*Advances in Consumer Research*
https://acr-journal.com/
Volume-3 | Issue-2 | Feb 2026

*Original Researcher Article*

# Balancing AI Autonomy and Managerial Support: Insights into Sales Motivation in Vietnam's Hospitality and Tourism Industry

**Nguyen Thi Phuong Hao** [1]
[1]Thai Nguyen University of Economics and Business Administration
Email ID : haontp@tueba.edu.vn
Orcid ID: 0009-0006-9861-4124

**Received: Dec. 5, 2025**
**Revised: Jan. 10, 2026**
**Accepted: Jan. 28, 2026**
**Published: Feb. 13, 2026**

**ABSTRACT**
In the context of rapid digital transformation, artificial intelligence (AI) has been increasingly adopted in the tourism and hospitality industry, particularly in sales and customer service activities. The growing autonomy of AI systems has reshaped employees' work processes. While AI improves efficiency and productivity, it may undermine employees' sales motivation if not accompanied by appropriate managerial support. Empirical evidence explaining how AI affects individual sales motivation remains limited, especially in emerging economies. This study aims to examine the effects of AI autonomy and managerial support on sales motivation, considering the mediating roles of technology acceptance, AI explainability, employee AI capability, and intrinsic motivation. Data were collected from 357 sales and customer service employees in tourism and hospitality firms in Vietnam. A quantitative research design was adopted, and hypotheses were tested using partial least squares structural equation modeling (PLS-SEM). The results reveal that technology acceptance strongly affects employee AI capability ($\beta = 0.537$). Employee AI capability ($\beta = 0.400$) and intrinsic motivation ($\beta = 0.228$) exert direct positive effects on sales motivation. The model explains 29.4% of the variance in sales motivation ($R^2 = 0.294$). Moreover, AI autonomy indirectly influences sales motivation through technology acceptance and managerial support. This study provides important implications for managers by emphasizing the need to balance AI autonomy with human-centered management practices. Developing employee AI capability helps organizations sustain sales motivation and performance outcomes effectively.

**Keywords**: AI Autonomy; Intrinsic Motivation; Managerial Support; Sales Motivation; Technology Acceptance.

## INTRODUCTION:

The rapid advancement of digital technologies, particularly artificial intelligence (AI), has fundamentally transformed the nature of work, organizational structures, and employee motivation across service industries (Davenport & Ronanki, 2018). In hospitality and tourism, AI is increasingly embedded in sales and customer service functions, including customer relationship management systems, demand forecasting, dynamic pricing, and personalized service delivery, reshaping how frontline employees interact with customers and perform sales-related tasks (Kim et al., 2025).

While AI offers substantial opportunities to enhance productivity and service quality, its growing autonomy in decision-making also raises concerns regarding employee motivation, perceived control, and job meaning. As AI systems become capable of independently analyzing customer data, recommending sales strategies, or automating routine interactions, employees may experience reduced autonomy and heightened job insecurity if organizational support mechanisms are insufficient (Yakovenko et al., 2022; Hauptman et al., 2024). These tensions are particularly salient in sales-oriented service contexts, where motivation and human interaction remain critical determinants of performance.

From a motivational perspective, Self-Determination Theory (SDT) posits that intrinsic motivation is fostered when individuals' basic psychological needs for autonomy, competence, and relatedness are satisfied (Deci & Ryan, 2000; Adams et al., 2017). In AI-integrated workplaces, employees' sense of competence increasingly depends on their ability to understand and effectively use AI tools, while perceived autonomy may be threatened by highly autonomous systems. Managerial support therefore becomes essential in helping employees adapt to technological change, maintain a sense of control, and sustain intrinsic motivation (Le et al., 2025).

Technology Acceptance Theory emphasizes that perceived usefulness, ease of use, and performance expectancy strongly influence individuals' willingness to adopt and utilize new technologies (Venkatesh et al., 2012). Prior research demonstrates that technology acceptance plays a pivotal role in translating AI adoption into improved employee competence, performance, and motivation (Croitoru et al., 2025). Without sufficient acceptance and trust, AI systems may be perceived as burdensome or threatening rather than supportive, thereby undermining motivation in sales roles.

Goal-Setting Theory further explains how motivation and performance are enhanced when employees pursue clear, challenging, and attainable goals supported by feedback mechanisms (Locke & Latham, 1990; Lunenburg, 2011). AI technologies have the potential to support goal achievement by providing real-time analytics, performance insights, and sales recommendations. However, these benefits are contingent upon employees' technological competence, acceptance of AI, and intrinsic motivation to leverage AI as a performance-enhancing tool rather than as a source of pressure or surveillance (Vroom, 1964; Kim et al., 2025).

Despite the growing body of research on AI adoption in service industries, significant gaps remain. Existing studies tend to focus either on the technological capabilities of AI or on organizational outcomes such as efficiency and performance, while paying limited attention to the micro-level motivational processes of employees working alongside AI (Koponen et al., 2025). Moreover, research examining AI autonomy often overlooks the moderating or complementary role of managerial support in shaping employees' motivational responses to AI-enabled work environments (Hauptman et al., 2024; Davenport & Ronanki, 2018).

These gaps are particularly evident in the context of emerging economies such as Vietnam, where the hospitality and tourism sector is undergoing rapid digital transformation. Although recent studies have explored work motivation, job effectiveness, and supervisory support in Vietnamese hospitality organizations, they rarely integrate AI-related factors such as AI autonomy, explainability, and technology acceptance into a unified motivational framework (Van et al., 2024; Le et al., 2025; Fang et al., 2025). Consequently, there is limited empirical evidence explaining how AI-driven changes in work design interact with managerial practices to influence sales motivation among frontline employees.

Addressing this research gap, the present study investigates how AI autonomy and managerial support jointly influence sales motivation in Vietnam's hospitality and tourism industry. Drawing on Self-Determination Theory, Technology Acceptance Theory, Goal-Setting Theory, and expectancy-based perspectives, this study proposes an integrative model incorporating AI autonomy, managerial support, technology acceptance, AI explainability, employee AI competence, intrinsic motivation, and sales motivation. By empirically testing this model, the study contributes to a deeper understanding of how organizations can balance AI autonomy with human-centered management practices to sustain employee motivation and sales performance in AI-integrated service environments.

## 2. THEORETICAL FRAMEWORK AND RESEARCH METHODOLOGY

### 2.1 Theoretical Framework

#### 2.1.1 Self-Determination Theory (SDT)

Self-Determination Theory (SDT), developed by Deci and Ryan (2000), is one of the most important theories explaining human work motivation. According to SDT, individual behaviors and motivations are driven by three core psychological needs: autonomy, competence, and relatedness. When these needs are satisfied, intrinsic motivation is enhanced, thereby improving job satisfaction, performance, and engagement (Adams, Little & Ryan, 2017).

In the context of enterprises integrating AI, the need for competence becomes particularly important. Employees must feel that they possess sufficient skills and knowledge to use AI technologies effectively; this enhances their sense of control over their work and reduces anxiety about labor replacement (Yakovenko et al., 2022). Additionally, the need for autonomy may be affected when AI reaches a high level of automation, leading to a perceived loss of control. When receiving managerial support, employees feel safer experimenting with new technologies, thereby strengthening their intrinsic motivation (Le et al., 2025).

Therefore, SDT is a critical theoretical foundation for explaining the role of Managerial Support, Employee AI Competence, Intrinsic Motivation and how these factors influence Sales Motivation in the context of increasingly autonomous AI technologies.

#### 2.1.2 Technology Acceptance Theory (UTAUT/TAM)

Technology Acceptance Theory originates from the TAM model and was expanded into UTAUT by Venkatesh et al. (2012). According to this theory, factors such as perceived usefulness, perceived ease of use, performance expectancy, and effort expectancy determine employees' willingness to adopt and use technology.

In workplaces applying AI, the degree of technology acceptance plays a crucial role in operational effectiveness. If employees believe that AI helps improve sales performance, increase accuracy in demand forecasting, or support customer interactions, they are more likely to adopt AI (Croitoru et al., 2025). Conversely, if they perceive AI as difficult to use or lacking transparency, acceptance decreases, negatively affecting work motivation.

