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From Technology to Engagement: The Impact of AI on Job Characteristics and Employee Involvement

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Abstract: *From the organizational learning perspective, this study investigates the impact of artificial intelligence (AI) technology transformation on job involvement in the hospitality industry. The rapid integration of AI in this sector has led to significant changes in job roles and organizational dynamics. Key questions are explored regarding the effects of transformation on organizational learning, employee job involvement, and the mediating role of different organizational learning models. Utilizing a comprehensive theoretical framework, including the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Job Characteristics Model (JCM), the research reveals that AI technology transformation, particularly through the Job Characteristics Model, redefines job function enriches job content, and imbues work with meaning, thereby enhancing employee job involvement. Additionally, flexible organizational structures, open communication, and encouragement of employee participation and innovation facilitate the rapid integration of AI. Finally, the findings of this study assist organizational decision-makers in identifying factors influencing employee job involvement in the competitive environment of advancing AI capabilities. This insight aids in developing strategies that promote positive employee experiences amidst AI integration, designing job content that aligns with employee and AI capabilities, and ultimately enhancing organizational operational efficiency.*
Keywords: AI technology transformation, organizational learning, job involvement

INTRODUCTION

Organizations increasingly turn to artificial intelligence (AI) technology to transform their operational methods and enhance efficiency and innovation capabilities in today's rapidly changing business environment. The need for effective utilization of internal knowledge resources and adaptation to external environmental opportunities is highlighted by Dynamic Capability Theory (Teece et al., 1997). The study by Eisenhardt and Martin (2000) emphasizes continuous knowledge accumulation and sharing through learning processes for improved organizational adaptability and performance. Knowledge Management Capability (KMC), comprising Knowledge Infrastructure Capability (KIC) and Knowledge Process Capability (KPC), plays a crucial role in this context (Gold et al., 2001).

The hospitality industry is undergoing a significant transformation by incorporating AI technologies. Various establishments deploy AI-powered systems for customer service, reservations, and personalized experiences. However, this transformation has also led to changes in job roles and responsibilities, potentially affecting employees' job involvement (Nimmi et al., 2021). Furthermore, the cognitive shift required for this transformation can challenge organizational learning processes (Chen et al., 2023). This transition also poses challenges related to workforce adaptation, job role changes, and potential employee resistance (Smith, 2019).

In the contemporary hospitality industry landscape, the rapid integration of artificial intelligence (AI) technology is a pivotal force shaping organizational dynamics across various sectors. Integrating Artificial Intelligence (AI) technology in the hospitality industry has become increasingly prevalent, bringing opportunities and challenges. This rapid advancement has permeated various sectors, including the hospitality industry, leading to significant changes in job involvement and organizational learning. This study delves into a comprehensive exploration of the profound impact of AI technology transformation on job involvement within the hospitality industry, employing the perspective of organizational learning. Moreover, it provides an in-depth analysis of AI adoption in the hospitality sector, focusing on its impact on employee job involvement through organizational learning.

Research Questions

To comprehensively address the research objectives, this study focuses on the following key questions:
How does adopting AI technology transform organizational learning within the hospitality industry?
This question serves as the foundational inquiry, laying the groundwork to explore how AI technology is integrated into the specific organizational learning processes within the hospitality sector.

How does AI technology transformation impact employees' job involvement in the hospitality industry?
Understanding the impact of AI on job involvement in the hospitality industry is crucial for academics and practitioners. As AI becomes more ingrained in daily operations, there is a need to explore how employees perceive and engage with these technological changes. In order to investigate the direct consequences of AI technology integration, this question aims to reveal the influence on employee job involvement, encompassing motivation, satisfaction, and commitment.

What role do different organizational learning models play in mediating the relationship between AI technology transformation and job involvement?

Recognizing the varied approaches to organizational learning, this question seeks to unravel the intricate mechanisms through which distinct learning models impact the relationship between AI technology adoption and job involvement.

In summary, this study seeks to contribute to both academic knowledge and practical insights by unraveling the dynamics of AI technology transformation, organizational learning, and employee job involvement in the unique context of the hospitality industry. Through a nuanced exploration, the research aims to equip organizations with valuable knowledge to navigate the evolving landscape effectively. The subsequent sections will delve into the detailed examination of the theoretical model and hypotheses, providing a comprehensive understanding of the interconnections among AI technology, organizational learning, and job involvement.

Research Framework and Hypothesis Development

Anthropomorphism in Service:

Anthropomorphism in service refers to customers attributing human-like characteristics or traits to service robots, whether physical or virtual entities such as voice- or text-based chatbots. The degree of anthropomorphism in service robots can impact customers' intention to use them and their overall satisfaction. However, the influence of anthropomorphism is not consistent and can be positive, neutral, or negative, depending on factors such as customer characteristics, robot design features, and the type of service (Adam et al., 2021).

AI Technology Applications in the Hospitality Industry:

Currently, various AI technologies are being applied in the hospitality industry, particularly in hotels and restaurants. AI implementation in hotels often integrates with other enabling technologies such as facial recognition, automatic payments, drone deliveries, and self-driving cars. In restaurants, key applications include automated ordering systems, intelligent menu recommendation systems, robot waitstaff, kitchen automation, and data analytics with Customer Relationship Management (CRM).
These technologies enhance service efficiency, improve customer experiences, and reduce labor costs. In the hospitality industry context, the efficiency of employee tasks is measured by the time required, with shorter durations leading to lower labor costs. Consequently, investing in robotic labor is often more cost-effective than human labor (Osawa et al., 2017).

However, adopting service robots alters the nature of the service experience, as some service encounters are redefined by human-robot interaction (HRI). Unlike industrial robots that focus solely on efficiency, the success of service robots depends on user satisfaction (Cheng, 2018).

