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The Impact of Performance Expectations and Perceived Behavioral Control on Employees' AI Adoption

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Abstract

As AI technologies rapidly permeate industries, the key challenge for enterprises is no longer whether to adopt AI, but how to ensure employees can strategically and efficiently leverage AI tools to improve work performance meaningfully. This issue spans multiple dimensions, from employees' performance expectancy regarding AI's tangible value to their mastery of operations and application contexts, and their perceived behavioral control. It also involves whether organizations provide sufficient resources, training, and institutional support, and whether team culture and social influence foster learning and knowledge sharing. This study integrates Social Cognitive Theory and Expectation-Confirmation Theory to elucidate the critical roles of performance expectancy and perceived behavioral control in the AI adoption process and to examine how organizational support and social influence affect AI usage performance through these psychological mechanisms. In addition, we assess the moderating effect of creative self-efficacy on AI adoption. Using survey data from 392 technology-sector employees, we conduct an empirical analysis using structural equation modeling. The results indicate that social influence has a greater impact than organizational support. Performance expectancy is the key mediating variable through which AI use enhances work performance. Moreover, creative self-efficacy amplifies the positive effects of managerial support and social influence on performance expectancy and perceived behavioral control. These findings deepen the theoretical foundation of AI adoption and provide practical guidance for enterprises seeking to improve organizational performance and employee productivity through AI technology.

Keywords: Artificial Intelligence; Performance Expectation; Self-Efficacy; Creativity; Structural Equation Modeling.

1. Introduction

With accelerating digitalization, artificial intelligence (AI) has become a critical driver of competitive advantage for firms [1]. Given AI's substantial potential, adoption is no longer discretionary but a top strategic priority for sustaining competitiveness. A growing body of research shows that AI can enhance employee efficiency and performance [2], thereby supporting organizational sustainability [3]. These developments underscore the importance of AI usage as a core research topic in sustainable business operations. As AI technologies permeate diverse industries, the focal challenge for enterprises has shifted from deciding to adopt AI to enabling employees to deploy AI strategically and efficiently for measurable performance gains. This challenge is multidimensional, encompassing employees' performance expectancy regarding AI's tangible value, their operational fluency and context-specific application capabilities, and their perceived behavioral control. It also depends on whether organizations provide adequate resources, training, and institutional support, and whether team culture and social influence cultivate continuous learning and knowledge sharing.

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This highlights the importance of AI technology usage as a research topic in sustainable business operations. Social Cognitive Theory (SCT) emphasizes the reciprocal influence between individuals, environments, and behaviors [4]. Within SCT, perceived behavioral control reflects an individual's evaluation of their capability and the availability of resources to use technology [5]. It impacts IT adoption behavior more than self-efficacy [6]. Beyond SCT, Expectation-Confirmation Theory (ECT) also emphasizes the importance of performance expectations, noting that when the experience of technology meets or exceeds expectations, satisfaction and performance increase [7-8].

As AI technologies are products of recent technological advances, employees' creative self-efficacy affects their motivation and behavior toward AI applications, further driving innovative use [9-10]. This enables employees to explore AI technologies and actively enhance work efficiency [11]. Previous research on information technology has mainly focused on frameworks such as TAM and UTAUT, emphasizing users' intentions to adopt [12], but has overlooked changes in job performance following AI adoption. This study combines SCT and ECT to examine the mediating roles of performance expectation and perceived behavioral control in the relationship between organizational support, social influence, and employees' AI technology use performance in the technology industry, and to explore the moderating effect of creative self-efficacy. This fills a research gap by linking AI technology adoption to actual performance outcomes. Beyond advancing research from technology acceptance to usage outcomes, this integration of SCT and ECT offers a more theoretical understanding of how AI technology usage translates into improved performance. This research provides practical guidance for companies seeking to enhance employee performance and achieve sustainable development through AI technologies.

This study integrates Social Cognitive Theory and Expectation-Confirmation Theory to conduct a questionnaire survey of 392 technology industry employees. It employs structural equation modeling to examine the critical roles of performance expectations and perceived behavioral control in AI technology adoption. The study examines how organizational support and social influence impact AI usage performance through psychological mechanisms and investigates the moderating effect of creative self-efficacy. The research findings reveal that social influence is more important than organizational support; performance expectation serves as a key mediating factor in the impact of AI technology use on performance; and creative self-efficacy can enhance the effects of managerial support and social influence on performance expectation and perceived behavioral control. These research results deepen the theoretical foundation for AI technology adoption and provide practical recommendations for enterprises to promote AI application adoption among employees.

This study consists of five parts. Section 2 presents a literature review exploring the critical drivers of AI usage performance, grounded in the theoretical foundations of performance expectations and perceived behavioral control. Section 3 constructs an evaluation framework for AI usage performance in the technology industry. Section 4 employs Structural Equation Modeling (SEM) to validate the effectiveness of the AI usage performance evaluation framework developed in this study in the technology industry. Finally, Section 5 provides relevant recommendations and practical application strategies based on the research findings.

2. Literature Reviews

2.1. Performance Expectation

Expectation-Confirmation Theory (ECT) posits that individuals compare their initial expectations of a technology's outcomes with their experience; when the experience meets or exceeds expectations, positive confirmation occurs, increasing satisfaction and the intention to continue using the technology [13]. These expectations thus serve as a crucial baseline for the subsequent confirmation process [14], guiding employees in assessing the effectiveness of AI. If AI technology performs as expected or better, satisfaction, continued use, and performance are enhanced; conversely, negative confirmation lowers the intention to continue if benefits fall short. Therefore, performance expectations bridge the "expectation" and "confirmation" stages in ECT, reinforcing its theoretical value for technology adoption and performance improvement [15].

2.1.1. The Impact of Organizational Support on Performance Expectation

Organizational support refers to the resources and assistance management provides to help employees achieve their work goals [16]. It includes technical support (such as training, expert guidance, and problem-solving mechanisms) and infrastructure support (including IT equipment, network systems, and technical resources), which ensures the smooth implementation of technologies [17]. Some studies indicate that when employees perceive organizational support, they form positive performance expectations and show higher engagement [18]. According to ECT, organizational support enhances expectations for AI applications, further promoting technology adoption [15]. This study, therefore, proposes the following hypothesis:

H1: Organizational support has a positive impact on performance expectations.

2.1.2. The Impact of Social Influence on Performance Expectation

Social influence refers to the perceived expectations of significant others regarding the use of technology [19]. It is similar to the subjective norm in the Theory of Planned Behavior (TPB) and reflects pressure from supervisors, peers, or the organization [20]. According to ECT, social influence shapes individuals' performance expectations regarding technology use, thereby affecting their satisfaction and intention to continue using it [21]. Through mechanisms such as observational learning and social comparison, positive evaluations and successful experiences of significant others—such as managers and peers—can enhance employees' positive performance expectations regarding AI applications [22-23]. Therefore, social influence strengthens performance expectations, and this study proposes the following hypothesis:

H2: Social influence has a positive impact on performance expectations.

2.2. Perceived Behavioral Control

Social Cognitive Theory (SCT), proposed by Bandura [4], asserts that an individual's behavior is influenced not only by personal cognition but also by environmental factors (such as organizational expectations and social influence), which together determine behavioral outcomes. Perceived behavioral control represents an individual's assessment of the ease or difficulty of performing a behavior, shaped by both internal factors (such as knowledge and skills) and external factors (like resources and opportunities), ultimately influencing behavioral intentions and actual performance [5]. The researchers also found that when people feel they possess sufficient capability and resources, they are more likely to adopt new technologies proactively [24]. By investigating how perceived behavioral control influences technology use, this study examines its mediating role in the relationships among organizational support, social influence, and AI adoption behavior. It provides theoretical and practical insights for businesses aiming to implement AI technology.

2.2.1. The Impact of Organizational Support on Perceived Behavioral Control

Some study notes that perceived behavioral control derives from the availability of technical equipment, human resources, and organizational conditions [5]. When em-ployees believe their organization provides sufficient resources and technical support, their sense of control over technology increases; conversely, resource scarcity reduces their willingness to adopt technology [25]. Well-developed AI infrastructure can reduce resistance, increase familiarity and operational skills, and optimize job performance [26]. Furthermore, ongoing training and educational programs help employees overcome learning barriers, strengthening their understanding and ability to apply technology [27]. Employees facing new technologies gain greater confidence and resources through these organizational support initiatives, further enhancing their perceived behavioral control. This leads to the following hypothesis:

H3: Organizational support has a positive impact on perceived behavioral control.

2.2.2. The Impact of Social Influence on Perceived Behavioral Control

Drawing on Social Cognitive Theory (SCT), this study highlights the vital role that peer support and collaboration play in shaping employees' adoption of AI systems. When colleagues share technical expertise and provide assistance, employees' sense of competence with AI is enhanced. This supportive atmosphere helps increase employees' confidence in working with AI and strengthens their belief in their ability to complete job tasks using this technology [25]. In essence, when coworkers are willing to offer technical help, employees become more confident in their ability to use AI tools effectively to meet work goals, thereby improving their perceived behavioral control. Accordingly, this study puts forward the following hypothesis:

H4: Social influence has a positive impact on perceived behavioral control.