The UTAUT/TAM theory is particularly relevant for explaining the variables Technology Acceptance, Employee AI Competence, and AI Explainability, while also clarifying their mediating roles in the relationships among AI Autonomy, Managerial Support, and Sales Motivation.

#### 2.1.3 Goal-Setting Theory

Goal-Setting Theory, developed by Locke and Latham (1990), asserts that work performance improves when employees set specific, clear, and reasonably challenging goals and receive appropriate feedback (Lunenburg, 2011). Work motivation becomes stronger when employees feel that their goals are attainable and aligned with their personal competencies.

In the context of AI application, AI systems can provide analytical data, forecasting, and real-time feedback, helping sales employees adjust their personal goals and enhance performance (Kim et al., 2025). When employees possess strong intrinsic motivation and receive managerial support, they are more likely to embrace AI as a supportive tool rather than perceive it as a threat.

Goal-Setting Theory supports the argument that Sales Motivation is indirectly influenced by Intrinsic Motivation, Employee AI Competence, and Technology Acceptance, as these factors help employees recognize the alignment between their personal goals and the AI tools that support them.

2.1.4 AI Autonomy and AI Explainability

AI Autonomy refers to the degree to which AI systems can independently make decisions or perform tasks without human intervention (Hauptman et al., 2024). As AI becomes more autonomous, work productivity improves but may simultaneously reduce employees' sense of control, affecting their motivation and engagement (Chui et al., 2016).

An essential factor in mitigating the negative impacts of AI is AI Explainability-the ability of AI systems to clearly explain how they generate decisions or recommendations (Hauptman et al., 2024). When employees understand AI mechanisms, they develop higher trust, greater acceptance, and more proactive collaboration with AI.

In sales, AI explainability helps employees understand why AI recommends a customer segment or suggests the optimal timing for customer outreach, thereby enhancing cooperation and improving sales performance. This is closely linked to the EAC (Employee AI Competence) variable in the research model.

Recent research emphasizes that high levels of AI autonomy must be balanced with strong explainability and managerial support to ensure employees do not feel a loss of control (Davenport & Ronanki, 2018; Koponen et al., 2025).

2.1.5 AI Applications in the Hospitality and Tourism Industry

AI is widely applied in the hospitality and tourism industry, ranging from operational management to customer service and sales management. Both international and Vietnamese studies show that AI significantly supports personalizing customer experiences, automating processes, forecasting demand, and enhancing sales performance (Kim et al., 2025; Fang et al., 2025).

Some common applications include:

AI chatbots providing 24/7 customer support.

Intelligent CRM systems analyzing customer behavior to suggest sales strategies.

AI systems forecasting tourism demand, optimizing room pricing, and recommending upsell opportunities.

Employee performance analytics systems assessing goal achievement levels.

In Vietnam, digital transformation in hospitality and tourism is progressing rapidly. Enterprises are actively adopting AI to improve competitiveness, yet employee readiness and technological competencies remain inconsistent (Van et al., 2024). Managerial support and AI capability training therefore become critical for helping employees adapt to change, maintain work motivation, and achieve higher performance.

These applications demonstrate the significant role of AI not only from a technological perspective but also in influencing intrinsic motivation, technology acceptance, AI competence, and ultimately sales motivation.

2.2 Research Methodology

2.2.1 Research Design

The study was conducted in two phases: qualitative and quantitative, in which the qualitative phase was used to develop and refine the measurement scales, while the quantitative phase was employed to test the theoretical model and research hypotheses.

Qualitative phase – Scale development and refinement

The qualitative phase was carried out through semi-structured interviews with several experts and employees working in the hospitality and tourism sectors. The objectives of this phase were to:

(1) identify the semantic appropriateness of research concepts in the Vietnamese context;

(2) adjust wording, structure, and content of measurement items;

(3) add or remove inappropriate observed indicators.

The qualitative findings were used to finalize the questionnaire before the official survey.

Quantitative phase – Testing the research model

The quantitative phase was conducted through an online survey using a standardized questionnaire. The collected data were analyzed using variance-based structural equation modeling (PLS-SEM). This approach is suitable for the research objectives, the complexity of the model with multiple mediating variables, and the medium sample size.

2.2.2 Research Subjects and Sampling

The survey targeted sales staff, customer service staff, supervisors, and managers working in hotels, travel companies, and tour agencies in Vietnam.

The sampling method used was convenience sampling, appropriate for online data collection and the dispersed nature of the service workforce.

A total of 357 valid responses were collected and included in the analysis. This number satisfies the minimum requirement for the PLS-SEM method (≥ 10 times the number of maximum structural paths pointing to a dependent variable in the model).

2.2.3 Measurement Scales

The research variables include:

AI Autonomy (AIA)

Managerial Support (MS)

Technology Acceptance (TA)

AI Explainability (AE)

Employee AI Competence (EAC)

Intrinsic Motivation (IM)

Sales Motivation (SM)

Each variable was measured using multiple observed indicators on a 5-point Likert scale (1 = Completely disagree, 5 = Completely agree). The scales were adapted from previous studies and refined through the qualitative phase to ensure their relevance to the hospitality–tourism context in Vietnam.

2.2.4 Data Collection

Data were collected through an online survey using a questionnaire designed on Google Forms. The questionnaire was distributed via email, professional social networks, and online groups related to the hospitality–tourism industry.

The data collection procedure consisted of the following steps:

(1) introduction of research objectives and provision of a consent form;

(2) collection of responses;

(3) screening and removal of incomplete or suspicious responses;

(4) data coding and preprocessing before analysis.

2.2.5 Data Analysis

Survey data were processed using SPSS 26 and SmartPLS 4. SPSS was used for descriptive statistics and preliminary reliability testing of the scales through Cronbach's Alpha. SmartPLS 4 was then used to analyze the PLS-SEM structural model, including assessment of the measurement model (reliability, convergent validity, discriminant validity) and the structural model (path coefficients, $R^2$, $f^2$, $Q^2$, SRMR). Bootstrapping with 5,000 subsamples was employed for hypothesis testing.

2.3 Proposed Research Model

Based on foundational theories and prior empirical findings-including Self-Determination Theory (Deci & Ryan, 2000; Adams et al., 2017), Technology Acceptance Theory (Venkatesh et al., 2012), Goal-Setting Theory (Locke & Latham, 1990), and recent studies on artificial intelligence applications in service environments (Hauptman et al., 2024; Kim et al., 2025; Fang et al., 2025)-a research model is proposed to analyze how AI Autonomy (AIA) and Managerial Support (MS) influence Sales Motivation (SM) among employees in the hospitality and tourism industry.

The model focuses on clarifying the roles of key mediating variables, including Technology Acceptance (TA), AI Explainability (AE), Employee AI Competence (EAC), and Intrinsic Motivation (IM). The hypothesized relationships are presented as follows:

Relationships related to AI Autonomy (AIA)

H1: AI Autonomy has a positive impact on Technology Acceptance.

H2: AI Autonomy has a positive impact on Managerial Support.

Relationships related to Managerial Support (MS)

H3: Managerial Support has a positive impact on Intrinsic Motivation.

Relationships related to Technology Acceptance (TA)

H4: Technology Acceptance has a positive impact on Intrinsic Motivation.

H5: Technology Acceptance has a positive impact on AI Explainability.

H6: Technology Acceptance has a positive impact on Employee AI Competence.

Relationships related to AI Explainability (AE)

H7: AI Explainability has a positive impact on Employee AI Competence.

Relationships related to Employee AI Competence (EAC)

H8: Employee AI Competence has a positive impact on Sales Motivation.

Relationships related to Intrinsic Motivation (IM)

H9: Intrinsic Motivation has a positive impact on Sales Motivation.

Figure 1 illustrates the proposed research model and the hypothesized relationships among AI autonomy, managerial support, mediating variables, and sales motivation in the hospitality and tourism context.