AI Technology Transformation in Knowledge Process Capability (KPC)

Teece et al. (1997) proposed the Dynamic Capability Theory, which focuses on how organizations effectively utilize internal knowledge resources and grasp external environmental opportunities to cope with rapidly changing environments. Dynamic capabilities are rooted in the management and operational processes within an organization. Eisenhardt and Martin (2000) highlighted that continuous accumulation and knowledge sharing through constant learning enhance organizational adaptability and operational performance. Liao and Wu (2010) used structural equation modeling to demonstrate the significant and positive relationship between knowledge management and organizational innovation, emphasizing that increased knowledge management improves organizational learning. Lin and Lee (2005) employed empirical analysis to describe the substantial impact of organizational learning and knowledge management factors on companies adopting enterprise electronic systems. Therefore, the investment in knowledge capability and knowledge management processes significantly impacts the introduction of new technologies to businesses.

Knowledge Management Capability (KMC) refers to the continuous mechanism of creating and utilizing knowledge within an organization (Von Krogh et al., 2001). According to Gold et al. (2001), KMC consists of two main dimensions: Knowledge Infrastructure Capability (KIC) and Knowledge Process Capability (KPC). KIC refers to foundational capabilities supporting organizational knowledge activities, including structure, information technology, and culture. KPC refers to the organization's ability to operate and apply stored knowledge, including acquisition, transformation, and application. Gold et al. (2001) argue that KPC, as part of managing organizational knowledge assets, should involve four essential processes: knowledge acquisition, knowledge transformation, knowledge application, and knowledge protection. Specifically, knowledge acquisition aims to facilitate effective access to useful knowledge resources for company employees, while knowledge transformation involves converting structured or unstructured knowledge into usable knowledge. Knowledge application pertains to using personal or organizational knowledge to solve problems and make successful decisions. Knowledge protection emphasizes safeguarding knowledge as a vital organizational asset to prevent improper use by employees.

AI Technology Transformation refers to using artificial intelligence (AI) technology to change the operational methods of organizations, enhancing efficiency and innovation capabilities. The study explores AI Technology Transformation as acquiring, transforming, and applying AI technology within an organization.

Benson, P. G., & Brown, M. (2007) pointed out that knowledge workers exhibit higher attitudinal commitment and lower intention to quit than routine-task workers. The antecedents of commitment to knowledge and routine-task workers differ in many important respects. Previous studies on knowledge process capability have predominantly focused on knowledge workers. In contrast, the majority of employees in the hospitality industry are routine-task workers. This might be different from the previous research.

Moreover, this study investigates the impact of AI technology transformation in different learning

Figure 1: Framework of this Study

organizations (adaptive and innovative) and further delves into the organizational forms (organic and mechanical) structures. The research focuses on how these forms influence the perception and integration of AI technology into organizational processes. The core of the study lies in AI technology transformation cognition, exploring its implications through three perspectives: the technology acceptance model, innovation diffusion theory, and job characteristics model. This cognition plays a crucial role in connecting organizational learning and job involvement. Finally, the framework will examine the impact of organizational learning and organizational forms on employee job involvement with AI technology transformation cognition as the mediating variable. This study's theoretical model and hypotheses are outlined below, as depicted in Figure 1.

The theoretical model presented in Figure 1 illustrates the interconnected relationships among AI technology transformation cognition, organizational learning, organizational forms, and job involvement, providing a comprehensive framework for understanding the complex dynamics within organizations undergoing technological transformation.

Types of Organizational Learning

A learning organization is a framework capable of continuously acquiring, creating, disseminating, and applying knowledge from internal and external environments to enhance organizational performance and adaptability (Garvin, 1993). The significance of learning organizations lies in their ability to assist organizations in coping with rapidly changing competitive environments, fostering and maintaining core competencies, and promoting organizational innovation and development (Senge, 1990; Prahalad & Hamel, 1990). The formation and development of learning organizations involve multiple dimensions, including individuals, teams, organizations, and the environment (Crossan et al., 1999). Different learning organizations may exhibit distinct learning patterns, such as different learning goals, processes, content, and outcomes (McGill et al., 1992).

Scholars have proposed various classification methods for learning patterns based on different theoretical foundations and research perspectives. One common classification is based on how learning changes conform to organizational norms, distinguishing learning patterns into single and double-loop learning (Argyris & Schon, 1978). Single-loop learning involves correcting errors or deviations without altering organizational norms and assumptions while achieving established goals. In contrast, double-loop learning entails correcting errors or deviations and examining and modifying organizational norms and assumptions in goal achievement. Single-loop learning is often associated with conservative, adaptive, and incremental changes, while double-loop learning is associated with innovative, transformative, and fundamental changes (Argyris, 1999).

Another common classification is based on knowledge acquired through learning, categorizing learning patterns into self-generated knowledge, external coaching, and market purchase (Ansoff & Brandenburg, 1971). Self-generated knowledge involves organizations creating new knowledge or technology through internal research and development activities and applying it to product or service development. External coaching refers to organizations acquiring and sharing knowledge or technology through collaboration with external partners, such as suppliers, customers, consultants, universities, etc., and transforming it into organizational capabilities. The market purchase involves organizations obtaining the right to use or own external knowledge or technology through purchasing or licensing, integrating it into their operations. Self-generated knowledge is typically associated with high innovation, uniqueness, and competitive advantage but comes with drawbacks such as high risk, high cost, and long cycles. External coaching is often associated with rapid learning, a wide range of knowledge sources, and low cost, but it comes with risks like knowledge loss, dependence, and uncertainty. Market purchase is usually associated with immediate knowledge acquisition, low risk, and short cycles but faces disadvantages like high cost, low innovativeness, and susceptibility to imitation (Petroni, 1996).

The third common classification is based on internal organizational mechanisms and whether employees actively or passively engage in self-learning to improve learning and output. This classification differentiates learning patterns into adaptive and innovative learning (McGill et al., 1992; O'Neil, 1995). Adaptive learning involves organizations maintaining stability and efficiency through hierarchical, formalized, and centralized organizational structures and passive control systems to adapt to external environmental changes. Innovative learning involves organizations pursuing organizational transformation and innovation through flexible, agile, team-complementary organizational structures, proactive self-management, and shared values. Adaptive learning is typically associated with low learning attitudes, low learning capabilities, and low learning motivation. In contrast, innovative learning is associated with high learning attitudes, capabilities, and motivation (Bennett & O'Brien, 1994).

