THE INFLUENCE OF ARTIFICIAL INTELLIGENCE ADOPTION AND INNOVATIVE BEHAVIOR ON THE PERFORMANCE OF EMPLOYEE IN TOURISM INDUSTRY IN DIGITAL-BASED ECONOMY ERA

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ABSTRACT
This research aims to study the impact of the introduction of artificial intelligence (AI) and innovative behavior on the performance of employees in the tourism industry in the digital economy era. The data were collected from 400 employees of China Tourism Group Co., Ltd. and Hong Kong China Travel Service (Group) Co., Ltd. The descriptive and inferential statistics were analyzed. The results of the study found that: Employee demographics, such as gender, age, and income, do not affect overall performance. However, AI adoption has a significant impact on performance, especially Automation of Processes ($\beta = 0.516$), Personalized Customer Experiences ($\beta = 0.121$), and Skill Development and Training ($\beta = 0.106$), which increase employee performance. Innovative behavior has a significant impact on performance ($R^2 = 0.332$), with Collaboration Networks ($\beta = 0.278$) having the highest impact, followed by Technological Integration ($\beta = 0.210$), Policy-Driven Innovation ($\beta = 0.174$), and Capability Building ($\beta = 0.161$). Policy recommendations include developing collaborative networks, AI training for employees, and setting policies to support innovation. In addition, in-depth research on the long-term impact of AI and the role of organizational culture and leadership in supporting innovative behavior should be conducted to develop effective management approaches in the technology-driven tourism industry.
Keywords: Artificial Intelligence Adoption, Innovative Behavior, Performance, Tourism Industry, Digital-Based Economy Era

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INTRODUCTION

The tourism industry is undergoing a major transformation due to the development of digital technologies and rapidly changing consumer behavior. Several studies indicate that the adoption of Artificial Intelligence (AI) in the tourism sector is likely to continue to expand, with the global AI market in the tourism industry expected to grow at a compound annual growth rate (CAGR) of 12.5% between 2023 and 2030 (Market Research Future, 2023). Data from Statista (2023) also indicates that over 60% of travel companies worldwide have integrated AI into their operational processes, such as automated customer service, predictive analytics, and intelligent booking systems, to improve efficiency and enhance competitiveness. Advancements in AI have not only enabled tourism businesses to better respond to customer needs, but have also impacted employee behavior in terms of innovation (Scott & Bruce, 1994), which is a key factor in adapting to the digital economy. In addition, the adoption of AI has also improved the efficiency of internal management, reduced costs, and supported strategic decision-making by executives (Radhakrishnan & Chattopadhyay, 2020). However, despite AI being an important tool that helps businesses develop and compete in the digital age. However, employee adaptation and organizational culture are also important factors that need to be carefully considered for sustainable and successful AI implementations (Jain et al., 2024).

