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Driving Sustainable Innovation Outcomes Through Employee AI Collaboration with the Mediating Role of Sustainable Career Capacities

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Abstract

Amid digital transformation, artificial intelligence (AI) integration into organizational work has reshaped employee-technology interactions and career trajectories. Despite growing interest in Employee-AI Collaboration (EAC), there is little research examining its impact on both sustainable career development and innovation outcomes. Drawing on Conservation of Resources (COR) theory and Social Cognitive Theory (SCT), this study examines how EAC influences Sustainable Innovation Outcomes (SIO) via Sustainable Career (SC) capacities and the moderating effect of Self-Efficacy in Using AI (SEUA). Using a cross-sectional survey of 294 employees, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to test our hypotheses. Results show that EAC significantly enhances all the four SC dimensions: Resourceful, Flexible, Renewable, and Integrative capacities. These dimensions mediate the relationship between EAC and SIO, while EAC also exerts direct effects. Alternative model analysis suggests a mutually reinforcing relationship between SC and SIO. Notably, SEUA negatively moderates the relationship between EAC and the Integrative dimension, suggesting a counterintuitive attribution mechanism. These findings reveal how EAC drives innovation through both direct technological enhancement and indirect career capacity development pathways. This research extends technology empowerment theory into career

development contexts, providing evidence-based recommendations for organizations to optimize AI integration strategies and career development policies.

Keywords: employee-AI collaboration; sustainable career; sustainable innovation outcomes; self-efficacy in using AI; human-AI interaction

Introduction

AI's rapid proliferation in the workplace is reshaping how employees work and their career development trajectories [1,2]. AI provides employees with unprecedented efficiency gains and cognitive support by automating routine tasks, enhancing decision-making capabilities, and optimizing workflows [3,4]. Beyond immediate productivity improvements, AI also has the potential to impact employees' long-term career development capabilities and subsequent innovation outcomes [5,6]. Yet what specific aspects of SC are shaped by AI, and what kind of innovation outcomes this leads to, remains a central issue [7].

In contemporary business environments, employee collaboration with AI has permeated every aspect of work [8]. Employees employ AI systems for data analysis and prediction in decision-making, utilize AI tools to identify risks and evaluate solutions in problem-solving processes, and leverage AI to integrate multi-source data and extract key insights in information processing [9-11]. This EAC represents a new form of human-machine interaction that changes the way tasks are executed, and reshapes employees' work rhythms, cognitive loads, and capability development paths [12,13]. The time and cognitive resources released by EAC create possibilities for employees to invest in learning, explore new opportunities, and advance innovation projects [14,15]. However, the extent to which employees benefit from EAC may vary across individuals [16], and the process is likely to be influenced by individual differences such as employees' confidence and self-efficacy in AI use [17].

As the role of AI in work scenarios becomes increasingly prominent, its impact on employee career sustainability has begun to attract attention. SC emphasizes the ability of employees to maintain career competitiveness in dynamic environments [18]. As a multidimensional construct, SC encompasses the accumulation of career resources, the acquisition of work flexibility, continuous skill renewal, and the cultivation of information integration capabilities, capturing both the resources employees possess and their adaptive capacities to navigate changing work demands [34]. SC is not only an important outcome of career development but may also become the capability foundation for employees to achieve innovation [19,20]. When employees develop enhanced Resourceful, Flexible, Renewable, and Integrative capacities through EAC, these capability reserves may further turn into innovative behaviors and outcomes [19,21]. Beyond generating innovative ideas, organizations increasingly value whether these ideas can be applied successfully and sustainably [22]. SIO captures this emphasis, referring to the successful and sustainable application of innovative ideas within organizations, this reflects not just the generation of innovation but its actual realization and long-term organizational impact [23]. Therefore, understanding how EAC influences SIO through the four dimensions of SC has become key to grasping the relationship between career development and innovation in the AI era [24-27].