2.3. AI Usage Performances

AI usage performance refers to the impact of AI technologies on employees' job performance after their introduction and application [28]. This includes fulfilling job responsibilities, complying with organizational standards, and enhancing organizational value [29]. Furthermore, performance expectation and perceived behavioral control are also critical influencing factors. Performance expectation refers to employees' anticipation that AI will enhance their performance [30], which influences their willingness and engagement in using AI [14].

2.3.1. The Impact of Performance Expectations on AI Usage Performance

Some studies suggest that individuals' performance with technological tools is primarily influenced by their expectations [31]. Compared with external feedback (such as social recognition or material rewards), employees' self-assessed performance expectations may significantly impact their behavior [32]. When employees believe that using AI will lead to personal growth and satisfaction, their motivation to learn and engage increases, thereby promoting the effective implementation of AI. Additionally, some studies suggest that performance expectations reflect beliefs about the connection between actions and outcomes [33]. Employees must believe their actions will result in positive outcomes before committing themselves [34]. When employees expect AI to directly enhance work efficiency and results, their motivation and behavior in using AI are further strengthened [35]. This study proposes the following hypothesis based on the previous current studies:

H5: Performance expectation has a positive impact on AI usage performance.

2.3.2. The Impact of Perceived Behavioral Control on AI Usage Performance

Some studies identify that when individuals perceive the availability of resources and abilities, their behavioral intentions are significantly strengthened [6]. The researchers propose that perceived behavioral control can effectively enhance employees' self-efficacy, so when employees believe they possess sufficient skills and resources to operate AI technologies, they are more likely to proactively explore and learn the functions of AI tools, leading to more effective application of AI to solve complex work problems [36]. Furthermore, research by [37] has confirmed that increasing perceived behavioral control can effectively reduce employees' anxiety and resistance to new technologies. When employees feel a strong sense of power, they focus on the practical use of AI technology rather than worrying about potential failures, which further promotes improvements in work efficiency and performance. Therefore, this study hypothesizes:

H6: Perceived behavioral control has a positive impact on AI usage performance.

2.3.3. The Impact of Organizational Support on AI Usage Performance

Suppose an organization applies principles of social cognitive theory (SCT) to create a supportive culture and a psychologically safe environment. In that case, it can help reduce employees' resistance to new technologies while increasing their acceptance and willingness to use artificial intelligence tools. In this context, employees are motivated to engage in technological innovation and its application [38]. When the organizational environment encourages experimentation and supports innovation, employees become more active in learning and testing AI technologies, which in turn can enhance their work performance. In addition, leaders who serve as role models and actively promote the benefits of new technologies provide employees with clear examples of behavior, thereby increasing confidence and motivation [39]. This type of leadership helps reduce employees' uncertainty about technology and encourages them to participate in learning and applying AI, thereby improving the effectiveness of their use. Based on these perspectives, the following hypothesis is proposed.

H7: Organizational support positively impacts AI usage performance.

2.3.4. The Impact of Social Influence on AI Usage Performance

In the workplace, when employees observe colleagues actively using AI technologies to improve efficiency and reduce errors, these observations, from an SCT perspective, not only provide behavioral references but also stimulate the willingness to learn and apply such technologies [31]. Peer interaction and technology-enabled experience sharing further strengthen the learning process and improve AI performance. Additionally, when employees witness others achieving positive outcomes and organizational recognition through AI applications, it enhances their performance expectations and motivation to learn [40]. Through a positive cycle of social influence, employees become more proactive in applying AI technology, leading to improved job performance and efficiency. Therefore, this study proposes the following hypothesis:

H8: Social influence has a positive impact on AI usage performance.

2.4. AI Usage Performances-Performance Expectation as a Mediating Role

Organizational support can strengthen employees' perceived positive relationship between effort and outcomes, increasing their engagement [41]. Moreover, an innovation-friendly organizational climate enhances performance expectations and provides necessary resources, making employees more willing to participate in innovative activities [18]. Within the Expectation-Confirmation Theory (ECT), the use of technological tools (such as AI) depends on employees' performance expectations [14]. Performance expectations reflect employees' beliefs about the outcomes of their actions, influencing work behavior and innovation performance [42]. The researchers noted that employees must believe their actions are related to actual outcomes to invest proactively in innovation and, through performance expectation, promote the adoption of technology and improvement in performance [31]. Combining the perspectives of SCT and ECT, this study argues that performance expectation is the key mechanism through which organizational support influences AI usage performance, and thus proposes the following hypothesis:

H9: Organizational support enhances employees' AI usage performance by mediating performance expectations.

From the perspective of performance expectation, employees reinforce their beliefs in AI's ability to improve job performance through observational learning [43]. When organizations widely adopt AI and achieve positive results, employees deepen their expectations for AI's performance through imitation learning. In addition, AI symbolizes modernization and innovation; the successful use of AI can enhance an employee's image and standing within the organization and reduce anxiety about its usage [23]. According to ECT, the usage performance of technological tools is highly influenced by performance expectations [31]. If employees believe that AI can promote personal growth and satisfaction, they will be more motivated to apply it, thereby improving their job performance. Therefore, this study proposes the following hypothesis:

H10: Social influence enhances employees' AI usage performance by mediating performance expectations.

2.5. Perceived Behavioral Control as a Mediating Role

The strength of organizational resources and support directly impacts employees' perceived behavioral control. Santoso (2021) notes that this perception originates from beliefs about the availability of resources and opportunities [5]. If employees believe their organization provides sufficient resources and technical support, their sense of control over their actions will increase, strengthening their intention to adopt new technologies [25]. This study posits that well-developed technical equipment and training mechanisms can improve employees' acceptance and application of AI, reduce resistance, and enhance operational skills, ultimately optimizing work performance [44]. Continuous education and training help employees overcome learning challenges, increasing their understanding and application of AI technology [27]. Therefore, when employees believe they possess sufficient skills and resources to operate AI technology, they will learn and apply it more actively, reducing anxiety and resistance [45] and improving work efficiency and performance. Based on this, the study suggests that perceived behavioral control positively affects AI usage performance. In summary, organizational support strengthens employees' perceived behavioral control, thereby improving AI usage performance. The following hypothesis is proposed:

H11: Organizational support enhances employees' AI usage performance by mediating perceived behavioral control.

Social Cognitive Theory (SCT) emphasizes the interaction between the environment and individual behavior. Especially in the adoption of technology, peer support and collaboration can significantly influence employees' behavioral intentions and actual behaviors [46]. The sharing of technical knowledge and operational experience among colleagues not only improves employees' familiarity with AI tools but also boosts their confidence in applying AI to work tasks [47], thereby creating a supportive environment in which resources are accessible and perceived behavioral control is enhanced. According to ECT, employees will increase their willingness and performance to use AI when they believe they have sufficient skills and resources. Perceived behavioral control can reduce anxiety and resistance to new technologies [45], promote focus and application, and improve job performance. Therefore, social influence directly enhances AI adoption and promotes AI usage performance by strengthening perceived behavioral control. On this basis, the study proposes the following hypothesis:

H12: Social influence enhances employees' AI usage performance by mediating perceived behavioral control.

2.6. Creative Self-Efficacy as a Moderating Role

Creative self-efficacy (CSE) is an extension of Self-Efficacy Theory, referring to an individual's belief in their innovative abilities [9]. Organizational support can help employees adapt to new technologies and raise performance expectations; however, its effectiveness depends partly on CSE [10]. Employees with higher CSE are better able to transform organizational resources into innovative outcomes, thereby strengthening performance expectations [39]. Therefore, CSE is expected to enhance the positive effect of organizational support on performance expectations. Based on SET, this study proposes the following hypothesis:

H13: Creative self-efficacy strengthens the positive effect of organizational support on performance expectations.

Employees with high CSE are more effective at transforming social influence into personal innovation motivation, whereas those with low CSE may rely more heavily on external opinions [48]. Social influence also affects employees' performance expectations regarding new technologies [49]. When colleagues and supervisors advocate AI technology, employees are more likely to believe AI can improve work performance. Therefore, CSE is expected to enhance the positive relationship between social influence and performance expectations.

H14: Creative self-efficacy strengthens the positive effect of social influence on performance expectation.

Perceived behavioral control refers to an individual's perception of their ability to perform a specific behavior, affecting their behavioral intention and actual behavior [5]. When organizations provide sufficient resources and training, employees can better master AI technologies [50]. However, the enhancement of perceived control is also in-fluenced by creative self-efficacy [25]. Employees with high CSE can transform organizational support into improved capabilities, enhancing perceived behavioral control. Therefore, CSE is expected to strengthen the positive effect of organizational support on perceived behavioral control.

H15: Creative self-efficacy strengthens the positive effect of organizational support on perceived behavioral control.

Social influence affects employees' performance expectations for AI technology, as well as their confidence and sense of control [49]. When employees observe the successful application of AI technology and receive positive support from peers and leaders, their sense of mastery over AI increases. However, employees with high CSE are more able to internalize social influence, thereby enhancing their perceived behavioral control. Therefore, CSE is expected to strengthen the positive effect of social influence on perceived behavioral contro,l as shown in Figure 1.