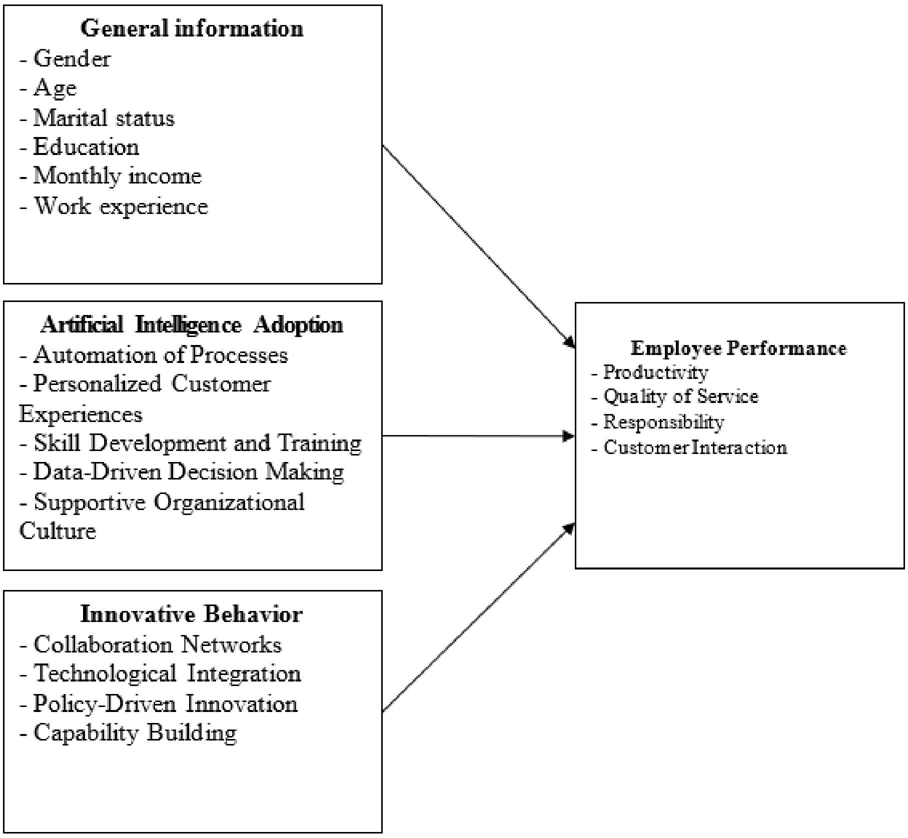
Although several studies have highlighted the important role of AI and employee innovative behavior in enhancing performance across industries, there has been limited study of this relationship in the context of the tourism industry, especially in the era of the digital economy where consumer demands and business environments are rapidly changing. Most research has focused on the use of AI in technical processes, such as customer data analytics, marketing optimization, and automated booking systems (Chen et al., 2021), but has neglected to study employee behavior and organizational culture related to AI adoption. The lack of conceptual frameworks that integrate AI adoption with human factors, such as trust, motivation, and resistance to change, has led to a lack of understanding of the role of AI in employee performance (Herath & Mittal, 2022). Furthermore, a Deloitte (2023) report stated that AI adoption in the tourism industry increased employee performance by 70%. However, 45% of employees still have concerns about job security and adaptability to new technologies, while McKinsey and Company (2022) indicated that companies that invested in developing employees' skills in AI had a 25% higher rate of innovation. These findings highlight the need for research linking AI to employee innovative behavior in the tourism industry. To be able to develop strategic approaches that promote employee adaptation to technological changes and create long-term competitive advantage (Chen et al., 2021; Herath & Mittal, 2022).

Given this importance, the researcher aims to study the relationship between AI adoption, innovative behavior, and the impact on employee performance in the tourism industry in the digital economy era. This research aims to fill the gap of previous studies by focusing on the human perspective instead of focusing only on the technical aspects of AI. This study analyzes key factors such as employee motivation, trust in AI, and resistance to change to propose a conceptual framework that can help organizations foster an innovation-driven culture and support the effective adoption of AI. It is important to note that this study employs a cross-sectional research design, which limits the ability to establish direct causality between AI adoption, innovative behavior, and employee performance. The observed relationships may be influenced by unmeasured factors, such as leadership style, corporate culture, or employee motivation. To draw stronger causal inferences, future research should consider using longitudinal studies or experimental designs, as well as incorporating mediating variables, such as digital literacy or organizational support for AI implementation. This research will help organizations in the tourism industry understand how to develop an environment that supports employee learning and adaptation, reduce barriers to AI adoption, and enhance the potential of employees to create innovations that enhance service quality. It also provides insights that can be used to plan human resource strategies and technology management to maximize positive outcomes. Finally, this research aims to help tourism businesses use AI as a key tool to create competitive advantages and sustainable development in the digital era. While this study provides valuable insights into the relationship between AI adoption, innovative behavior, and employee performance, its findings are based on data from two major tourism organizations in China and Hong Kong. The generalizability of these results to other regions or tourism sectors may be limited due to differences in digital infrastructure, corporate culture, and regulatory environments. Future research should explore similar relationships in different geographical contexts, particularly in developing economies or among small and medium-sized tourism enterprises (SMEs), to assess the consistency and applicability of these findings.

Objectives

1) To study the influence of different general information of employees on employee performance differently.
2) To study the influence of artificial intelligence adoption on employee performance.
3) To study the influence of innovative behavior on employee performance.

Conceptual Framework and Hypotheses



Hypothesis

Hypothesis 1: Different general information of employees influences employee performance differently.
Hypothesis 2: Artificial intelligence adoption influences employee performance.
Hypothesis 3: Innovative behavior influences employee performance.

LITERATURE REVIEWS

Artificial intelligence adoption

The adoption of AI in an organization refers to the process by which an organization integrates AI technology into its work processes, organizational structure, and organizational culture to increase efficiency, reduce costs, and add value to its products and services (Nnadozie, 2024). There are five key elements that contribute to success: 1) automation of processes: using AI to reduce repetitive tasks and allow employees to focus on more strategic and creative tasks (Zebec & Stemberger, 2020); 2) personalized customer experiences: AI analyzes customer behavior in real time, enabling the delivery of personalized service experiences to customers (Chen et al., 2021); 3) skill development and training: organizations must invest in training their employees to effectively use AI. 4) data-driven decision making: the use of AI to analyze data helps organizations make more accurate decisions, reduce risks, and increase business opportunities (Poba-nzaou & Tchibozo, 2022); and 5) supportive organizational culture: having an organizational culture that supports digital transformation makes it easier for employees to adapt and accept AI (Alsheibani et al., 2020). However, major challenges in AI adoption include high costs, complexity of the technology, and employee resistance (Kurup & Gupta, 2022).