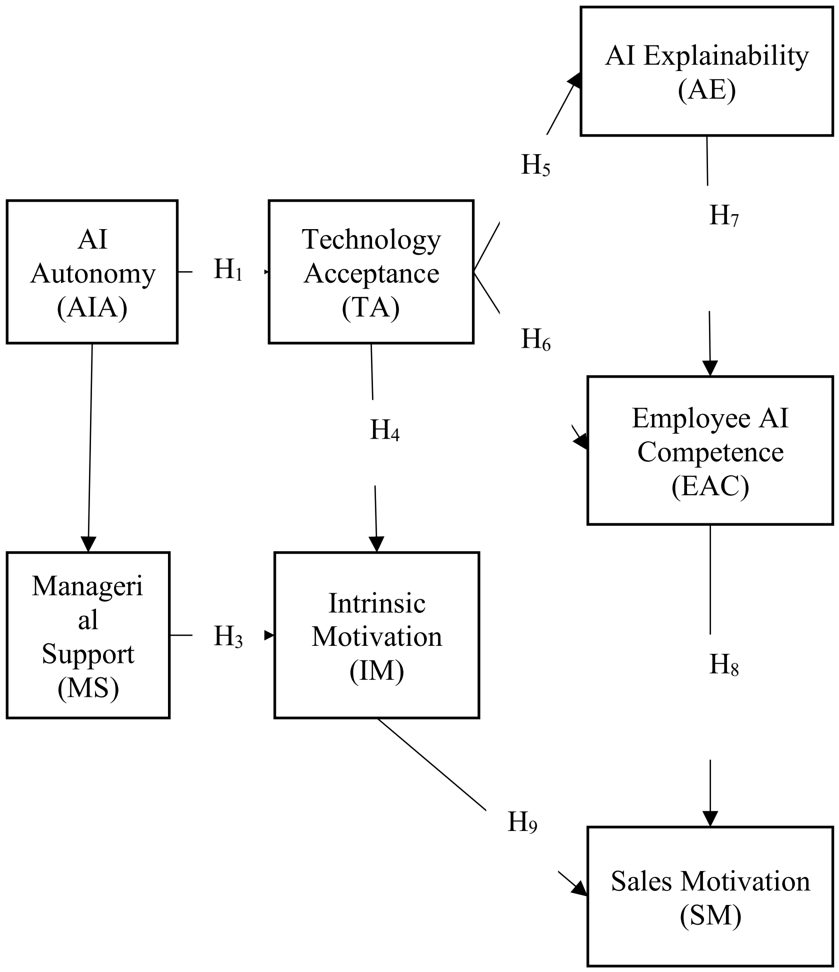


**Figure 1. Research Model**

3. Research results

3.1. Descriptive statistics

3.1.1. Characteristics of the Measurement Scales

**Table 1. Descriptive Statistics of Observed Variables**

| Observed Variable | N | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|---|
| Sales Motivation (SM) | | | | | |
| SM1 | 357 | 2 | 5 | 3.82 | 0.740 |
| SM2 | 357 | 2 | 5 | 3.81 | 0.736 |
| SM3 | 357 | 1 | 5 | 3.78 | 0.783 |
| SM4 | 357 | 1 | 5 | 3.73 | 0.746 |
| SM5 | 357 | 2 | 5 | 3.88 | 0.754 |
| Intrinsic Motivation (IM) | | | | | |
| IM1 | 357 | 2 | 5 | 3.75 | 0.791 |
| IM2 | 357 | 2 | 5 | 3.82 | 0.770 |
| IM3 | 357 | 1 | 5 | 3.83 | 0.785 |
| IM4 | 357 | 2 | 5 | 3.78 | 0.766 |

| | | | | | |
|---|---|---|---|---|---|
| IM5 | 357 | 2 | 5 | 3.84 | 0.743 |
| Technology Acceptance (TA) | | | | | |
| TA1 | 357 | 2 | 5 | 3.81 | 0.808 |
| TA2 | 357 | 2 | 5 | 3.83 | 0.759 |
| TA3 | 357 | 2 | 5 | 3.81 | 0.739 |
| TA4 | 357 | 1 | 5 | 3.81 | 0.770 |
| TA5 | 357 | 2 | 5 | 3.75 | 0.823 |
| AI Explainability (AE) | | | | | |
| AE1 | 357 | 2 | 5 | 3.83 | 0.700 |
| AE2 | 357 | 1 | 5 | 3.69 | 0.707 |
| AE3 | 357 | 2 | 5 | 3.76 | 0.710 |
| AE4 | 357 | 2 | 5 | 3.76 | 0.727 |
| Managerial Support (MS) | | | | | |
| MS1 | 357 | 2 | 5 | 3.82 | 0.793 |
| MS2 | 357 | 1 | 5 | 3.82 | 0.754 |
| MS3 | 357 | 2 | 5 | 3.77 | 0.714 |
| MS4 | 357 | 2 | 5 | 3.86 | 0.705 |
| AI Autonomy (AIA) | | | | | |
| AIA1 | 357 | 2 | 5 | 3.73 | 0.798 |
| AIA2 | 357 | 2 | 5 | 3.66 | 0.779 |
| AIA3 | 357 | 1 | 5 | 3.65 | 0.813 |
| AIA4 | 357 | 2 | 5 | 3.70 | 0.745 |
| AIA5 | 357 | 2 | 5 | 3.65 | 0.812 |
| Employee AI Competence (EAC) | | | | | |
| EAC1 | 357 | 2 | 5 | 3.77 | 0.734 |
| EAC2 | 357 | 2 | 5 | 3.74 | 0.751 |
| EAC3 | 357 | 2 | 5 | 3.74 | 0.737 |
| EAC4 | 357 | 2 | 5 | 3.72 | 0.768 |

*(Source: Processed survey data)*

Table 1 presents the descriptive statistics of the study variables. The results indicate that SM5 has the highest mean value within the sales motivation group at 3.88, reflecting that workers in the hospitality and tourism industries tend to seek ways to improve sales performance. Conversely, SM4 shows a lower mean of 3.73, suggesting a greater dispersion in perceived commitment to organizational performance. Within the intrinsic motivation group, IM3 and IM5 have relatively high mean values of 3.83 and 3.84, while IM1 is lower at 3.75.

For the technology acceptance group, variables TA1 to TA4 exhibit relatively consistent mean values around 3.81, but TA5 is slightly lower at 3.75 and has the highest standard deviation in the group at 0.823. This indicates substantial differences in respondents' willingness to continue using AI. AI explainability ranges from 3.69 to 3.83, with AE2 having the lowest mean, suggesting that the explanations provided by AI are not rated as highly as other aspects of this construct.

Managerial support is assessed quite positively, with MS4 achieving the highest score of 3.86, reflecting employees' perception of being supported when adapting to AI-integrated workflows. However, MS3 has a lower mean of 3.77, indicating that managers' explanations regarding AI's role remain limited in some settings. The AI autonomy group shows lower mean values compared to other groups, ranging from 3.65 to 3.73, with AIA3 and AIA5 both at 3.65 and also having the highest standard deviations in the group (0.813 and 0.812, respectively). This suggests considerable variability in perceptions of AI handling human-substituting tasks and reducing employee involvement in routine work.

Employee AI competence shows relatively consistent mean values from 3.72 to 3.77, with EAC1 being the highest at 3.77, indicating that workers self-evaluate their AI tool usage skills positively, while EAC4 has the lowest mean at 3.72, suggesting that understanding of how AI supports sales and customer service operations remains uneven.