Learning patterns reflect organizational learning goals, processes, content, and outcomes. Different learning patterns have different characteristics, advantages, and disadvantages. Organizations should choose the learning pattern that suits their characteristics and environmental requirements, continually adjusting and improving it to enhance organizational learning effectiveness and performance. This study adopts a classification of organizational learning patterns into "adaptive learning" (low learning patterns) and "innovative learning" (high learning patterns). Moreover, different organizational patterns may present different organizational learning effects based on their structural characteristics.

AI Technology Transformation

Artificial Intelligence (AI) refers to technologies that simulate human intelligence, including machine learning, natural language processing, computer vision, and other fields (Choi et al., 2021). The application of AI technology in the hospitality industry is becoming increasingly widespread, contributing to improved performance, cost reduction, increased efficiency, and meeting customer needs in areas such as customer service, marketing strategies, operational management, and product innovation (Wang et al., 2020).

However, the transformation of AI technology is not without challenges and difficulties, such as technology maturity, data quality, human resources, legal regulations, ethical considerations, etc. (Li & Wang, 2019). Therefore, hospitality businesses need clear awareness and planning when implementing AI technology to fully leverage its advantages while avoiding or mitigating potential risks and negative impacts (Wang et al., 2020).

AI technology transformation perception involves how organizations understand and respond to the impact of AI technology. This includes perceptions of AI technology, acceptance, willingness to use, and actual usage (Venkatesh et al., 2003). The study of AI technology transformation cognition can be explored through three dimensions: the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Job Characteristics Model (JCM).

Technology Acceptance Model (TAM): Davis (1989) introduced the Technology Acceptance Model, which posits that users' acceptance of technology depends on their perceptions of its usefulness and ease of use. In the transformation of AI technology, organizations need to ensure that employees recognize the usefulness of AI technology and make it easy to use to facilitate acceptance and application.

Innovation Diffusion Theory (IDT): Rogers (2003) proposed the Innovation Diffusion Theory, which emphasizes the diffusion process of innovation, including the knowledge stage, persuasion stage, decision stage, implementation stage, and confirmation stage. In the AI technology transformation process, organizations need to go through these stages to promote the use of AI technology. Job Characteristics Model (JCM): Hackman and Oldham (1976) developed the Job Characteristics Model, suggesting that the five core characteristics of a job (skill variety, task identity, task significance, autonomy, and feedback) influence employee job satisfaction and performance. In the AI technology transformation process, organizations must consider how to design jobs to utilize AI technology while meeting employees' job needs.

Adaptive Learning Organizations and AI Technology Transformation

Adaptive learning organizations are essential for quickly adjusting and adapting to environmental changes, crucial for the success of AI technology transformation (Senge, 1990). The Technology Acceptance Model emphasizes the individual acceptance of new technology, where organizational learning can influence employees' acceptance of AI technology (Venkatesh et al., 2003). The Innovation Diffusion Theory highlights the internal diffusion process of innovation, and adaptive learning organizations may lead to a more cautious approach to the diffusion of new technology

(Rogers, 2003). Additionally, the Job Characteristics Model focuses on internal job design within organizations, and adaptive learning organizations may promote AI technology awareness by providing a favorable work environment (Hackman & Oldham, 1976; Parker & Wall, 1998).

Hypotheses:

H1a: Adaptive learning organizations positively influence the Technology Acceptance Model in the perception of AI technology transformation

Adaptive learning organizations provide an environment for learning and adaptation, facilitating a more positive acceptance of new technology.

H1b: Adaptive learning organizations negatively influence the Innovation Diffusion Theory in the perception of AI technology transformation.

Such organizations may be more cautious about the diffusion speed of new technology.

H1c: Adaptive learning organizations positively influence the Job Characteristics Model in the perception of AI technology transformation.

Providing a favorable work environment promotes awareness and acceptance of AI technology.

Innovative Learning Organizations and AI Technology Transformation

Innovative learning organizations emphasize superiority in creativity and flexibility, offering different solutions to the challenges of AI technology transformation (Crossan & Apaydin, 2010). In the Technology Acceptance Model, innovative learning organizations may increase employees' resistance toward new technology (Venkatesh et al., 2003; Rogers, 2003). The Innovation Diffusion Theory emphasizes the rapid diffusion of innovation, suggesting that innovative learning organizations may more effectively drive the dissemination of new technology (Rogers, 2003). Regarding the Job Characteristics Model, innovative learning organizations may provide a more challenging and motivating work environment, facilitating the awareness of AI technology.

Hypotheses:

H2a: Innovative learning organizations negatively impact the Technology Acceptance Model in the perception of AI technology transformation.

Such organizations may lead to stronger resistance attitudes.

H2b: Innovative learning organizations have a stronger positive impact on the Innovation Diffusion Theory in the perception of AI technology transformation.

They could drive the dissemination of new technology more effectively.

H2c: Innovative learning organizations have a stronger positive impact on the Job Characteristics

Model in the perception of AI technology transformation.
A challenging and motivating work environment promotes awareness and acceptance of AI technology.

Organization Form and AI Technology Transformation Cognition
Organizational form is a human-designed structure that is not fixed but needs to be moderately adjusted with environmental changes (Kast & Rosenzweig, 1974). From the perspective of the evolution of organizational forms, scholars agree that organizational structures should change in response to changes in time and space. However, one common classification of organizational structure is based on the degree of formalization, complexity, and centralization. It categorizes organizational forms into mechanistic and organic structures. Mechanistic organizational forms refer to more rigid structures with clear divisions of labor and centralized authority. They emphasize characteristics such as systems, congruence of authority and responsibility, and division of labor. They suit traditional organizations and bureaucratic structures, such as functional, divisional, product, and geographical area departments. On the other hand, organic organizational forms are characterized by flexibility, blurred divisions of labor, and decentralized authority. They emphasize improving administrative efficiency, agility, flexibility, and innovation. They are suitable for organizations facing rapid environmental changes or requiring innovation, such as simple structures, matrix structures, innovative team-based structures, self-managing team-based structures, and dynamic network-based structures.