H16: Creative self-efficacy strengthens the positive effect of social influence on perceived behavioral control.

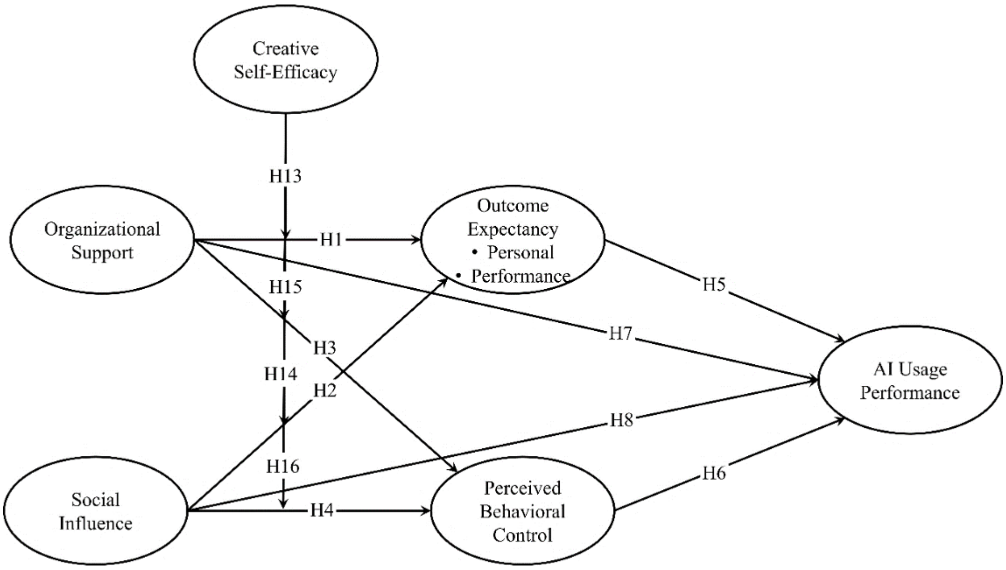

Figure 1. Research framework

3. Research Design and Methodology

3.1. Research Subjects

This study focused on software engineers, as AI has increasingly assisted them in debugging and programming, significantly impacting their work. Data were collected via an online questionnaire distributed through the HR departments of relevant companies. A total of 420 questionnaires were returned. After excluding 28 invalid responses due to high answer consistency or excessively short completion times, 392 valid responses remained. Among the respondents, females comprised the most significant proportion, with 206 individuals (52.6%). The largest age group was 30-39, accounting for 166 people (42.3%). For educational background, most had a university or college degree, totaling 298 people (76.0%). As for marital status, the number of unmarried and married respondents was equal, each at 196 (50.0%). Regarding years of experience, the largest group was those with over 10 years, comprising 166 people (42.3%). Most held general staff positions, totaling 275 people (70.2%). In terms of company size, the most significant number of people worked at companies with fewer than 50 employees, totaling 157 individuals (40.1%).

3.2. Variables and Measurement

This study examined the effects of organizational support and social influence on employees' performance in using AI. The questionnaire consisted of seven sections: the first collected demographic information, while sections two to seven used a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). The scales were adapted from existing literature, initially in English, and translated using the back-translation method to ensure semantic equivalence [51]. Step 1 covered demographics, including gender, age, and education. Step 2 measured organizational support using the scale [52]. Step 3 measured social influence using the [53] scale. Step 4 measured performance expectations; using the scale from [54], Step 5 measured perceived behavioral control, using the scale from [6]. Step 6 measured AI usage performance using the scale [55]. Step 7 measured creative self-efficacy using the scale [56].

3.3. Research Methodology

The collected respondent data were analyzed using structural equation modeling (SEM), with AMOS used to verify the relationships among the research variables. The data processing first conducted confirmatory factor analysis (CFA) to examine the reliability and validity of each construct's scales. Subsequently, path analysis based on SEM was performed to evaluate the direct effects of the research hypotheses. For the mediation analysis, the bootstrap method recommended by Hayes [57] was adopted, with 5,000 re-samples to estimate the indirect effects of the mediating relationships among the structural paths. In addition, for the moderation analysis, beyond applying the approach suggested by Ping [58] to assess the moderating role of innovation self-efficacy, the model also incorporated corresponding interaction terms and significance tests to ensure the statistical interpretability of the moderating effects and the robustness of the study's conclusions.

4. Results

4.1. Convergent Validity

Confirmatory factor analysis (CFA) was conducted to evaluate the structural reliability and validity of the measurement model, followed by an analysis of the structural model's path effects [59]. As shown in Table 1, the standardized factor loadings for all items ranged from 0.663 to 0.935, exceeding the recommended threshold of 0.6 [60]. The composite reliability values ranged from 0.819 to 0.905, all exceeding the 0.7 benchmark, confirming an acceptable level of internal consistency [61]. In addition, Cronbach's α values ranged from 0.873 to 0.908, exceeding the 0.7 criterion and indicating strong reliability of the questionnaire [62]. The average variance extracted (AVE) for each variable ranged from 0.576 to 0.697, all above the minimum requirement of 0.5, providing evidence of satisfactory convergent validity for all variables [60, 63] as shown in Table 1.

Table 1. The Convergent validity of proposed model

Variables	Indicators	Mean	Standard deviation	Standardized factor loading	Component reliability (CR)	Average variance extracted (AVE)
OSUP	OSUP01	4.946	1.311	0.820	0.887	0.664
OSUP	OSUP02	5.082	1.355	0.867		
OSUP	OSUP03	5.033	1.395	0.843		
OSUP	OSUP04	4.793	1.497	0.722		
SOIN	SOIN01	4.906	1.355	0.680	0.877	0.588
SOIN	SOIN02	4.832	1.380	0.715		
SOIN	SOIN03	4.931	1.351	0.798		
SOIN	SOIN04	5.005	1.340	0.806		
SOIN	SOIN05	5.038	1.307	0.825		
PEXP	PEXP01	5.288	1.178	0.700	0.873	0.579
PEXP	PEXP02	5.446	1.170	0.800		
PEXP	PEXP03	5.411	1.204	0.745		
PEXP	PEXP04	5.362	1.125	0.819		
PEXP	PEXP05	5.378	1.160	0.734		
IPEX	IPEX01	5.043	1.191	0.752	0.871	0.576
IPEX	IPEX02	5.156	1.269	0.698		
IPEX	IPEX03	4.890	1.305	0.786		
IPEX	IPEX04	4.663	1.394	0.776		
IPEX	IPEX05	4.668	1.290	0.779		
PCBC	PCBC01	5.138	1.216	0.663	0.876	0.587
PCBC	PCBC02	5.064	1.224	0.746		
PCBC	PCBC03	5.138	1.189	0.818		
PCBC	PCBC04	5.151	1.235	0.804		
PCBC	PCBC05	5.224	1.216	0.790		
AIEP	AIEP01	5.224	1.178	0.765	0.905	0.655
AIEP	AIEP02	5.194	1.308	0.806		
AIEP	AIEP03	5.204	1.230	0.841		
AIEP	AIEP04	5.168	1.306	0.823		
AIEP	AIEP05	5.194	1.271	0.811		
REXP	PEXP	5.377	0.948	0.935	0.819	0.697
REXP	IPEX	4.884	1.047	0.721		

Note: Organizational support (OSUP), Social influence (SOIN), Performance expectation (REXP), Perceived behavioral control (PCBC), and AI usage performance (AIEP).

4.2. Discriminant Validity

This study examined discriminant validity using the AVE method. According to Fornell & Larcker [60], the square root of the AVE for each construct should be greater than the correlation coefficients between the construct and any other construct, which indicates that the constructs have adequate discriminant validity. In this study, the square roots of the AVE for each variable (shown in bold) ranged from 0.767 to 0.835. As shown in Table 2, the bold numbers along the diagonal are all greater than the corresponding off-diagonal values, indicating that all variables exhibit good discriminant validity [60].

Table 2. AVE & discriminant validity analysis

	AVE	OSUP	SOIN	REXP	PCBC	AIEP
OSUP	0.664	0.815				
SOIN	0.588	0.436	0.767			
REXP	0.697	0.559	0.532	0.835		
PCBC	0.587	0.461	0.472	0.724	0.766	
AIEP	0.655	0.615	0.551	0.750	0.694	0.809

Note: Organizational support (OSUP), Social influence (SOIN), Performance expectation (REXP), Perceived behavioral control (PCBC), and AI usage performance (AIEP)

4.3. Model Fit

This study used the Bollen-Stine p correction to assess and adjust model fit. All fit indices met the recommended standards for SEM analysis: the normed chi-square ($\chi 2/df$) was 1.543; GFI, AGFI, TLI, and CFI ranged from 0.917 to 0.972; RMSEA and SRMR were 0.037 and 0.078, respectively. These results indicate a good model fit, as shown in Table 3.