In tourism industry, artificial intelligence (AI) is increasingly transforming the tourism industry by enhancing efficiency and personalization in service delivery. Ivanov and Webster (2019) noted that AI-driven automation in tourism businesses reduces operational costs and improves service efficiency, particularly in hotel management and travel agencies. The integration of AI into customer service operations, such as chatbots and virtual assistants, has led to an improvement in customer satisfaction and engagement (Tussyadiah & Miller, 2020). Moreover, AI-based recommendation systems are playing a crucial role in shaping consumer travel decisions by providing real-time, personalized travel experiences (Gretzel et al., 2020). However, despite these advantages, research by Jain, Singh, and Jain (2024) indicates that AI adoption in the tourism industry faces challenges related to employee acceptance and skill adaptation. Many employees perceive AI as a threat to job security, which can create resistance to its implementation. Furthermore, studies by Mogaji et al. (2021) and Buhalis and Leung (2018) highlight that while AI enhances service quality, its effectiveness is dependent on human oversight to manage complex decision-making tasks that AI alone cannot handle. This suggests that AI should be integrated as a complement to human labor rather than a replacement, ensuring that employees are adequately trained to leverage AI technologies effectively.

Innovative Behavior

Innovative behavior refers to the behavior of individuals or organizations that focus on developing, improving, and creating new things to increase efficiency and create value for the organization (Efandi & Syuhada, 2021). This behavior is very important in the context of fast-changing and complex competition. Promoting this behavior requires many factors, which can be divided into 4 main dimensions: 1) Collaboration Networks Collaboration networks are an important factor that allows individuals and organizations to better exchange knowledge and resources, which are the foundation for developing and leading to improvements in work processes (Mosquera et al., 2021). In addition, collaboration networks also help create business model innovation, which is an important factor in driving organizations (Hock-Doepgen et al., 2024). 2) Technological Integration The integration of technologies increases work efficiency and reduces human errors, such as the use of AI and automation in work processes to reduce repetitive tasks, allowing employees to focus more on creative tasks (Zehir & Ozturk, 2023). 3) Policy-Driven Innovation Policies that promote innovation, such as R&D support policies or tax incentives. It is an important mechanism that helps drive the development and adoption of new technologies (Mansoor et al., 2020). In addition, organizations with good policy support tend to have more innovative behaviors (Mariana et al., 2024). 4) Capability Building Developing employee skills and capabilities is an important component of innovative behavior. Promoting learning and training helps employees develop new skills necessary for digital transformation (Lim, 2024). Organizations that focus on developing employee capabilities are more likely to be able to continuously innovate (Ranihusna et al., 2021). In summary, promoting innovative behavior requires collaborative networks, technology integration, supportive policies, and the development of personnel capabilities, all of which are important factors that enable organizations to create sustainable innovation.

Employee Performance

Employee Performance refers to the ability of employees to perform assigned tasks to achieve the organization's goals, covering efficiency, work quality, responsibility, and customer interaction (Lailla & Mardi, 2022). Measuring employee performance can be divided into 4 main dimensions: 1) Productivity or employee productivity refers to the quantity and quality of work that employees can perform in a given time frame. Having good motivation and a suitable working environment increases employee efficiency (Rahmadi & Partiwi, 2021). 2) Quality of Service The quality of service that employees provide to customers is an important indicator reflecting employees' ability to create customer satisfaction. Organizations with a work culture that promotes employee engagement will be able to increase the quality of services (Arimie & Oronsaye, 2020). 3) Responsibility or employee responsibility for their own duties is an important factor affecting organizational performance. Employees with high levels of responsibility tend to show it through their dedication to their work and compliance with organizational standards (Chen, 2024). 4) Customer Interaction or the ability to interact with customers is an important factor that helps strengthen relationships between the organization and customers. Employees with communication skills and complaint management can increase satisfaction and build long-term relationships with customers. (Kalogiannidis, 2020) In addition, organizational culture and training factors also directly affect employee performance. Developing skills through training can help increase work efficiency and reduce errors (Khilukha, 2021). In summary, effectively developing Employee Performance requires a comprehensive strategy, whether it is promoting productivity, improving service quality, creating responsibility, and developing the ability to interact with customers, all of which have a direct impact on the success of the organization.