In the hospitality industry, the choice of organizational form significantly impacts the operation and development of businesses. Organic organizational forms, which emphasize flexibility and adaptability, tend to perform better in environments with high uncertainty (Burns & Stalker, 1961). In the hospitality industry, organic organizational forms may be more capable of quickly adapting to market changes and meeting diverse customer demands (Ottenbacher & Harrington, 2007).

Hypotheses:
H3a: Organic organizational forms characterized by flexibility, decentralization, and employee empowerment are expected to positively impact the Technology Acceptance Model (TAM) in AI technology transformation.
Organic structures create an environment that encourages employees to accept new technologies by emphasizing their usefulness and ease of use, thereby promoting the acceptance and application of AI technology.
H3b: It is hypothesized that organic organizational forms have a negative impact on Innovation Diffusion Theory (IDT) in AI technology transformation.

Organizations with organic structures may adopt a more cautious attitude towards the rapid diffusion of new technologies, emphasizing flexibility and adaptability rather than rapid technological changes.
H3c: Organizations with organic organizational forms are expected to positively impact the Job Characteristics Model (JCM) in AI technology transformation.
Organic structures provide a challenging, motivating, and conducive learning environment that helps increase employee awareness and acceptance of AI technology.

Conversely, mechanistic organizational forms emphasize stability and efficiency, performing better in stable environments (Burns & Stalker, 1961). In the hospitality industry, mechanistic organizational forms may be more capable of providing consistent service quality and achieving economies of scale (Pizam & Holcomb, 2008).

Hypotheses:
H4a: Mechanistic organizational forms characterized by rigid structures, centralization, and formalization are expected to have a negative impact on the Technology Acceptance Model (TAM) in AI technology transformation.
Mechanistic structures may hinder employees' positive perceptions of AI technology's usefulness and ease of use, leading to a slower adoption process.
H4b: It is hypothesized that mechanistic organizational forms positively impact Innovation Diffusion Theory (IDT) in AI technology transformation.
Organizations with mechanistic structures may exhibit faster diffusion of new technologies, emphasizing efficiency and compliance with norms, resulting in a faster adoption process.
H4c: Organizations with mechanistic organizational forms are expected to have a negative impact on the Job Characteristics Model (JCM) in AI technology transformation.
Mechanistic structures may provide a less challenging and motivating work environment, potentially hindering employees' awareness and acceptance of AI technology.

Job Involvement
In the hospitality industry, the influence of AI technology transformation cognition on job involvement is a significant research area. Job involvement is typically defined as an attitude toward work, indicating an individual's psychological identification with their job and the importance they attribute to it (Van den Bossche, Segers, & Woltjer, 2006). It is crucial to differentiate between job involvement and work commitment. Early socialization processes condition work commitment. It is related to an individual's values regarding work and its benefits. At the same time, job involvement is associated

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with the current job and depends on one's current employment situation and the extent to which it satisfies one's needs.

Based on Brown's (1996) research, job involvement represents an attitude towards work, often defined as the degree to which an individual psychologically identifies with their job, indicating how much importance they attribute to their work. Brown further distinguishes between work participation and job involvement. Early socialization processes regulate work commitment and are related to an individual's values regarding work and its benefits. In contrast, job involvement is associated with the current job and depends on one's current employment situation and the extent to which it satisfies one's needs. This study aims to understand the impact of AI technology transformation cognition as a mediating variable on job involvement in the hospitality industry, as introducing AI technology introduces new dimensions to job involvement.

Hypotheses:

H5a: Innovative organizational learning positively impacts job involvement through the Job Characteristics Model in AI technology transformation.

Innovative organizational learning is expected to enhance job involvement by promoting positive perceptions of the Job Characteristics Model. Previous research indicates that organizational learning increases employee acceptance of new technologies.

H5b: Innovative organizational learning positively impacts job involvement through the innovation diffusion theory in AI technology transformation.

This hypothesis posits that innovative organizational learning influences the positive effects of the innovation diffusion theory in AI technology transformation cognition, thereby positively affecting job involvement. Previous studies suggest an organization's innovative culture and learning orientation increase employee innovation involvement.

H5c Adaptive organizational forms positively impact job involvement through the Job Characteristics Model in AI technology transformation.

This hypothesis suggests that adaptive organizational forms positively influence job involvement by affecting the effects of the Job Characteristics Model in AI technology transformation. Previous research indicates that adaptive organizational forms may resist rapid technological changes and exhibit a more conservative approach to new ideas.

H5d. Organic organizational forms positively impact job involvement through the Diffusion of Innovation Theory in AI technology transformation.

Organic organizational forms are expected to positively influence job involvement by affecting the effects of the Diffusion of Innovation Theory in AI technology transformation. Research indicates that organic organizational structures generally provide a more challenging and motivating work environment, contributing to employee job involvement (Morgeson & Humphrey, 2006).

H5e. Mechanistic organizational forms have a negative impact on job involvement through the technology acceptance model in AI technology transformation.

This hypothesis proposes that mechanical organizational forms are expected to negatively influence job involvement by affecting the effects of the technology acceptance model in AI technology transformation. Previous studies have found that mechanical organizational structures may limit employee acceptance of new technologies (Yoo & Kanawattanachai, 2001).

H5f: Mechanistic organizational forms have a negative impact on job involvement through the job characteristics model in AI technology transformation cognition

This hypothesis proposes that mechanical organizational forms negatively influence job involvement by affecting the effects of the job characteristics model in AI technology transformation cognition. Relevant studies have found that mechanical organizational structures may provide a relatively less challenging and motivating work environment, potentially hindering employee participation and involvement in their work (Morgeson & Humphrey, 2006).