Table 3. Goodness of fit measurement of the proposed model

Model fit	Criteria	Model fit of research model	Bollen-Stine Model fit
MLχ^2	The small the better	968.253	564.658
df	The large the better	366	366
Normed Chi-sqr ($\chi 2/df$)	$1<\chi^2/df<3$	2.645	1.543
GFI	>=0.9	0.852	0.925
AGFI	>=0.9	0.824	0.917
RMSEA	<=0.08	0.065	0.037
SRMR	<=0.08	0.078	0.078
TLI (NNFI)	>=0.9	0.906	0.969
CFI	>=0.9	0.915	0.972

4.4. Path Analysis

Organizational support (OSUP) ($b=0.297$, $p<0.001$) and social influence (SOIN) ($b=0.312$, $p<0.001$) both have significant effects on performance expectation (REXP), jointly explaining 44.5% of the variance in performance expectation, thus supporting Hypotheses 1 and 2, as shown in Table 4. At the same time, organizational support (OSUP) ($b = 0.247$, $p < 0.001$) and social influence (SOIN) ($b = 0.307$, $p < 0.001$) both significantly affect perceived behavioral control (PCBC), accounting for 33.2% of its variance, thereby supporting Hypotheses 3 and 4. Organizational support (OSUP) ($b=0.188$, $p<0.001$), performance expectation (REXP) ($b=0.411$, $p<0.001$), perceived behavioral control (PCBC) ($b=0.351$, $p<0.001$). Social influence (SOIN) ($b=0.117$, $p<0.05$) significantly influences AI usage performance (AIEP), with these four variables together explaining 65.5% of the variance in AI usage performance, thus supporting Hypotheses 5 through 8 as shown in Figure 2. The path analysis shows that both organizational support and social influence have significant effects on performance expectancy and perceived behavioral control, consistent with SCT and ECT. When employees receive sufficient organizational resources and managerial encouragement, their confidence in and positive expectations toward AI technologies increase, thereby promoting proactive technology adoption. Meanwhile, the effect of social influence is slightly more substantial than that of organizational support, suggesting that peers' and supervisors' attitudes play a more critical role in shaping employees' attitudes toward AI. This aligns with the theoretical foundation of SCT's observational learning.

Table 4. The result of path analysis

Dependent Variable	Independent Variable	Unstandardized regression coefficient (B)	p-value	Standardized Regression Coefficient (β)	Explained Variance
REXP	OSUP	0.297	p＜0.001	0.414	0.445
	SOIN	0.312	p＜0.001	0.373	
PCBC	OSUP	0.247	p＜0.001	0.329	0.332
	SOIN	0.307	p＜0.001	0.350	
AIEP	OSUP	0.188	p＜0.001	0.227	0.655
	SOIN	0.117	0.026	0.122	
	REXP	0.411	p＜0.001	0.357	
	PCBC	0.351	p＜0.001	0.318	

Note: Organizational support (OSUP), Social influence (SOIN), Performance expectation (REXP), Perceived behavioral control (PCBC), and AI usage performance (AIEP).

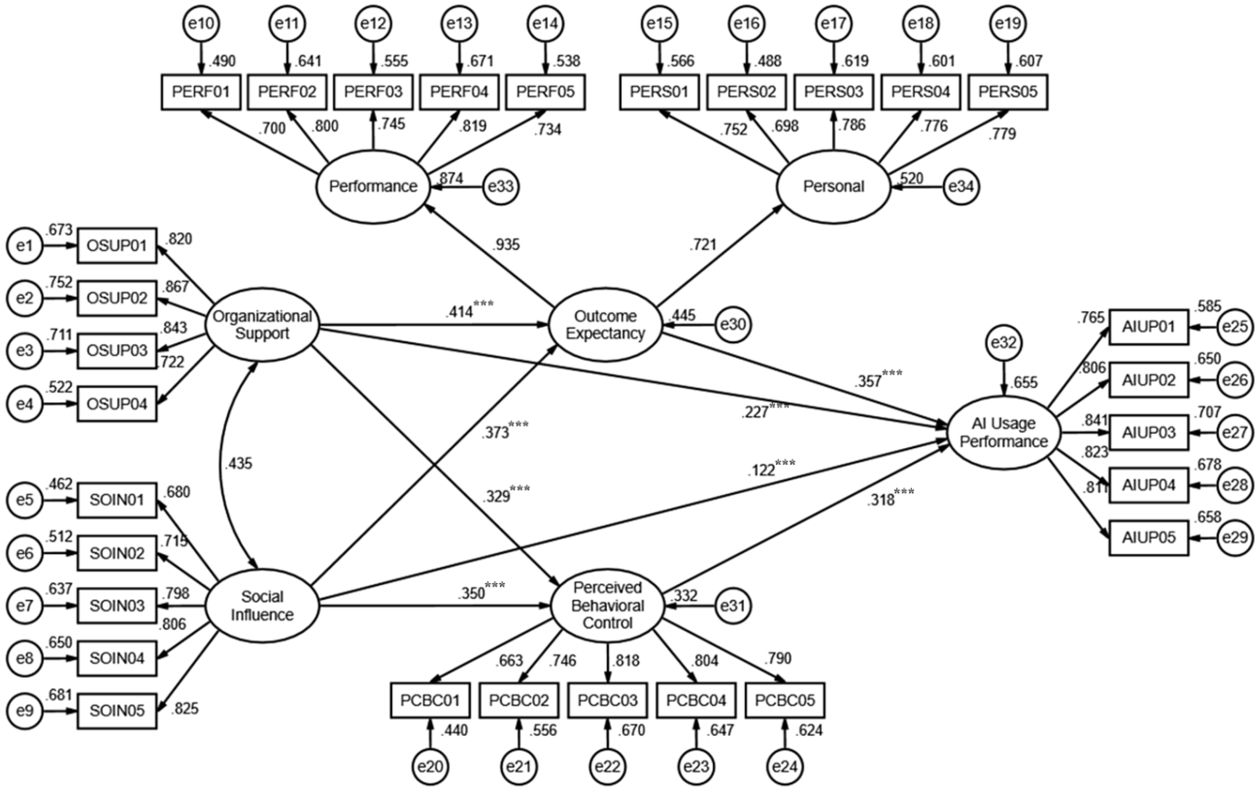

Figure 2. The model diagram based on SEM approach

4.5. Mediating Effects

The bootstrap procedure is a commonly used method for testing the indirect effects of mediating variables. Compared with the causal steps approach and the product-of-coefficients method, the bootstrap method offers greater statistical power [61-64]. As shown in Table 5, the confidence intervals for the specific indirect effects do not include zero, indicating the presence of mediating effects. The mediating effect results reveal the following pathways: organizational support (OSUP) → performance expectation (REXP) → AI usage performance (AIEP) (C.I. [0.006, 0.376]); organizational support (OSUP) → perceived behavioral control (PCBC)→AI usage performance (AIEP) (C.I. [0.020, 0.210]); social influence (SOIN)→performance expectation (REXP)→AI usage performance (AIEP) (C.I. [0.010, 0.412]); and social influence (SOIN)→perceived behavioral control (PCBC)→AI usage performance (AIEP) (C.I. [0.016, 0.270]). These results support hypotheses H9-H12. The mediation analysis reveals that the mediating effect of social influence is more potent than that of organizational support, indicating that peer culture and leadership modeling have a more substantial motivational impact on employees' psychological mechanisms. This result further suggests that observing others successfully apply AI strengthens employees' performance expectancy and sense of control, thereby improving behavioral performance.

Table 5. The mediation analysis of proposed model

Effect	Point Estimate	Bootstrap 1000 times	
		Bias-corrected 95%	
		Lower bound	Upper bound
Total effect			
OSUP →AIEP	0.396	0.177	0.589
Indirect effect			
OSUP→REXP→AIEP	0.122	0.006	0.376
OSUP →PCBC→AIEP	0.087	0.020	0.210
Direct effect			
OSUP→AIEP	0.188	-0.035	0.437
Total effect			
SOIN →AIEP	0.354	0.122	0.643
Indirect effect			
SOIN →REXP →AIEP	0.129	0.010	0.412
SOIN→ PCBC→AIEP	0.108	0.016	0.270
Direct effect			
SOIN→AIEP	0.117	-0.159	0.472

Note: Organizational support (OSUP), Social influence (SOIN), Performance expectation (REXP), Perceived behavioral control (PCBC), and AI usage performance (AIEP)

4.6. Moderating Effects Analysis

In the model of this study (see Figure 1), ISES serves as the moderating variable. As shown in Table 6, the moderating effect of OSUP*ISES on REXP is 0.072 ($z = |2.660| > 1.96$, $p = 0.008 < 0.01$), indicating a significant moderating effect. The moderating effect of OSUP*ISES on PCBC is 0.110 ($z = |4.000|$, $p < 0.001$), indicating a significant impact. The moderating effect of SOIN*ISES on REXP is 0.098 ($z = |3.649|$, $p < 0.001$), indicating a significant impact. However, the moderating effect of SOIN*ISES on PCBC is -0.024 ($z = |-0.881| < 1.96$, $p = 0.378 > 0.05$), indicating that it is insignificant. Among the four moderation hypotheses, Hypotheses 13-15 are supported, while Hypothesis 16 is not supported. The moderation analysis finds that creative self-efficacy strengthens the positive relationships of organizational support and social influence with performance expectancy and perceived behavioral control, indicating that employees with higher innovation confidence are better able to internalize external resources into motivation for learning and action. This result also suggests that during AI implementation, individual psychological traits play a key role in both technology acceptance and translating acceptance into performance.