Innovative Behavior and Employee Performance in Tourism

Innovative behavior plays a critical role in shaping employee performance in the tourism industry. According to Hjalager (2015), tourism businesses that promote a culture of continuous innovation experience higher levels of employee engagement and service quality. Innovation in tourism is particularly important in areas such as customer service, digital marketing, and experience customization, where competition is intense and consumer preferences are rapidly evolving (Zhang et al., 2022). Research by Lim (2024) and Ranihusna et al. (2021) indicates that fostering innovation in tourism requires a combination of technological integration and capability building. Employees who are exposed to digital tools and encouraged to develop creative solutions tend to exhibit higher levels of innovative behavior, leading to improved service performance. Furthermore, Mosquera et al. (2021) suggest that collaboration networks within the tourism industry are a key enabler of innovation, as they facilitate knowledge-sharing and cross-industry partnerships that drive new service developments. However, policy-driven innovation alone is not sufficient to foster long-term change in employee behavior. Mariana et al. (2024) argue that organizations must not only implement innovation-friendly policies but also actively engage employees in co-creation processes to maximize the impact of innovation. This aligns with findings from Teece et al. (1997), who emphasize that dynamic capabilities, such as continuous learning and adaptation, are essential for sustaining innovation in fast-changing industries like tourism.

METHODOLOGY

The population used in this study was the employees of China Tourism Group Co., Ltd. and Hong Kong China Travel Service (Group) Co., Ltd., which have a total number of more than 10,000 employees. According to the United Nations World Tourism Organization (2022), China Tourism Group Corporation Limited has more than 45,000 employees and China Travel Service (H.K.) Ltd. has more than 1,000 employees in Hong Kong. To determine the appropriate sample size, the researchers used the Krejcie and Morgan (1970) table with a 95% confidence level and a ±5% error margin, resulting in a minimum sample size of 370 people. However, to prevent errors that may arise from incomplete questionnaire responses, the sample size was increased by another 5-10%, resulting in a final sample size of 400 people. The sampling method used a multi-stage sampling method, starting with stratified random sampling, dividing the employees into two groups according to the companies they belong to. Within each company, there is further stratification by job level, including executives, managers and general employees. Simple random sampling is then used to select respondents from each stratum to ensure that the sample is appropriately representative of the overall population.

The data collection in this research used both primary and secondary data. For primary data, the researcher used a questionnaire as the main tool to collect data from a sample of 400 employees of China Tourism Group Co., Ltd. and Hong Kong China Travel Service (Group) Co., Ltd. The questionnaire was designed based on the study of related literature and was checked for content validity by three experts through the process of Index of Item Objective Congruence (IOC). In addition, the questionnaire was tested for reliability through the analysis of the reliability of the instrument using Cronbach's Alpha Coefficient, which must be greater than 0.7 to ensure that the questionnaire can measure the variables to be studied accurately and internally consistent. For data collection, the researcher used both paper questionnaires and online questionnaires to facilitate the respondents. The distribution of the questionnaires was randomly selected according to the quota of employees in each company and position level to ensure diversity and representativeness of the entire population. The researcher explained the purpose of the research and asked for the cooperation of the respondents to answer the questionnaire completely and correctly. For secondary data, the researcher collected data from academic journals, annual reports, books, and related online databases to support the analysis of the research results. The study area was China and Hong Kong. This is where the organizations in the sample are located.

In data analysis, this research used both descriptive and inferential statistics. Descriptive statistics were used to describe the basic characteristics of the sample, using frequency and percentage to distribute the demographic information of the respondents, such as gender, age, education level, and work experience. In addition, the mean and standard deviation were used to analyze the main variables, including Artificial Intelligence Adoption, Innovative Behavior, and Employee Performance. For inferential statistics, the researchers used the Independent Sample t-test to examine the differences in employee performance between population groups with different genders and used the One-way ANOVA to examine the differences in performance between population groups with different ages, education levels, incomes, and work experiences. In addition, Multiple Regression Analysis (Stepwise Method) was used to analyze the influence of independent variables, including Artificial Intelligence Adoption and Innovative Behavior, on employee performance. The researchers tested the assumptions of the regression analysis, such as the Multicollinearity test through the Variance Inflation Factor (VIF) value and the independence of the residual variables with the value Durbin-Watson to ensure that the data is reliable and can be used to draw accurate conclusions.

