

AI-Driven Innovation for Operational Transformation: A Case Study of Organizational, Technological, and Human Factors in WH Company

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Abstract

The research objectives were 1) to examine how artificial intelligence technologies are applied to support operational innovation in a traditional manufacturing enterprise, 2) to identify the key organizational, technological, and human factors influencing the effectiveness of AI-driven operational transformation, and 3) to propose practical guidelines for enhancing the effectiveness of AI-driven operational transformation in traditional manufacturing enterprises. A qualitative case study approach was employed. The data were collected through semi-structured in-depth interviews with 20 purposively selected participants, including senior managers, middle managers, frontline employees, and IT and engineering staff. The interview data were triangulated with internal documents and on-site observations. Thematic analysis was conducted using open coding, axial coding, and selective coding to identify major patterns and core themes. The findings indicated that AI has significantly contributed to operational innovation, particularly in production automation, quality control, warehousing, and logistics management. AI-enabled systems improved operational efficiency, reduced labor intensity, lowered defect rates, and enhanced decision-making accuracy. However, AI adoption remains uneven across departments, with limited integration in customer service, sales support, and administrative functions. The effectiveness of AI-driven transformation is strongly influenced by organizational factors (leadership support, strategic

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alignment, and change management), technological factors (data quality, system integration, and IT infrastructure readiness), and human factors (employee digital literacy, training, and acceptance of AI). Practical guidelines for enhancing the effectiveness of AI-driven transformation include positioning AI as a long-term organizational strategy, improving system integration and data quality, designing role-based skill development, and institutionalizing systematic change management.

Keywords

AI-driven innovation; Operational transformation; A Case study; Technology–Organization–Environment Framework, Innovation Diffusion Theory

Introduction

Artificial intelligence (AI) has become a critical driver of operational innovation across industries, particularly in traditional manufacturing sectors facing increasing pressure to improve efficiency, quality, and competitiveness. Advances in machine learning, data analytics, and intelligent automation have enabled manufacturing enterprises to redesign production processes, optimize resource allocation, and enhance decision-making capabilities. As a result, AI-driven operational transformation is increasingly regarded as a strategic pathway for sustaining long-term organizational performance (Ali et al., 2024; Harahap et al., 2024; Su et al., 2024).

In this study, a traditional manufacturing company is a business organization with standard production processes, highly labor-oriented activities, vertical organizational hierarchy, and limited incorporation of advanced digital technologies (Swierczek & Kisperska-Moron, 2016; Lay-Raby et al., 2025). These companies are being reformed into more sophisticated and intelligent businesses via the implementation of artificial intelligence technologies. However, the degree of this reform varies greatly from firm to firm and even within different departments within the same company.

Despite the growing adoption of AI technologies, many traditional manufacturing enterprises encounter substantial challenges during implementation. These challenges include fragmented digital infrastructure, insufficient data quality, limited employee digital competencies, and organizational resistance to change. Prior studies have largely focused on the technical capabilities of AI systems or their performance outcomes, while comparatively

less attention has been paid to the organizational and human factors that shape the effectiveness of AI-driven operational innovation, particularly in emerging economies and transitional industrial contexts (Li et al., 2025).

The problems stem from the issue of multi-level transformation challenges, from macro levels such as industry issues (e.g., cost competitiveness and regulation), meso levels such as organizational problems (e.g., strategic alignment and coordination), and micro levels such as personal issues (e.g., skill and attitude toward AI). This underlines the fact that transformation through AI adoption is a socio-technical activity and not merely a technology-based initiative (Uren, & Edwards, 2023; Herrmann & Pfeiffer, 2023).

Existing research on AI adoption has often relied on quantitative surveys or conceptual discussions, which may overlook the complexity of organizational processes and employee experiences during AI-driven transformation (Fenwick et al., 2024; Murire, 2024). Moreover, empirical studies grounded in real-world manufacturing cases remain limited, especially those that integrate multiple theoretical perspectives to explain AI-driven operational change at different organizational levels (Tian et al., 2023). More specifically, the diffusion of AI in traditional manufacturing companies is still an area that requires further investigation. Current research literature lacks a proper understanding of the manner in which the use of AI technology spreads throughout the organization from top management down to the middle and lower levels of management as well as across core and support processes.

This study fills these gaps through the use of qualitative case study approach in exploring the use of AI in operational innovation in a traditional manufacturing firm. Using the WH Company, the study evaluates how AI technology is being utilized in the firm's operations, as well as the key enablers and barriers involved, while analyzing the interplay between technological, organizational and individual elements at the top-management, middle-management and employee level. The study combines the TOE framework and IDT to offer a multi-level analysis of AI-led operational innovation. In particular, the study examines how technological elements, organizational processes and individual capabilities contribute to the adoption and implementation of AI technology.

Objectives

1. To examine how artificial intelligence technologies are applied to support operational innovation in a traditional manufacturing enterprise.

2. To identify the key organizational, technological, and human factors influencing the effectiveness of AI-driven operational transformation.

3. To propose practical guidelines for enhancing the effectiveness of AI-driven operational transformation in traditional manufacturing enterprises.

Review of Literature

Artificial intelligence is recognized as one of the key drivers of innovations and organizational change (Su et al., 2024, 59-85). In manufacturing industries, the use of AI technology such as machine learning, intelligent sensing, and analytics is becoming more common for improving production process, quality assurance, and coordinating supply chains (Sorooshian et al., 2022; Ferrara et al., 2024). Existing literature suggests that AI implementation could increase efficiency and support better decision-making.

1) The Adoption of AI Technologies in Companies

Indeed, AI adoption in organizations is no longer merely about technology but has been transformed into organizational transformation. Successful adoption of AI has been influenced by technological readiness, organizational readiness, and other contextual aspects according to TOE theory (Khanfar et al., 2025, 3727–3755). As regards manufacturing industries, it should be said that AI adoption in such sectors usually starts with automation of production and quality assurance process, then gradually spreading throughout other operational processes.