3.1.2. Demographic Characteristics

**Table 2. Demographic Characteristics of the Survey Sample**

| **Characteristic** | **Category** | **Frequency** | **Percentage (%)** | **Cumulative Percentage (%)** |
|---|---|---|---|---|
| Gender | Male | 168 | 47.1 | 47.1 |
| | Female | 189 | 52.9 | 100.0 |
| Age | Under 25 | 68 | 19.0 | 19.0 |
| | 25–34 | 164 | 45.9 | 64.9 |
| | 35–44 | 86 | 24.1 | 89.0 |
| | 45 and above | 39 | 10.9 | 100.0 |
| Type of Organization | Hotel | 139 | 38.9 | 38.9 |
| | Travel Agency | 96 | 26.9 | 65.8 |
| | Restaurant | 64 | 17.9 | 83.7 |
| | Resort/Tourism Complex | 58 | 16.2 | 100.0 |
| Work Experience | Under 1 year | 55 | 15.4 | 15.4 |
| | 1–3 years | 142 | 39.8 | 55.2 |
| | 3–5 years | 77 | 21.6 | 76.8 |
| | Over 5 years | 83 | 23.2 | 100.0 |
| Job Position | Sales Staff | 185 | 51.8 | 51.8 |
| | Customer Service | 90 | 25.2 | 77.0 |
| | Supervisor | 53 | 14.8 | 91.8 |
| | Manager | 22 | 6.2 | 98.0 |
| | Other | 7 | 2.0 | 100.0 |

*(Source: Processed survey data)*

Table 2 summarizes the demographic characteristics of the respondents. Regarding gender, the sample shows a relatively balanced distribution, with 189 females accounting for 52.9% and 168 males accounting for 47.1%. This reflects the workforce structure in Vietnam's hospitality and tourism sector, where both genders participate fairly equally in sales and customer service roles.

The age distribution shows that the 25–34 age group accounts for the largest proportion with 164 respondents (45.9%), followed by the 35–44 age group with 86 respondents (24.1%). The under-25 group includes 68 respondents (19.0%), while those aged 45 and above represent 10.9% with 39 respondents. This distribution indicates that the workforce is concentrated mainly among young and middle-aged employees, who tend to adapt more effectively to new technologies.

Regarding the type of organization, hotels account for the highest proportion with 139 respondents (38.9%), followed by travel agencies with 96 respondents (26.9%). Restaurants make up 64 respondents (17.9%), and resorts or tourism complexes represent 58 respondents (16.2%). This distribution aligns with the structure of Vietnam's tourism sector, where hotels and travel agencies are the two predominant business types.

In terms of work experience, the group with 1–3 years of experience accounts for the highest proportion with 142 respondents (39.8%). The group with more than 5 years of experience includes 83 respondents (23.2%), while those with 3–5 years of experience number 77 (21.6%). The group with under 1 year of experience has the smallest proportion with 55 respondents (15.4%). This distribution demonstrates diversity in experience levels, allowing the study to capture differences in perceptions of AI between newcomers and more experienced employees.

Job positions in the sample show that sales staff constitute the majority with 185 respondents (51.8%), followed by customer service staff with 90 respondents (25.2%). Supervisors account for 53 respondents (14.8%), managers include 22 respondents (6.2%), and other positions represent only 7 respondents (2.0%). The concentration in sales and customer service roles aligns with the study's focus on sales motivation in the context of AI adoption.

3.2. Scale Assessment

3.2.1. Reliability and Convergent Validity

**Table 3. Results of Reliability and Convergent Validity Testing**

| Variable | Cronbach's Alpha | Composite Reliability (rho_a) | Composite Reliability (rho_c) | AVE |
|---|---|---|---|---|
| AE | 0.774 | 0.884 | 0.846 | 0.580 |
| AIA | 0.814 | 0.818 | 0.870 | 0.572 |
| EAC | 0.779 | 0.784 | 0.858 | 0.601 |
| IM | 0.798 | 0.798 | 0.861 | 0.553 |
| MS | 0.783 | 0.788 | 0.860 | 0.605 |
| SM | 0.778 | 0.779 | 0.849 | 0.529 |
| TA | 0.786 | 0.787 | 0.854 | 0.539 |

*(Source: Results processed from SmartPLS)*

Table 3 reports the results of the reliability and convergent validity assessment. Results show that all variables have Cronbach's Alpha coefficients ranging from 0.774 to 0.814, exceeding the acceptable threshold of 0.7 in social science research. The variable AIA has the highest coefficient at 0.814, while SM has the lowest at 0.778, but is still within the acceptable range. This indicates that the observed variables within each scale exhibit relatively strong internal correlations.

Composite reliability rho_a ranges from 0.779 to 0.884, with AE showing the highest value of 0.884 and SM the lowest at 0.779. The rho_c values fall between 0.846 and 0.870, all exceeding the 0.7 threshold, demonstrating satisfactory internal consistency. The differences between rho_a and rho_c across variables are minimal, reflecting the stability of the scales in the sample.

The AVE values range from 0.529 to 0.605, with MS showing the highest AVE at 0.605 and SM showing the lowest at 0.529. Although SM has an AVE slightly above the 0.5 threshold, it remains acceptable when considered alongside the satisfactory composite reliability indicators. All remaining variables have AVE values exceeding 0.5, indicating that their observed variables explain over 50% of the variance of their corresponding latent constructs.

3.2.2. Discriminant Validity

**Table 4. Fornell–Larcker Criterion Matrix**

| | AE | AIA | EAC | IM | MS | SM | TA |
|---|---|---|---|---|---|---|---|
| AE | 0.761 | | | | | | |
| AIA | 0.309 | 0.757 | | | | | |
| EAC | 0.258 | 0.562 | 0.775 | | | | |
| IM | 0.110 | 0.385 | 0.446 | 0.744 | | | |
| MS | 0.090 | 0.430 | 0.548 | 0.312 | 0.778 | | |
| SM | 0.126 | 0.321 | 0.502 | 0.407 | 0.343 | 0.727 | |
| TA | 0.187 | 0.418 | 0.566 | 0.361 | 0.414 | 0.315 | 0.734 |

*Note: Diagonal values are the square roots of AVE*

*Source: Results processed from SmartPLS*

Table 4 presents the results of the discriminant validity assessment using the Fornell–Larcker criterion. According to the Fornell–Larcker criterion, the square root of AVE on the diagonal must be greater than the correlation coefficients between constructs. Results indicate that all variables satisfy this condition. The diagonal values range from 0.727 to 0.778, whereas the inter-construct correlations are lower. The highest correlation is between TA and EAC at 0.566, yet it remains below the square root of AVE of both constructs. The lowest correlation is between AE and MS at 0.090, indicating a large degree of distinction.

**Table 5. HTMT Ratio Matrix**

| | AE | AIA | EAC | IM | MS | SM | TA |
|---|---|---|---|---|---|---|---|
| AE | | | | | | | |
| AIA | 0.377 | | | | | | |
| EAC | 0.304 | 0.702 | | | | | |
| IM | 0.140 | 0.478 | 0.567 | | | | |
| MS | 0.107 | 0.530 | 0.697 | 0.389 | | | |
| SM | 0.159 | 0.398 | 0.635 | 0.512 | 0.434 | | |
| TA | 0.204 | 0.518 | 0.723 | 0.455 | 0.525 | 0.397 | |

*(Source: Results processed from SmartPLS)*

Table 5 reports the results of discriminant validity assessment using the Heterotrait–Monotrait (HTMT) ratio and cross-loading analysis. The HTMT ratio is used to assess discriminant validity, with the commonly accepted threshold being below 0.85 or 0.90. Results show that all variable pairs have HTMT ratios below 0.85, with the highest value being 0.723 between TA and EAC. Other pairs range from 0.107 to 0.702, all within acceptable limits. This confirms that the constructs are clearly distinct and not easily confused with one another.

Cross-loading analysis shows that all observed variables load highest on the latent construct they are intended to measure. For example, AE1 has a loading of 0.732 on AE, which is significantly higher than its loadings on other constructs, ranging from 0.023 to 0.228. Similarly, EAC2 has the highest loading at 0.814 on EAC, whereas its loadings on other constructs range only from 0.260 to 0.469. This demonstrates that the observed variables align well with their respective constructs and do not overlap with others in the model.