STUDY RESULTS

General Information of Respondents

From the study, it was found that the majority of respondents were male, accounting for 206 individuals (51.50%). Most respondents were aged 31-40 years, totaling 156 individuals (39.00%). In terms of marital status, the majority were married, with 386 individuals (96.50%). The most common monthly income category was between 3,001 - 4,000 CNY, reported by 225 individuals (56.25%). Additionally, most respondents had more than 10 years of work experience, with 219 individuals (54.75%).

Opinion level on Artificial Intelligence Adoption, Innovative Behavior, and Employee Performance

Table 1 Opinion level on Artificial Intelligence Adoption, Innovative Behavior, and Employee Performance

Variables	Mean	S.D.	Opinion Level
Artificial Intelligence Adoption			
- Automation of Processes	3.65	0.96	High
- Personalized Customer Experiences	3.72	0.85	High
- Skill Development and Training	3.67	0.92	High
- Data-Driven Decision Making	3.81	0.74	High
- Supportive Organizational Culture	3.95	0.77	High
Overall of Artificial Intelligence Adoption	**3.76**	**0.59**	**High**
Innovative Behavior			
- Collaboration Networks	4.07	0.74	High
- Technological Integration	4.01	0.74	High
- Policy-Driven Innovation	3.76	0.82	High
- Capability Building	4.04	0.73	High
Overall of Innovative Behavior	**3.97**	**0.53**	**High**
Employee Performance			
- Productivity	4.07	0.72	High
- Quality of Service	3.63	0.98	High
- Responsibility	3.87	0.75	High
- Customer Interaction	3.90	0.76	High
Overall of Employee Performance	**3.67**	**0.93**	**High**

From Table 1, the results of the study found that the respondents had a high level of opinion in all the studied variables. For the use of artificial intelligence (AI), the mean score was 3.76 (S.D. = 0.59), with Supportive Organizational Culture (Mean = 3.95, S.D. = 0.77) receiving the highest score, indicating that organizational culture supporting AI plays an important role. Innovative behavior had a mean score of 3.97 (S.D. = 0.53), with Collaboration Networks (Mean = 4.07, S.D. = 0.74) receiving the highest score, reflecting the importance of collaborative networks in promoting innovation. As for employee performance, the mean score was 3.67 (S.D. = 0.93), with Productivity (Mean = 4.07, S.D. = 0.72) receiving the highest score, indicating that the use of AI and innovative behavior has a positive effect on employee performance, especially in terms of productivity and collaboration.

Hypothesis Testing

Hypothesis 1: Different general information of employees influences employee performance differently.

Table 2 Hypothesis result of influence of employee's general information on employee performance

General Information	Statistics and p-value	Results
- Gender	t-value = -0.004, Sig. = .997	Rejected
- Age	f-value = 1.607, Sig. = .172	Rejected
- Marital status	f-value = 1.867, Sig. = .156	Rejected
- Monthly Income	f-value = 1.564, Sig. = .198	Rejected
- Work experience	f-value = 1.695, Sig. = .168	Rejected

From Table 2, the results of the study found that general information of employees did not significantly affect work performance, with no difference between gender (t = -0.004, p = .997), age (f = 1.607, p = .172), marital status (f = 1.867, p = .156), monthly income (f = 1.564, p = .198) and work experience (f = 1.695, p = .168) on employee performance in the tourism industry. The statistical significance (p-value) of more than .05 in all variables indicates that Hypothesis 1 is rejected, which means that even though employees have different demographic information, the overall work performance is not different.

Hypothesis 2: Artificial intelligence adoption influences employee performance.

Table 3 the hypothesis testing results of artificial intelligence adoption on overall employee performance

Artificial Intelligence Adoption	b	Std. Error	β	t-value	Sig.	Tolerance	VIF
Constant	1.937	.136		14.283	.000***		
- Automation of Processes	.289	.027	.516	10.887	.000***	.568	1.759
- Personalized Customer Experiences	.076	.025	.121	2.980	.003**	.780	1.282
- Skill Development and Training	.061	.024	.106	2.504	.013*	.719	1.390
- Data-Driven Decision Making	.055	.029	.076	1.893	.059	.792	1.263
- Supportive Organizational Culture	.040	.028	.058	1.459	.145	.803	1.246
R = 0.705, R^2 = 0.496, Adjusted R^2 = 0.490, SE_{EST} = 0.383, F = 77.683, Sig. = .000***							

*** Statistically significant at the .001 level.

** Statistically significant at the .01 level.

* Statistically significant at the .05 level.