AI solutions and technologies, such as automation and analytics, have been utilized to increase effectiveness, productivity, and optimize supply chain management (Sorooshian et al., 2022; Tian et al., 2023). However, traditional manufacturing companies often face certain challenges associated with legacy technologies, infrastructure, and insufficient skills of employees (Atieh et al., 2023, e12578, which makes such environment highly suitable for AI operational transformation study. Earlier research shows that successful adoption of AI technologies is influenced by strategic alignment, digital capabilities, and skills possessed by organization's employees (Tursunbayeva & Gal, 2024; Satyro et al., 2024). Thus, organizations, which have well-established digital processes, integration of data and employee training programs, are much more likely to benefit from the use of AI technologies, while lack of skills and resistance to changes remain important obstacles to adoption. Moreover, current digital

transformation literature highlights the role played by AI in improving organizational performance, skills of workers, and innovations (Wamba-Taguimdje et al., 2020; Nijhum, 2025).

2) AI and Operational Innovation

Operational innovation involve the use of new or improved procedures that increase the efficiency and effectiveness of organizations. From previous studies, AI-based systems increase operational innovations through automation, accuracy of processes, and real-time analysis and optimization of procedures (Lee, 2015, 8). Manufacturing firms make use of AI for predictive maintenance, defect detection, stock control, and logistic optimization. However, the effects of AI on operations depend on its degree of adoption, level of technology readiness, and support provided by organizations (Khanfar et al., 2025, 3727–3755).

Despite the proof by studies showing performance improvements from AI integration, past research focuses on the efficiency gains made through technology adoption. The adoption of AI and innovation operations and how stakeholders adapt to it in organizations have been overlooked. From previous research conducted in manufacturing and digital transformation domains, it becomes clear that innovation in operations is not only about technology. Innovation arises when artificial intelligence capabilities, such as automation and forecasting, are integrated with organizational mechanisms, including organizational management and process reengineering, as well as human capabilities. All these aspects combine and determine how AI enables process innovation or innovation at the systems level (Tian et al., 2023; Sorooshian et al., 2022).

3) Technology–Organization–Environment (TOE) Framework

Technology-Organization-Environment (TOE) model has been widely used to explain organizational technology adoption and implementation decisions. In the TOE model, the technology perspective consists of components like system compatibility, data integrity, and technology complexity (Baker, 2012, 231-245), whereas the organization perspective includes items like supportive management, organizational structure, and resource availability. Environmental perspective focuses on outside forces like market competition, industry dynamics, and regulatory aspects. For AI adoption literature, TOE model has been used to explain the factors that contribute to organizational readiness and successful implementation of AI solutions. Yet there is limited literature on the application of TOE for investigating how AI technology contributes to organizational change in manufacturing operations (Satyro et al., 2024, 11064).

For instance, in relation to the AI-based transformation, the TOE framework can not only be used to determine static factors, but also help in illustrating the dynamics of interactions among technological aspects (such as data integration and interoperability), organizational processes (such as alignment of leaders and managing changes), and external environment when transforming (Sánchez et al., 2025, 6465). AI implementation necessitates the ongoing interaction of organization members (such as managers and workers) and artificial intelligence technologies, whereby the functionality of the latter influences the work process, and actions taken by individuals impact the use of the technology and performance results. Such a focus on dynamic interaction expands the scope of TOE model from the static approach to technology adoption to a process model of AI-based operational transformation.

4) Innovation Diffusion Theory (IDT)

Innovation Diffusion Theory (IDT) explains how new technologies are adopted and diffused within social systems over time. Core attributes such as relative advantage, compatibility, complexity, trialability, and observability are considered essential in shaping adoption decisions. In organizational settings, IDT highlights the role of individual perceptions, communication channels, and social influence in facilitating or constraining innovation diffusion (Rogers et al., 2014, 432-448).

In organizational settings, IDT theory also places importance on the impact of varying adopter types such as innovators, early adopters, early majority, late majority, and laggards (FakhrHosseini et al., 2024, 986-998). The five groups have different levels of readiness, perceived risks, and receptiveness towards new technology, which is highly significant for the adoption of AI due to its uncertain nature and complexity. Prior research applying IDT to digital and AI-related innovations emphasizes employee acceptance, learning processes, and the perceived usefulness of new technologies (Satyro et al., 2024; Rogers et al., 2014).

Technology acceptance levels in IDT are important because the use of AI requires not only the ability of the systems to perform but also the perception and use of such technologies by various members of the organization. In manufacturing organizations, for instance, innovation is carried out by top management, interpretation and diffusion by middle management, and acceptance by front-line workers (Colombari & Neirrotti, 2023, 13840-13851). Hence, IDT helps complete TOE framework by offering a micro-analysis of the diffusion process in AI adoption in organizations. These studies suggest that even technologically advanced systems may fail to generate expected benefits if employees lack understanding, skills, or trust

in AI-driven solutions. Nevertheless, empirical research integrating IDT with organizational-level frameworks such as TOE framework in the context of AI-driven operational innovation remains scarce.

5) Human Factors in AI-Driven Organizations

Human factors have a pivotal role in determining the efficacy of AI-enabled organizational transformation. In organizational contexts, workers are not mere passive subjects but proactive interpreters, users, and sometimes even resisters of technology changes (Murire, 2024, 316). Important human factors include digital literacy, development, attitudes, and inter-departmental cooperation. Digital literacy is responsible for the effectiveness of the use of AI by workers, whereas training plays a role in developing the skills needed for effective use of AI as well as in fostering acceptance (Fenwick et al., 2024, 34). Attitudes towards the implementation of AI technologies, including potential job loss and productivity surveillance, may have a significant impact on the process of implementation.

Additionally, cross-departmental cooperation is necessary to ensure that innovations enabled through AI technologies lead to innovation in organizational systems as well, since innovations provided by AI need to be translated into systems innovations through the cooperation of production, logistics, and management departments.