3.2.3. Multicollinearity Assessment

**Table 6. VIF of Observed Variables**

| Observed Variable | VIF | Observed Variable | VIF | Observed Variable | VIF |
|---|---|---|---|---|---|
| AE1 | 1.480 | IM1 | 1.540 | SM1 | 1.519 |
| AE2 | 1.440 | IM2 | 1.433 | SM2 | 1.509 |
| AE3 | 1.634 | IM3 | 1.618 | SM3 | 1.336 |
| AE4 | 1.500 | IM4 | 1.601 | SM4 | 1.410 |
| AIA1 | 1.612 | IM5 | 1.518 | SM5 | 1.545 |
| AIA2 | 1.588 | MS1 | 1.597 | TA1 | 1.471 |
| AIA3 | 1.561 | MS2 | 1.492 | TA2 | 1.555 |
| AIA4 | 1.571 | MS3 | 1.645 | TA3 | 1.474 |
| AIA5 | 1.561 | MS4 | 1.440 | TA4 | 1.449 |
| EAC1 | 1.447 | | | TA5 | 1.438 |
| EAC2 | 1.645 | | | | |
| EAC3 | 1.478 | | | | |
| EAC4 | 1.551 | | | | |

*(Source: Results processed from SmartPLS)*

Table 6 presents the results of the multicollinearity assessment using variance inflation factor (VIF) values. The VIF values of observed variables range from 1.336 to 1.645, all below the threshold of 5 and even below the safer threshold of 3. The highest VIF value is 1.645 for MS3 and EAC2, while the lowest is 1.336 for SM3. This indicates that there is no severe multicollinearity among the observed variables, and they can be safely used in structural model analysis.

**Table 7. VIF between Latent Variables**

| Relationship | VIF |
|---|---|
| AE -> EAC | 1.036 |
| AIA -> MS | 1.000 |
| AIA -> TA | 1.000 |
| EAC -> SM | 1.249 |
| IM -> SM | 1.249 |
| MS -> IM | 1.207 |
| TA -> AE | 1.000 |
| TA -> EAC | 1.036 |
| TA -> IM | 1.207 |

*(Source: Results processed from SmartPLS)*

Table 7 reports the variance inflation factor (VIF) values among latent variables in the structural model. The VIF values between latent variables in the structural model show similar results. VIF values range from 1.000 to 1.249, indicating no multicollinearity between independent variables when predicting dependent variables. The highest VIF is 1.249, observed in the relationships EAC -> SM and IM -> SM, while some relationships have a VIF of 1.000, indicating no linear correlation between the independent variables. These results confirm that the research model does not face multicollinearity issues, allowing causal relationship analysis to proceed.

3.2.4. Model Fit Assessment

**Table 8. Model Fit Indices**

| Index | Saturated Model | Estimated Model |
|---|---|---|
| SRMR | 0.059 | 0.105 |
| d_ULS | 1.827 | 5.824 |
| d_G | 0.501 | 0.621 |
| Chi-square | 1044.477 | 1188.346 |
| NFI | 0.755 | 0.722 |

*(Source: Results processed from SmartPLS)*

Table 8 presents the model fit indices of the structural model. The SRMR index of the saturated model is 0.059, while the estimated model has an SRMR of 0.105. Although this value is higher than the commonly recommended threshold of 0.08, it is still below 0.12 and can be acceptable in some complex research scenarios. The NFI of the saturated model is 0.755 and 0.722 for the estimated model, indicating that the model explains approximately 72–75% of the variance relative to the baseline model. The d_ULS and d_G indices of the estimated model are higher than those of the saturated model, reflecting differences between the empirical correlation matrix and the estimated correlation matrix. The Chi-square value of the estimated model is 1188.346, higher than that of the saturated model at 1044.477, indicating a certain discrepancy between observed data and model-predicted data.

The scale assessment results indicate that the variables in the research model meet the requirements for reliability, convergent validity, and discriminant validity. Multicollinearity does not affect the analysis results. The model exhibits acceptable fit, allowing subsequent analysis steps to test the research hypotheses.

3.3. Model estimation

3.3.1. Coefficient of Determination $R^2$

**Table 9. $R^2$ of Endogenous Variables**

| Variable | $R^2$ | Adjusted $R^2$ |
|---|---|---|
| AE | 0.035 | 0.032 |
| EAC | 0.345 | 0.341 |
| IM | 0.162 | 0.157 |
| MS | 0.185 | 0.183 |
| SM | 0.294 | 0.290 |
| TA | 0.175 | 0.172 |

*(Source: Results processed from SmartPLS)*

Table 9 reports the coefficients of determination ($R^2$) and adjusted $R^2$ values for the endogenous constructs in the structural model. The results indicate that EAC has the highest $R^2$ at 0.345, showing that the independent variables in the model explain 34.5% of the variance in employees' AI competence. The main dependent variable, SM, has an $R^2$ of 0.294, meaning that 29.4% of the variance in sales motivation is explained by the antecedent variables. MS has an $R^2$ of 0.185, indicating that AI autonomy explains 18.5% of the variance in management support.

TA and IM have $R^2$ values of 0.175 and 0.162, reflecting moderate to low explanatory power. AE has the lowest $R^2$ at only 0.035, indicating that technology acceptance explains only 3.5% of the variance in AI explainability. The difference between $R^2$ and adjusted $R^2$ for all variables is very small, ranging from 0.003 to 0.005, suggesting that the model is stable and not significantly affected by the number of independent variables.

3.3.2. Effect Size $f^2$

**Table 10. Effect Size $f^2$ among Variables**

| Relationship | $f^2$ |
|---|---|
| TA -> EAC | 0.425 |
| AIA -> MS | 0.227 |
| AIA -> TA | 0.211 |
| EAC -> SM | 0.182 |
| TA -> IM | 0.077 |
| IM -> SM | 0.059 |
| MS -> IM | 0.038 |
| AE -> EAC | 0.036 |
| TA -> AE | 0.036 |

*(Source: Results processed from SmartPLS)*

Table 10 presents the effect size ($f^2$) values for the structural relationships in the model. The analysis shows that technology acceptance has the largest effect on employees' AI competence with $f^2 = 0.425$. This indicates that removing TA from the model significantly reduces the explanatory power of EAC. AI autonomy has a medium effect on both management support and technology acceptance, with $f^2$ values of 0.227 and 0.211, respectively. Employees' AI competence also has a medium effect on sales motivation with $f^2 = 0.182$.

Other relationships have smaller effects, including TA -> IM ($f^2 = 0.077$), IM -> SM ($f^2 = 0.059$), and MS -> IM, AE -> EAC, and TA -> AE with $f^2$ ranging from 0.036 to 0.038. Although these effects are small, they still contribute to the overall structure of the model and help explain the dependent variables.

3.3.3. Predictive Relevance $Q^2$

**Table 11. $Q^2$ Predictive Relevance and Accuracy**

| Variabl e | SSO | SSE | $Q^2$ | RMS E | MA E |
|---|---|---|---|---|---|
| EAC | 1428.00 0 | 1139.63 9 | 0.20 2 | 0.896 | 0.72 4 |
| SM | 1785.00 0 | 1517.51 0 | 0.15 0 | 0.972 | 0.75 0 |
| MS | 1428.00 0 | 1273.73 2 | 0.10 8 | 0.915 | 0.70 9 |
| TA | 1785.00 0 | 1623.15 8 | 0.09 1 | 0.920 | 0.69 4 |
| IM | 1785.00 0 | 1632.25 1 | 0.08 6 | 0.950 | 0.73 7 |
| AE | 1428.00 0 | 1409.25 0 | 0.01 3 | 0.987 | 0.79 5 |
| AIA | 1785.00 0 | 1785.00 0 | 0.00 0 | - | - |

*(Source: Results processed from SmartPLS)*

Table 11 presents the predictive relevance of the structural model based on $Q^2$ values and PLSpredict accuracy measures. The results indicate that EAC has the highest $Q^2$ at 0.202, suggesting that the model has good predictive power for employees' AI competence. The main dependent variable SM has $Q^2 = 0.150$, reflecting acceptable predictive power for sales motivation. MS, TA, and IM have $Q^2$ values of 0.108, 0.091, and 0.086, respectively, indicating low to moderate predictive relevance but still positive.