Research Subjects and Sampling Method

This study employed a questionnaire survey to test the proposed hypotheses, targeting employees in international chain hospitality organizations that have adopted artificial intelligence (AI) technologies. The research was conducted in two phases: a pre-test stage and a formal survey to ensure robust and reliable data collection.

Pre-Test Stage:

The development of the questionnaire was guided by established theoretical frameworks, including the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Job Characteristics Model (JCM). A draft questionnaire was initially designed and reviewed by academic scholars and industry experts specializing in hotel management. Their feedback focused on clarity, scale design, and potential biases.A pilot test was conducted with 24 hospitality employees to evaluate comprehensibility, time efficiency, and linguistic clarity. Based on the pilot results, questions with ambiguous or low comprehensibility were either refined or removed. Content validity was assessed using an item-level content validity index (CVI), while internal consistency was verified using Cronbach's α coefficient, with a target value above 0.7. Structural validity was confirmed through exploratory factor analysis (EFA), ensuring factor loadings exceeded 0.5. These efforts resulted in a refined questionnaire optimized for clarity, precision, and alignment with research objectives.

Formal Survey

After completing the pre-test and validation process, the finalized questionnaire was distributed to 300 employees in international chain hospitality organizations implementing AI technology. Out of the distributed surveys, 208 valid responses were collected, resulting in an effective response rate of 69.3%. The demographic analysis of respondents revealed that 56.4% were female, while 43.6% were male. Regarding age distribution, 36.5% were below 25 years old, 43.1% were between 25 and 30, 15.3% were between 31 and 40, and 5.1% were between 41 and 50 years old. Regarding work experience, 28.2% of participants had less than 5 years of experience, 25.3% had 5 to 10 years, 38.9% had 11 to 15 years, and 7.6% had over 15 years of experience. Regarding job roles, the majority (80.2%) were non-supervisory employees, while only 19.8% held supervisory positions.

Data Analysis Methods

The first stage of this study involved descriptive statistics for each variable, including measures such as mean and standard deviation, correlation coefficients, reliability analysis, and exploratory factor analysis. Structural Equation Modeling (SEM) was applied in the second stage for Confirmatory Factor Analysis (CFA). The purpose was to understand the internal consistency and fit of each variable under the measurement model of this study, examining the indicators of fit, including Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and Construct Reliability (CR). These indicators help evaluate the coherence and adequacy between factors and measurement items. Finally, Structural Equation Modeling was used to explore the causal relationships among variables in the model.

Results-Validity, Reliability, and Descriptive Statistics of Variables.

The AI technology transformation questionnaire was self-compiled, so an exploratory factor analysis was conducted on its dimensions. The number of factors was determined by the standard of obtaining an Eigenvalue greater than 1 in the analysis, and the factor loadings of each item were obtained using the varimax rotation method. Items with an absolute value greater than 0.5 were selected as the factors constituting the factor.

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As shown in Table 1, the factor analysis results of AI Technology transformation show that each item's factor loadings are above 0.5 and can be classified into three factors. Questions 1-3 are 'Technology Acceptance Model(TAM),' questions 4 -8 are 'Diffusion of Innovation Theory(DIT),' and questions 9-12 are 'Job Characteristics Model (JCM).' The cumulative explained variance of the three factors is 69.10%.

Table 1 Confirmatory Factor Analysis Factor Load Table- AI Technology Transformation Cognition and Job Involvement

Research Variables	Measurement Items	Load Factor (Standardized)	Cronbach's α
AI Technology Transformation Technology Acceptance Model	The application of AI technology in my company is useful.	0.775	0.756
	The application of AI technology in my company is easy to use.	0.696	
	I am willing to accept and use AI technology to improve my work in my company.	0.842	
AI Technology Transformation – Diffusion of Innovations Theory	I understand the application of AI technology in my company.	0.832	0.818
	I am interested in the application of AI technology in my company.	0.758	
	The application of AI technology in my company is valuable.	0.878	
	I have tried the application of AI technology in my company.	0.769	
	I have adopted and used the application of AI technology in my company.	0.886	
AI Technology Transformation – Job Characteristics Model	The use of AI technology has changed my job characteristics in my company.	0.717	0.789
	The use of AI technology has improved my job satisfaction in my company.	0.834	
	Applying AI technology has given me a new level of cognitive scale and speed in my work.	0.861	
	The application of AI technology will change the way I think about ethical, social, and intellectual issues at work.	0.827	
Job Involvement	I will actively gather relevant information needed for work or learn job-related skills.	0.764	0.878
	I am willing to put in extra effort to achieve work goals.	0.863	
	I consider the future development direction of my current job as my personal aspiration.	0.781	
	The current job service is meaningful to me personally.	0.811	
	I will overcome difficulties encountered in my work	0.836	

Note: ** indicates a significance level of P less than 0.01.(** = P < 0.01)

The main variables of this study include "AI Technology Transformation-TAM," "AI Technology Transformation-DIT," "AI Technology Transformation-JCM," "Adaptive Organizational Learning," "Innovative Organizational Learning," "Organic Organizational Form," "Mechanistic Organizational Form," and "Job Involvement." The means, standard deviations, Cronbach's alpha reliability values, and correlations between variables are detailed in Table 2 . The reliability of Cronbach's alpha values for each variable in the scale is all above 0.7, indicating acceptable internal consistency among the items in each scale.