6) Integration of TOE Framework and IDT

TOE framework explained an account of the organizational context for technology adoption, while IDT gives an explanation of the diffusion process from an individual's perspective, and the integration of TOE framework and IDT helps to provide a more holistic perspective of AI-induced transformation (Alka'awneh et al., 2025, 2118-2129). TOE framework provided an account at both macro and meso levels of structural and technological readiness, whereas IDT is an account of adoption and usage behavior of individuals at a micro level (Satyro et al., 2024, 11064).

7) Research Gap

Based on the above-mentioned reviewed literature by Khanfar et al. (2025, 82), Sorooshian et al. (2022, 82), Ferrara et al. (2024, 3), Lee (2015, 8), Satyro et al. (2024, 11064), and Rogers et al. (2014, 432-448), a number of knowledge gaps can be revealed. Existing research tends to focus mostly on the technological side of the discussed issues and fails to analyze possible relations between technological, organizational, and human factors. In addition, there is not much research about AI adoption within organizational layers in

traditional manufacturing enterprises and the application of both the TOE and IDT approaches in explaining this kind of innovation. Hence, in order to fill existing knowledge gaps, this paper examines AI adoption and its effects using the TOE-IDT framework and the method of qualitative case study analysis with respect to the WH Company.

8) Justification of WH Company as Research Context

WH Company represents a typical traditional manufacturing enterprise undergoing digital transformation. The company operates in a production-intensive environment characterized by standardized processes, high operational complexity, and increasing pressure for efficiency and quality improvement. It has adopted AI technologies in core operational areas such as production, quality control, warehousing, and logistics, while still facing challenges in extending AI applications to non-core functions. This combination of advanced adoption and existing limitations makes WH Company an appropriate and representative case for examining AI-driven operational transformation in traditional manufacturing contexts.

9) Conceptual framework

The conceptual framework of this study, as illustrated in Figure 1., is designed to investigate how AI drives operational innovation within WH Company by examining the interplay of organizational, technological, and human factors.

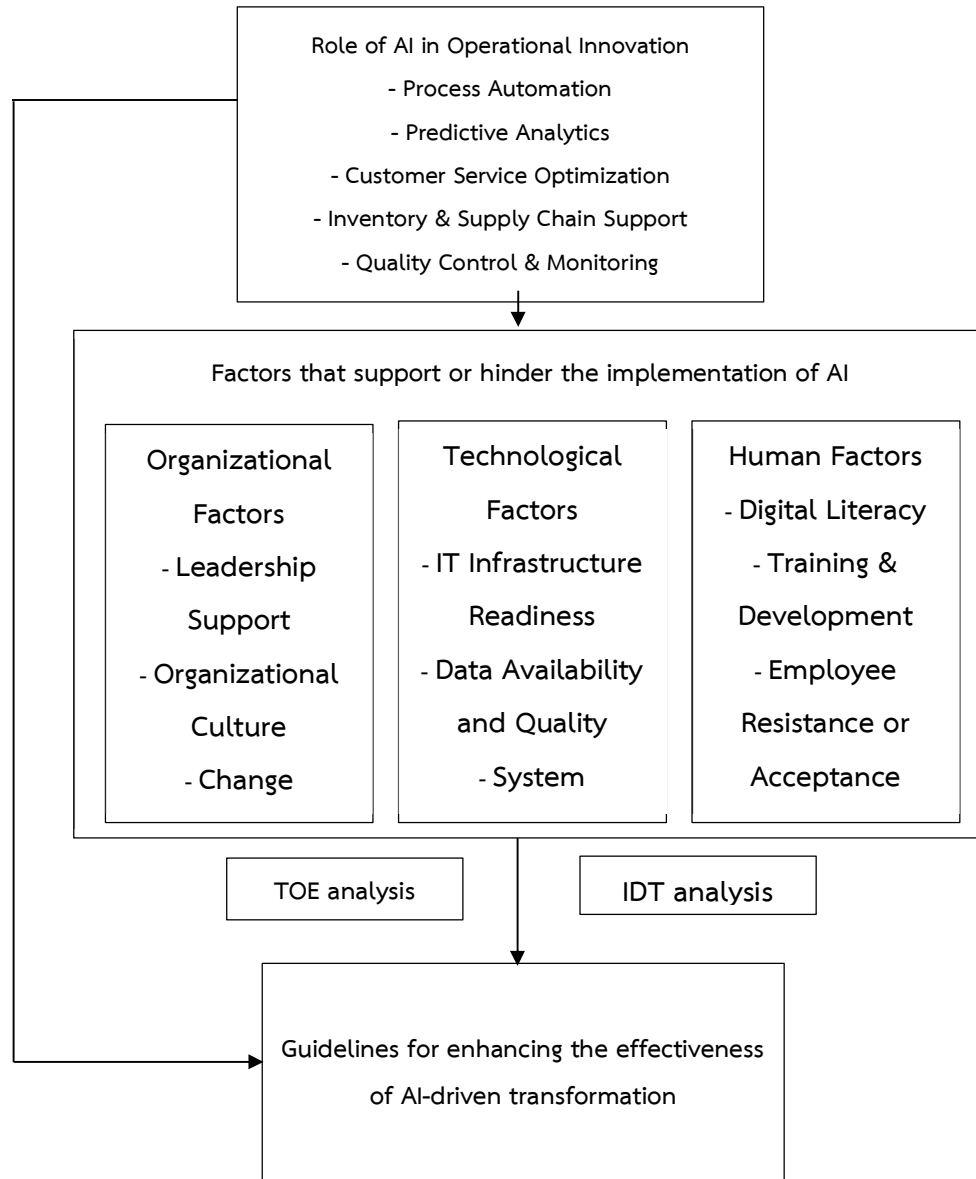


Figure 1: Conceptual Framework

The choice of AI capabilities, such as process automation, predictive analytics, and quality monitoring, is supported by studies that focus on their use for improving the efficiency of operations and decision-making in manufacturing companies (Tian et al., 2023). The three categories of determinants, such as organizational, technological, and human, are justified based on the theoretical foundation formed by the technology-organization-environment (TOE) framework, information systems development theory (IDT), and studies of human-centered artificial intelligence. Existing research findings prove that the determinants

mentioned above are interdependent. In particular, technological capabilities affect organizational processes while human capabilities affect the success of implementing AI solutions and thus impact the outcomes in relation to innovation (Alka'awneh et al., 2025; Mpanza, 2025).

