



# Artificial Intelligence, Transformational Leadership, and Job Performance: Mediating Role of Job Engagement and Moderating Role of Work Passion

Phuong Thao Nguyen<sup>1</sup>, Phuc Quy Thanh Nguyen<sup>2\*</sup>, Minh Tuan Nguyen<sup>3</sup>

<sup>1,2</sup>*Faculty of Business Administration, Ho Chi Minh University of Banking, Vietnam*

<sup>3</sup>*Faculty of Postgraduate Education, Ho Chi Minh University of Banking, Vietnam*

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## Abstract

This study investigates the relationships among Artificial Intelligence (AI), perceived usefulness of AI, transformational leadership, job engagement, and job performance, with the moderating role of work passion. Drawing on the Job Demands–Resources (JD–R) model and the Technology Acceptance Model (TAM), the study proposes a research model explaining how technological and leadership resources jointly influence employee performance in the context of digital transformation. A quantitative approach was employed, with data collected through an online survey of 345 employees at five leading joint-stock commercial banks in Vietnam. Partial Least Squares Structural Equation Modeling (PLS–SEM) was applied to test the proposed hypotheses. The findings reveal that perceived usefulness of AI is the strongest indirect predictor of job performance through the mediating role of job engagement. The results also confirm that transformational leadership significantly enhances employee engagement, particularly through inspirational motivation and individualized consideration. Artificial Intelligence, as an organizational resource, further strengthens engagement by reducing workload and supporting decision-making processes. Furthermore, work passion plays a moderating role in the relationship between job engagement and job performance, with harmonious passion amplifying this relationship while obsessive passion may reduce its marginal effect. These findings highlight the importance of integrating AI applications with effective leadership practices to foster employee engagement and improve job performance in modern digital organizations.

*Keywords:* AI, Usefulness of Artificial Intelligence, Transformational Leadership, Job Engagement, Work Passion, Job Performance, Digital Transformation.

## 1. Introduction

The rapid and profound advancement of technology, particularly AI, is fundamentally reshaping operational and managerial practices across modern organizations. Numerous studies have highlighted that the accelerating pace of technological change compels businesses to swiftly adapt by integrating AI into their decision-making processes and developing comprehensive digital transformation strategies [1]. In the banking sector, an industry particularly sensitive to technological shifts, AI has emerged as a critical tool for personalizing financial services, developing intelligent products, and establishing business models that respond to increasingly complex customer demands [2]. Despite its considerable benefits, the adoption of AI also presents significant managerial challenges. These include strategic planning difficulties, system compatibility issues, and concerns over data security and financial transaction privacy [3], [4]. Such challenges underscore the urgent need for innovative leadership, particularly among those with strategic thinking capabilities and a strong foundation in digital technologies. These leaders are essential not only for the effective implementation of AI but also for guiding organizations through the continuous changes in today's business environment. In this context, transformational leadership has gained prominence as an effective leadership style to navigate the complexities of technological transformation.

Although technological advancements provide significant advantages for organizations, the successful adoption and use of new technologies by employees require that organizations ensure employees perceive these technologies as both useful and easy to use. According to the Technology Acceptance Model (TAM) proposed by Davis [5] employees' perceived usefulness of AI in organizational contexts reflects the extent to which they believe that the technology can enhance their job performance, improve decision-making quality, and optimize operational processes. In the context of financial institutions, when employees perceive AI as providing tangible benefits to their work, they are more likely

\*Corresponding author: Phuc Quy Thanh Nguyen ([thanhpq@hub.edu.vn](mailto:thanhpq@hub.edu.vn))

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to adopt the technology and engage more actively in organizational activities. Recent studies have also demonstrated that positive perceptions of digital technologies can enhance work motivation, strengthen employee engagement, and improve overall organizational performance [3], [6].

Beyond technological factors, research in organizational behavior highlights the critical role of the work environment and organizational resources in shaping employee motivation and performance. Drawing on the Job Demands–Resources (JD–R) model [7], [8], employee performance is influenced by the interaction between job demands and job resources. Within this framework, job resources, such as leadership support, career development opportunities, and technological tools, can help employees reduce work-related pressures while simultaneously fostering intrinsic motivation and work engagement. In the context of this study, AI and transformational leadership can be conceptualized as important job resources that enable employees to perform their tasks more effectively by supporting decision-making, providing timely information, and automating work processes. According to the JD–R model, when employees are provided with sufficient job resources, they are more likely to experience higher levels of job engagement, which ultimately leads to improved job performance.

This leadership approach emphasizes vision-building, inspiration, individualized development, and innovation, all of which are crucial in helping employees adapt to change, enhance motivation, and improve performance [6], [9]. When combined with AI, transformational leaders are better positioned to leverage technology as a tool for informed decision-making, process optimization, and organizational performance enhancement [10]. In practice, AI can support the customization of training programs and performance assessments, enabling employees to identify strengths and areas for improvement while aligning their skills with job requirements. When transformational leadership is effectively exercised alongside AI, the workplace evolves into a more dynamic environment that nurtures employee potential and strengthens organizational engagement. Kannan and Msila affirm that the synergy between AI and transformational leadership positively contributes to job performance and employee satisfaction [11].

In the Vietnamese context, recent research by Nguyen and Pham [12] has demonstrated that AI and job engagement exert a positive impact on employee performance. Complementing this, Nguyen [13] found that job stress has a detrimental effect on performance, whereas work motivation acts as a moderator that can mitigate stress and enhance outcomes. While digital transformation offers substantial benefits for organizations, its high-intensity implementation may also have psychological repercussions for employees, especially amid growing concerns that AI may increase the risk of job displacement. These anxieties can affect employees' passion for their work, which is a crucial psychological factor in sustaining motivation, managing stress, and adapting proactively to technological changes. According to Vallerand et al. [14], work passion plays a vital role in promoting job performance and fostering a more cohesive and productive workplace.

Building on the theoretical and practical foundations outlined above, this study is guided by three interrelated research questions. Specifically, the study examines: how AI, together with its perceived usefulness and transformational leadership, influences job engagement within the banking sector; what mediating role job engagement plays in the relationships between AI, transformational leadership, and job performance; and in what way work passion moderates the relationship between job engagement and job performance.

This research is conducted in the context of joint-stock commercial banks in Ho Chi Minh City, where AI is being vigorously deployed in both business operations and marketing activities. Employing a quantitative approach via a staff survey, the study seeks to provide empirical evidence to inform human resource management policies that can enhance performance and foster talent development within Vietnam's banking industry.

## 2. Literature Review

### 2.1. Theoretical Background

#### 2.1.1. Technology Acceptance Model (TAM)

The TAM was developed by Davis [5] to explain individuals' acceptance and use of information technologies. According to TAM, two core cognitive beliefs, perceived usefulness and perceived ease of use, determine users' attitudes toward a technology, which subsequently influence their behavioral intention and actual usage [5]. Among these determinants, perceived usefulness is considered the most important factor influencing technology adoption because individuals are more likely to accept a technology when they believe it can enhance their job performance and work efficiency [5], [15]. In the context of AI adoption in organizations, TAM provides an important theoretical

framework for understanding how employees evaluate the value of AI-based systems. The concept of perceived usefulness is particularly relevant when examining employees' perceptions of AI features, such as decision-support capabilities, automation of routine tasks, and improvements in work efficiency. Therefore, TAM is applied in this study to explain how the perceived usefulness of AI influences employees' work-related attitudes and behaviors. By incorporating TAM into the research framework, this study aims to capture the cognitive mechanisms through which AI-related perceptions contribute to employee engagement and performance in technology-driven workplaces.

### 2.1.2. Job Demands–Resources (JD-R)

The Job Demands–Resources model (JD–R) was introduced by Evangelia Demerouti and Arnold B. Bakker to explain how different job characteristics influence employee well-being and performance [7]. The model suggests that all occupations involve two main categories of job characteristics: job demands and job resources. Job demands refer to aspects of work that require sustained effort and may lead to strain, such as workload or time pressure. In contrast, job resources refer to physical, psychological, social, or organizational factors that help employees achieve work goals, reduce job demands, and stimulate motivation and personal development [8]. According to the JD–R model, job resources play a critical role in fostering work engagement, which subsequently leads to higher job performance [8]. In technology-driven work environments, resources may include advanced digital tools and supportive leadership practices. In this study, artificial intelligence and transformational leadership are conceptualized as important organizational resources that support employees in performing their tasks more effectively. By applying the JD–R framework, this research explains how these resources enhance employees' job engagement, which ultimately contributes to improved job performance.