Table 6. The analysis of moderating effects analysis

DV	IV	Estimate	S.E.	z -value	p-value
REXP	OSUP	0.215	0.048	4.518	p＜0.001
PCBC	OSUP	0.214	0.048	4.439	p＜0.001
REXP	SOIN	0.286	0.045	6.283	p＜0.001
PCBC	SOIN	0.153	0.046	3.307	p＜0.001
REXP	CSE	0.319	0.048	6.585	p＜0.001
PCBC	CSE	0.402	0.049	8.176	p＜0.001
AIEP	REXP	0.380	0.043	8.938	p＜0.001
AIEP	PCBC	0.443	0.043	10.416	p＜0.001
REXP	OSUP* CSE	0.072	0.027	2.660	0.008
PCBC	OSUP* CSE	0.110	0.028	4.000	p＜0.001
REXP	SOIN* CSE	0.098	0.027	3.649	p＜0.001
PCBC	SOIN* CSE	-0.024	0.027	-0.881	0.378

Note: Organizational support (OSUP), Social influence (SOIN), Performance expectation (REXP), Perceived behavioral control (PCBC), AI usage performance (AIEP), Creative self-efficacy (CSE).

In this study, participants with scores within one standard deviation (SD) above the mean were classified as the high group. In comparison, those with scores within one standard deviation below the mean were classified as the low group. As shown in Figure 3, when creative self-efficacy is high, the effect of organizational support on performance expectations is more pronounced (β = 0.574, $p < 0.05$), indicating that increased organizational support is associated with a significant increase in performance expectations among those with high creative self-efficacy. Conversely, when creative self-efficacy is low, the effect of organizational support on performance expectation is more moderate (β = 0.286, $p < 0.05$). Similarly, as shown in Figure 4, when creative self-efficacy is high, the effect of social influence on performance expectation is more substantial (β = 0.768, $p < 0.05$), indicating that greater social influence significantly increases performance expectations among those with high creative self-efficacy. When creative self-efficacy is low, the effect of social influence on performance expectations is weaker (β = 0.376, $p < 0.05$). As shown in Figure 5, when creative self-efficacy is high, the effect of organizational support on perceived behavioral control is also more substantial (β = 0.648, $p < 0.05$), indicating that increased organizational support significantly enhances perceived behavioral control for those with high creative self-efficacy. Conversely, when creative self-efficacy is low, the effect of organizational support on perceived behavioral control is more moderate (β = 0.208, $p < 0.05$).

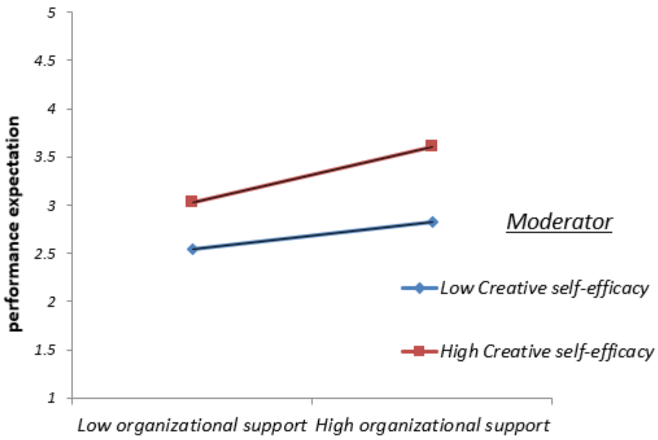

Figure 3. The moderating effect of creative self-efficacy on the relationship between organizational support and performance expectation

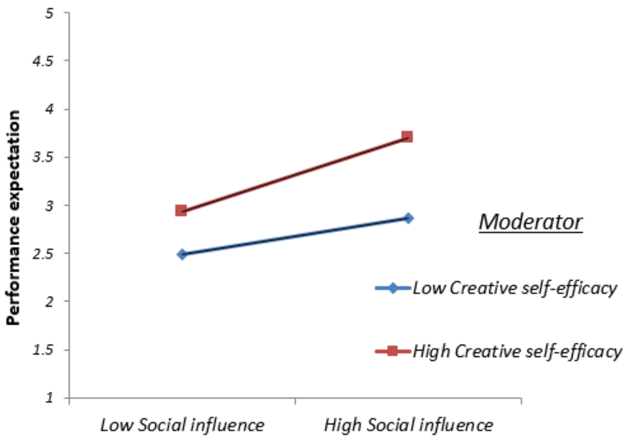

Figure 4. The moderating effect of creative self-efficacy on the relationship between social influence and performance expectation

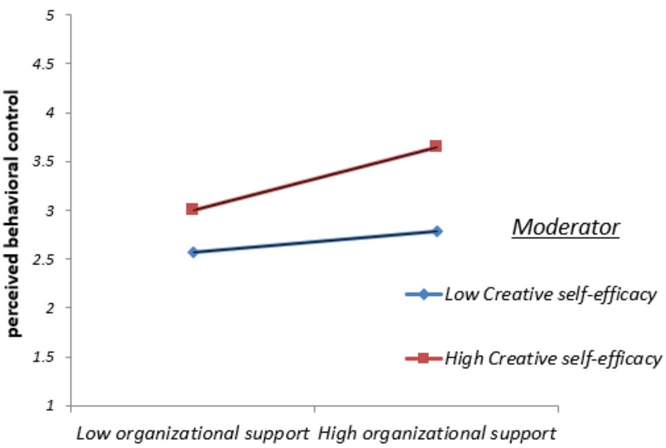

Figure 5. The moderating effect of creative self-efficacy on the relationship between organizational support and perceived behavioral control

As shown in Table 6, the moderating effect of OSUP*ISES on REXP is 0.072, the moderating effect of OSUP*ISES on PCBC is 0.110, and the moderating effect of SOIN*ISES on REXP is 0.098. A comparison of the three significant interaction effects reveals that all three have a positive impact on the dependent variables, as illustrated in the bar charts. This indicates that, under certain conditions, core self-evaluation (CSE) has a significant positive moderating effect on the relationships between organizational support (OSUP) and social influence (SOIN) with the respective outcome variables, as shown in Figure 6.

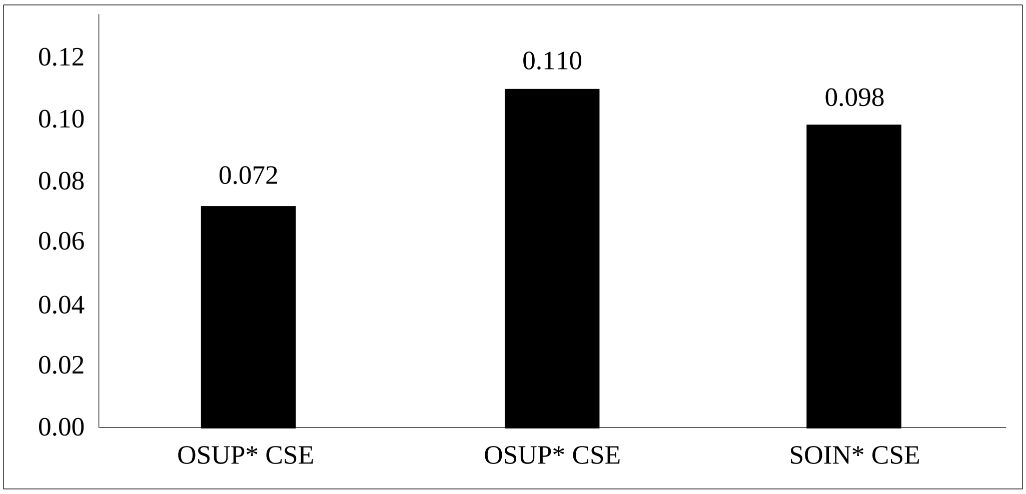

Figure 6. The moderating effect of creative self-efficacy

5. Discussion

This study explored the factors influencing AI usage performance, confirmed the mediating role of performance expectations in the relationship between organizational support and social influence, and found that social influence improves employees' perceived behavioral control more than organizational support, thereby supporting the applicability of Social Cognitive Theory (SCT). In addition, creative self-efficacy (CSE) can enhance the impact of managerial support and social influence on technology applications, suggesting that organizations should consider not only technical support and social influence but also employees' innovative beliefs when promoting AI adoption. The research deepens the understanding of how AI adoption affects work performance and provides theoretical and practical references for enterprises aiming to improve employee performance for sustainable development. Future research can further investigate the long-term effects, cross-industry applicability, and mechanisms of influence of different AI technologies.