Research Methodology

1) Research Design

This study adopts a qualitative case study approach to explore AI-driven operational innovation in a traditional manufacturing enterprise. A case study design is appropriate for this research because it allows for an in-depth understanding of complex organizational processes, technological implementation, and human interactions within a real-world context (Rashid et al., 2019, 1-13).

WH Company was chosen as the case study company because of the following criteria: 1) It is an example of a conventional manufacturing company that is currently transforming into a digitalized company, 2) WH Company actively introduces artificial intelligence into different business processes, including production operations, quality assurance, inventory management, logistics, maintenance of equipment, and several support processes such as marketing and administrative functions, according to the conceptual framework.

The research was conducted during the period August to December 2025 when artificial intelligence had already been introduced into the company and transformed into business processes. Given the exploratory nature of AI-driven operational transformation, a qualitative approach enables the capture of rich, contextualized insights that may not be fully revealed through quantitative methods.

2) Key Informants

This study conducted semi-structured in-depth interviews with 20 participants. A purposive sampling approach was adopted to ensure that all participants would have some direct or indirect experience related to AI adoption, deployment, and application within WH Company. The selection of a sample size of 20 key informants is appropriate for qualitative case studies as it provides enough diversity of perspectives among the informants without compromising data saturation (Yin, 2018).

Table 1 Key Informants

Informant Code	Position Level	Department / Function	Years of Experience	AI Involvement Role
R-1	Middle Manager	marketing management	10 years	Strategic awareness; limited AI use in bidding and document support
R -2	Middle Manager	Production Management	7 years	Operational decision-maker; oversees AI-enabled production processes
R-3	Middle Manager	Quality Management	7 years	User and coordinator of AI systems in inventory and quality control
R-4	Senior Managers	General Management	10 years	Strategic sponsor; AI adoption decision-maker with risk oversight
R-5	Senior Managers	Deputy General Manager	10 years	Strategic initiator; benchmarked peers and approved AI investment
R-6	Frontline staff	Sales	5 years	Indirect user; basic AI tools for non-sensitive documentation
R-7	Frontline staff	Transportation (Driver)	10 years	End-user of AI-enabled navigation tools
R-8	Frontline staff	Production (Mold Filling)	6 years	Direct operator of automated production equipment
R-9	Frontline staff	Production (Mold Cleaning)	6 years	Affected by AI indirectly through increased workload
R-10	Frontline staff	Production (Curing / Steaming)	5 years	Operator of AI-controlled curing systems
R-11	Frontline staff	Production (Raw Material Mixing)	2 years	Direct operator of AI-assisted proportioning systems
R-12	Frontline staff	Production (Mold Placement & Filling)	6 years	Core AI equipment operator

Table 1 Key Informants (Continue)

Informant Code	Position Level	Department / Function	Years of Experience	AI Involvement Role
R-13	Frontline staff	Production (Boiler / Curing Support)	10 years	Auxiliary operator; monitors AI-controlled curing process
R-14	Frontline staff	Quality Management	4 years	Operator of AI-based demolding and inspection equipment
R-15	Frontline staff	Quality Management	4 years	User of AI inspection systems with manual verification
R-16	Frontline staff	Warehouse Management	5 years	User of AI inventory warning and space optimization systems
R-17	Frontline staff	Warehouse / Handling	6 years	No direct AI use; indirectly affected by AI-driven operations
R-18	IT and Engineers	Equipment Maintenance / IT Support	5 years	Technical maintainer; evaluator of AI system readiness
R-19	IT and Engineers	IT / Data Integration	2 years	Data integration and AI system support role
R-20	IT and Engineers	Technical R&D / Quality Testing	4 years	Data provider; supports AI decision logic in material formulation

The participants had been carefully chosen because of their role in the process of implementing artificial intelligence within the business operations of the company. The informants (R1-R20) spanned various levels of organizational hierarchy; these include senior managers (strategic decision makers), middle managers (implementers), frontline staff (end-users) as well as the IT engineers who deployed the systems. This diversity of the participants added to the quality of the data gathered as well as its analysis.

3) Research Instruments

The main research instruments used to collect data during this research project is an interview protocol aimed at acquiring qualitative data concerning the operational

transformations that take place due to AI in WH Company. For developing the interview questions, The interview questions were carefully developed based on the study's conceptual framework and grounded in established theories, includes TOE Framework and IDT.

The interview guide was structured around six key themes, including the context and decision-making processes of AI adoption, application scenarios and process changes, employee and managerial attitudes toward AI, perceived achievements and challenges, organizational support and resource allocation, as well as recommendations for future improvement. This thematic structure allowed for both consistency across interviews and flexibility to explore participants' experiences in depth.

To ensure high quality of data, prior to conducting interviews, the researcher revised the interview guide in order to enhance its alignment with the research questions posed and eliminate any gaps. Besides using an interview guide, there were a number of other instruments used during the research process for increasing the reliability of collected information.

4) Data Collection

Data were primarily collected through semi-structured, in-depth interviews. A purposive sampling strategy was used to ensure that participants possessed relevant experience and knowledge regarding AI implementation and operational processes within the organization. In total, 20 interviewees (R1-R20) were included, comprising senior managers, middle managers, frontline employees, and personnel from IT and engineering departments.