## 2.2. Relationship between Artificial Intelligence and Perceived Usefulness of AI

From a theoretical perspective, the relationship between AI and the perceived usefulness of AI needs to be clearly conceptualized in order to better understand the mechanisms through which technology influences employee behavior and performance. In organizational contexts, AI is commonly defined as technological systems based on algorithms and data that can support or automate analytical, predictive, and decision-making activities [16]. As a technological resource, AI has the potential to optimize operational processes and enhance organizational efficiency. However, the mere implementation of AI technologies within organizations does not necessarily guarantee that employees will effectively utilize these technologies in their work.

According to the TAM proposed by Davis [5], employees' adoption and use of technology depend not only on the availability of the technology but also on users' perceptions of its usefulness. Specifically, employees are more likely to accept and utilize technological systems when they believe that such systems can improve their job performance. In this sense, AI represents the technological infrastructure or the level of technology implementation within the organization, whereas the perceived usefulness of AI reflects employees' subjective evaluation of the benefits that such technologies bring to their work. This perspective is consistent with the argument of Berente et al. [6], who describe AI as a significant advancement in organizations' computational and data-processing capabilities, enabling technological systems to address complex decision-making problems in modern business environments. Nevertheless, research on attitudes toward and acceptance of AI suggests that individuals' perceptions of the usefulness of AI play a crucial role in shaping positive attitudes toward the technology and encouraging its use in the workplace [17]. Furthermore, in the context of digital transformation, Meijerink et al. [16] emphasize that algorithmic and AI systems implemented in organizations primarily function as technological infrastructures supporting decision-making processes. In contrast, employees' reactions to these systems, including trust, acceptance, and perceived value, are rooted in users' cognitive and psychological evaluations.

Therefore, distinguishing between AI as an organizational technological resource and the perceived usefulness of AI as employees' cognitive evaluation of that resource allows researchers to simultaneously capture both the objective aspect of technology implementation and the subjective perception of users. Such an approach provides a clearer explanation of how AI can influence job engagement and job performance in the context of organizational digital transformation.

## 2.3. Research Hypothesis

### 2.3.1. The Relationship between Usefulness of AI and Job Engagement

The perceived usefulness of AI reflects employees' subjective evaluations regarding the extent to which artificial intelligence technologies can enhance their work performance. This perception is closely related to employees' psychological responses when interacting with technological systems [18]. According to the Technology Acceptance Model (TAM), perceived usefulness represents a critical cognitive factor that determines whether users believe that utilizing a technological system can improve their job performance and work effectiveness [19]. Accordingly, in the context of this study, AI represents the technological functions and systems implemented within organizations, whereas the perceived usefulness of AI refers to employees' subjective evaluation of the benefits that such technologies bring to their work.

Recent studies suggest that employees' willingness to adopt AI in the workplace is strongly influenced by their perceptions of its usefulness and their expectations that AI can support them in performing tasks more efficiently [20]. When employees perceive that AI reduces workload, provides timely information, and supports decision-making processes, they are more likely to view the technology as beneficial to their job tasks [16]. These advantages can enhance employees' sense of control, autonomy, and confidence in performing their work, which are important psychological conditions for fostering job engagement.

According to Schaufeli et al. [21], job engagement represents a positive work-related psychological state characterized by vigor, dedication, and absorption in work. When employees perceive AI as a supportive tool that enhances their work effectiveness, they tend to invest greater cognitive and emotional effort into their job tasks. Moreover, AI can strengthen employees' sense of competence and professional value when it is perceived as augmenting rather than replacing human work [6]. In such circumstances, employees are more likely to develop positive attitudes toward their work and become more actively involved in their job roles. Therefore, when employees perceive AI technologies as useful and beneficial to their work activities, they are more likely to experience higher levels of job engagement. Based on the above theoretical and empirical foundations, the following hypothesis is proposed:

*H1: Perceived usefulness of AI positively influences job engagement.*

### 2.3.2. The Relationship between Transformational Leadership and Job Engagement

Transformational leadership is a leadership style that is both strategically and emotionally driven, emphasizing inspiration, the stimulation of creative thinking, and the personal development of followers to enhance organizational effectiveness. This leadership approach comprises four core components: inspirational motivation, idealized influence, intellectual stimulation, and individualized consideration [22].

These elements not only influence job performance but also play a central role in strengthening employees' job engagement. The inspirational motivation refers to a leader's ability to instill confidence and enthusiasm in employees by articulating a clear vision, fostering a sense of purpose, and motivating individuals to overcome challenges. Encouragement and motivation from leaders serve as a source of inspiration that promotes collaboration and enhances the ability to achieve shared goals. This cultivates a positive emotional bond between employees and the organization, thereby reinforcing job engagement [23]. In addition, idealized influence reflects the leader's role as an ethical role model who demonstrates positive behaviors within the organization. Bass and Bass [24] argue that transformational leaders gain trust and respect from their subordinates by acting with integrity and prioritizing collective interests. When leaders alleviate employee stress and foster inspiration, they not only create a supportive environment but also enhance job satisfaction and commitment [25]. As such, idealized influence strengthens the leader–employee relationship and contributes to the development of sustainable job engagement. Intellectual stimulation refers to a leader's ability to encourage critical thinking, creativity, and innovative problem-solving. Transformational leaders empower employees to question assumptions, explore new ideas, and actively contribute to organizational innovation [26]. Afsar et al. [26] suggest that such active participation in creative activities fosters a sense of personal value and contribution, which in turn deepens psychological connection and enhances engagement. Individualized consideration involves a leader's genuine understanding of employees' needs, capabilities, and goals [27]. Holten and Brenner [28] note that transformational leaders often act as mentors, coaches, and developmental guides. When employees perceive that their

leaders care deeply and personally about their growth, they tend to put in greater effort, gain a clearer sense of self-efficacy, and pursue both individual and organizational goals with greater purpose [29]. Handayani [30] reinforces this perspective by emphasizing that individualized consideration, expressed through specific actions that respond to employees' needs and expectations, strengthens leader–employee relationships and fosters job engagement.

From the employee's perspective, job engagement is understood as a positive work-related attitude characterized by a willingness to invest physical, cognitive, and emotional resources to perform effectively [31]. When leaders provide direction, support, and developmental opportunities, they not only improve performance but also activate intrinsic motivation, thereby deepening employees' engagement with their work and the organization. In sum, transformational leadership, characterized by inspiration, value orientation, and people development, plays a fundamental role in enhancing job engagement. Based on the aforementioned theoretical and empirical foundations, the following hypothesis is proposed:

*H2: Transformational leadership positively influences job engagement.*

### 2.3.3. The Relationship between AI and Job Engagement

In the context of rapid digital transformation in the banking sector, an industry highly sensitive to technology and data, the application of AI not only enhances operational efficiency but also exerts a profound influence on human resource dynamics, particularly employees' job engagement. According to Chen et al. [32], organizations seeking to maintain a competitive advantage must proactively invest in and effectively leverage organizational resources. AI is considered a strategic intangible asset that contributes to long-term value and can amplify both individual and collective performance [33]. AI's exceptional capabilities, including decision-making support, personalized service, and automation, are reshaping how employees interact with their work. Integrating AI into decision-making processes helps reduce repetitive manual tasks while enabling employees to access data and information more quickly and accurately. This, in turn, fosters a sense of importance, recognition, and growth, critical components of job engagement. As Kaur et al. [34] define it, job engagement is a positive psychological state characterized by enthusiasm, pride, and a desire for long-term commitment to one's work. When AI is deployed as a supportive tool rather than a replacement, it creates an environment in which employees feel empowered and experience greater control over their workflow. The real-time feedback provided by AI not only enhances performance but also strengthens employees' self-perception of their value within the organization.

In the contemporary workplace, AI is increasingly embedded in daily operations, reshaping how employees interact with their work and redefining service delivery processes [35]. Employees are not only using AI to accomplish tasks but also benefiting from personalized learning programs tailored to their competencies and development needs [36]. These learning opportunities enhance professional capabilities and generate a sense of progress, thereby reinforcing the connection between individuals and the organization. Organizational efforts to apply AI in human resource processes aim to enhance engagement and performance while ensuring job security. AI is increasingly used to automate administrative tasks and create optimal working environments, leading to improved efficiency and employee satisfaction.