Existing research has begun to explore the impact of AI on work performance and innovation. Kong et al. [21] found that EAC can enhance employee SC, while Dabić et al. [28] pointed out that AI creates opportunities for skill renewal and career flexibility by automating routine tasks. Regarding innovation research, some scholars have explored how AI promotes innovation output by improving efficiency and decision quality [26,29,30].

However, existing research still has certain limitations [19,21,26,28-31]. First, although prior studies have separately examined the effects of EAC on SC and innovation, the multidimensional characteristics of SC and its transformation mechanism between AI collaboration and innovation have not been fully elucidated [18,21,26,29,32,33]. Second, although SCT emphasizes the importance of self-efficacy in technology use, and recent studies have examined AI self-efficacy as a moderating variable in workplace contexts [17,34,35], these studies only focus on buffering negative outcomes such as job stress and job insecurity. How SEUA moderates the empowering effect of AI collaboration on positive developmental outcomes, particularly sustainable career capacities, remains unexplored. Finally, most research focuses on general innovative behaviors or intentions with insufficient attention to the successful implementation and sustainable application of innovation outcomes and the potential reciprocal dynamics between career sustainability and innovation, making it difficult to reflect the long-term impact of AI collaboration on actual organizational innovation output [19,31]. In summary, existing research lacks an integrated framework linking EAC, SC, and SIO, and the role of individual differences in this process remains underexplored.

To address these gaps, this study poses the following research questions:

1. How does EAC influence SIO through the mediating mechanism of SC?
2. How does SEUA moderate the relationship between EAC and SC?

To address these questions, this study integrates COR theory and SCT to construct a theoretical framework. COR theory suggests that resource gains can spiral into further positive outcomes [36], providing a lens to understand how EAC enables employees to accumulate SC, which may subsequently translate into SIO. SCT emphasizes that self-efficacy influences how individuals perceive and utilize environmental opportunities [37], explaining how SEUA may shape the effectiveness of EAC. This study employs PLS-SEM with data from 294 employees to empirically test this framework.

Theoretically, this study innovatively integrates COR theory and SCT to construct a framework of career development and innovation in the context of AI collaboration. SC is identified as a key mediating mechanism through which EAC transforms into SIO. In addition, the study reveals the moderating role of SEUA in specific dimensions, and expands the application boundaries of technology empowerment theory in career development and innovation research. Practically, this study provides empirical evidence and implementation pathways through which organizations optimize AI tool application, design human-AI collaboration training programs, and formulate career development support policies.

Theoretical Foundation and Hypothesis Development

COR theory and EAC

COR theory has been increasingly applied to understand how technology shapes employee resources and outcomes in contemporary workplaces [38,39]. Some research has adopted a resource depletion perspective, examining how technology-related stressors can threaten employees' resource reservoirs and lead to negative outcomes [40-42]. Meanwhile, a growing body of research has adopted a resource acquisition perspective. Together, this research reveals that technology can serve as a valued resource that employees proactively leverage to accumulate additional resources and achieve positive outcomes. For instance, Liu et al. [43] applied COR theory to demonstrate that employees who adopt generative AI can engage in job crafting behaviors such as seeking resources and challenges, and optimizing demands, since these behaviors can enhance their career commitment and lead to positive behavioral outcomes. Similarly, van Zoonen et al. [44] found that technology-enabled connectivity can function as a resource investment that increases employees' autonomy and reduces exhaustion, instead of merely serving as a source of demands. These findings suggest that AI-enabled work practices trigger resource gain spirals wherein initial resource investments generate further resource accumulation [45]. Aligning with this resource acquisition perspective, this study applies COR theory to examine how EAC enables employees to accumulate SC and subsequently translate these career resources into SIO.

COR theory posits that individuals are motivated to acquire, protect, and accumulate valued resources [46]. Resources include objects, characteristics, conditions, or energies that facilitate goal attainment [47]. Central to COR theory is that individuals experience stress when resources are lost and well-being is gained [48]. COR theory's investment principle suggests individuals strategically invest resources to generate future gains [47,49], which is particularly relevant in contexts where employees leverage resources to enhance career outcomes [50,51].