From Table 3 , it was found that artificial intelligence adoption in the aspects of automation of processes, personalized customer experiences, and skill development and training had a statistically significant impact on overall employee performance in the tourism industry, with significance levels ranging from .000 to .013. The predictive power of the model was 49.0% (Adjusted R^2 = 0.490), with a Standard Error of Estimate (SEEST) of 0.383. Additionally, the Multicollinearity test results indicated that the Tolerance values ranged between 0.568 and 0.803, exceeding the threshold of 0.100, while the Variance Inflation Factor (VIF) values ranged between 1.246 and 1.759, remaining below the threshold of 10.000. Since both criteria fall within acceptable limits, there is no issue of Multicollinearity in the model. Among the artificial intelligence adoption factors, the strongest influence on overall employee performance in the tourism industry was observed in Automation of Processes (β = 0.516), followed by Personalized Customer Experiences (β = 0.121), and the least influential factor was Skill Development and Training (β = 0.106). This relationship can be expressed in unstandardized forms:

$$\hat{y} = 1.937 + .289_{\text{Automation of Processes}} + .076_{\text{Personalized Customer Experiences}} + .061_{\text{Skill Development and Training}}$$

A deeper analysis of the results reveals that not all aspects of AI adoption contribute equally to employee performance. The strongest predictor of performance is automation of processes (β = 0.516), which significantly reduces task redundancy and allows employees to focus on higher-value activities. This aligns with previous research by Radhakrishnan and Chattopadhyay (2020), which found that automation enhances efficiency and employee satisfaction. However, while automation improves productivity, it may also increase job insecurity among employees, as suggested by Jain et al. (2024). Interestingly, personalized customer experiences (β = 0.121) show a significant impact on performance, particularly in roles that require frequent customer interaction. This finding is consistent with Huang and Rust (2018), who suggest that AI-powered personalization enhances customer engagement and service ratings. However, as Bolton et al. (2018) caution, excessive reliance on AI-driven personalization may reduce employee autonomy and affect service authenticity.

Hypothesis 3: Innovative behavior influences employee performance.

Table 4 Hypothesis testing results of innovative behavior on overall employee performance

Innovative Behavior	**b**	**Std. Error**	**β**	**t-value**	**Sig.**	**Tolerance**	**VIF**
Constant	1.937	.136		14.283	.000***		
- Automation of Processes	.289	.027	.516	10.887	.000***	.568	1.759
- Personalized Customer Experiences	.076	.025	.121	2.980	.003**	.780	1.282
- Skill Development and Training	.061	.024	.106	2.504	.013*	.719	1.390
- Data-Driven Decision Making	.055	.029	.076	1.893	.059	.792	1.263
- Supportive Organizational Culture	.040	.028	.058	1.459	.145	.803	1.246
$R = 0.705$, $R^2 = 0.496$, Adjusted $R^2 = 0.490$, $SE_{EST} = 0.383$, $F = 77.683$, Sig. = .000***							

*** Statistically significant at the .001 level.
** Statistically significant at the .01 level.
* Statistically significant at the .05 level.

From Table 4, it was found that innovative behavior in the aspects of collaboration networks, technological integration, policy-driven innovation, and capability building had a statistically significant impact on overall employee performance in the tourism industry, with significant levels at .000. The predictive power of the model was 33.2% (Adjusted $R^2 = 0.332$), with a Standard Error of Estimate (SEEST) of 0.438. Additionally, the Multicollinearity test results indicated that the Tolerance values ranged between 0.768 and 0.856, exceeding the threshold of 0.100, while the Variance Inflation Factor (VIF) values ranged between 1.168 and 1.302, remaining below the threshold of 10.000. Since both criteria fall within acceptable limits, there is no issue of Multicollinearity in the model. Among the innovative behavior factors, the strongest influence on overall employee performance in the tourism industry was observed in Collaboration Networks (β = 0.278), followed by Technological Integration (β = 0.210), Policy-Driven Innovation (β = 0.174), and the least influential factor was Capability Building (β = 0.161). This relationship can be expressed unstandardized forms:

$\hat{y} = 1.535 + .200_{\text{Collaboration Networks}} + .152_{\text{Technological Integration}} + .114_{\text{Policy-Driven Innovation}} + .118_{\text{Capability Building}}$

Among the innovative behavior factors, collaboration networks ($\beta = 0.278$) have the highest influence on employee performance. This supports the social capital theory (Nahapiet & Ghoshal, 1998), which highlights the role of knowledge-sharing in fostering innovation. Organizations that encourage collaboration across departments and external partnerships tend to develop more adaptive and innovative workforces (Bresciani, Ferraris, & Del Giudice, 2018). However, the relatively lower influence of policy-driven innovation ($\beta = 0.174$) suggests that while policies may provide structural support for innovation, they do not directly drive employee performance unless combined with strong leadership and employee engagement initiatives. This finding is in line with Mariana et al. (2024), who argue that innovation policies alone are insufficient without active organizational support.