Moreover, AI functions as an effective internal communication channel. AI-powered chatbots, for example, are used to answer frequently asked questions regarding policies, benefits, or administrative procedures, enabling employees to resolve issues quickly without manual intervention from HR departments. This enhances transparency, reduces ambiguity, and reinforces employees' perception of organizational support [37]. Transparency and continuous support are critical to maintaining high levels of job engagement. More importantly, AI plays a role in restructuring job roles by eliminating repetitive tasks, freeing up time for employees to focus on creative and strategic activities, fostering a deeper sense of meaning and fulfillment at work [16]. When work transitions from being purely mechanical to a process of learning, creativity, and collaboration, employees are more likely to develop strong intrinsic engagement with the organization. In sum, AI is not merely a technological tool that supports organizational operations; it also acts as a catalyst for initiating and sustaining job engagement. By enhancing the work experience, supporting personal development, and optimizing communication and decision-making processes, AI contributes to creating a workplace where employees feel valued, supported, and empowered to grow. Based on the aforementioned theoretical and empirical foundations, the following hypothesis is proposed:

*H3: Artificial Intelligence positively influences job engagement.*

#### 2.3.4. The Relationship between Job Engagement and Job Performance

Job performance is defined as the overall value that an employee contributes to an organization, encompassing both direct contributions through task execution and indirect contributions through behaviors that support the work environment [38]. In the contemporary workplace, enhancing performance depends not only on professional competencies but also significantly on the level of job engagement. Job engagement is described as a psychological state in which employees invest personal resources, including physical, cognitive, and emotional energy, into fulfilling their roles and responsibilities within the organization [39]. When employees feel engaged, they exert greater physical effort, maintain heightened cognitive focus, and develop a positive emotional attachment to their work [40]. Conversely, a lack of engagement often leads to psychological withdrawal, passivity, detachment, and diminished motivation, which can undermine work effectiveness [41].

Analyzing each dimension, physical investment in one's role enables employees to sustain long-term effort. This not only meets the behavioral expectations of the organization but also reflects a strong commitment to one's professional responsibilities. Individuals who are willing to take on more challenging tasks are more likely to exhibit higher levels of performance. In addition, cognitive engagement helps employees remain highly focused, proactive in learning, and committed to developing professional skills to meet the organization's increasing demands [41]. Such cognitive effort improves individual performance and contributes to the overall productivity of the organization. Emotional investment, meanwhile, fosters a strong sense of connection between employees and the organization's goals. This emotional bond motivates cooperative behavior, peer support, and improved team effectiveness, an increasingly vital factor in today's collaborative work environments [40]. Based on these insights, it can be concluded that highly engaged employees tend to work with greater intensity, demonstrate stronger responsibility, and sustain a positive emotional connection to their tasks. Therefore, job engagement stands out as a significant predictor of employee job performance. Based on the aforementioned theoretical and empirical foundations, the following hypothesis is proposed:

*H4: Job engagement positively influences job performance.*

#### 2.3.5. The Moderating Role of Work Passion

While job engagement has long been recognized as a key driver of job performance (facilitating the investment of physical, cognitive, and emotional resources into one's role [39]), its influence is not always consistent. Recent research suggests that the impact of job engagement on performance may be contingent upon certain psychological factors, among which work passion plays a prominent moderating role. According to the Dualistic Model of Passion proposed by Vallerand et al. [14], work passion can be categorized into two types: harmonious passion and obsessive passion. Harmonious passion reflects an individual's voluntary engagement in work, where the activity is perceived as intrinsically valuable and integrated harmoniously with other areas of life. In contrast, obsessive passion arises when individuals feel compelled to pursue their work due to internal pressures, often leading to conflict between their professional and personal lives.

Empirical studies have consistently shown that harmonious passion amplifies the positive relationship between job engagement and job performance. Specifically, Forest et al. [42] and Ho et al. [43] found that harmonious passion encourages employees to sustain cognitive engagement, which leads to more enduring and effective work outcomes. Ho et al. [43] further noted that harmonious passion enables individuals to fully capitalize on the benefits of engagement by transforming positive psychological energy into effective work behaviors. Similarly, Carbonneau et al. [44], in their study on teachers, observed that individuals with high levels of work passion tend to achieve superior teaching performance and greater job satisfaction compared to those with lower passion levels. Furthermore, Chen et al. [45] demonstrated that individuals displaying higher passion exhibit more compelling performance behaviors, suggesting that passion functions as a behavioral amplifier in achievement-oriented contexts. Theoretically, work passion can be conceptualized as a moderator that influences the strength and direction of the relationship between job engagement and job performance. When harmonious passion is high, individuals not only sustain long-term commitment to their roles but also demonstrate resilience, continuous learning, and a proactive approach to achieving professional goals. In this context, passion functions not merely as an emotional state but as a behavioral regulatory mechanism within the organizational setting. It fosters the maintenance of positive psychological energy, facilitates productive work

behaviors, and ultimately enhances individual performance and organizational outcomes. Based on the aforementioned theoretical and empirical foundations, the following hypothesis is proposed:

*H5: Work passion moderates the relationship between job engagement and job performance.*

### 2.3.6. The Mediating Role of Job Engagement

Job engagement is defined as the extent to which employees are willing to mobilize and invest their physical, cognitive, and emotional resources in the execution of their work roles [39]. According to Bakker and Demerouti [46], engagement arises when individuals are provided with sufficient job resources, such as technological support or effective leadership, and it is this engagement that ultimately determines performance-related behaviors. Engaged employees are typically more responsible, proactive, and creative, thereby making direct contributions to organizational outcomes. Empirical studies by [39] and [47] confirm the mediating role of job engagement in the relationship between various input factors (e.g., work conditions, organizational culture, leadership behavior) and output variables such as job performance, satisfaction, and organizational commitment.

When employees utilize technology and feel supported by AI, such as receiving timely information, benefiting from personalized learning, or offloading repetitive tasks, they are more likely to perceive greater self-efficacy, autonomy, and professional value. These positive perceptions form the basis for increased engagement, which in turn drives proactive, creative, and committed work behavior, key components of high job performance. Similarly, transformational leadership, through its dimensions of inspirational motivation, individualized consideration, intellectual stimulation, and idealized influence, not only fosters a supportive work environment but also cultivates positive emotional states among employees. Such leaders encourage learning, resilience, and a deeper sense of meaning in one's work [48]. These factors activate engagement as both a psychological and behavioral response, thereby motivating employees to perform with greater intensity, accountability, and long-term effectiveness. Based on the above theoretical and empirical foundations, the following hypothesis is proposed:

*H6: Job engagement mediates the relationship between Artificial Intelligence, transformational leadership, and job performance.*

## 3. Methodology

### 3.1. Research Method

This study employs both qualitative and quantitative research methods to examine the relationships among Artificial Intelligence, Usefulness of Artificial Intelligence, Transformational Leadership, Job Engagement, and Job Performance, as well as the moderating role of Work Passion in the proposed model. The qualitative stage involved a review of relevant literature and expert discussions with academics and practitioners in the banking and digital transformation fields to refine the research constructs and measurement items. The research was conducted through an online survey targeting employees working at five leading joint-stock commercial banks in Vietnam. These banks were identified based on the 2024 ranking of reputable banking brands published by Brand Finance. The selected banks include the Bank for Investment and Development of Vietnam (BIDV), the Joint Stock Commercial Bank for Foreign Trade of Vietnam (Vietcombank), the Vietnam Joint Stock Commercial Bank for Industry and Trade (VietinBank), the Military Commercial Joint Stock Bank (MB Bank), and the Vietnam Technological and Commercial Joint Stock Bank (Techcombank). These institutions are recognized for their strong digital transformation efforts and advanced applications of AI in business and marketing operations.

The study employed a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The scale for Usefulness of AI comprises four items adapted from the Technology Acceptance Model (TAM) by Davis [5]. These items are tailored to capture not only the impact of AI on work productivity but also the users' subjective evaluations of AI in the workplace. The Transformational Leadership scale includes four items based on the framework developed by [24], which has been widely validated in academic research to measure the core dimensions of transformational leadership. The Artificial Intelligence scale consists of three items developed from the work of Schepman & Rodway [18], focusing on the technical features of AI that enhance employee performance. The Job Engagement scale comprises four items adapted from [39], reflecting employees' emotional involvement, concentration, and physical

effort in their job roles. The Job Performance scale includes four items based on the measure developed by [49], capturing performance outcomes in the context of AI integration. Finally, the Work Passion scale consists of three items adapted from [49], emphasizing the moderating role of harmonious passion in promoting voluntary engagement and improved performance, while also highlighting employees’ work–life balance.