In this study, EAC represents a mechanism for resource acquisition in contemporary work environments [21]. By automating routine tasks and augmenting cognitive capabilities, AI technologies reduce resource depletion and create resource surpluses [52,53]. From a COR perspective, such technology-enabled resource gains provide employees with expanded opportunities to develop career-sustaining capabilities [28,32].

SC, conceptualized through four dimensions (Resourceful, Flexible, Renewable, and Integrative) [18,54], represents an accumulated reservoir of personal resources. These dimensions capture distinct yet complementary resource types that enable individuals to maintain career viability across time and changing circumstances [33]. From a COR perspective, SC dimensions constitute higher-order resources that facilitate acquisition of additional resources and buffer against future resource loss [48,55]. Consequently, SC serves as both an outcome of resource accumulation and a platform for subsequent resource investment [56,57].

COR theory's investment principle predicts that resource-rich individuals are more likely to engage in resource-intensive activities such as innovation [47,50]. Innovation inherently requires resource expenditure, including time, cognitive effort, social capital, and psychological resources [42,58]. Employees possessing SC resources are better positioned to absorb these costs while maintaining resource equilibrium [36,51].

SCT and SEUA

While COR theory explains the resource accumulation mechanism, it does not fully account for individual differences in how employees respond to and benefit from AI collaboration. SCT provides a complementary lens for understanding such differences, positing that self-efficacy plays a central role in shaping how individuals interpret environmental demands and mobilize personal resources [59,60].

Self-efficacy has been extensively applied to understand technology adoption, demonstrating that individuals' confidence in their technological capabilities significantly influences their willingness to engage and the extent to which they benefit from new technologies [61,62]. As AI becomes integrated into workplace operations, recent research has applied SCT to examine AI-related self-efficacy and its effects on employee outcomes. Kim and Kim [63] found that employees with higher self-efficacy in AI learning were better able to maintain psychological safety despite AI-induced job insecurity. Zhou and Lyu [35] revealed that employees' AI self-efficacy moderates the effect of leaders' AI awareness on their intrinsic motivation and voice behavior. Liu and Mei [64] demonstrated that AI adoption was positively associated with employees' problem-solving efficacy, which enhanced adaptive performance. These findings collectively suggest that employees' beliefs about their AI capabilities determine whether they perceive AI as a threat or an opportunity, consequently shaping their behavioral responses to AI-enabled work environments.

In this study, SEUA reflects employees' beliefs about their ability to effectively leverage AI tools to accomplish work-related tasks [65,66]. This suggests that SEUA may shape the extent to which employees can translate EAC into SC accumulation.

The Relationship between EAC and SC

Based on the resource acquisition perspective discussed above, EAC enables employees to preserve and accumulate multidimensional career resources. AI collaboration reduces resource depletion by automating routine tasks, enabling better work outcomes with less effort [67]. This can lead to improved work–life balance, greater financial security, and more positive expectations, which in turn enhance career resourcefulness. [68-71]. After AI assumes structured tasks, employees gain time for opportunity exploration, continuous learning, and flexible work arrangements [28,32,72].

Collaborating with AI exposes employees to emerging technologies, creating skill renewal opportunities [21]. AI facilitates continuous learning through real-time feedback [73], while saved resources can be invested in professional development [55]. AI excels at information processing while human judgment remains critical for evaluation and integration [17], enhancing employees' capacity to synthesize complex information [74,75].

Therefore, this study proposes:

H1a: EAC positively influences the Resourceful dimension of SC

H1b: EAC positively influences the Flexible dimension of SC

H1c: EAC positively influences the Renewable dimension of SC

H1d: EAC positively influences the Integrative dimension of SC

The Relationship between SC and SIO

As previously discussed, the investment principle of COR theory indicates that individuals with abundant resources are more likely to engage in resource-intensive activities such as innovation. The four dimensions of SC serve as different types of resource reserves, providing necessary support for employees to implement and sustain innovation outcomes.