The interview protocol was designed based on research objectives and theoretical frameworks, focusing on participants' experiences with AI applications, perceived benefits and challenges, organizational support mechanisms, and individual attitudes toward AI-driven changes. Each interview lasted approximately 45–90 minutes and was conducted either face-to-face or online. With participants' consent, interviews were audio-recorded and transcribed verbatim. To enhance data credibility, interview data were triangulated with internal company documents and on-site observations related to AI-enabled operational systems and processes (Gabelaia & Hendieh, 2025, 657–677).

5) Data Analysis

Thematic analysis was employed to analyze the qualitative data. The analysis followed a systematic coding process, including open coding, axial coding, and selective coding (Naeem et al., 2023, 1-18). During open coding, interview transcripts were examined line by line to identify initial concepts and meaningful units. Axial coding was then used to group related

codes into higher-level categories, reflecting organizational, technological, and human dimensions of AI-driven operational innovation. Finally, selective coding was conducted to integrate core themes and establish relationships among key factors influencing AI-driven operational transformation.

The analysis took place within the context of the TOE framework and IDT in order to provide the theory that can help in interpreting the findings while allowing emerging themes to develop during the process. This research methodology approach was fitting since it enabled systematic examination of the relationships between various technological, organizational, and human elements involved in the AI revolution.

In order to increase the validity of the research, data triangulation was utilized in the form of semi-structured interviews with managers, staff members, and IT/Engineering specialists along with organizational documentation and field notes. In addition, member checking was done in order to verify the correctness of the interpretations. Lastly, the theoretical triangulation was performed by considering the findings within the framework of the TOE and IDT models.

6) Ethical Considerations

Ethical principles were strictly followed throughout the research process. All participants were informed of the purpose of the study and their right to withdraw at any time. Participation was voluntary, and confidentiality and anonymity were ensured by removing identifiable information from transcripts and research outputs.

Research Results

1) The role of AI in operational innovation at WH Company

Thematic analysis indicates that AI adoption at WH Company follows a pattern of core-process prioritization and support-process lag (See Table 2.).

Table 2 The Role of AI in Operational Innovation at WH Company

Operational Domain	AI Application Areas	Nature of AI Role	Key Outcomes	Evidence from Interviews
Manufacturing Processes	Intelligent raw material proportioning; automated filling, curing, and demolding	Core-process automation and control	Reduced labor input, lower defect rates, improved production stability and productivity	R2, R8, R10, R11, R12, R13, R15
Quality Control	Computer vision-based defect detection combined with manual reinspection	Human-AI collaborative decision-making	Improved quality consistency; reduced defects while maintaining risk control	R2, R3, R15, R18, R20
Warehousing Management	Inventory early warning systems; space optimization algorithms	Data-driven coordination and optimization	Reduced inventory imbalance; improved space utilization and cross-department coordination	R3, R4, R16
Logistics Management	Intelligent navigation and route planning tools	Efficiency-enhancing decision support	Shorter delivery times; reduced fuel consumption; high user acceptance	R7
Equipment Maintenance	Early-stage data monitoring and alert systems	Exploratory decision-support role	Improved planning awareness; limited predictive capability; manual confirmation still required	R18, R19
Customer Service & Sales Support	Digitalized but non-AI-integrated systems	Lagging and minimal AI application	Limited operational innovation due to institutional and industry constraints	R1, R4, R6
Non-Core Processes (Marketing & Administration)	AI-assisted document drafting and office tools	Localized, tool-based empowerment	Improved individual efficiency; no systemic process innovation	R1, R6, R16

Note: R1–R20 refer to key informants from different organizational levels within WH Company. Specifically, R4 and R5 represent senior management, R1–R3 represent middle management, R6–R17 represent frontline employees, and R18–R20 represent IT and engineering personnel. This classification reflects the hierarchical structure of the organization and supports the analysis of AI adoption and usage across strategic, managerial, and operational levels.

AI has been deeply integrated into manufacturing, quality control, warehousing, and logistics, improving automation, production stability, quality consistency, and operational efficiency. In manufacturing and quality control, AI reduces labor intensity and human error through intelligent systems and human–AI collaboration, while in warehousing and logistics it enhances coordination, space utilization, and delivery efficiency. In contrast, AI application in equipment maintenance remains exploratory and mainly serves as a decision-support tool requiring human confirmation. Customer service, sales, and non-core administrative functions show limited and fragmented AI use, largely constrained by institutional and industry factors. In these areas, AI is mainly used for individual productivity rather than systemic innovation.

The findings in Table 1 indicate that the role of AI into operational innovation depends on organizational levels. Automated and quality control procedures powered by AI are linked to the involvement of frontline and technical workers (e.g., R2, R8, R15). This is due to the reason that such operations allow combining human efforts with the use of advanced technologies. Meanwhile, the middle-level management takes the coordinating role using AI outcomes in order to make decisions and integrate operations. At the top-management level, AI serves only a strategic purpose (R4 and R5), which can be related to making important investments within organizations.

AI applications in equipment maintenance remains exploratory and mainly serve as a decision-support tool requiring human confirmation. Customer service, sales, and non-core administrative functions show limited and fragmented AI use, largely constrained by institutional and industry factors. In these areas, AI is mainly used for individual productivity rather than systemic innovation. Overall, AI at WH Company primarily supports process optimization in core operations, while its broader strategic potential for organizational transformation remains underdeveloped. The findings indicate that AI-driven operational innovation at WH Company follows a “core-process prioritization and support-process lag” pattern. AI plays a transformative role in production, quality control, and logistics, where processes are standardized and data-intensive. In contrast, AI adoption in customer service, sales support, and administrative functions remains fragmented and tool-based, reflecting organizational caution, institutional constraints, and limited system integration.

2) The key organizational, technological, and human factors influencing the effectiveness of AI-driven operational transformation.