### 3.2. Proposed Research Model

Figure 1 illustrates the proposed research model, depicting the hypothesized relationships among the six constructs examined in this study: Artificial Intelligence (AI), Usefulness of Artificial Intelligence (UAI), Transformational Leadership (TL), Job Engagement (JE), Work Passion (WP), and Job Performance (JP). In the model, AI, UAI, and TL are positioned as independent variables that directly influence JE (H1, H2, H3), while JE serves as the mediating variable between these antecedents and JP (H4, H6). Work Passion is included as a moderating variable that regulates the strength of the JE-JP relationship (H5).

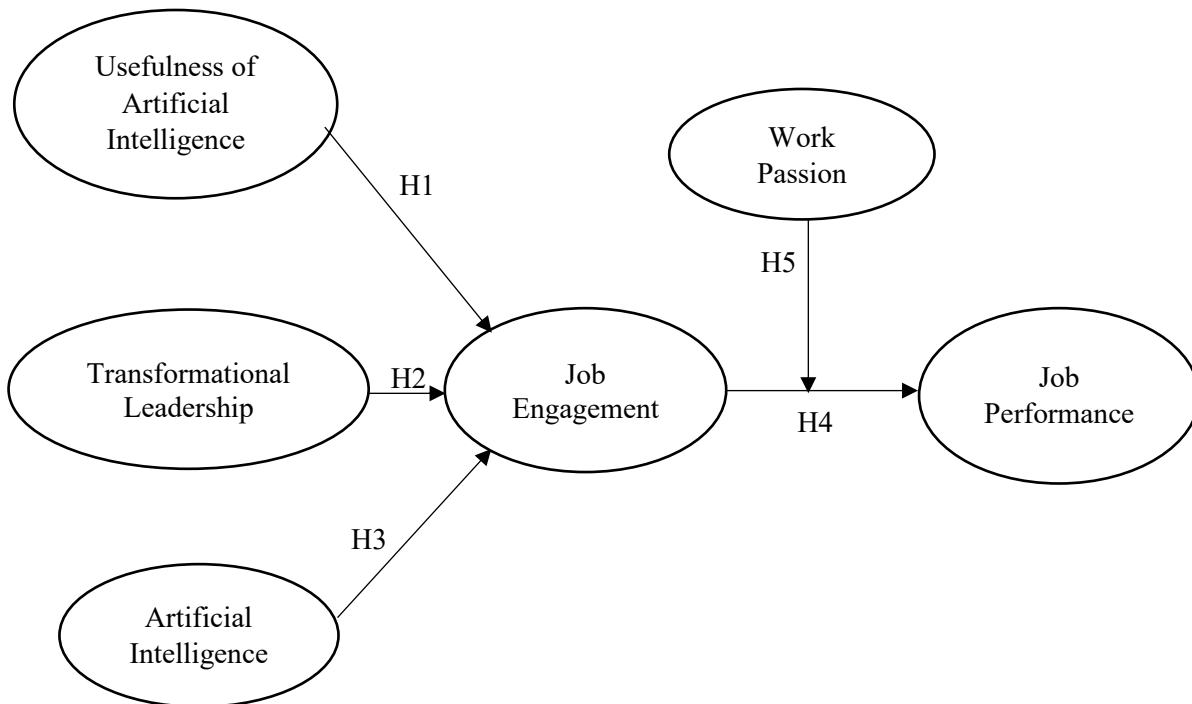


Figure 1. Proposed Research Model

#### 3.2.1. Research Flowchart

The research process follows a structured six-stage flowchart: (1) Literature Review and Hypothesis Development: theoretical frameworks (TAM and JD-R) are reviewed and five hypotheses (H1–H5) are proposed; (2) Questionnaire Design: measurement scales are adapted from validated instruments for AI, UAI, TL, JE, WP, and JP constructs; (3) Data Collection: an online survey is distributed to 500 employees at five leading joint-stock commercial banks in Vietnam, yielding 345 valid responses; (4) Data Screening: incomplete and inconsistent responses are removed; (5) PLS-SEM Analysis: measurement model assessment (reliability, convergent validity, discriminant validity) is performed, followed by structural model testing (path coefficients, mediation analysis, moderation analysis); and (6) Interpretation and Reporting: findings are discussed in relation to prior literature, and practical implications are drawn for managers and policymakers.

#### 3.2.2. Research Formulas

The study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS. The core statistical formulas used are as follows:

Reflective Measurement Model:

$$x_{ij} = \lambda_{ij} \xi_j + \delta_{ij} \tag{1}$$

$x_{ij}$  is the  $i$ -th indicator of latent construct  $\xi_j$ ,  $\lambda_{ij}$  is the outer loading, and  $\delta_{ij}$  is the measurement error.

Composite Reliability (CR):

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum(1 - \lambda_i^2)} \quad (2)$$

Threshold:  $CR \geq 0.70$  [50]

Average Variance Extracted (AVE):

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum(1 - \lambda_i^2)} \quad (3)$$

Threshold:  $AVE \geq 0.50$  confirms convergent validity [50].

Structural Path Equations:

$$JE = \beta_1(AI) + \beta_2(UAI) + \beta_3(TL) + \zeta_1 \quad (4a)$$

$$JP = \beta_4(JE) + \beta_5(WP) + \beta_6(JE \times WP) + \zeta_2 \quad (4b)$$

$\beta$  values are path coefficients estimated via bootstrapping (5,000 resamples), and  $\zeta$  represents the residual error term.

Indirect Effect (Mediation):

$$Indirect\ Effect = \beta(X \rightarrow JE) \times \beta(JE \rightarrow JP) \quad (5)$$

Significance assessed via bootstrapped 95% confidence intervals.

Predictive Relevance ( $Q^2$  via Blindfolding):

$$Q^2 = 1 - \left( \frac{SSE}{SSO} \right) \quad (6)$$

$Q^2 > 0$  indicates predictive relevance;  $Q^2 > 0.35$  indicates strong predictive relevance [50].

### 3.2.3. Research Pseudocode

The following algorithm 1, describes the analytical procedure implemented in SmartPLS:

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**Algorithm 1.** PLS Path Modeling with Bootstrapping, Mediation, and Moderation Analysis

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*INPUT: Survey dataset (n = 345), 6 constructs (AI, UAI, TL, JE, WP, JP), 22 indicators*

**STEP 1: Measurement Model Assessment:**

*FOR each construct C in {AI, UAI, TL, JE, WP, JP}:*  
     *Compute Cronbach Alpha and Composite Reliability (CR)*  
     *IF (Alpha below 0.70) OR (CR below 0.70) THEN flag reliability issue*  
     *Compute AVE for construct C*  
     *IF AVE below 0.50 THEN flag convergent validity issue*  
     *Remove indicators with outer loading below 0.70*  
*END FOR*

**STEP 2: Discriminant Validity (HTMT Criterion):**

*FOR each pair of constructs (Ci, Cj):*  
     *Compute HTMT ratio*  
     *IF HTMT ratio above 0.85 THEN flag discriminant validity violation [51]*  
*END FOR*

**STEP 3: Structural Model (Path Coefficients):**

*Run PLS algorithm to estimate path coefficients beta*

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*Run bootstrapping ( $B = 5,000$  resamples) to obtain  $t$ -statistics and  $p$ -values  
FOR each hypothesis  $H$  in  $\{H1, H2, H3, H4, H5\}$ :  
IF  $p$ -value below 0.05 THEN Accept hypothesis ELSE Reject hypothesis  
END FOR*

**STEP 4: Mediation Analysis:**

*Compute indirect effect =  $\beta(X \text{ to } JE) \times \beta(JE \text{ to } JP)$   
Assess significance via bootstrapped 95% confidence interval  
IF confidence interval excludes 0 THEN mediation is statistically significant*

**STEP 5: Moderation Analysis:**

*Mean-center  $JE$  and  $WP$  variables  
Compute interaction term:  $INT = JE\_centered \times WP\_centered$   
Estimate  $\beta(INT \text{ to } JP)$  and assess significance via bootstrapping*

**STEP 6: Predictive Relevance:**

*Run blindfolding procedure (omission distance  $d = 7$ )  
Compute  $Q^2$  for each endogenous construct*

*OUTPUT: Path coefficients,  $t$ -statistics,  $p$ -values,  $R^2$ ,  $Q^2$ , mediation and moderation results*

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## 4. Results and Discussion

### 4.1. Measurement Model Assessment Results

The study conducted an online survey via Google Forms using a convenience sampling approach, targeting employees from the five aforementioned joint-stock commercial banks. Out of 500 distributed questionnaires, 345 valid responses were retained for analysis. Data were analyzed using SmartPLS software, applying the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. This approach was employed to evaluate the reliability and convergent validity of the measurement scales, discriminant validity, path coefficients, mediation and moderation effects, as well as predictive relevance through  $Q^2$  values.