The Resourceful dimension ensures employees possess material and psychological reserves to bear innovation risks [76,77]. Resource satisfaction increases willingness to invest in new ideas [77,78], while positive expectations reduce perceived failure threats [79,80]. The Flexible dimension provides autonomous space for innovation [33,81] and allows schedule adjustments for innovation projects [82,83].

The Renewable dimension ensures employees possess the latest capabilities for innovation implementation [36,84]. Capability reassessment helps identify strengths for innovation [85], while self-reinvention enables adaptation to role changes [86]. The Integrative dimension provides cognitive foundation for innovation [17]. Information integration enables opportunity identification [87]; critical evaluation ensures evidence-based decisions [88]; and knowledge absorption facilitates organizational adoption [89].

Therefore, this study proposes:

H2a: The Resourceful dimension of SC positively influences SIO

H2b: The Flexible dimension of SC positively influences SIO

H2c: The Renewable dimension of SC positively influences SIO

H2d: The Integrative dimension of SC positively influences SIO

The Direct Relationship between EAC and SIO

COR theory suggests that resource-enhancing mechanisms can directly facilitate positive outcomes by providing immediate support for goal-directed activities. In the context of EAC, the participation of AI systems in decision-making, prediction, and problem-solving processes provides employees with data-driven insights and intelligent support, enabling them to more accurately identify innovation opportunities and assess implementation feasibility [26,29,30]. AI assistance in information identification and evaluation processes reduces the cognitive load required for innovation, allowing employees to devote more energy to creative thinking and solution optimization [90,91]. Furthermore, AI involvement in problem and risk identification processes can provide early warnings of potential obstacles, increasing the probability that innovative ideas will be successfully implemented and sustainably adopted by organizations [92].

Therefore, this study proposes:

H3: EAC positively influences SIO

The Mediating Role of SC

Integrating the logic of H1a-d and H2a-d, EAC influences innovation outcomes by promoting the four dimensions of SC. Specifically, the resources, time, and cognitive space released by AI collaboration first transform into enhanced Resourceful, Flexible, Renewable, and Integrative capacities [21,32]. The accumulation of these career resources subsequently provides employees with the material foundation, psychological safety, learning capabilities, and cognitive tools needed to engage in innovative activities [33,36]. In other words, the four dimensions of SC serve as resource transformation mechanisms, converting the immediate efficiency gains from AI collaboration into long-term innovation capabilities and outcomes [18,93].

Therefore, this study proposes:

H4a: The Resourceful dimension of SC mediates the relationship between EAC and SIO

H4b: The Flexible dimension of SC mediates the relationship between EAC and SIO

H4c: The Renewable dimension of SC mediates the relationship between EAC and SIO

H4d: The Integrative dimension of SC mediates the relationship between EAC and SIO

The Moderating Role of SEUA

As previously discussed, SCT posits that self-efficacy shapes how individuals interpret environmental demands and mobilize personal resources. SEUA, as an individual difference variable, may affect the process through which EAC transforms into SC resources [17]. However, existing literature has yielded mixed findings regarding the moderating direction of SEUA, with some studies suggesting positive effects and others indicating more complex patterns [66,94-96].

Therefore, this study proposes:

H5a: SEUA moderates the relationship between EAC and the Resourceful dimension of SC

H5b: SEUA moderates the relationship between EAC and the Flexible dimension of SC

H5c: SEUA moderates the relationship between EAC and the Renewable dimension of SC

H5d: SEUA moderates the relationship between EAC and the Integrative dimension of SC

In summary, this study develops a moderated mediation model to examine how EAC influences SIO through the four dimensions of SC, and the moderating role of SEUA in this process. The complete conceptual model of this study is illustrated in Figure 1.