Table 3 Key Factors Influencing the Effectiveness of AI Implementation at WH Company

Factors		Description of Empirical Findings	Effect Type	Organizational Level	Implications for AI Effectiveness	Evidence from Interviews
Organizational Factors	Pragmatic top management orientation	AI adoption driven mainly by cost reduction; strategy initially fragmented	Barrier	Top	Led to uneven adoption and lack of long-term direction	R4, R5
	Leadership support	Strong support for AI in core operations	Enabler	Top	Facilitated resource allocation and initial adoption	R4, R5
	Middle-management resistance and adaptation	Resistance due to job insecurity and role changes	Barrier	Middle	Slowed diffusion and increased adaptation costs	R2, R14
	Cross-departmental collaboration	Weak coordination across functions (e.g., sales, finance)	Barrier	Middle	Limited system-wide value creation	R1, R6, R15
	Change management capability	Lack of structured communication and long-term change mechanisms	Barrier	Top / Middle	Reduced trust and organizational readiness	R2, R8, R12, R13
	Strategic alignment	AI initiatives not fully aligned with long-term strategy	Barrier	Top	Fragmented implementation across departments	R4, R5
Technological Factors	System integration capability	AI systems operate in parallel with ERP/CRM	Barrier	Operational / Technical	Limited interoperability and data flow	R18, R19, R20
	Data availability and quality	Incomplete and inconsistent data	Barrier	Operational / Technical	Reduced predictive accuracy and AI performance	R18, R20

Table 3 Key Factors Influencing the Effectiveness of AI Implementation at WH Company (Continue)

Factors		Description of Empirical Findings	Effect Type	Organizational Level	Implications for AI Effectiveness	Evidence from Interviews
	IT infrastructure readiness	Core systems support AI in production areas	Enabler	Operational / Technical	Enabled automation and efficiency gains in core processes	R2, R3
	Cybersecurity & data privacy	Strict data protection limits system expansion	Barrier	Top / Technical	Restricted broader AI adoption and integration	R4, R20
Human Factors	Digital literacy	Uneven digital skills across employees	Barrier	Operational	Limited effective use of AI systems	R7, R8, R16
	Training and development	Training programs are basic and task-oriented	Barrier	Operational / Middle	Weak long-term capability development	R7, R8, R16
	Employee acceptance	Gradual shift from resistance to acceptance	Enabler	Operational	Improved adoption in performance-related roles	R2, R3, R8
	Compensation and incentives	Bonus adjustments reduce resistance	Enabler	Operational	Increased short-term adoption and stability	R9, R12
	Role-based differentiation	AI impact varies by job role	Barrier	All Levels	Uneven engagement and learning outcomes	R7, R17
	Participation and career concerns	Fear of job loss affects engagement	Barrier	Operational	Passive compliance and reduced motivation	R8, R12, R13

Note: R1–R20 refer to key informants from different organizational levels within WH Company. Specifically, R4 and R5 represent senior management, R1–R3 represent middle management, R6–R17 represent frontline employees, and R18–R20 represent IT and engineering personnel. This classification reflects the hierarchical structure of the organization and supports the analysis of AI adoption and usage across strategic, managerial, and operational levels.

As Table 3 illustrates, the success of implementing AI at WH Company was affected by the organizational, technological, and human aspects. The organizational factors, such as a lack of unity between different strategic initiatives, reluctance on the part of middle managers, absence of effective cross-functional cooperation, and weak managerial capabilities have impeded the successful implementation and transformation processes. In terms of technological factors, they involved the problems of system integration, low-quality data, and data insecurity, all of which could negatively affect decision-making. With regard to the human resources aspect, despite the change in employee attitude towards AI from negative to positive, the lack of digital skills, poor training, differences in roles, and job insecurity have hindered further development of capabilities.

The results shown in Table 3 have been analyzed based on the conceptual framework by classifying the factors under organizational, technological, and human dimensions. The results have helped distinguish between factors that facilitate success (leadership support, incentive alignment, etc.) and factors that hinder the success of AI (system integration difficulty, lack of digital skills, etc.), thus helping understand their effect on AI success. In addition to this, the results show that these factors are not only present at one organizational level but span several organizational levels. The organizational factors tend to be mainly related to senior and mid-level managers (R1-R5), whereas the technological factors relate to IT and engineering employees (R18-R20). Human factors can mostly be observed amongst operational employees (R6-R17).

3. The guidelines for enhancing the effectiveness of AI-driven operational transformation in traditional manufacturing enterprises.

The guidelines presented in Table 4 are directly derived from the key factors identified in Table 3. Specifically, organizational barriers such as fragmented strategy and weak cross-functional coordination led to the recommendation of reframing AI as a systemic strategy. Technological limitations, including poor system integration and data quality issues, inform the need to strengthen data connectivity and infrastructure. Similarly, human-related challenges such as digital literacy gaps and employee resistance underpin the emphasis on role-based training and structured change management. This linkage ensures that the proposed guidelines are grounded in empirical findings and address the root causes of AI implementation challenges.

Table 4 Guidelines for enhancing the effectiveness of AI-driven transformation at WH Company

Guideline	Core Issue Identified	Key Recommendation
Reframing AI as a systemic strategy	AI adoption driven mainly by cost reduction, leading to fragmented implementation	Position AI as a long-term strategic transformation tool supported by a clear roadmap, phased goals, and performance indicators
Strengthening system integration and data connectivity	Limited integration between AI systems and ERP/CRM platforms	Integrate high-value data flows through standardized interfaces or a centralized data layer to enable end-to-end process optimization
Expanding AI use to knowledge and quality enhancement	AI applications remain execution-oriented	Enrich data capture in quality and maintenance processes to support learning, predictive analytics, and decision support
Designing role-differentiated training pathways	Uneven digital literacy and AI adaptability across employee groups	Implement differentiated training for managers, frontline workers, and technical staff aligned with role requirements
Institutionalizing change management	Employee anxiety and resistance due to job security concerns	Establish transparent communication, reskilling pathways, and internal mobility mechanisms to sustain engagement
Adopting a gradual AI diffusion strategy	Uneven diffusion across organizational functions	Maintain incremental expansion starting from standardized, low-risk processes and leverage visible successes for wider diffusion

Enhancing the effectiveness of AI-driven transformation at WH Company requires a balanced and integrated approach that simultaneously addresses strategic alignment, technological integration, and human factors. By transitioning from fragmented automation to system-level intelligence, strengthening cross-departmental coordination, and embedding AI within organizational learning and change management structures, WH Company can achieve more sustainable and scalable operational innovation. These guidelines provide a practical bridge between the empirical findings and the broader theoretical frameworks underpinning this study.