The demographic profile of the 345 respondents reveals that 149 were female and 196 were male. Participants ranged in age from 18 to 55, with 61% falling within the 26 to 40 age group, an age range generally associated with the core workforce in most industries, particularly in banking, where employees tend to have gained experience and demonstrate strong job commitment. The majority of respondents held a university degree (59%), while 4.9% held postgraduate qualifications, 20.9% held college diplomas, and 14.5% had other educational backgrounds. Monthly income levels ranged from below VND 10 million to above VND 25 million, with 33.6% earning over VND 25 million and 18.8% earning under VND 10 million. As shown in [table 1](#), the reliability and convergent validity results demonstrate that all measurement scales achieved Cronbach's Alpha coefficients above 0.70 (ranging from 0.772 to 0.863), indicating a high level of internal consistency among observed items [50]. Regarding indicator loadings, all items exceeded the 0.70 threshold, confirming strong convergent validity. For the AI construct, all three items, AI1 (0.869), AI2 (0.877), and AI3 (0.911), showed strong loadings, confirming high reliability and convergence. For the JE construct, the four items, JE1 (0.864), JE2 (0.827), JE3 (0.706), and JE4 (0.800), all met the minimum threshold for factor loadings. Although JE3 had the lowest loading (0.706), it was still within the acceptable range. The JP construct also showed high reliability with JP1 (0.801), JP2 (0.787), JP3 (0.876), and JP4 (0.852).

Composite Reliability (CR) values ranged from 0.867 to 0.916, exceeding the recommended threshold of 0.70 and confirming the stability and strong reliability of the scales used in the model. In terms of Average Variance Extracted (AVE), all constructs had AVE values greater than 0.50 (ranging from 0.642 to 0.785), indicating that the observed variables explain a substantial portion of the variance in their respective latent constructs.

**Table 1.** The reliability and convergent validity of the measurement scales

Research constructs	Items	Factor Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Artificial Intelligence (AI)	AI1	0.869	0.863	0.876	0.916	0.785
	AI2	0.877				
	AI3	0.911				
Job Engagement (JE)	JE1	0.864	0.815	0.835	0.877	0.642
	JE2	0.827				
	JE3	0.706				
	JE4	0.8				
Job Performance (JP)	JP1	0.801	0.849	0.86	0.898	0.689
	JP2	0.787				
	JP3	0.876				
	JP4	0.852				
Transformational Leadership (TL)	TL1	0.812	0.884	0.901	0.856	0.694
	TL2	0.84				
	TL3	0.839				
	TL4	0.842				
Usefulness of Artificial Intelligence (UAI)	UAI1	0.76	0.843	0.856	0.895	0.68
	UAI2	0.873				
	UAI3	0.822				
	UAI4	0.839				
Work Passion (WP)	WP1	0.876	0.772	0.824	0.867	0.687
	WP2	0.897				
	WP3	0.699				

After assessing the reliability and convergent validity, we proceeded to evaluate discriminant validity using the Heterotrait-Monotrait ratio (HTMT) as recommended by [51]. This method aims to determine the degree of distinction between the constructs within the research model. According to Henseler et al. [51], HTMT values should be below 0.85 or 0.90 to confirm that the latent constructs are empirically distinct from one another. Based on the data presented in table 2, all construct pairs exhibit HTMT values below 0.85, thereby confirming the presence of discriminant validity and indicating that there is no significant conceptual overlap among the theoretical constructs in the model.

**Table 2.** Result of Heterotrait-monotrait ratio

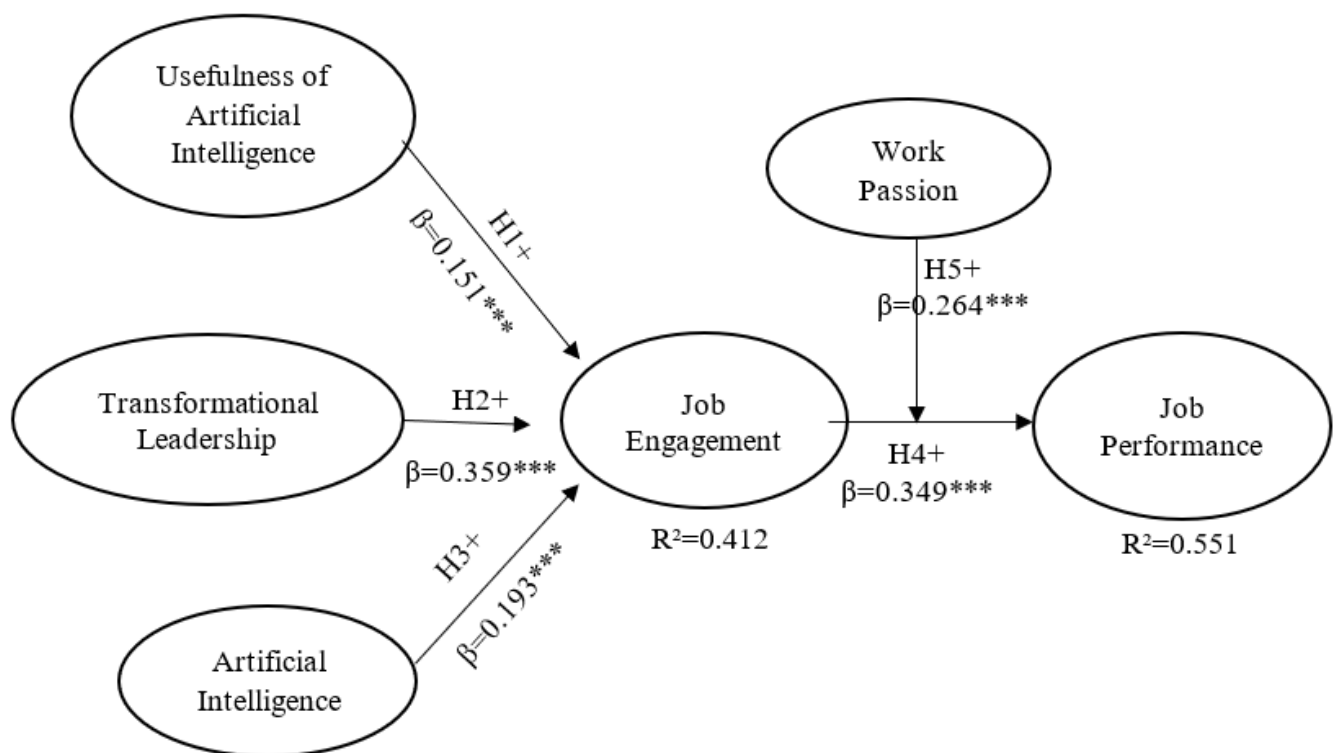
Factor	AI	JE	JP	TL	UAI	WP	WP x JE
AI							
JE	0.362						
JP	0.58	0.63					
TL	0.292	0.407	0.605				
UAI	0.355	0.554	0.647	0.422			
WP	0.421	0.499	0.601	0.461	0.471		
WP x JE	0.309	0.341	0.492	0.378	0.415	0.422	

## 4.2. Result of Mediation Analysis

To examine the mediating variable in the model, we conducted a structural model analysis. The results of the path coefficient analysis, as presented in table 3 and Validated Structural Model with Computed Path Coefficients (figure 2), indicate that all path coefficients are statistically significant at a high level of confidence ( $p < 0.05$ ). These findings demonstrate meaningful linear relationships among the latent constructs in the proposed research model.