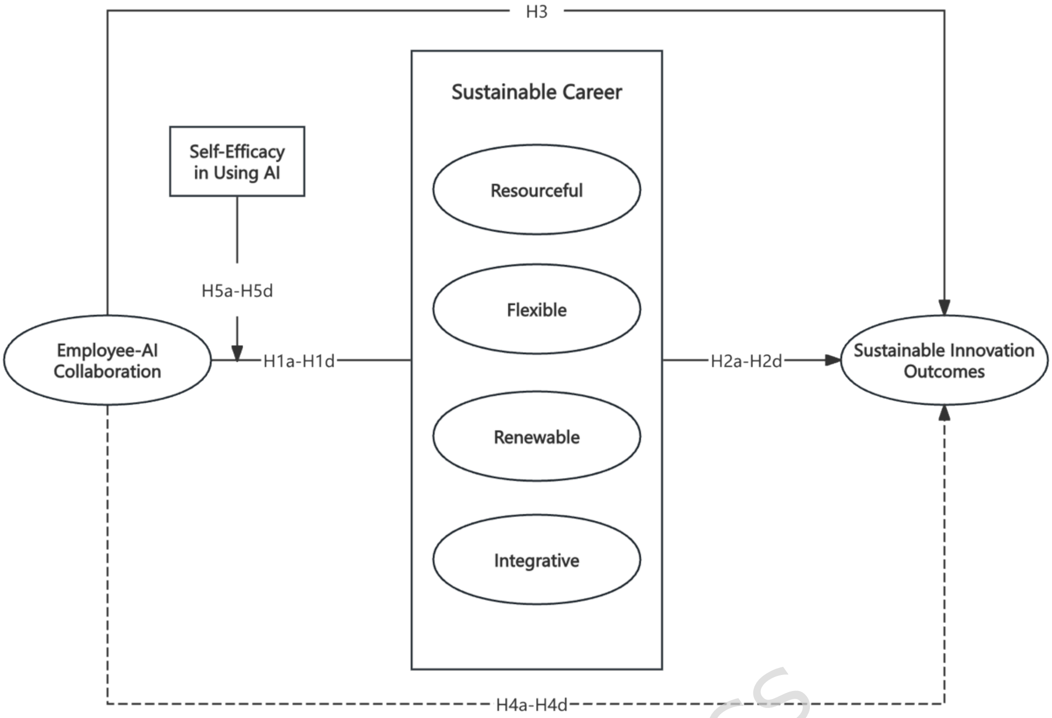

Figure 1. Conceptual Framework

Method

Measurement Tools

In accordance with structural equation modeling requirements and established validation practices, this study utilized adapted versions of previously validated scales [97,98]. All constructs were measured using established scales that have demonstrated good reliability and validity in prior research. A pretest with 56 participants confirmed adequate reliability, with all Cronbach's α values exceeding 0.70, and good comprehensibility prior to formal data collection [98,99]. The complete measurement items are presented in Supplementary Table S1.

EAC was measured using the 5-item scale developed by Kong et al. [21], which assesses the extent to which employees collaborate with AI systems in their work processes, specifically covering AI participation in decision-making, predictive analysis, problem-solving, information identification and evaluation, and opportunity and risk identification.

SC was measured using the multidimensional scale developed by Chin et al. [18], which contains 12 items covering four dimensions that collectively capture the sustainability of individual career trajectories. The

Resourceful dimension (3 items) measures the sufficiency and effective utilization of resources in individual careers. The Flexible dimension (3 items) assesses the space for opportunity exploration, continuous learning capacity, and work arrangement flexibility. The Renewable dimension (3 items) captures opportunities for skill renewal, capability reassessment, and self-reinvention. The Integrative dimension (3 items) evaluates the ability to integrate multiple information sources and absorb knowledge.

SIO was measured using a 3-item scale adapted from Lukes and Stephan [100], which assesses the degree of successful implementation of innovative ideas in organizational contexts and their sustainable application effects.

SEUA was measured using the 5-item scale from Falebita and Kok [65], which assesses individuals' confidence in effectively using AI tools to accomplish work tasks. This construct serves as a moderating variable to examine the moderating effect of individual SEUA on the relationships between EAC and the dimensions of SC.

All scales employed a 7-point Likert scale ranging from "1 = strongly disagree" to "7 = strongly agree" to ensure adequate reliability and validity [101,102].