1) Organizational support, social influence, performance expectation, and perceived behavioral control each have a significant positive impact on AI usage performance

This study found that the factors influencing AI usage performance include performance expectation, perceived behavioral control (PBC), organizational support, and social influence. The order of influence on AI usage performance is performance expectation, PBC, managerial support, and social influence. Results indicate that performance expectation has the most significant effect on AI usage performance. Employees with high-performance expectations for AI are more likely to engage with it and achieve better application outcomes, which aligns with the Expectation-Confirmation Theory (ECT) perspective [41]. Additionally, PBC has a significant positive effect, reflecting employees' beliefs in their ability to control AI technology; when resources and skills are sufficient, usage performance improves. Organizational support also has a positive effect: ample resources, training, and technical support contribute to better technology application outcomes, consistent with previous research on information systems [27, 65]. Although social influence has a relatively lower impact, it remains statistically significant, indicating that colleagues, supervisors, and organizational culture all affect AI application, which supports the social influence theory viewpoint [47].

2) The mediating effect of performance expectation validates the importance of ECT

The study validates a core ECT hypothesis by showing that performance expectation plays a key mediating role in the relationship between organizational support/social influence and AI usage performance. When companies provide technical training, resources, and management encouragement, or when colleagues and supervisors influence employees, performance expectations are significantly enhanced, promoting AI usage performance [66]. According to ECT, technology use behavior is driven by performance expectations and adjusts according to usage experience and the support environment. When those expectations are confirmed, usage behavior and performance continue to improve. This study also verifies the applicability of SCT in technology adoption, identifying perceived behavioral control as a secondary mediator. However, compared to performance expectations, the mediating effect of PBC is weaker, indicating that in the early stages of adoption, employee behavior is mainly driven by performance expectations rather than confidence in their technical control. This study addresses the research gaps in Min [67] and Jemini Gashi et al. [68]. While Min's work is limited to the context of educational reform, this study extends the mediating mechanism of outcome expectancy to AI application scenarios, confirming its cross-context applicability. Although Jemini Gashi et al. [68] noted that outcome expectancy increases with the accumulation of social support, their results were not significant; by contrast, under sustained organizational support, this study verifies a significant mediating effect, thereby strengthening the explanatory power of Social Cognitive Theory in research on behavioral performance.

3) Antecedents of PBC validate the importance of SCT

PBC reflects individuals' beliefs in their ability to perform actions and is influenced by external environmental support [9]. This study confirms that organizational support and social influence have a significant impact on PBC. When employees receive sufficient resources and social support, their sense of control over AI technology increases, thereby improving their performance. However, social influence exerts a more substantial effect on PBC than organizational support, suggesting that social environments shape employee behavioral beliefs more than organizational resources do. Organizational support improves technical skills through training, resources, and institutional guarantees, but has a negligible effect on PBC. This suggests that a sense of control over AI use relies more on daily social interactions and the learning environment [69]. In the rapidly developing context of AI, single-session training cannot continuously update knowledge; therefore, learning from peers and receiving real-time technical support are necessary to fill knowledge gaps, further confirming SCT's core idea that behavioral competency is influenced by social interaction and observational learning [43]. This study addresses the gaps in Oh et al. (2022) and Fawehinmi et al. (2024). In contrast to Oh et al., who focused on the inhibitory effect of ethical control on performance, this study finds that organizational support and social influence positively enhance perceived behavioral control (PBC), thereby promoting AI use performance. It also extends the mediation model of Fawehinmi et al. to the domain of green behavior, demonstrating that in technology application contexts, PBC can be directly translated into performance, thereby expanding its theoretical applicability [70, 71].

4) Creative self-efficacy as a moderator in the relationship between performance expectation and perceived behavioral control

This study confirms that creative self-efficacy (CSE) moderates the relationship between organizational support/social influence and performance expectation/PBC, with partially significant effects. Grounded in SCT and self-efficacy theory, CSE reflects an individual's belief in their creative abilities, which affects their initiative and adaptability in the application of technology [9]. The study finds that CSE significantly strengthens the effects of organizational support on performance expectation (H13) and PBC (H15), as well as social influence on performance expectation (H14). This demonstrates that CSE can enhance the impact of external environmental support on beliefs about the application of technology. Further analysis reveals that employees with high CSE are more effective at internalizing the technical resources and support provided by organizations [49]. Compared to those with lower CSE, they are quicker to convert training and resources into higher performance expectations and technical control, demonstrating stronger adaptability. Additionally, CSE enhances the effect of social influence on performance expectations, aligning with SCT's observational learning and role modeling effects [39]. Employees with high CSE learn more easily from successful examples, whereas those with low CSE may not convert observations into action due to a lack of confidence. However, CSE did not significantly moderate the effect of social influence on PBC (H16), indicating that a sense of technical control depends more on direct learning and operational experience than merely on social influence [47]. This may be related to PBC, which reflects confidence in the application of technology. Employees with high CSE rely more on their creative problem-solving ability than on peers or supervisors, leading to a non-significant moderating effect.

5) Management strategies for enhancing performance expectations

This study demonstrates that performance expectations have a significant impact on AI usage performance, suggesting that companies should prioritize strategies to enhance employees' expectations of AI outcomes. Companies can improve employees' expectations of AI benefits by using use cases, providing performance data and feedback, and sharing successes. For example, the construction of internal data analysis systems helps employees understand how AI improves productivity, reduces errors, and optimizes decision-making. Management should communicate the strategic value of artificial intelligence, emphasizing its contribution to individual performance and company competitiveness. Additionally, pilot projects that allow employees to experience the benefits of artificial intelligence personally can effectively reduce resistance and improve performance expectations.

6) Strengthening the antecedents of PBC in management

PBC is influenced by organizational support and social influence, and plays a crucial role in the adoption and application of technology. The study suggests that companies adopt multi-layered management measures to enhance PBC, ensuring resource availability and a supportive learning environment. Continuous training programs, online learning platforms, and technical consultants can help employees overcome technical barriers. In addition, internal technical communities and mentorship programs can promote technology learning and exchange, allowing employees to strengthen their sense of control through observation and practice [25]. Organizations should also provide timely technical support, such as an AI expert team, to help employees promptly resolve technical issues and reduce uncertainty.

6. Conclusions

According to SCT, individuals' beliefs in their creativity influence their adaptability to and innovative application of new technologies. Companies can strengthen CSE by creating mechanisms to incentivize innovation, such as reward programs to encourage AI applications, or by organizing innovation challenges to promote inter-departmental collaboration. For example, fostering an innovation culture is essential by providing an open forum where employees can exchange ideas and receive feedback on new AI applications. Companies should ensure that their employees have sufficient time and resources to perform technical exploration and experimentation, thereby reducing the impact of workplace pressures on their innovation capacity. Organizations can improve employee CSE by driving digital transformation and innovation through these measures. In addition, this study aims to extend the application of the Expectation Confirmation Theory (ECT) from the consumer domain to the context of work behavior. In consumer settings, expectations primarily concern satisfaction with usage outcomes, whereas in workplace contexts, expectations focus on task efficiency, learning capability, and innovative performance. Although these two contexts differ, both are associated with outcome variables, indicating that ECT can be effectively extended to a broader range of application domains.

Although this study identified essential factors influencing the adoption of AI technologies, several limitations should be considered. The use of a cross-sectional design limits the ability to track how technology adoption changes over time. Future studies may adopt a longitudinal approach to monitor employee attitudes toward AI as the technology develops, and to investigate how performance expectations and perceived behavioral control (PBC) roles change at different stages of adoption, thereby affecting use performance. Furthermore, since this research is primarily focused on the technology industry, future research may extend the analysis to other sectors to investigate whether industrial differences affect AI adoption. Additional research could also distinguish between AI technologies, such as machine learning and natural language processing, to better understand their specific impacts on performance expectations and PBC. It provides organizations with more precise recommendations for implementing AI solutions. Finally, future research may explore whether potential cultural factors moderate the relationships identified in this study. Moreover, cross-cultural comparisons could be conducted to determine whether these relationships remain consistent across different cultural contexts.

This study further broadens the application scope of the Expectation-Confirmation Theory (ECT), extending it beyond the traditional consumer-use context into organizational work and behavioral settings. In consumer contexts, the gap between individuals' initial expectations and subsequent usage experiences primarily influences their continuance intentions through "satisfaction." By contrast, in workplace contexts, employees' expectations are more directly oriented toward achieving task performance and work value, such as efficiency in task completion, the ability to learn new skills and tools, and the potential of technology to spur process innovation and improve outcomes. Although the mechanisms of expectation and confirmation operate differently across these two contexts, both fundamentally involve the generation and assessment of "outcome variables," indicating that ECT possesses strong transferability and external applicability at the level of theoretical structure. Building on this, the present study uses employees' adoption of artificial intelligence (AI) as an example to validate ECT's explanatory power for adoption and continuance intentions in the workplace, thereby suggesting possibilities for cross-context theoretical integration.