DISCUSSION OF RESULTS

Influence of Personal Factors on Employee Performance in the Tourism Industry

The results of this study indicate that overall personal factors do not significantly affect the performance of employees in the tourism industry. However, the performance in terms of customer interaction is influenced by the age and income of the employees. Employees under the age of 30 have lower customer interaction performance than those aged 31-60, which may be due to their experience, communication skills, and problem-solving abilities that are not fully developed (Chiang, Jang, Canter, & Prince, 2021). This is consistent with the Job Demand-Control (JDC) model, which states that employees with more experience have better job control, allowing them to deal with customers more effectively (Karasek, 1979). In addition, employees aged 41-50 are more efficient than those over 60, which may be due to physical limitations and reduced adaptability (Kanfer & Ackerman, 2004; Wang & Shultz, 2010). In terms of income, employees with an income of less than 3,000 yuan have lower customer interaction performance than those with a higher income, which can be explained by Maslow’s Hierarchy of Needs and Self-Determination Theory (SDT). Low-income employees tend to experience financial stress. This affects motivation and job security (Kurtessis et al., 2017; Salanova, Agut, & Peiró, 2005), while employees with higher incomes have access to skill development and experience greater job satisfaction, which in turn allows them to provide better customer service (Karatepe & Olugbade, 2017). However, although age and income factors affect customer interactions, personal factors do not affect overall employee performance in the tourism industry, suggesting that experience, training, and financial security are more important factors influencing the quality of performance than personal factors (Lam & Chen, 2012).

The Influence of Artificial Intelligence Adoption on Employee Performance in the Tourism Industry

This study confirms that the use of artificial intelligence (AI) affects the performance of employees in the tourism industry, with a predictive power of 49.0%. It was found that important factors, including automation of processes, personalized customer experiences, and skill development and training, influenced performance, especially automation, which had the greatest impact because it reduced redundant work and increased efficiency in customer service. This is consistent with the Resource-Based View (RBV) that suggests that technology enhances organizational potential and creates competitive advantage (Barney, 1991; Wirtz & Müller, 2019). However, employees had a relatively low opinion of AI's ability to reduce errors in complex processes, which is consistent with studies that indicate that AI is highly effective in structured tasks, but still relies on human skills in complex tasks (Mogaji, Balmer, & Bourlakis, 2021). In terms of creating personalized customer experiences, it was found that it influenced employee performance, as AI enabled real-time analysis of customer behavior and improved service quality to better meet customer needs, which is consistent with the concept Service-Dominant Logic (SDL) emphasizes that technology can help create value for employees and customers (Vargo & Lusch, 2004; Huang & Rust, 2018). Although employees agree that AI can make better recommendations to customers, they also emphasize that human interaction is a key factor in creating customer satisfaction (Bolton et al., 2018). In addition, skills development and training, despite having a minimal impact on overall performance, remain an important factor in preparing employees for an AI-enabled work environment, as training can enhance job performance and enhance technology use (Becker, 1964; Neirotti & Raguseo, 2021). However, concerns about job security and uncertainty about the role of AI can make employees feel uncertain about AI training (Davenport & Ronanki, 2018). Finally, data-driven decision-making has been found to have an impact on customer interactions, with employees using AI to support their decisions being able to make recommendations that better meet customer needs (Buhalis & Leung, 2018; Ivanov & Webster, 2020). Consequently, the variations in findings between this study and prior research may be attributed to differences in industry context and organizational size. The tourism sector, particularly in China and Hong Kong, relies heavily on direct customer interactions, making collaboration and service personalization more crucial than policy-driven innovation. This contrasts with industries like manufacturing or finance, where strict policies and structured innovation frameworks may play a more significant role (Mariana et al., 2024). Additionally, AI adoption levels vary significantly across organizations. Large tourism corporations, such as those studied in this research, may have the financial resources to implement AI efficiently, while small and medium-sized enterprises (SMEs) may struggle with integration due to budget constraints or lack of digital literacy among employees. Future research should investigate these factors to determine whether the effects of AI adoption differ based on organizational size and technological readiness.

