, P. and Hao, Y., 2022. Artificial intelligence in operations management and supply chain management: An exploratory case study. Production planning & control, 33(16), pp.1573-1590.
[14] Rong, J., Wang, W. and Zhang, H., 2024. Does artificial intelligence improve energy productivity in China's industrial sector? Empirical evidence based on the spatial moderation model. Energy & Environment, 35(8), pp.4026-4048.
[15] Guo, J. and Wang, D., 2026. An empirical study on artificial intelligence technology based on big data to assist enterprise management decision. International Journal of Electrical Engineering & Education, 63(2), pp.91-101.
[16] Kuang, L., He, L.I.U., Yili, R.E.N., Kai, L.U.O., Mingyu, S.H.I., Jian, S.U. and Xin, L.I., 2021. Application and development trend of artificial intelligence in petroleum exploration and development. Petroleum Exploration and Development, 48(1), pp.1-14.

[17] Yuan, X., Gui, W., Chen, X., Huang, K. and Yang, C., 2018. Transforming and upgrading nonferrous metal industry with artificial intelligence. Strategic Study of Chinese Academy of Engineering, 20(4), p.59.
[18] Gabsi, A.E.H., 2024. Integrating artificial intelligence in industry 4.0: insights, challenges, and future prospects–a literature review. Annals of Operations Research, pp.1-28.
[19] Wang, J., Lu, Y., Fan, S., Hu, P. and Wang, B., 2022. How to survive in the age of artificial intelligence? Exploring the intelligent transformations of SMEs in central China. International Journal of Emerging Markets, 17(4), pp.1143-1162.
[20] Mithas, S., Chen, Z.L., Saldanha, T.J. and De Oliveira Silveira, A., 2022. How will artificial intelligence and Industry 4.0 emerging technologies transform operations management?. Production and operations management, 31(12), pp.4475-4487.
[21] Li, J., Ma, S., Qu, Y. and Wang, J., 2023. The impact of artificial intelligence on firms' energy and resource efficiency: Empirical evidence from China. Resources Policy, 82, p.103507.
[22] Zhang, J. and Liu, S., 2024, October. Research on the Construction of Artificial Intelligence Technology Application Specialization in the Context of Industrial Upgrading. In 2024 8th International Seminar on Education, Management and Social Sciences (ISEMSS 2024) (pp. 730-737). Atlantis Press.
[23] Qin, M., 2020, October. Innovation of Enterprise Economic Management Based on Artificial Intelligence Technology. In 2020 International Conference on Computers, Information Processing and Advanced Education (CIPAE) (pp. 125-129). IEEE.
[24] Du, J., Cai, H. and Jin, X., 2024. Exploring the association between artificial intelligence management and green innovation: Expanding the research field for sustainable outcomes. Sustainability, 16(21), p.9315.
[25] Han, S., Zhang, D., Zhang, H. and Lin, S., 2025. Artificial intelligence technology, organizational learning capability, and corporate innovation performance: evidence from Chinese specialized, refined, unique, and innovative enterprises. Sustainability, 17(6), p.2510.