AE has a very low $Q^2$ of 0.013, indicating that the model poorly predicts AI explainability. AIA has $Q^2 = 0$ as it is an exogenous variable not predicted by other variables in the model. RMSE and MAE indices reflect prediction accuracy, with EAC having the lowest RMSE and MAE at 0.896 and 0.724, respectively, while AE has the highest values at 0.987 and 0.795.

3.3.4. Testing Direct Relationships

**Table 12. Results of Direct Relationships**

| Relationship | Path Coefficient | Std. Dev. | t-value | p-value |
|---|---|---|---|---|
| TA -> EAC | 0.537 | 0.044 | 12.198 | 0.000 |
| AIA -> MS | 0.430 | 0.050 | 8.609 | 0.000 |
| AIA -> TA | 0.418 | 0.059 | 7.136 | 0.000 |
| EAC -> SM | 0.400 | 0.063 | 6.360 | 0.000 |
| TA -> IM | 0.280 | 0.057 | 4.937 | 0.000 |
| IM -> SM | 0.228 | 0.060 | 3.815 | 0.000 |
| MS -> IM | 0.196 | 0.052 | 3.739 | 0.000 |
| TA -> AE | 0.187 | 0.056 | 3.352 | 0.001 |
| AE -> EAC | 0.157 | 0.050 | 3.169 | 0.002 |

*(Source: Results processed from SmartPLS)*

Table 12 presents the results of hypothesis testing and direct path relationships in the structural model. All direct relationships in the model are statistically significant with $p < 0.05$. The strongest relationship is between TA and EAC with a path coefficient of 0.537 and t-value = 12.198, indicating that technology acceptance strongly and positively affects employees' AI competence. AI autonomy positively affects both management support and technology acceptance, with coefficients of 0.430 and 0.418, respectively.

Employees' AI competence positively influences sales motivation with a coefficient of 0.400, while intrinsic motivation also positively affects sales motivation with a coefficient of 0.228. Technology acceptance positively affects intrinsic motivation (0.280), and management support positively influences intrinsic motivation (0.196). Weaker relationships include TA -> AE (0.187) and AE -> EAC (0.157), but these are still statistically significant.

3.3.5. Testing Indirect Effects

**Table 13. Results of Key Indirect Effects**

| Indirect Relationship | Coefficient | Std. Dev. | t-value | p-value |
|---|---|---|---|---|
| AIA -> TA -> EAC | 0.224 | 0.044 | 5.128 | 0.000 |
| TA -> EAC -> SM | 0.215 | 0.037 | 5.737 | 0.000 |
| AIA -> TA -> IM | 0.117 | 0.032 | 3.678 | 0.000 |
| AIA -> TA -> EAC -> SM | 0.090 | 0.022 | 4.069 | 0.000 |
| AIA -> MS -> IM | 0.084 | 0.025 | 3.316 | 0.001 |
| AIA -> TA -> AE | 0.078 | 0.030 | 2.614 | 0.009 |
| TA -> IM -> SM | 0.064 | 0.023 | 2.811 | 0.005 |
| AE -> EAC -> SM | 0.063 | 0.022 | 2.826 | 0.005 |
| MS -> IM -> SM | 0.045 | 0.017 | 2.596 | 0.009 |
| TA -> AE -> EAC | 0.029 | 0.012 | 2.433 | 0.015 |
| AIA -> TA -> IM -> SM | 0.027 | 0.011 | 2.344 | 0.019 |
| AIA -> MS -> IM -> SM | 0.019 | 0.008 | 2.481 | 0.013 |
| AIA -> TA -> AE -> EAC | 0.012 | 0.006 | 2.155 | 0.031 |
| TA -> AE -> EAC -> SM | 0.012 | 0.005 | 2.297 | 0.022 |
| AIA -> TA -> AE -> EAC -> SM | 0.005 | 0.002 | 2.077 | 0.038 |

*(Source: Results processed from SmartPLS)*

Table 13 reports the results of the indirect effects and mediation analysis in the structural model. The analysis shows that all indirect effects are statistically significant. The largest indirect effect is from AIA to EAC via TA with a coefficient of 0.224, indicating that AI autonomy affects employees' AI competence through increased technology acceptance. The indirect effect from TA to SM via EAC has a coefficient of 0.215, highlighting the mediating role of AI competence in transforming technology acceptance into sales motivation.

AI autonomy indirectly affects intrinsic motivation through technology acceptance (0.117) and also affects sales motivation via the chain TA -> EAC -> SM (0.090). Management support indirectly affects intrinsic motivation through AIA with a coefficient of 0.084. Other indirect effects have smaller coefficients but remain significant, demonstrating the complexity of interactions among variables in the model.

Longer effect chains, such as AIA -> TA -> IM -> SM and AIA -> MS -> IM -> SM, have coefficients of 0.027 and 0.019, respectively, reflecting that AI autonomy can influence sales motivation through multiple pathways. The weakest indirect effect is in the chain AIA -> TA -> AE -> EAC -> SM with a coefficient of 0.005, yet it is still statistically significant at $p = 0.038$.

The model estimation results indicate that the variables in the research model have complex relationships through both direct and indirect effects. Technology acceptance plays a central role in linking AI autonomy to employee competence and work motivation. Employees' AI competence and intrinsic motivation are key factors directly affecting sales motivation, while management support and AI explainability act as supportive factors through indirect effects.

3.4. Testing mean differences

3.4.1. Gender Differences

**Table 14. Gender Differences Test**

| Variable | Male (n=168) | Female (n=189) | F | Sig. |
|---|---|---|---|---|
| | Mean (SD) | Mean (SD) | | |
| SM | 3.80 (0.52) | 3.81 (0.57) | 0.023 | 0.881 |
| IM | 3.79 (0.60) | 3.81 (0.55) | 0.130 | 0.719 |
| TA | 3.78 (0.59) | 3.82 (0.56) | 0.435 | 0.510 |
| AE | 3.79 (0.56) | 3.74 (0.54) | 0.755 | 0.385 |
| MS | 3.82 (0.57) | 3.81 (0.59) | 0.012 | 0.914 |
| AIA | 3.70 (0.64) | 3.66 (0.56) | 0.557 | 0.456 |
| EAC | 3.78 (0.59) | 3.71 (0.57) | 1.320 | 0.251 |

*(Source: Results processed from SPSS)*

Table 14 presents the results of the gender-based comparison of the research variables. The results show no statistically significant differences between male and female respondents for all research variables, with p-values greater than 0.05. The mean scores range from 3.66 to 3.82 and are quite similar across the two groups. Levene's test indicated homogeneity of variance for most variables ($p > 0.05$), except IM ($p = 0.041$), but Welch's test produced similar results.

3.4.2. Age Differences

**Table 15. Age Differences Test**

| Variable | <25 (n=68) | 25–34 (n=164) | 35–44 (n=86) | 45+ (n=39) | F | Sig. |
|---|---|---|---|---|---|---|
| SM | 3.68 | 3.84 | 3.78 | 3.89 | 1.729 | 0.161 |
| IM | 3.88 | 3.73 | 3.81 | 3.98 | 2.708 | 0.045 |
| TA | 3.86 | 3.78 | 3.77 | 3.87 | 0.611 | 0.608 |
| AE | 3.35 | 3.74 | 3.79 | 4.51 | 54.366 | 0.000 |
| MS | 3.81 | 3.82 | 3.73 | 3.99 | 1.850 | 0.138 |
| AIA | 3.63 | 3.62 | 3.72 | 3.92 | 3.124 | 0.026 |
| EAC | 3.70 | 3.69 | 3.80 | 3.88 | 1.584 | 0.193 |

*(Source: Results processed from SPSS)*

Table 15 presents the results of age-group comparisons for the research variables. Statistically significant differences were found by age for three variables: IM ($p=0.045$), AE ($p=0.000$), and AIA ($p=0.026$). The 45+ age group reported the highest mean scores for these variables, especially AE at 4.51 compared to 3.35 for the under-25 group. This indicates that older employees have more positive perceptions of AI explainability and intrinsic motivation. Other variables did not show significant differences across age groups.