**Table 3.** Result of Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values	Result
AI → JE	0.151	0.152	0.045	3.341	0.001	Acceptance
JE → JP	0.349	0.351	0.045	7.689	0	Acceptance
TL → JE	0.193	0.195	0.044	4.367	0	Acceptance
UAI → JE	0.359	0.36	0.051	7.087	0	Acceptance
WP → JP	0.264	0.269	0.046	5.697	0	Acceptance
WP x JE → JP	-0.192	-0.189	0.036	5.315	0	Acceptance



**Figure 2.** Validated Structural Model with Computed Path Coefficients (SmartPLS Results)

The mediation analysis results presented in [table 4](#) indicate that Job Engagement plays a statistically significant mediating role in the relationships between three key predictors, AI, Transformational Leadership, and Usefulness of AI, and Job Performance. The indirect effect of the AI → JE → JP pathway is  $\beta = 0.053$ , with a t-value of 2.923 and  $p = 0.003$ , suggesting that AI has a significant indirect impact on job performance through job engagement. This result confirms that the effectiveness of AI tools lies not only in their technical features but also in how they support employees in achieving their work goals. These findings reinforce the argument by Pillai and Sivathanu [20] that employees' perceptions of AI are critical predictors of AI acceptance and effective utilization in the workplace.

**Table 4.** The result of Mediation Analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P- values	Result
AI → JE → JP	0.053	0.053	0.018	2.923	0.003	Acceptance
TL → JE → JP	0.067	0.069	0.018	3.678	0	Acceptance

UAI → JE → JP	0.125	0.127	0.027	4.599	0	Acceptance
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Additionally, the indirect effect of TL → JE → JP is  $\beta = 0.067$ , with  $t = 3.678$  and  $p < 0.001$ , indicating that transformational leadership influences job performance through employee engagement. This finding is consistent with the work of [48], who emphasized the crucial role of leadership in fostering a positive work environment, building trust, and inspiring employees, factors that drive dedication and commitment at work [24],[48]. Components of transformational leadership such as individualized consideration, intellectual stimulation, and inspirational motivation serve as key mechanisms that enhance engagement and, in turn, improve job performance.

Finally, the UAI → JE → JP path shows the strongest indirect effect, with  $\beta = 0.125$ ,  $t = 4.599$ , and  $p < 0.001$ . This indicates that the perceived usefulness of AI has the most substantial indirect influence on performance through job engagement. The findings suggest that when employees perceive AI as supportive in reducing workload, enhancing capabilities, and improving decision-making, they are more likely to invest emotional, cognitive, and physical resources into their work, leading to improved overall performance. This result aligns with studies by Meijerink et al. [16] and Berente et al. [6], which argue that AI-driven personalization and intelligent support contribute to a stronger sense of autonomy and organizational commitment among employees [6], [16].

### 4.3. Moderation Analysis

In examining the moderating effect of Work Passion (WP), we assessed the model’s predictive relevance using the Q<sup>2</sup> statistic (predictive relevance coefficient). In PLS-SEM, the Q<sup>2</sup> value is generated through the blindfolding procedure and is used to evaluate the predictive capability of the model. According to [50], a Q<sup>2</sup> value greater than zero indicates that the model has predictive relevance. The results from the current research model show that all endogenous constructs exhibit Q<sup>2</sup> values above 0.35, indicating strong predictive relevance, surpassing the threshold for strong predictive relevance as classified by [50]. The result of table 5, the construct Artificial Intelligence recorded the highest Q<sup>2</sup> value (0.541), indicating that its observed indicators strongly reflect the underlying concept, i.e., the selected measurement items provide a robust representation of AI. Other constructs, including Job Engagement, Job Performance, Transformational Leadership, and Usefulness of AI, recorded Q<sup>2</sup> values ranging from 0.408 to 0.479, demonstrating strong explanatory power of the endogenous variables.

**Table 5.** The result of Moderation Analysis

Construct cross - Validated redundancy - Total				Construct cross - Validated communality - Total			
	SSO	SSE	Q <sup>2</sup> (=1-SSE/SSO)		SSO	SSE	Q <sup>2</sup> (=1-SSE/SSO)
<b>AI</b>	1035	1035	0	<b>AI</b>	1035	475.392	0.541
<b>JE</b>	1380	1136.841	0.176	<b>JE</b>	1380	817.481	0.408
<b>JP</b>	1380	987.601	0.284	<b>JP</b>	1380	724.644	0.475
<b>TL</b>	1380	1380	0	<b>TL</b>	1380	719.134	0.479
<b>UAI</b>	1380	1380	0	<b>UAI</b>	1380	741.569	0.463
<b>WP</b>	1035	1035	0	<b>WP</b>	1035	635.091	0.386

In addition, the results of the moderation analysis show that the interaction term (WP × JE) has a statistically significant effect on job performance, with a path coefficient of  $-0.192$ , a t-value of  $5.315$ , and  $p < 0.001$ . This indicates that Work Passion significantly moderates the relationship between Job Engagement and Job Performance. The negative coefficient ( $-0.192$ ) suggests that as the level of work passion increases, the strength of the relationship between JE and JP tends to weaken.

This finding suggests that the moderating role of work passion may reflect the complex nature of passion in the workplace. According to the Dualistic Model of Passion, work passion can manifest in two forms: harmonious passion and obsessive passion [14]. While harmonious passion is generally associated with positive outcomes such as motivation and well-being, excessively strong passion may shift toward obsessive passion, which is characterized by internal pressure, difficulty disengaging from work, and an imbalance between work and personal life. In such situations, employees may already invest substantial cognitive and emotional energy in their work, so additional

increases in job engagement may not proportionally enhance performance outcomes. This result suggests that although job engagement generally enhances performance, higher levels of work passion may reduce the marginal impact of job engagement on job performance. This finding aligns with the Dualistic Model of Passion proposed by Vallerand et al. [14], which distinguishes between harmonious passion, linked to positive outcomes, and obsessive passion, which may lead to burnout, internal pressure, and reduced performance [14]. These findings are also consistent with Ho et al. [42] and Forest et al. [43], who emphasize that employees with harmonious passion, those who maintain balance between work and life, tend to achieve higher performance by fostering greater focus, creativity, and initiative.

## 5. Conclusion

The findings of this study confirm that the perceived usefulness of Artificial Intelligence (AI) is the strongest indirect predictor of job performance through the mediating role of job engagement. This highlights the importance of AI features, such as decision-making support, workload reduction, and personalized user experiences, as valuable organizational resources that foster positive employee attitudes. This result is consistent with Grassini [17], who emphasized that the perceived usefulness of AI is a core factor in shaping positive employee attitudes and increasing their intention to adopt technology in the workplace. Similarly, Cicero et al. [52] found that when employees clearly understand and appreciate the value of AI features, they are more likely to develop positive attitudes, resulting in higher levels of engagement with both their work and the organization, ultimately enhancing individual performance. Additionally, this study reveals that employees' acceptance of AI at work depends significantly on the level of comfort and perceived safety associated with its use. This aligns with findings by Schepman and Rodway [18], who noted that the degree of comfort in interacting with AI is a significant predictor of employees' positive attitudes and their willingness to adopt technology. However, the results also suggest that despite AI's evident potential to improve work efficiency and productivity, concerns remain about job displacement and loss of control over information. This supports the argument by Kostopoulos et al. [53], who emphasized that AI-based decision support systems must be designed with transparency in mind to foster employee trust and a sense of security when using these technologies.

Regarding the role of transformational leadership, the current study reinforces the findings of Handayani [30], which highlighted the positive relationship between transformational leadership and job engagement. Two key dimensions, Inspirational Motivation and Individualized Consideration, were found to significantly influence employee engagement. The results suggest that transformational leaders are capable of reducing work-related stress, providing psychological support, and enhancing job effectiveness. Furthermore, the study clearly establishes the mediating role of job engagement (JE) in the relationship between input factors (AI and transformational leadership) and job performance. Employee engagement serves as a mechanism that translates both organizational and personal resources into actual job performance. This finding is consistent with Corbeanu and Iliescu [54], who argued that job engagement is a critical driver of both individual and organizational performance. Finally, the study sheds light on the moderating role of work passion. The level of work passion can alter the strength and direction of the relationship between job engagement and job performance. In particular, harmonious passion emerges as a positive moderator, facilitating a healthy balance between job performance and personal life. This view aligns with Cabrita and Duarte [55], who emphasized that while work passion can amplify the positive relationship between engagement and performance, it must be effectively managed to avoid slipping into obsessive passion, which can lead to stress and reduced job effectiveness.