Table 2 Mean, Standard Deviation, Correlation Coefficient, and Reliability

Research Variables	Mean	Standard Deviation	1	2	3	4	5	6	7	8
1. Adaptive Organizational Learning	3.37	0.76	(0.93)							
2. Innovative Organizational Learning	3.08	0.65	0.23*	(0.86)						
3. Organic Organizational Form	3.67	0.86	0.33*	0.28*	(0.81)					
4. Mechanistic Organizational Form	3.15	0.71	0.17	0.35*	0.18*	(0.85)				
5.AI Technology-Technology Acceptance Model	3.88	0.69	0.47*	0.01	0.28*	0.17*	(0.83)			
6.AI Technology-Diffusion of Innovations Theory	3.49	0.59	0.39*	0.21*	0.01	0.25*	0.22*	(0.77)		
7.AI Technology-Job Characteristics Model	4.21	0.32	0.21*	0.01	0.32*	0.00	0.02	0.03	(0.71)	
8.Job Involvement	4.05	0.54	0.12*	0.27*	0.00	0.24*	0.05	0..04	0.19*	(0.87)

Note: 1 Sample size = 208

2. The value of Cronbach's α for each variable is in ( ).

3. The asterisk * in the correlation coefficient analysis indicates a significant level where the P-value is above 0.05.

In the context of confirmatory factor analysis, scholars suggest that the Composite Reliability (CR) value should ideally be above 0.5 (Garver & Mentzer, 1999). Furthermore, in terms of "Convergent Validity," after calculating each variable's measurement model, the items' loading and T-value for all variables were obtained. Table 3 shows that the absolute values of T-values between variables are all above 1.96, reaching a significance level of α=0.05 or higher. This indicates that the scale possesses good convergent validity.

Table 3 Confirmatory Factor Analysis Table

Research Variables	Number of Question	CR	GFI	AGFI	RMSEA	Load Factor	T-value
Organizational Learning Learning Structure Characteristics	6	0.922	0.855	0.802	0.105	0.403-0.848	8.333-19.507
Organizational Learning Managerial Behavior	6	0.893	0.961	0.912	0.075	0.599-0.828	11.839-18.991
Organic Organizational Form	5	0.876	0.954	0.871	0.107	0.581-0.948	9.848-16.534
Mechanistic Organizational Form	5	0.928	0.918	0.758	0.168	0.462-0.878	9.073-18.991
AI Technology Transformation-Technology Acceptance Model	3	0.866	0.965	0.878	0.088	0.443-0.946	9.640-18.792
AI Technology Transformation-Diffusion of Innovations Theory	5	0.768	0.912	0.851	0.101	0.176-0.773	6.831-17.818
AI Technology Transformation—Job Characteristics Model	4	0.875	0.963	0.866	0.106	0.582-0.947	9.858-16.555
Job Involvement	5	0.933	0.922	0.761	0.141	0.461-0.877	9.062-18.981

Path Analysis Results

This study employed a structural equation modeling approach to conduct path analysis, with all variables used in the path analysis being first-order latent variables. These latent variables are composed of relevant observed variables (i.e., items). Parameter estimates, such as exogenous variable → endogenous variable and endogenous variable → endogenous variable, were obtained through ML estimation, and the T-values were used to test whether the paths hypothesized in this study reached a significant level. In the T-test, if the absolute value is greater than 2, the estimated parameters have reached a significant standard, confirming the acceptance of the hypothesized path.

In Figure 2, the paths of Adaptive Organizational Learning →DIT, Innovative Organizational Learning → TAM, TAM → Job Involvement and DIT → Job Involvement (β = -0.055, -0.089, -0.068, -0.058 T-values -1.131, 1.886, -1.443, -1.253) did not reach a significant level. Following the principle of path simplicity, non-significant paths were systematically removed.

First, the path Adaptive organizational → DIT ($\chi2$ = 42.43, df = 2, GFI = 0.97, AGFI = 0.756, RMSEA = 0.13) and Innovative organizational → DIT ($\chi2$ = 41.63, df = 2, GFI = 0.95, AGFI = 0.778, RMSEA = 0.15) were removed. Next, the path TAM → Job Involvement ($\chi2$ = 44.30, df = 3, GFI = 0.97, AGFI = 0.80, RMSEA = 0.15) and DIT → Job Involvement ($\chi2$ = 45.10, df =3 , GFI = 0.97, AGFI = 0.80, RMSEA = 0.15) were finally detached. A latent variable controlling for common method variance was introduced to account for possible influences of common method variance, and the results were re-estimated ($\chi2$ = 15.22, df = 3, GFI = 0.99, AGFI = 0.91, RMSEA = 0.10). The final estimated results are shown in the path of Adaptive Organizational learning. →JCM → Job Involvement and Innovative Organizational learning. →JCM → Job Involvement received support.

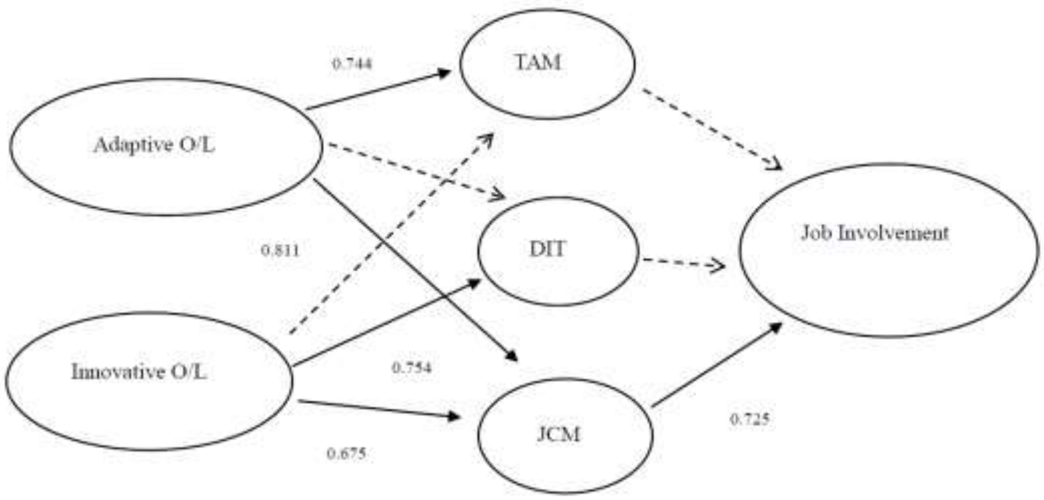

Figure 2 Organizational Learning Orientation- Results of the path analysis for this study framework (dashed lines indicate insignificant paths)

In Figure 3, the paths of Organic Organization Form →TAM, Mechanistic Organization Form → DIT, TAM → Job Involvement and JCM → Job Involvement (β = -0.065, -0.029, -0.061, -0.057 T-values -1.142, 1.486, -1.423, -1.353) did not reach a significant level. Following the principle of path simplicity, non-significant paths were systematically removed.