3.4.3. Organizational Type Differences

**Table 16. Organizational Type Differences Test**

| Variable | Hotel (n=139) | Travel (n=96) | Restaurant (n=64) | Resort (n=58) | F | Sig. |
|---|---|---|---|---|---|---|
| SM | 3.84 | 3.81 | 3.73 | 3.78 | 0.587 | 0.624 |
| IM | 3.75 | 3.88 | 3.82 | 3.80 | 1.080 | 0.357 |
| TA | 3.81 | 3.72 | 3.84 | 3.89 | 1.270 | 0.285 |
| AE | 3.83 | 3.70 | 3.83 | 3.65 | 2.282 | 0.079 |
| MS | 3.79 | 3.82 | 3.82 | 3.90 | 0.499 | 0.684 |
| AIA | 3.66 | 3.63 | 3.74 | 3.73 | 0.696 | 0.555 |
| EAC | 3.76 | 3.74 | 3.76 | 3.68 | 0.293 | 0.830 |

*(Source: Results processed from SPSS)*

Table 16 presents the results of the one-way ANOVA comparing research variables across different organizational types. No statistically significant differences were found between organizational types, with all p-values > 0.05. Mean scores are relatively similar across hotels, travel companies, restaurants, and resorts, indicating that perceptions of AI and work motivation are consistent across different types of organizations in the hospitality and tourism sector.

3.4.4. Work Experience Differences

**Table 17. Work Experience Differences Test**

| Variable | <1 year (n=55) | 1–3 years (n=142) | 3–5 years (n=77) | >5 years (n=83) | F | Sig. |
|---|---|---|---|---|---|---|
| SM | 3.77 | 3.81 | 3.81 | 3.81 | 0.071 | 0.975 |
| IM | 3.81 | 3.76 | 3.83 | 3.85 | 0.571 | 0.634 |
| TA | 3.80 | 3.81 | 3.77 | 3.83 | 0.149 | 0.930 |
| AE | 3.52 | 3.63 | 3.90 | 4.03 | 16.253 | 0.000 |
| MS | 3.84 | 3.77 | 3.79 | 3.90 | 0.945 | 0.419 |
| AIA | 3.61 | 3.60 | 3.74 | 3.79 | 2.279 | 0.079 |
| EAC | 3.75 | 3.68 | 3.78 | 3.80 | 0.965 | 0.409 |

*(Source: Results processed from SPSS)*

Table 17 presents the results of the one-way ANOVA examining differences across work experience groups. Only AE showed statistically significant differences by work experience (F=16.253, p=0.000). Employees with more than 5 years of experience reported the highest mean (4.03), whereas those with less than 1 year had the lowest mean (3.52). This indicates that more experienced employees have a better understanding of how AI functions. Other variables did not show significant differences across experience groups.

3.4.5. Job Position Differences

**Table 18. Job Position Differences Test**

| Variable | Sales (n=185) | CS (n=90) | Supervisor (n=53) | Manager (n=22) | Others (n=7) | F | Sig. |
|---|---|---|---|---|---|---|---|
| SM | 3.79 | 3.79 | 3.75 | 4.03 | 3.97 | 1.243 | 0.292 |
| IM | 3.81 | 3.76 | 3.78 | 3.93 | 3.91 | 0.484 | 0.748 |
| TA | 3.80 | 3.87 | 3.66 | 3.90 | 3.74 | 1.323 | 0.261 |
| AE | 3.71 | 3.70 | 3.93 | 4.03 | 3.82 | 3.399 | 0.010 |
| MS | 3.82 | 3.84 | 3.73 | 3.92 | 3.71 | 0.568 | 0.686 |
| AIA | 3.67 | 3.64 | 3.74 | 3.69 | 3.77 | 0.290 | 0.885 |
| EAC | 3.71 | 3.80 | 3.65 | 3.85 | 4.00 | 1.234 | 0.296 |

*(Source: Results processed from SPSS)*

Table 18 presents the results of the one-way ANOVA examining differences across job positions. Only AE showed statistically significant differences by job position (F=3.399, p=0.010). Managers had the highest mean score (4.03), followed by supervisors (3.93). This indicates that employees in higher positions have better knowledge of AI explainability. Other variables did not show significant differences across job positions, reflecting a generally consistent perception of AI and work motivation across organizational roles.

The tests indicate that AI explainability is the variable with the most noticeable differences according to demographic characteristics, particularly age, work experience, and job position. Older employees, those with longer experience, and those in higher positions tend to rate AI explainability more positively. Other variables such as sales motivation, technology acceptance, and AI competence show no significant differences between groups, indicating homogeneity within the research sample.

3.5. Discussion

The study results indicate that most hypotheses in the research model are supported by empirical data. Firstly, Technology Acceptance (TA) plays a central role, having the strongest influence on Employee AI Competence (EAC) ($\beta = 0.537$; $f^2 = 0.425$). This finding reinforces the UTAUT framework (Venkatesh et al., 2012) and empirical studies on digital transformation (Davenport & Ronanki, 2018; Kim et al., 2025), confirming that employees' acceptance and readiness for technology are prerequisites for developing digital competence, especially in service business environments. When employees perceive AI as useful, easy to use, and contextually relevant, they proactively engage with technology and enhance their skills, thereby improving performance and work motivation.

Next, AI Autonomy (AIA) significantly affects both TA ($\beta = 0.418$) and Managerial Support (MS) ($\beta = 0.430$). This reflects a bidirectional relationship between AI system autonomy and organizational management behavior. As Brynjolfsson & McAfee (2014) and Hauptman et al. (2024) highlighted, increased AI autonomy alters task structures and decision-making mechanisms, requiring managers to enhance guidance, training, and support to maintain employee engagement and adaptation. From the employees' perspective, higher AI autonomy helps them perceive clearer benefits, thus promoting technology acceptance.

Regarding psychological factors, Intrinsic Motivation (IM) is influenced by both TA (β = 0.280) and MS (β = 0.196). This is consistent with Self-Determination Theory (Deci & Ryan, 2000; Adams et al., 2017), which posits that competence and relatedness needs are crucial in driving intrinsic motivation. Employees who feel capable of mastering technology and supported by supervisors maintain interest and effort in their work, thereby enhancing sales motivation.

For the model outcomes, EAC and IM are the two direct determinants of Sales Motivation (SM), with EAC exerting a stronger effect (β = 0.400 vs. β = 0.228). This aligns with Vroom (1964) and Yakovenko et al. (2022), who argue that work motivation in high-tech contexts largely depends on individuals' ability to utilize technology to achieve performance goals. Employees with strong AI competence experience lower cognitive load, higher efficiency, and greater confidence, resulting in increased motivation.

AI Explainability (AE) positively but modestly affects EAC (β = 0.157), with a relatively low $R^2$ of 0.035. This implies that while AI explainability is important for building trust and reducing perceived risk (Hauptman et al., 2024), it is not a decisive factor in this research context. This aligns with the characteristics of the service-tourism sector in Vietnam, where employees often prioritize usefulness and operational efficiency over deep algorithmic understanding. However, mean difference tests show that AE varies significantly by age, experience, and job position, reflecting higher transparency needs among long-tenured employees or managers, consistent with Fang et al. (2025) regarding the importance of accountability in AI leadership.

The $R^2$ for SM reached 0.294, indicating that the model explains approximately 29.4% of the variance in sales motivation. This is appropriate for research on human factors in service industries, which are influenced by multiple external factors such as organizational culture, compensation policies, work environment, and sales pressure (Nguyen et al., 2023; Van et al., 2024). The potential impact of factors outside the model suggests the need to expand the model in future studies.