However, situational and cultural factors may moderate how employees perceive performance improvement, learning benefits, and innovation value, which in turn shape their evaluations of AI adoption and behavioral responses. The sample in this study consists primarily of employees in Taiwan. While this captures features of local organizational culture, management styles, and the maturity of technology implementation, it may also limit the external validity and cross-cultural generalizability of the findings. For instance, cultures differ in power distance, risk-taking propensity, and levels of collectivism, which may influence employees' expected returns from adopting AI, their acceptance of process change, and the degree to which they depend on managerial support and training resources. To address this limitation, the study concludes that future research should employ multi-site sampling across different cultures and industries. It also suggests incorporating cultural dimensions (such as uncertainty avoidance, long-term orientation, and power distance) as moderating variables to examine the robustness of ECT's mechanisms under varied cultural contexts.

In addition, future research can further strengthen the methodological inferential validity. First, longitudinal designs are recommended to link employees' initial expectations, actual AI usage experiences, the process of confirmation or disconfirmation, and subsequent performance and continuance intentions, thereby avoiding the causal inference constraints of cross-sectional data. Second, subjective perceptions can be integrated with objective performance indicators (such as task processing time, error rates, and the number of innovation proposals) to more comprehensively assess the impact of AI implementation at both the individual and team levels. Besides, a multilevel analytical framework is suggested to simultaneously consider individual-level factors (such as self-efficacy, perceived behavioral control, and technology acceptance tendencies) and organizational-level factors (such as technical support resources, training quality, managerial support, and data governance norms), to clarify how ECT operates in tandem with key psychological mechanisms of employees' AI adoption under different structural and cultural conditions. In sum, extending ECT from consumer contexts to workplace settings not only helps connect satisfaction and work-performance outcome variables but also provides a theoretical framework for understanding the mechanisms underlying employees' AI adoption. Nevertheless, cultural and contextual variations may influence the magnitude and direction of theoretical effects. These issues call for further validation through cross-cultural, longitudinal, and multilevel research designs to establish an AI adoption model with stronger external validity and practical value.

7. Declarations

7.1. Author Contributions

Conceptualization, C.-H.W. and R.-D.T.; methodology, C.-H.W.; investigation, K.-C.H.; resources, K.-C.H.; data curation, K.-C.H.; writing—original draft preparation, C.-H.W. and R.-D.T.; writing—review and editing, K.-C.H.; supervision, C.-H.W. and R.-D.T.; project administration, C.-H.W. and R.-D.T.; funding acquisition, C.-H.W. and R.-D.T. 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 in the article.

7.3. Funding

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

Informed consent was obtained from all subjects involved in the study.

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.

8. References

[1] Earley, S. (2019). The AI Advantage: How to Put the Artificial Intelligence Revolution to Work by Tom Davenport. Applied Marketing Analytics: The Peer-Reviewed Journal, 4(3), 264-267. doi:10.69554/vsws6836.

[2] Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21(2), 155–172. doi:10.1177/1094670517752459.

[3] Fechete, F., & Nedelcu, A. (2019). Performance Management Assessment Model for Sustainable Development. Sustainability (Switzerland), 11(10), 2779. doi:10.3390/su11102779.

[4] Bandura, A. (1988). Organisational Applications of Social Cognitive Theory. Australian Journal of Management, 13(2), 275–302. doi:10.1177/031289628801300210.

[5] Santoso, S. (2021). Relationship between Social Media, Organizational Support, Subjective Norms and Perceived Behavioral Control to Form Entrepreneurial Intention. Expert Journal of Business and Management, 9(1), 1–10.

[6] Chu, T. H., & Chen, Y. Y. (2016). With Good We Become Good: Understanding e-learning adoption by theory of planned behavior and group influences. Computers and Education, 92–93, 37–52. doi:10.1016/j.compedu.2015.09.013.

[7] Fu, J. R., Farn, C. K., & Chao, W. P. (2006). Acceptance of electronic tax filing: A study of taxpayer intentions. Information and Management, 43(1), 109–126. doi:10.1016/j.im.2005.04.001.

[8] Lin, H., & Fan, W. (2011). Leveraging organizational knowledge through electronic knowledge repositories in public accounting firms: An empirical investigation. Behavioral Research in Accounting, 23(2), 147–167. doi:10.2308/bria-10062.

[9] Liao, J., Chen, J., & Mou, J. (2021). Examining the antecedents of idea contribution in online innovation communities: A perspective of creative self-efficacy. Technology in Society, 66, 101644. doi:10.1016/j.techsoc.2021.101644.

[10] Tierney, P., & Farmer, S. M. (2011). Creative Self-Efficacy Development and Creative Performance over Time. Journal of Applied Psychology, 96(2), 277–293. doi:10.1037/a0020952.

[11] Newman, A., Tse, H. H. M., Schwarz, G., & Nielsen, I. (2018). The effects of employees' creative self-efficacy on innovative behavior: The role of entrepreneurial leadership. Journal of Business Research, 89, 1–9. doi:10.1016/j.jbusres.2018.04.001.

[12] Aravindan, K. L., Thurasamy, R., Raman, M., Ilhavenil, N., Annamalah, S., & Rathidevi, A. S. (2022). Modeling Awareness as the Crux in Solar Energy Adoption Intention through Unified Theory of Acceptance and Use of Technology. Mathematics, 10(12), 2045. doi:10.3390/math10122045.

[13] Hossain, M. A., & Quaddus, M. (2012). Expectation–Confirmation Theory in Information System Research: A Review and Analysis. Information Systems Theory: Explaining and Predicting Our Digital Society, 1, 441–469. doi:10.1007/978-1-4419-6108-2_21.

[14] Lin, H. Y., & Hsu, M. H. (2015). Using Social Cognitive Theory to Investigate Green Consumer Behavior. Business Strategy and the Environment, 24(5), 326–343. doi:10.1002/bse.1820.

[15] Zhou, T. (2011). An empirical examination of users' post-adoption behaviour of mobile services. Behaviour and Information Technology, 30(2), 241–250. doi:10.1080/0144929X.2010.543702.

[16] Alnasrallah, W., & Saleem, F. (2022). Determinants of the Digitalization of Accounting in an Emerging Market: The Roles of Organizational Support and Job Relevance. Sustainability (Switzerland), 14(11), 6483. doi:10.3390/su14116483.

[17] Chouchane, R., Fernet, C., Austin, S., & Karoui Zouaoui, S. (2023). Organizational support and intrapreneurial behavior: On the role of employees' intrapreneurial intention and self-efficacy. Journal of Management and Organization, 29(2), 366–382. doi:10.1017/jmo.2021.14.

[18] Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. Academy of Management Journal, 53(2), 323–342. doi:10.5465/amj.2010.49388995.

[19] Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioral intention to use. Computers and Education, 109, 56–73. doi:10.1016/j.compedu.2017.02.005.

[20] Oh, J. C., & Yoon, S. J. (2014). Predicting the use of online information services based on a modified UTAUT model. Behaviour and Information Technology, 33(7), 716–729. doi:10.1080/0144929X.2013.872187.

[21] Wang, X., & Zhou, R. (2023). Impacts of User Expectation and Disconfirmation on Satisfaction and Behavior Intention: The Moderating Effect of Expectation Levels. International Journal of Human-Computer Interaction, 39(15), 3127–3140. doi:10.1080/10447318.2022.2095479.

[22] Van den Broeck, L., Vandelannote, I., Demanet, J., & Van Houtte, M. (2023). High school never ends. Normative and comparative peer group effects on higher education outcomes through the school-level students' expectation culture. Educational Review, 75(2), 217–242. doi:10.1080/00131911.2021.1923459.

[23] Yang, T., & Jiang, X. (2023). When colleague got recognized: Third party's reaction to witnessing employee recognition. Frontiers in Psychology, 14, 968782. doi:10.3389/fpsyg.2023.968782.

[24] Bux, S. (2016). The effect of entrepreneurship education programmes on the mind-set of South African youth. University of Pretoria, Pretoria, South Africa.

[25] Zhao, F., Ahmed, F., Iqbal, M. K., Mughal, M. F., Qin, Y. J., Faraz, N. A., & Hunt, V. J. (2020). Shaping Behaviors through Institutional Support in British Higher Educational Institutions: Focusing on Employees for Sustainable Technological Change. Frontiers in Psychology, 11, 584857. doi:10.3389/fpsyg.2020.584857.

[26] Nguyen, M., Rundle-Thiele, S., Malik, A., & Budhwar, P. (2023). Impact of technology-based knowledge sharing on employee outcomes: moderation effects of training, support and leadership. Journal of Knowledge Management, 27(8), 2283–2301. doi:10.1108/JKM-07-2022-0552.

[27] Bhattacherjee, A., Davis, C. J., Hikmet, N., & Kayhan, V. (2008). User reactions to information technology: Evidence from the healthcare sector. ICIS 2008 Proceedings, 211.

[28] Tisu, L., Lupșa, D., Vîrgă, D., & Rusu, A. (2020). Personality characteristics, job performance and mental health the mediating role of work engagement. Personality and Individual Differences, 153, 109644. doi:10.1016/j.paid.2019.109644.

[29] Hamzah, M. I., Othman, A. K., & Hassan, F. (2020). Mediating effects of individual market orientation on the link between learning orientation and job performance. Journal of Business and Industrial Marketing, 35(4), 655–668. doi:10.1108/JBIM-08-2018-0239.