The Influence of Innovative Behavior on Employee Performance in the Tourism Industry

The study results confirmed that innovative behavior significantly affects employee performance in the tourism industry, with a predictive power of 33.2%. The main dimensions, namely Collaboration Networks, Technological Integration, Policy-Driven Innovation, and Capability Building, all affect performance. Collaboration networks have the highest influence, reflecting the importance of knowledge exchange and innovation creation through collaboration with business partners and teams from different fields, which is consistent with the Social Capital Theory, which indicates that the quality of professional networks directly affects knowledge exchange and innovation potential (Nahapiet & Ghoshal, 1998; Bresciani, Ferraris, & Del Giudice, 2018). In terms of technology integration, it was found that digital technology helps increase efficiency in work management and reduces redundant workloads. And help employees focus on higher-value tasks, supporting the Technology Acceptance Model (TAM) that states that the perceived usefulness and ease of use of technology affects work performance (Davis, 1989; Marinova et al., 2017). However, employees are concerned that technology may not reduce all errors in complex processes (Huang & Rust, 2018). For innovation driving policies, it was found to play an important role in shaping the direction of innovation within an organization. Employees perceived those supportive policies helped them to adapt faster, consistent with the idea that clear regulations reduce uncertainty and promote innovative learning (Teece, Pisano, & Shuen, 1997; Hogan & Coote, 2014). However, employees had the least opinions on the role of government in supporting innovation, which may reflect the perception that internal organizational policies have a more direct impact (OECD, 2019). In terms of capability development, despite having the lowest impact. However, it remains an important factor in increasing problem-solving abilities and employee readiness for technological change, in line with the Human Capital Theory, which emphasizes that investment in employee skills increases productivity and organizational growth in the long run (Becker, 1964; Bakker & Demerouti, 2017). However, there are concerns about the lack of motivation or opportunities for skills development, suggesting that training should be coupled with reward incentives and application opportunities (Brynjolfsson & McAfee, 2017; Spreitzer, Porath, & Gibson, 2012). Among the innovative behavior factors, collaboration networks had the highest impact on employee performance. This finding aligns with Nahapiet and Ghoshal (1998), who emphasized that knowledge exchange in strong professional networks enhances innovation capacity. Similarly, Mosquera et al. (2021) found that organizations fostering cross-departmental collaboration tend to have higher levels of service innovation and employee adaptability. However, our study contradicts findings by Mariana et al. (2024), who reported that policy-driven innovation plays a more dominant role in employee performance. One possible explanation for this discrepancy is that Mariana et al.'s research focused on highly regulated industries such as finance, whereas our study examines the tourism sector, where flexibility and adaptability may be more critical than formal innovation policies.

Recommendations from the study

1) Policy and Practical Recommendations

Tourism organizations should develop targeted training programs for young and low-income employees, using mentorship and financial incentives to enhance customer service skills and reduce financial stress. In terms of AI, automation should be used to reduce redundant tasks, free up employees to focus on strategic tasks, and investment in AI-driven personalization to tailor customer service and train employees to use AI effectively without feeling like it is a threat to their careers. In addition, networks should be fostered to increase creativity and problem-solving efficiency. Technology should be integrated with humans so that AI supports rather than replaces employees. A clear policy for driving innovation should be established to enable employees to adapt to new technologies faster. Employee capabilities should be developed through skill-building programs that are aligned with digital technologies to create a workforce that is resilient and can effectively drive innovation in the tourism industry using technology.

2) Academic Recommendations

Educational institutions should integrate the concepts of artificial intelligence (AI) and innovation into the curriculum of tourism management and human resources, as AI and innovative behaviors have an impact on employee performance. Curricula should emphasize the role of automation, customer service customization, and data-driven decision-making in increasing labor productivity and service quality. In addition, teaching should be provided through case studies and practical training on the use of AI in the tourism industry to prepare graduates for an AI-driven work environment. In addition, interdisciplinary approaches should be developed to study employee performance in the tourism industry using AI by integrating tourism management, artificial intelligence, organizational behavior, and human resource development to understand the interactions between technology, workforce adaptation, and innovative service strategies. Educational institutions should promote joint research, joint degree programs, and cross-disciplinary learning to equip learners with the technical and managerial skills necessary to work effectively in the tourism industry using such technology.

3) Suggestions for future research

While this study provides valuable insights, several limitations should be acknowledged. First, the research relied on cross-sectional data, limiting the ability to establish causal relationships between AI adoption, innovative behavior, and employee performance. Future studies should use longitudinal data to track changes over time and better determine causality. Second, the study focused solely on large tourism corporations in China and Hong Kong. The findings may not be directly applicable to smaller tourism businesses or different cultural contexts. Future research should explore AI adoption and innovation strategies in small and medium-sized tourism enterprises (SMEs) and across different regions to assess the generalizability of these results.

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