Regarding sample characteristics and descriptive statistics (M = 3.65–3.88), employees generally hold positive attitudes toward AI-related factors and sales motivation. Standard deviations ranging from 0.700 to 0.823 reflect relatively large dispersion among employee groups, consistent with service sector diversity in age, experience, and job roles. These results partly explain why AE and AIA show significant differences across demographic groups.

The study highlights that developing AI competence and facilitating technology acceptance are key factors in enhancing sales motivation. AI's value arises not only from automation functions but also from enabling employees to feel competent, supported, and capable of achieving better work outcomes. These findings contribute to research on AI in human resource and sales management (Croitoru et al., 2025; Koponen et al., 2025) and provide practical implications for service-tourism businesses in Vietnam deploying AI technologies.

## 4. Conclusions and recommendations

### 4.1. Conclusions

This study aimed to assess the impact of AI-related factors in sales operations on Sales Motivation (SM) among employees in the Vietnamese tourism-hospitality sector. The research model integrates technical factors (AI Autonomy – AIA, AI Explainability – AE), organizational factors (Managerial Support – MS), cognitive-behavioral factors (Technology Acceptance – TA), and psychological-competence factors (Employee AI Competence – EAC; Intrinsic Motivation – IM) to explain the mechanism of sales motivation formation in the context of increasing AI adoption in service businesses.

PLS-SEM results indicate that most hypotheses are supported. TA plays a central role, exerting the strongest influence on EAC and indirectly affecting SM via both EAC and IM. This confirms that technology acceptance is a crucial first step for employees to develop AI adaptation capabilities and improve work outcomes. AIA significantly affects MS and TA, showing that AI autonomy impacts not only job experience but also prompts organizations to adjust support and management mechanisms.

EAC and IM are direct determinants of SM, with EAC exerting a stronger effect. This emphasizes that employees' AI competence is a core condition for achieving work effectiveness and maintaining intrinsic motivation. Although AE positively affects EAC, its influence is limited, suggesting that employees prioritize practical AI use over deep understanding of operational mechanisms.

The model explains 29.4% of SM variance-a level consistent with human-factor research in service industries, influenced by external factors such as organizational culture, compensation policies, and sales pressure. Descriptive statistics and mean difference tests also show diversity in perceptions across age, experience, and job positions.

The study confirms that effective AI deployment in sales depends not only on technical factors but also on building a supportive environment, promoting technology acceptance, and developing employees' AI competence. These findings contribute to the theoretical foundation of work motivation in digitalized contexts and provide empirical evidence for the Vietnamese tourism-hospitality sector.

### 4.2. Recommendations

#### 4.2.1. For Tourism-Hospitality Businesses

Enhance internal communication about AI benefits and promote technology acceptance (TA): Businesses should provide clear, transparent information about AI's role in work support, organize training sessions, share experiences, and implement pilot programs for employees to experience the technology's effectiveness directly.

Invest in training programs to enhance employees' AI competence (EAC): Since EAC strongly affects SM, training should be tiered: basic for new employees, advanced for experienced staff, and specialized for management. Training content should focus on AI tool operation, data processing, and AI application in sales processes.

Strengthen managerial support (MS) during digital transformation: Managers should lead, accompany, and create an innovation-friendly environment. Timely support helps reduce employees' anxiety when using AI and motivates them to stay engaged with the organization.

Design appropriate AI autonomy levels (AIA): High autonomy can both support and pressure employees; businesses need to select an optimal automation level to ensure AI assists rather than fully replaces human roles in customer interaction decisions.

Improve AI explainability (AE) for employees with higher transparency needs.: Although AE's impact on EAC is limited, businesses should provide clear guidance and dashboards explaining AI recommendations, particularly for older employees or managers who require clarity, accountability, and trust.

4.2.2. For Government Authorities

Encourage the development of digital infrastructure and AI platforms in tourism-hospitality: Building a coherent digital ecosystem helps businesses access technology and deploy AI effectively.

Issue guidelines for responsible AI usage: Focus on data transparency, algorithm explainability, and protecting employees' rights in automated contexts.

4.2.3. For Future Research

Expand the model by adding factors such as compensation policies, sales pressure, organizational culture, or job characteristics.

Use longitudinal or experimental research designs to examine causal relationships between AI deployment and sales motivation.

Incorporate behavioral data such as actual sales performance, AI interaction history, or system logs to enhance reliability.

Survey multiple service industry groups to compare AI impacts across different work environments.

**Ethical Statement**

This study was conducted in compliance with established ethical standards for social science research. All participants were informed of the research objectives and provided voluntary consent prior to participation. Anonymity and confidentiality were strictly maintained, and no personally identifiable information was collected. The data were used exclusively for academic purposes. The study did not involve vulnerable populations or experimental manipulation; therefore, formal approval from an institutional ethics committee was not required.

**Disclosure of AI Use**

ChatGPT, developed by OpenAI (version released in December 2025), was used to support language editing, improvement of clarity, and refinement of academic writing during the manuscript preparation process. The use of ChatGPT was limited to linguistic assistance and organization of text and did not influence the research design, data collection, statistical analysis, or interpretation of results. All methodological decisions, analyses, and conclusions were conducted and verified by the authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript..

.

**REFERENCES**

1. Adams, N., Little, T. D., & Ryan, R. M. (2017). Self-determination theory. In Development of self-determination through the life-course (pp. 47-54). Dordrecht: Springer Netherlands.
2. Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & company.
3. Croitoru, M. B., Florea, N. V., Florea, D., Savu, M. O., & Croitoru, G. (2025). The Role of Artificial Intelligence in Human Resource Management: Implications for Employee Motivation, Performance, and Technology Acceptance. Economics and Applied Informatics, (2), 194-209.
4. Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans-and where they can't (yet). The McKinsey Quarterly, 1-12.
5. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard business review, 96(1), 108-116.
6. Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. Psychological inquiry, 11(4), 227-268.
7. Fang, M., Le Minh, T., Louie, J., Pham, L. N., & Hewson, C. (2025). Leadership networks: Shaping AI innovations through responsible practices in Vietnamese tourism and hospitality firms. Tourism Management, 113, 105317.
8. Hauptman, A. I., Schelble, B. G., Duan, W., Flathmann, C., & McNeese, N. J. (2024). Understanding the influence of AI autonomy on AI explainability levels in human-AI teams using a mixed methods approach. Cognition, Technology & Work, 26(3), 435-455.
9. Kim, H., So, K. K. F., Shin, S., & Li, J. (2025). Artificial intelligence in hospitality and tourism: Insights from industry practices, research literature, and expert opinions. Journal of Hospitality & Tourism Research, 49(2), 366-385.
10. Koponen, J., Julkunen, S., Laajalahti, A., Turunen, M., & Spitzberg, B. (2025). Sales managers' perceptions of interpersonal communication competence in leading AI-integrated sales teams. Industrial Marketing Management, 124, 57-72.
11. Le, B. H., Duong, C. H., & Nguyen, G. T. (2025). Perceived supervisor support and its impact to job performance: Dataset from the hospitality industry in

Vietnam. Data in Brief, 111649.
12. Locke, E. A., & Latham, G. P. (1990). A theory of goal setting & task performance. Prentice-Hall, Inc.
13. Lunenburg, F. C. (2011). Goal-setting theory of motivation. International journal of management, business, and administration, 15(1), 1-6.
14. Van, A. N. T., Tran, H. M. N., Kieu, D. T., Trung, L. V., Ngoc, N. T. N., & Cac, T. T. T. (2024). Exploring Work Motivation and Job Effectiveness in Mekong Delta's Hospitality: A Study Utilizing Partial Least Squares Structural Equation Modeling. Journal of Chinese Human Resources Management, 15(2), 101-112.
15. Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS quarterly, 157-178.
16. Vroom, V. H. (1964). Work and motivation.
17. Yakovenko, Y. Y., Bilyk, M. Y., & Oliinyk, Y. V. (2022, October). The transformative impact of the development of artificial intelligence on employment and work motivation in business in the conditions of the information economy. In 2022 IEEE 4th International Conference on Modern Electrical and Energy System (MEES) (pp. 01-06). IEEE.

.