Primary, the path Organic Organization Form →TAM ($\chi2$ = 41.63, df = 2, GFI = 0.88, AGFI = 0.786, RMSEA = 0.15) and Mechanistic Organization Form → DIT ($\chi2$ = 42.73, df = 2, GFI = 0.93, AGFI = 0.777, RMSEA = 0.11) were detached. Following, the path TAM → Job Involvement ($\chi2$ = 43.30, df = 3, GFI = 0.91, AGFI = 0.70, RMSEA = 0.13) and JCM → Job Involvement ($\chi2$ = 42.10, df =3 , GFI = 0.87, AGFI = 0.77, RMSEA = 0.12) were lastly removed. A latent variable controlling for common method variance was introduced to account for possible influences of common method variance, and the results were re-estimated ($\chi2$ = 13.82, df = 3, GFI = 0.89, AGFI = 0.87, RMSEA = 0.11). The last estimated outcomes are displayed in the path of Organic Organization →DIT → Job Involvement established support.

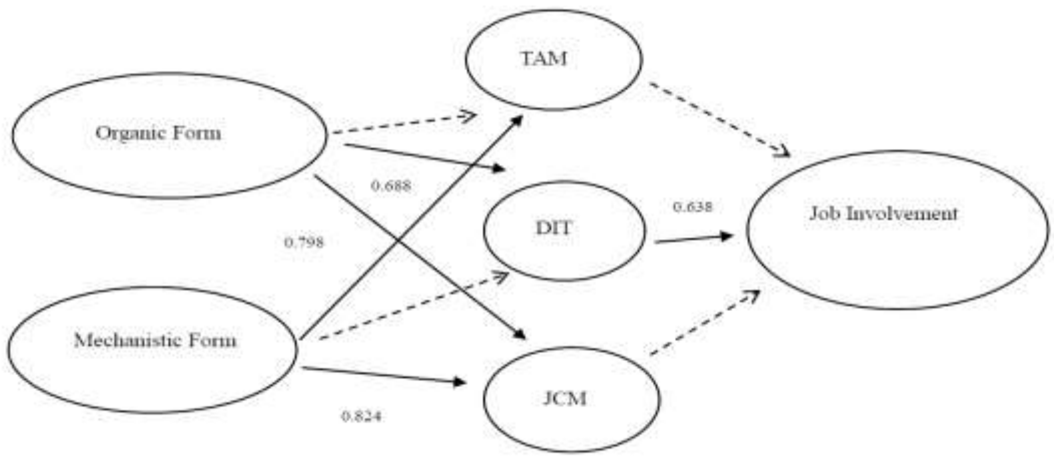

Figure 3 Organizational Form-Results of the path analysis for this study framework (dashed lines indicate insignificant paths)

DISCUSSION

The supported hypotheses H5a, H5c, and H5d highlight the crucial mediating roles of JCM and DIT of AI technology transformation in shaping the relationships among organizational learning, organizational form, and job involvement within the hospitality industry context. Let us delve into the implications of these findings.

Adaptive Organizational Learning and AI Technology Transformation

Through empirical results, this study identified a significant positive relationship between Adaptive Organizational Learning and the Job Characteristic Model in the context of AI Technology Transformation. Additionally, Adaptive Organizational Learning showed a positive relationship with the Technology Acceptance Model in AI Technology Transformation, but no significant impact was observed on the Diffusion of Innovation Theory. The potential reason for this could be that an Adaptive

Organization, emphasizing a high level of trust in employees, leading to a high level of compliance, aligns with the two main factors of the Technology Acceptance Model: Perceived Usefulness and Perceived Ease of Use. Perceived Usefulness refers to the extent to which people believe that using new technology is helpful, while Perceived Ease of Use pertains to how easy people find it to use the new technology. TAM suggests that these factors influence people's acceptance of new technology, subsequently affecting their willingness to use it. Due to the emphasis of an Adaptive Organization on designing organizational structures and processes for increased agility and adaptability, the transmission of technology is simplified and more comprehensible, resulting in higher acceptance levels facilitated by employees' high compliance.

Overall, the research findings indicate that when dealing with AI technology transformation, adaptive organizations need to focus on designing organizational processes to make new technology user-friendly. Additionally, job design should ensure that employees are aware of the usefulness of new technology and how it can assist them in their work.

Innovative Organizational Learning and AI Technology Transformation

This study, through empirical results, identified a significant positive relationship between Innovative Organizational Learning and the Job Characteristic Model as well as the Diffusion of Innovation Theory in the context of AI Technology Transformation. However, no significant impact was observed on the Technology Acceptance Model in AI Technology Transformation. Bennett and O'Brien (1994) emphasized that learning types help internal organizational members create new insights, promote internal understanding, and continuously improve learning methods for both self and output. Innovative learning is characterized by a high learning attitude, emphasizing the organizational structure features of agility, flexibility, and complementary teamwork. It is accustomed to pursuing change, often centered around creating, self-management learning, and strongly emphasizes achieving self-control through shared values. On the other hand, the Diffusion of Innovation Theory primarily explores how new ideas, technologies, or products spread and are adopted in society, categorizing people into different types based on their adoption speed of new things. These categories include innovators, early adopters, early majority, late majority, and laggards. The theory posits that different types of people adopt innovations at different rates during the diffusion process in society. Due to the inclination of innovative organizations to pursue change and exhibit high self-directed learning, they are more accepting of AI technology transformation.