[30] Lent, R. W., Brown, S. D., & Hackett, G. (2002). Social cognitive career theory. Career Choice and Development, 4(1), 255-311.

[31] Wang, R. T., & Lin, C. P. (2012). Understanding innovation performance and its antecedents: A socio-cognitive model. Journal of Engineering and Technology Management - JET-M, 29(2), 210–225. doi:10.1016/j.jengtecman.2012.01.001.

[32] McAlister, L., Srinivasan, R., & Kim, M. C. (2007). Advertising, research and development, and systematic risk of the firm. Journal of Marketing, 71(1), 35–48. doi:10.1509/jmkg.71.1.35.

[33] Yazdanpanah, M., Feyzabad, F. R., Forouzani, M., Mohammadzadeh, S., & Burton, R. J. F. (2015). Predicting farmers' water conservation goals and behavior in Iran: A test of social cognitive theory. Land Use Policy, 47, 401–407. doi:10.1016/j.landusepol.2015.04.022.

[34] Bandura, A. (2001). Social cognitive theory: An agentic perspective. Annual Review of Psychology, 52, 1–26. doi:10.1146/annurev.psych.52.1.1.

[35] Ratten, V., & Ratten, H. (2007). Social cognitive theory in technological innovations. European Journal of Innovation Management, 10(1), 90–108. doi:10.1108/14601060710720564.

[36] Hau, Y. S., & Kim, Y. G. (2011). Why would online gamers share their innovation-conducive knowledge in the online game user community? Integrating individual motivations and social capital perspectives. Computers in Human Behavior, 27(2), 956–970. doi:10.1016/j.chb.2010.11.022.

[37] Spaulding, A., Tudor, K., & Mahatanankoon, P. (2015). The Effects of Outcome Expectations on Individual's Anxiety and Continued Usage of Mobile Devices: A Post-Adoption Study. International Food and Agribusiness Management Review, 18(4), 173–188.

[38] Cai, L., Xiao, Z., & Ji, X. (2023). Impact of supervisor developmental feedback on employee innovative behavior: roles of psychological safety and face orientation. Journal of Managerial Psychology, 38(1), 73–87. doi:10.1108/JMP-12-2021-0670.

[39] Jaiswal, N. K., & Dhar, R. L. (2015). Transformational leadership, innovation climate, creative self-efficacy and employee creativity: A multilevel study. International Journal of Hospitality Management, 51, 30-41. doi:10.1016/j.ijhm.2015.07.002.

[40] Kim, H. J., Hur, W. M., Moon, T. W., & Jun, J. K. (2017). Is all support equal? The moderating effects of supervisor, coworker, and organizational support on the link between emotional labor and job performance. BRQ Business Research Quarterly, 20(2), 124–136. doi:10.1016/j.brq.2016.11.002.

[41] Zhu, J., Xu, S., Ouyang, K., Herst, D., & Farndale, E. (2018). Ethical leadership and employee pro-social rule-breaking behavior in China. Asian Business & Management, 17(1), 59-81. doi:10.1057/s41291-018-0031-0.

[42] Schaarschmidt, M. (2016). Frontline employees' participation in service innovation implementation: The role of perceived external reputation. European Management Journal, 34(5), 540–549. doi:10.1016/j.emj.2016.02.005.

[43] Pagnotta, M., Laland, K. N., & Coco, M. I. (2020). Attentional coordination in demonstrator-observer dyads facilitates learning and predicts performance in a novel manual task. Cognition, 201, 104314. doi:10.1016/j.cognition.2020.104314.

[44] Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. Computers in Human Behavior, 67, 221–232. doi:10.1016/j.chb.2016.10.028.

[45] Coetzee, M. (2019). Organisational Climate Conditions of Psychological Safety as Thriving Mechanism in Digital Workspaces. Thriving in Digital Workspaces: Emerging Issues for Research and Practice, 311–327. doi:10.1007/978-3-030-24463-7_16.

[46] Bandura, A. (2005). The social foundations of thought and action: A social cognitive theory. Prentice-Hall, New Jersey, United States.

[47] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems, 27(3), 425–478. doi:10.2307/30036540.

[48] Gong, Y. (2010). Employee learning orientation, transformational leadership, and employee creativity: The mediating role of employee creative self-efficacy. Development and Learning in Organizations: An International Journal, 24(2), 366–372. doi:10.1108/dlo.2010.08124bad.003.

[49] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly: Management Information Systems, 36(1), 157–178. doi:10.2307/41410412.

[50] Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206. doi:10.1086/651257.

[51] Brislin, R. W. (1980). Cross-cultural research methods: Strategies, problems, applications. Environment and Culture, 47-82. Springer, Boston, United States.

[52] Lee, H. Y., Lee, Y. K., & Kwon, D. (2005). The intention to use computerized reservation systems: The moderating effects of organizational support and supplier incentive. Journal of Business Research, 58(11), 1552-1561. doi:10.1016/j.jbusres.2004.07.008.

[53] Lu, J., Yao, J. E., & Yu, C. S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. Journal of Strategic Information Systems, 14(3), 245–268. doi:10.1016/j.jsis.2005.07.003.

[54] Lin, T. C., & Huang, C. C. (2008). Understanding knowledge management system usage antecedents: An integration of social cognitive theory and task technology fit. Information and Management, 45(6), 410–417. doi:10.1016/j.im.2008.06.004.

[55] Lin, C. P., Chen, K. J., Liu, C. M., & Liao, C. H. (2019). Assessing decision quality and team performance: perspectives of knowledge internalization and resource adequacy. Review of Managerial Science, 13(2), 377–396. doi:10.1007/s11846-017-0253-0.

[56] Suherman, S. (2024). Role of creative self-efficacy and perceived creativity as predictors of mathematical creative thinking: Mediating role of computational thinking. Thinking Skills and Creativity, 53, 101591. doi:10.1016/j.tsc.2024.101591.

[57] Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. Communication Monographs, 76(4), 408–420. doi:10.1080/03637750903310360.

[58] Ping, R. A. (1995). A Parsimonious Estimating Technique for Interaction and Quadratic Latent Variables. Journal of Marketing Research, 32(3), 336. doi:10.2307/3151985.

[59] Tabri, N., & Elliott, C. M. (2012). Principles and Practice of Structural Equation Modeling. Canadian Graduate Journal of Sociology and Criminology, 1(1), 3787. New York, NY, USA. doi:10.15353/cgjsc.v1i1.3787.

[60] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39–50. doi:10.1177/002224378101800104.

[61] Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74–94. doi:10.1007/BF02723327.

[62] Choon Hee, O. (2015). Validity and Reliability of the Customer-Oriented Behaviour Scale in the Health Tourism Hospitals in Malaysia. International Journal of Caring Sciences, 7(3), 771.

[63] Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2019). Multivariate data analysis. Cengage Learning EMEA, Boston, Massachusetts.

[64] Williams, J., & MacKinnon, D. P. (2008). Resampling and distribution of the product methods for testing indirect effects in complex models. Structural Equation Modeling, 15(1), 23–51. doi:10.1080/10705510701758166.

[65] Mitchell, J. I., Gagné, M., Beaudry, A., & Dyer, L. (2012). The role of perceived organizational support, distributive justice and motivation in reactions to new information technology. Computers in Human Behavior, 28(2), 729–738. doi:10.1016/j.chb.2011.11.021.

[66] Khan, A. N., Soomro, M. A., & Pitafi, A. H. (2025). AI in the Workplace: Driving Employee Performance Through Enhanced Knowledge Sharing and Work Engagement. International Journal of Human-Computer Interaction, 41(17), 10699–10712. doi:10.1080/10447318.2024.2436611.

[67] Min, M. (2023). School culture, self-efficacy, outcome expectation, and teacher agency toward reform with curricular autonomy in South Korea: a social cognitive approach. Asia Pacific Journal of Education, 43(4), 951–967. doi:10.1080/02188791.2019.1626218.

[68] Jemini Gashi, L., Bërxulli, D., Konjufca, J., & Cakolli, L. (2023). Effectiveness of career guidance workshops on the career self-efficacy, outcome expectations, and career goals of adolescents: an intervention study. International Journal of Adolescence and Youth, 28(1), 2281421. doi:10.1080/02673843.2023.2281421.

[69] Eisenberger, R., Fasolo, P., & Davis-LaMastro, V. (1990). Perceived Organizational Support and Employee Diligence, Commitment, and Innovation. Journal of Applied Psychology, 75(1), 51–59. doi:10.1037/0021-9010.75.1.51.

[70] Oh, J. H., Johnston, W. J., & Curasi, C. F. (2022). Too much of a good thing?: The impact of ethical controls and perceived controllability on salesforce job performance. Journal of Business and Industrial Marketing, 37(6), 1241–1254. doi:10.1108/JBIM-01-2021-0021.

[71] Fawehinmi, O., Yusliza, M. Y., Tanveer, M. I., & Abdullahi, M. S. (2024). Influence of green human resource management on employee green behavior: The sequential mediating effect of perceived behavioral control and attitude toward corporate environmental policy. Corporate Social Responsibility and Environmental Management, 31(3), 2514–2536. doi:10.1002/csr.2707.