Overall, the findings underscore the importance of integrating Artificial Intelligence with effective leadership styles in modern organizations. At the same time, managers should implement appropriate policies and provide supportive tools that enhance employee engagement and improve performance in an increasingly digital and complex work environment.

## 6. Conclusion and Limitations

This study provides important insights into the roles of AI, usefulness of AI, and transformational leadership in enhancing employee job engagement, thereby improving job performance in a digitalized work environment. The findings confirm that employees' positive perceptions of AI, particularly its usefulness, and their favorable attitudes toward transformational leadership serve as key organizational resources that foster psychological engagement. These

factors help build sustainable commitment and performance. In addition, the study highlights the significant moderating role of work passion, which shapes how engagement translates into performance, underscoring the complexity of psychological dynamics in modern human resource management. Despite its contributions, this study has several limitations. First, the research focuses only on the banking sector within the specific cultural and organizational context of Vietnam. As a result, the findings may not be fully generalizable to other industries or countries with different institutional environments. Second, the study employed a convenience sampling technique due to time and resource constraints. Although this method facilitated efficient data collection, it may introduce sampling bias because participants were not selected randomly. Consequently, the sample may not fully represent the broader population of employees in the Vietnamese banking sector. Future research should consider using probability sampling techniques and expanding the research context to other industries and countries to enhance the robustness and generalizability of the proposed model.

## 7. Declarations

### 7.1. Author Contributions

Conceptualization: P.T.N., P.Q.T.N., and M.T.N.; Methodology: P.Q.T.N.; Software: P.T.N.; Validation: P.T.N., P.Q.T.N., and M.T.N.; Formal Analysis: P.T.N., P.Q.T.N., and M.T.N.; Investigation: P.T.N.; Resources: P.Q.T.N.; Data Curation: P.Q.T.N.; Writing Original Draft Preparation: P.T.N., P.Q.T.N., and M.T.N.; Writing Review and Editing: P.Q.T.N., P.T.N., and M.T.N.; Visualization: P.T.N.; All authors have read and agreed to the published version of the manuscript.

### 7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

### 7.4. Institutional Review Board Statement

Not applicable.

### 7.5. Informed Consent Statement

Not applicable.

### 7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

- [1] G. Vial, "Understanding digital transformation: a review and a research agenda," *J. Strateg. Inf. Syst.*, vol. 28, no. Jun., pp. 118–144, 2019, doi: 10.1016/j.jsis.2019.01.003.
- [2] A. Agrawal, J. Gans, and A. Goldfarb, "The economics of artificial intelligence: an agenda," *J. Econ. Artif. Intell.*, vol. 2019, no. Jan., pp. 1–20, 2019.
- [3] S. Faraj, S. Pachidi, and K. Sayegh, "Working and organizing in the age of the learning algorithm," *Inf. Organ.*, vol. 28, no. Mar., pp. 62–70, 2018, doi: 10.1016/j.infoandorg.2018.02.005.
- [4] K. C. Kellogg, M. A. Valentine, and A. Christin, "Algorithms at work: the new contested terrain of control," *Acad. Manag. Ann.*, vol. 14, no. Jan., pp. 366–410, 2020, doi: 10.5465/annals.2018.0174.
- [5] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, no. Sep., pp. 319–340, 1989, doi: 10.2307/249008.
- [6] N. Berente, B. Gu, J. Recker, and R. Santanam, "Managing artificial intelligence," *MIS Q.*, vol. 45, no. Sep., pp. 1–8, 2021, doi: 10.25300/MISQ/2021/16274.

- [7] E. Demerouti, A. B. Bakker, F. Nachreiner, and W. B. Schaufeli, "The job demands–resources model of burnout," *J. Appl. Psychol.*, vol. 86, no. Jun., pp. 499–512, 2001, doi: 10.1037/0021-9010.86.3.499.
- [8] A. B. Bakker and E. Demerouti, "The job demands–resources model: state of the art," *J. Manag. Psychol.*, vol. 22, no. Apr., pp. 309–328, 2007, doi: 10.1108/02683940710733115.
- [9] S. Subhadarshini, "Building leadership in the artificial intelligence era: an overview," *J. Basic Sci.*, vol. 24, no. May, pp. 22–31, 2024, doi: 10.37896/JBSV24.5/3091.
- [10] S. Chatterjee, R. Chaudhuri, D. Vrontis, and A. Thrassou, "Adoption of artificial intelligence-integrated CRM systems: the role of transformational leadership," *J. Bus. Res.*, vol. 154, no. Jan., pp. 1–12, 2023, doi: 10.1016/j.jbusres.2022.113317.
- [11] A. Kannan and V. S. Msila, "The effect of artificial intelligence on employee engagement: a systematic literature review," *J. Bus. Res.*, vol. 140, no. Jan., pp. 404–421, 2021, doi: 10.1016/j.jbusres.2021.11.002.
- [12] X. N. Nguyen and Q. H. Pham, "Artificial intelligence, employee creativity and engagement: evidence from financial services," *Front. Psychol.*, vol. 16, no. Jan., pp. 1–12, 2025, doi: 10.3389/fpsyg.2025.1521083.
- [13] L. N. Nguyen, T. T. Nguyen, and T. H. Tran, "Work stress, job performance, and work motivation among bank employees: an empirical investigation," *Int. J. Bus. Manag.*, vol. 14, no. Jun., pp. 45–57, 2019, doi: 10.5539/ijbm.v14n6p45.
- [14] R. J. Vallerand, "Les passions de l'âme: on obsessive and harmonious passion," *J. Pers. Soc. Psychol.*, vol. 85, no. Oct., pp. 756–767, 2003, doi: 10.1037/0022-3514.85.4.756.
- [15] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: four longitudinal field studies," *Manag. Sci.*, vol. 46, no. Feb., pp. 186–204, 2000, doi: 10.1287/mnsc.46.2.186.11926.
- [16] S. Grassini, "Development and validation of the AI attitude scale (AIAS 4): a brief measure of general attitude toward artificial intelligence," *Front. Psychol.*, vol. 14, no. Jan., pp. 1–12, 2023, doi: 10.3389/fpsyg.2023.1191628.
- [17] J. Meijerink, M. Boons, A. Keegan, and J. Marler, "Algorithmic human resource management: synthesizing developments and cross disciplinary insights on digital HRM," *Int. J. Hum. Resour. Manage.*, vol. 32, no. Jun., pp. 2545–2562, 2021, doi: 10.1080/09585192.2021.1925326.
- [18] A. Schepman and P. Rodway, "Initial validation of the general attitudes towards artificial intelligence scale," *Comput. Hum. Behav. Rep.*, vol. 1, no. Jan., pp. 1–12, 2020, doi: 10.1016/j.chbr.2020.100014.
- [19] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: toward a unified view," *MIS Q.*, vol. 27, no. Sep., pp. 425–478, 2003, doi: 10.2307/30036540.
- [20] R. Pillai and B. Sivathanu, "Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations," *Benchmarking Int. J.*, vol. 27, no. Sep., pp. 2599–2629, 2020, doi: 10.1108/BIJ-04-2020-0186.
- [21] W. B. Schaufeli, M. Salanova, V. González-Romá, and A. B. Bakker, "The measurement of engagement and burnout: a two sample confirmatory factor analytic approach," *J. Happiness Stud.*, vol. 3, no. Mar., pp. 71–92, 2002, doi: 10.1023/A:1015630930326.
- [22] B. M. Bass and R. Bass, "The Bass handbook of leadership: theory, research, and managerial applications," *J. Leadersh. Stud.*, vol. 2008, no. Jan., pp. 1–20, 2008.
- [23] G. K. Iangat, T. K. Linge, and D. Sikalich, "Influence of inspirational motivation of employee job performance in the insurance industry in Kenya," *Int. J. Res. Bus. Soc. Sci.*, vol. 8, no. Nov., pp. 1–7, 2019, doi: 10.20525/ijrbs.v8i6.488.
- [24] B. M. Bass and B. J. Avolio, "Multifactor leadership questionnaire: manual and sampler set," *J. Leadersh. Assess.*, vol. 2004, no. Jan., pp. 1–15, 2004.
- [25] Syaifuddin, "The influence of work stress and transformational leadership on work motivation and implication of employee's performance (case study)," *Acad. Strateg. Manag. J.*, vol. 15, no. Jan., pp. 42–48, 2016.
- [26] P. G. Northouse, "Leadership: theory and practice," *J. Leadersh. Stud.*, vol. 2019, no. Jan., pp. 1–20, 2019.
- [27] B. Afsar, Y. F. Badir, B. B. Saeed, and S. Hafeez, "Transformational and transactional leadership and employee's entrepreneurial behavior in knowledge-intensive industries," *Int. J. Hum. Resour. Manage.*, vol. 28, no. Jan., pp. 307–332, 2017, doi: 10.1080/09585192.2016.1244893.
- [28] A. L. Holten and S. O. Brenner, "Leadership style and the process of organizational change," *Leadersh. Organ. Dev. J.*, vol. 36, no. Jan., pp. 2–16, 2015, doi: 10.1108/LODJ-11-2012-0155.