The findings across the research objectives are closely interconnected. The identified roles of AI in operational innovation provide the functional foundation for transformation, while the organizational, technological, and human factors explain the conditions that enable or constrain these roles. The proposed guidelines are therefore developed as targeted responses to these factors, ensuring alignment between AI capabilities, organizational readiness, and human adaptation. This integrated perspective highlights that effective AI-driven transformation requires not only technological deployment but also coordinated organizational and human development.

Discussion

This study provides empirical insights into AI-driven operational innovation in a traditional manufacturing enterprise by integrating the TOE framework and IDT (Tornatzky et al., 1990). The *findings* reveal that AI-driven transformation is not merely a technological process, but a complex socio-technical process shaped by the interaction of organizational structures, technological infrastructures, and human agency.

Figure 2 is developed based on the synthesis of findings from Tables 3 and 4. The TOE components are derived from the empirical categorization of organizational, technological, and environmental conditions. While technological and organizational factors are directly supported by interview data, the environmental dimension is inferred from industry-level constraints, regulatory conditions, and market pressures discussed by participants, particularly at the managerial level.

The human factors identified in Table 3 are reflected in Figure 2 through employee roles, skill levels, and behavioral responses to AI adoption. These elements are further interpreted using Innovation Diffusion Theory (IDT), where different adopter categories—such as innovators, early adopters, and late adopters—are derived from observed variations in acceptance, engagement, and usage patterns across informants. For example, senior managers and IT personnel demonstrate characteristics of innovators, while frontline employees exhibit patterns consistent with early and late majority groups. Operational innovation outcomes in Figure 2 are directly linked to the AI roles identified in Table 2, particularly in production, quality control, and logistics functions.

The findings of this study are consistent with prior research on AI adoption in manufacturing contexts, which emphasizes the importance of technological readiness and

organizational support in driving operational innovation (Tian et al., 2023, 108929). Similar to previous studies, this research confirms that AI is most effectively implemented in structured and data-intensive processes such as production and logistics.

However, this study extends existing literature by providing deeper insights into the uneven diffusion of AI within organizations. While earlier research often assumes relatively uniform adoption, the findings from WH Company reveal a clear distinction between core and non-core functions, as well as between different organizational levels. This supports and extends the findings of Sorooshian et al. (2022, 82), who highlight the operational benefits of AI, but adds a new dimension by explaining why such benefits are not uniformly realized across all functions.

Furthermore, the observed resistance among employees and the gradual shift toward acceptance align with prior studies on digital transformation and employee adaptation (Fenwick et al., 2024, 34). However, this study contributes additional empirical evidence by linking these behavioral patterns to specific organizational roles and diffusion stages, thereby providing a more nuanced understanding of AI adoption dynamics in traditional manufacturing enterprises.