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Organic Organization and AI Technology Transformation

Through empirical results, this study found a significant positive relationship between Organic Organization and the Job Characteristic Model as well as the Diffusion of Innovation Theory in the context of AI Technology Transformation. However, no significant impact was observed on the Technology Acceptance Model in AI Technology Transformation. An organic organization is characterized by flexibility and freedom, equal interaction and communication among members, and less rigid hierarchical structures. This organizational form is often more suitable for adapting to rapidly changing environments, allowing for greater flexibility in responding to external changes and challenges. Organic organizations emphasize teamwork, innovation, and flexibility, contributing to increased organizational adaptability and creativity. Hence, it aligns with the emphasis on innovative learning in the diffusion of innovation theory context. Additionally, the flexibility and freedom within organic organizations enable employees to resonate with the Job Characteristic Model that emphasizes diverse job skills in the AI Technology Transformation.

The research results indicate that flexibility and freedom within organic organizations significantly promote job characteristics and innovation when dealing with AI technology transformation. This contributes to enhancing organizational adaptability and creativity.

Mechanistic Organization and AI Technology Transformation

This study, through empirical results, found a significant positive relationship between Mechanistic Organization and the Job Characteristic Model as well as the Technology Acceptance Model in the context of AI Technology Transformation. However, no significant impact was observed on the Diffusion of Innovation Theory in AI Technology Transformation. The characteristics of a mechanistic organization include a tightly structured hierarchy, centralized decision-making authority, and clear job responsibilities. This organizational form is typically suitable for relatively simple and stable environments with a higher prevalence of repetitive and predictable tasks. Information flow is often top-down, with decision-making authority highly concentrated at the organization's top levels. However, the fundamental concept of the Technology Acceptance Model (TAM) is that an individual's acceptance and use of a new technology depend on their perception and attitude toward that technology. The key factors are the usefulness and ease of use of the technology. Therefore, the simple and repetitive work environment suitable for mechanistic organizations aligns with TAM's principles. Additionally, the explicit task delegation in the Job Characteristic Model (JCM) is applicable to the clear division of labor and decision-making within mechanistic organizations.

Mediator AI Technology Transformation and Job Involvement

Through empirical results, this study found that both Adaptive Organizational Learning and Innovative Organizational Learning Influence Job Involvement through the Job Characteristic Model in the context of AI Technology Transformation. The Job Characteristic Model emphasizes using job analysis and design methods to improve employees' work environments, facilitating meaningful work experiences and job satisfaction, ultimately increasing dedication, job satisfaction, and productivity. This research suggests that regardless of the organizational learning environment, the introduction of AI Technology requires a reevaluation and redesign of the entire job function within the organization, particularly to ensure that the implementation of AI Technology adds meaning to employees' work. In other words, making AI Technology more meaningful as a tool to assist employees in their work becomes crucial. As Amisha (2021) points out, the emergence of automated technology leading to job displacement can create a sense of job crisis among employees, necessitating a shift in perspective and collaboration between employees and employers.

This highlights that incorporating AI Technology into an organization goes beyond cost considerations; it requires a reexamination of the entire job function to enable employees to view it as an opportunity rather than a threat. This shift in perspective can enhance employee engagement and increase overall work efficiency.

Additionally, organic organizations influence job involvement through the diffusion of innovation theory in the context of AI technology transformation. Organic organizations, characterized by low complexity, low formalization, and decentralized structures, exhibit high adaptability and flexibility. According to the Diffusion of Innovation Theory, employees in organic organizations tend to be innovators and early adopters, making them more receptive to innovation. Therefore, introducing AI Technology in organic organizations will likely enhance job involvement. In other words, compared to traditional hierarchical structures, organizations with flexible and adaptable structures make it easier for employees to engage in their work when AI Technology is introduced.

In the hospitality industry, where automation equipment is becoming more intelligent and capable of replacing manual labor, employees in organic organizations have diverse job responsibilities and can adjust their roles flexibly. This facilitates seamless collaboration with AI, making it easier for AI to become a valuable assistant, share the workload with employees, and, importantly, mitigate concerns about job displacement. The diversified nature of work in organic organizations encourages employees to acquire a variety of job skills, reducing the risk of job displacement due to AI, and making employees more willing to embrace AI in their work.

Theoretical Contribution:
This study aims to provide valuable insights into the existing literature on AI in the hospitality industry by offering a comprehensive understanding of the influence of AI technology transformation on employee job involvement through three dimensions: Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Job Characteristics Model (JCM). Firstly, the research reveals that AI technology transformation, through job redesign, redefines job roles and enables employees to acquire diverse job skills, enriching job content and providing employees with a sense of purpose, increasing employee job involvement. For example, job rotation provides employees with opportunities for variability in their work, as enriching job content can make work more fulfilling, motivating learning and making work easier and more stimulating. Additionally, flexible organizational structures, adaptable authority structures, decentralized decision-making processes, open communication and information flow, and encouragement of employee participation and innovation are conducive to the swift integration of AI technology to adapt to market changes. This organizational format can often introduce AI technology to adapt to market changes quickly. Furthermore, this study aids organizational decision-makers in identifying factors that influence job involvement, contributing to developing strategies that promote positive employee experiences amidst AI integration.

CONCLUSION

As a highly labor-intensive and consumer-facing hospitality industry, it grapples with a severe labor shortage post-pandemic. Factors contributing to this shortage include the impact of the pandemic, challenging working conditions, and low wages. The reasons for the labor shortage in the hospitality industry are diverse and complex. The introduction of AI technology raises whether it is meant to replace or assist human labor, a matter worthy of reflection.

This study found that the impact of AI technology transformation on improving employee engagement is more related to organizational learning methods and organizational structure. Additionally, the manner in which AI technology is introduced is crucial in determining its acceptability among employees. Organizations with flexible structures are more adaptable to the integration of AI technology. Furthermore, as the capabilities of AI technology continue to advance, organizations should evaluate their entire set of job functions and design environments that complement both employees and AI to achieve higher operational efficiency.

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