- [29] H. Hetland, J. Hetland, C. S. Andreassen, S. Pallesen, and G. Notelaers, "Leadership and fulfillment of the three basic psychological needs at work," *Career Dev. Int.*, vol. 16, no. Aug., pp. 507–523, 2011, doi: 10.1108/13620431111168903.
- [30] N. P. Handayani, "Transformational leadership and employee engagement as a determinant of organizational citizenship behavior: case study on youth non-profit organization," *Int. J. Soc. Sci. Humanit.*, vol. 8, no. Feb., pp. 59–64, 2018, doi: 10.18178/ijssh.2018.8.2.934.
- [31] D. W. Ariani, "The relationship between employee engagement, organizational citizenship behavior, and counterproductive work behavior," *Int. J. Bus. Admin.*, vol. 4, no. Apr., pp. 46–56, 2013, doi: 10.5430/ijba.v4n2p46.
- [32] D. Chen, J. P. Esperança, and S. Wang, "The impact of artificial intelligence on firm performance: an application of the resource-based view to e-commerce firms," *Front. Psychol.*, vol. 13, no. Jan., pp. 1–12, 2022, doi: 10.3389/fpsyg.2022.884830.
- [33] R. Chaudhuri, S. Chatterjee, D. Vrontis, and A. Thrassou, "Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture," *Ann. Oper. Res.*, vol. 2021, no. Jan., pp. 1–35, 2021, doi: 10.1007/s10479-021-04407-3.
- [34] P. Kaur, K. Malhotra, and S. K. Sharma, "Moderation–mediation framework connecting internal branding, affective commitment, employee engagement and job satisfaction: an empirical study of BPO employees in Indian context," *Asia Pac. J. Bus. Admin.*, vol. 12, no. Jul., pp. 327–348, 2020, doi: 10.1108/APJBA-10-2019-0217.
- [35] M. H. Huang and R. T. Rust, "Artificial intelligence in service," *J. Serv. Res.*, vol. 22, no. May, pp. 155–172, 2019, doi: 10.1177/1094670519825928.
- [36] Z. Soltani, B. Zareie, L. Rajabiun, and A. A. M. Fashami, "The effect of knowledge management, e-learning systems and organizational learning on organizational intelligence," *Kybernetes*, vol. 49, no. Oct., pp. 2455–2474, 2020, doi: 10.1108/K-12-2018-0672.
- [37] K. Szczepańska-Woszczyzna and J. Kurowska-Pysz, "Sustainable business development through leadership in SMEs," *Ekon. Zarzadzanie*, vol. 8, no. Sep., pp. 57–69, 2016, doi: 10.1515/emj-2016-0024.
- [38] S. J. Motowidlo, W. C. Borman, and M. J. Schmit, "A theory of individual differences in task and contextual performance," *Hum. Perform.*, vol. 10, no. Jun., pp. 71–83, 1997, doi: 10.1207/s15327043hup1002\_1.
- [39] B. L. Rich, J. A. Lepine, and E. R. Crawford, "Job engagement: antecedents and effects on job performance," *Acad. Manag. J.*, vol. 53, no. Jun., pp. 617–635, 2010, doi: 10.5465/amj.2010.51468988.
- [40] B. E. Ashforth and R. H. Humphrey, "Emotion in the workplace: a reappraisal," *Hum. Relat.*, vol. 48, no. Jan., pp. 97–125, 1995, doi: 10.1177/001872679504800104.
- [41] W. A. Kahn, "Psychological conditions of personal engagement and disengagement at work," *Acad. Manag. J.*, vol. 33, no. Dec., pp. 692–724, 1990, doi: 10.5465/256287.
- [42] J. Forest, G. A. Mageau, C. Sarrazin, and E. M. Morin, "Work is my passion: the different affective, behavioural, and cognitive consequences of harmonious and obsessive passion toward work," *Can. J. Adm. Sci.*, vol. 28, no. Mar., pp. 27–40, 2011, doi: 10.1002/cjas.170.
- [43] V. T. Ho, S.-S. Wong, and C. H. Lee, "A tale of passion: linking job passion and cognitive engagement to employee work performance," *J. Manag. Stud.*, vol. 48, no. Jan., pp. 26–47, 2011, doi: 10.1111/j.1467-6486.2009.00878.x.
- [44] N. Carbonneau, R. J. Vallerand, C. Fernet, and F. Guay, "The role of passion for teaching in intrapersonal and interpersonal outcomes," *J. Educ. Psychol.*, vol. 100, no. Nov., pp. 977–987, 2008, doi: 10.1037/a0012545.
- [45] X. P. Chen, X. Yao, and S. Kotha, "Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions," *Acad. Manag. J.*, vol. 52, no. Feb., pp. 199–214, 2009, doi: 10.5465/amj.2009.36462018.
- [46] A. B. Bakker, E. Demerouti, and A. I. Sanz-Vergel, "Burnout and work engagement: the JD–R approach," *Annu. Rev. Organ. Psychol. Organ. Behav.*, vol. 1, no. Jan., pp. 389–411, 2014, doi: 10.1146/annurev-orgpsych-031413-091235.
- [47] M. S. Christian, A. S. Garza, and J. E. Slaughter, "Work engagement: a quantitative review and test of its relations with task and contextual performance," *Pers. Psychol.*, vol. 64, no. Mar., pp. 89–136, 2011, doi: 10.1111/j.1744-6570.2010.01203.x.

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- [48] K. Breevaart, "Daily transactional and transformational leadership and daily employee engagement," *J. Occup. Organ. Psychol.*, vol. 87, no. Mar., pp. 138–157, 2014, doi: 10.1111/joop.12041.
- [49] M. Abbasi, M. R. Monazzam, M. Karanika-Murray, M. Shamsipour, and H. Arabalibeik, "Development and validation of an individual job performance questionnaire (IJPQ)," *Work*, vol. 73, no. Jan., pp. 309–320, 2022, doi: 10.3233/WOR-211004.
- [50] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, "A primer on partial least squares structural equation modeling (PLS-SEM)," *J. Multivar. Anal.*, vol. 2017, no. Jan., pp. 1–20, 2017.
- [51] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. Acad. Mark. Sci.*, vol. 43, no. Jan., pp. 115–135, 2015, doi: 10.1007/s11747-014-0403-8.
- [52] L. Cicero, A. Russo, G. Di Stefano, and A. Zammitti, "The general attitudes towards artificial intelligence scale (GAAIS): validation and psychometric properties analysis in the Italian context," *BMC Psychol.*, vol. 13, no. Jan., pp. 1–12, 2025, doi: 10.1186/s40359-025-02935-2.
- [53] G. Kostopoulos, G. Davrazos, and S. Kotsiantis, "Explainable artificial intelligence based decision support systems: a recent review," *Electronics*, vol. 13, no. Jan., pp. 1–12, 2024, doi: 10.3390/electronics13142842.
- [54] A. Corbeanu and D. Iliescu, "The link between work engagement and job performance: a meta-analysis," *J. Pers. Psychol.*, vol. 22, no. Jul., pp. 111–122, 2023, doi: 10.1027/1866-5888/a000316.
- [55] C. Cabrita and A. P. Duarte, "Passionately demanding: work passion's role in the relationship between work demands and affective well-being at work," *Front. Psychol.*, vol. 14, no. Jan., pp. 1–12, 2023, doi: 10.3389/fpsyg.2023.1053455.