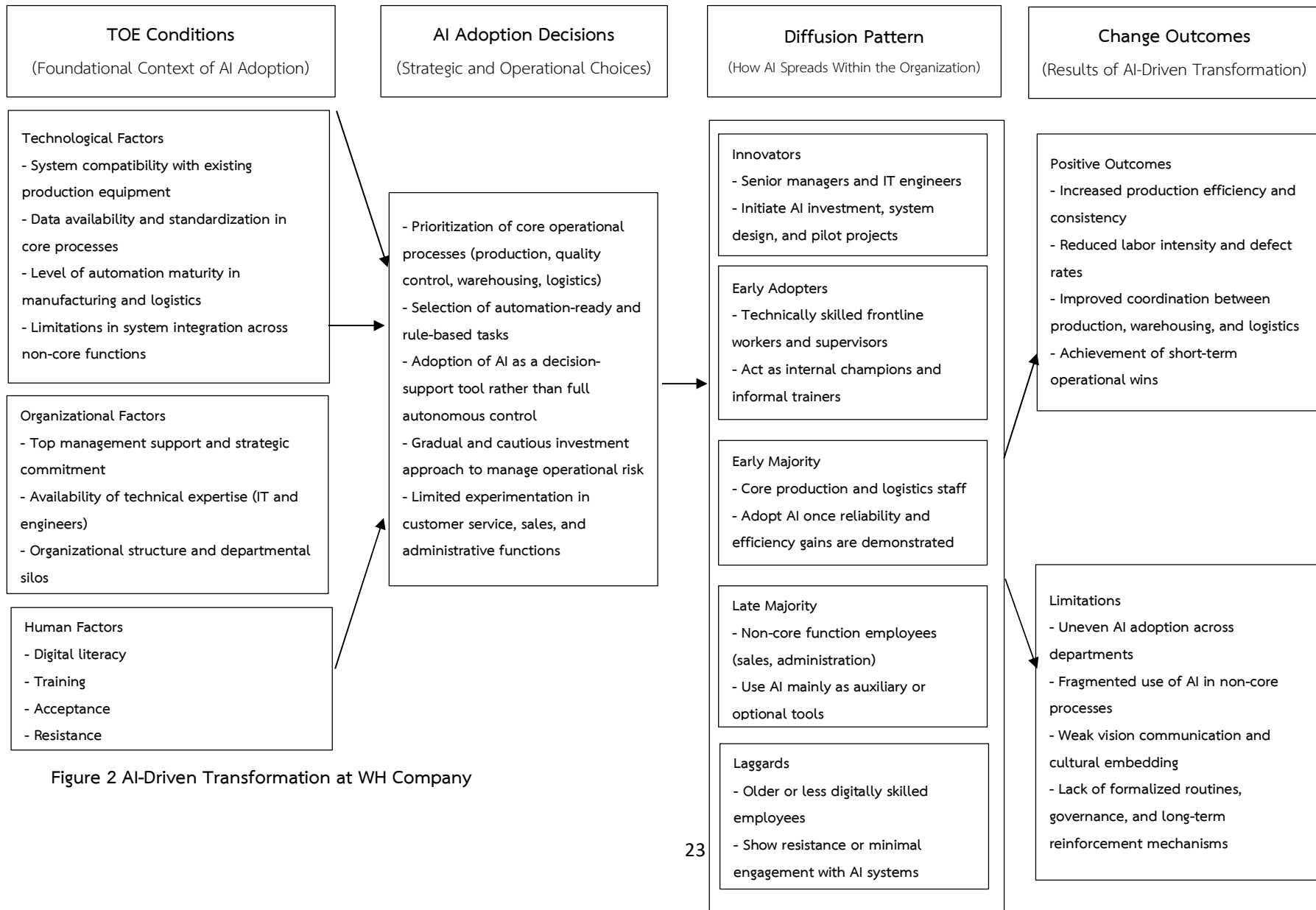


Figure 2 AI-Driven Transformation at WH Company

Technologically speaking, the results reveal that AI can help organizations become more efficient, effective, and coordinated, provided they have appropriate infrastructures and accurate data. However, fragmented systems and poor data consistency impede the ability of AI innovation to scale up, and therefore technological readiness has to be combined with system integration (Tornatzky et al., 1990; Sánchez et al., 2025, 6465). Organizational factors that play crucial roles in shaping the adoption of AI include leadership commitment and strategic alignment. Leadership commitment is instrumental in making resources available and coordinating efforts among various departments, while inconsistent integration among different departments implies certain barriers within the organization (Tornatzky et al., 1990; Leso et al., 2023).

The human factors such as digital literacy, training, adoption, and rejection have great impact on the efficacy of the AI adoption process. Employees who are adequately trained and supported tend to adopt the new technology in a positive manner while issues pertaining to job loss and surveillance could lead to adoption resistance (Tornatzky et al., 1990; Khan et al., 2024; Sánchez et al., 2025). According to IDT, employees could be classified as innovators, early adopters, early and late majorities, and laggards depending on their readiness to use the AI system. The results show that innovators were found among the management while IT professionals were considered early adopters while the rest were early and late majorities.

Through the use of the two theories of TOE and IDT, this research shows that the use of AI in organizational innovation is indeed a multilevel transformational process in which organization's structure influences the adoption of technology, whereas the perception and learning processes of employees affect the diffusion and usage of AI technologies.

The relationships between TOE characteristics, adoption decisions related to AI, innovations diffusion patterns, and change consequences are shown in Figure 2. The presence of technological compatibility and data standardization makes AI adoption possible in core business processes while insufficient system integration and regulation limits AI deployment in non-core activities. High levels of organizational commitment and IT proficiency lead to adoption while lack of cross-department collaboration and low IT competence hinder innovations diffusion. Pressure from environment aimed at costs cutting and quality improvement encourages AI adoption.

In such an environment, AI adoption occurs mostly in core processes of the company where work is more standardized and is mostly oriented towards supporting decision-making. Consistent with the Innovation Diffusion Theory (IDT), the adoption process starts with managers and technical personnel serving as the innovators and early adopters followed by other employees with a slower adoption pace. Therefore, AI helps to increase efficiency and coordination in core business processes. This paper provides empirical insights into operational innovation through artificial intelligence that is based on real-world case from a manufacturing firm and shows how the combination of technological, organizational, and human aspects shapes AI-related changes. The contribution of the research to existing knowledge consists of emphasizing transformation and organizational dynamics in contrast to prior studies.

The current research can be seen as having some important theoretical implications. To begin with, the Technology-Organization-Environment (TOE) framework gets expanded, as transformation due to the use of AI is understood as a dynamic relationship between the technological system and organizational actors, not just the adoption of the technology. Secondly, the current paper extends the Innovation Diffusion Theory (IDT), showing that the process of AI adoption differs depending on where employees stand in terms of hierarchy in their manufacturing organization. It becomes clear that the groups of adopters are directly associated with managerial status, technical knowledge, and specific job requirements. Lastly, since both TOE and IDT get applied in the current research, a multi-level approach to explaining AI-driven operational innovations becomes possible. It combines macro-level organization features with micro-level behavioral patterns, providing a more holistic perspective on the topic under discussion. From this perspective, the study makes an important contribution to the literature on digital transformation.

Conclusion

This study has systematically analyzed the impact of AI innovation at WH Company, which is based on achieving three research objectives. First, the findings suggest that AI creates the highest operational innovation in core activities, i.e., production, quality control, warehouse, and logistics, since such operations are well-integrated and provide substantial amounts of information. At the same time, non-core activities, including customer support and

administrative processes, are characterized by low innovation because of poor integration and lack of standardization.

Secondly, the research highlights that an effective AI transformation needs to consider both organizational, technology-related, and human dimensions. The organizational dimension provides strategic guidance, technology-related dimensions impact scalability and performance of the system, whereas the human dimension impacts adoption by employees. Therefore, an AI transformation needs to be perceived as a holistic approach, not just a technical one.

Finally, the research provides recommendations regarding implementation of AI. Organizations have to adopt a phased approach where they start with operational standardization to benefit from quick wins, improve on integration and use AI for further applications before extending AI to their strategic and supportive functions. The adoption of AI involves defining the role of managers, integrating systems, ensuring data quality management, and developing the workforce.

This study shows that the innovations driven by AI are task-specific but add up to create overall organizational change. These results can help traditional manufacturing organizations adopt AI successfully despite the difficulties associated with human resistance, information security issues, and technological adoption.

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