Research Design and Data Collection

Grounded in a positivist philosophy, this study adopted a quantitative cross-sectional survey design with a deductive approach, deriving hypotheses from COR theory and SCT and testing them with empirical data, to examine the relationships among EAC, SC, and SIO. Data were collected through Wenjuanxing (wjx.cn), a leading online survey platform in China with over 30 million registered users [103]. The platform has been widely adopted in peer-reviewed research across various disciplines [103-106], including employee-focused behavioral research [107-109]. It incorporates multiple quality control mechanisms, including response time monitoring, IP address verification, cross-referencing of related questions, and prevention of duplicate submissions, to ensure data reliability [103]. The platform also features a built-in informed consent function, and all participants were required to read and agree to the consent form before proceeding with the questionnaire [104].

Participants were recruited from various industries to enhance the generalizability of findings, given that AI tools have been widely adopted across diverse sectors [110]. China was selected as the research context due to its leading position in AI development and workplace integration.

According to the World Economic Forum's Future of Jobs Report 2025, more than 90% of organizations in China identify AI as a key technology to transform their business [111], and prior research on organizational AI adoption has similarly selected Chinese employees as the study population [112]. The research participants included frontline employees, functional staff, and grassroots managers to ensure sample diversity. Eligible participants were aged 18 years or older, were currently employed, had worked in their current position for at least six months, and had access to and used digital or AI tools in their daily work. Exclusion criteria included interns who had not been converted to regular employees, respondents with abnormal questionnaire completion times (too short or too long), and respondents exhibiting homogeneous response patterns. Ultimately, this study collected 294 valid questionnaires for subsequent data analysis.

The collected data were analyzed using SmartPLS 4.0. PLS-SEM was employed as it is suitable for prediction-oriented research, complex models with multiple mediators and a moderator, and robust to non-normal data. Additionally, PLS-SEM is recommended for exploratory research aimed at theory development, which aligns with this study's objective of examining the emerging construct of Employee-AI Collaboration and its relationships with career and innovation outcomes [113]. Sample size adequacy was confirmed via G*Power (five predictors, $f^2 = 0.15$, $\alpha = 0.05$, power = 0.80), yielding a minimum requirement of 92; sample size ($N = 294$) exceeded this threshold. To address potential reverse causality inherent in cross-sectional designs, the study conducted an alternative model analysis specifying SIO as an antecedent of the four SC dimensions [98,114].

Ethical Considerations

This study has been approved by the Ethics Committee of Nanfang College, Guangzhou (approval number: NF2025111001), and all research procedures comply with the ethical guidelines of the Declaration of Helsinki. All participants were informed of the research purpose, voluntary participation nature, data confidentiality measures, and the right to withdraw at any time before the questionnaire began and were required to confirm informed consent before proceeding. All participant responses were collected anonymously, data were used solely for academic research purposes, and all information was strictly confidential.

Sample Characteristic

Table 1 presents the demographic characteristics of the final sample (N =

294). The sample was relatively young, with the majority of respondents (80.9%) aged between 18 and 40 years. The education level was moderately high, with over half holding a bachelor’s degree (53.1%) and an additional 16.0% possessing a master’s degree or above. Regarding organizational tenure, most participants had been with their current organization for 1–6 years (64.0%). AI usage frequency at work was relatively high, with 73.8% of respondents using AI tools either daily (43.5%) or several times a week (30.3%). The sample represented diverse industries, with the largest proportion from Technology, Media & Telecom (26.5%), followed by Financial Services (16.3%) and Manufacturing (14.3%).

Table 1. Sample Characteristics (N = 294)

Characteristic	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	158	53.7
	Female	132	44.9
	Other / Prefer not to say	4	1.4
Age group (years)	18–30	140	47.6
	31–40	98	33.3
	41–50	42	14.3
	51–60	11	3.7
	Above 60	3	1
Education level	High school or below	18	6.1
	College diploma	73	24.8
	Bachelor's degree	156	53.1
	Master's degree or above	47	16
Organizational tenure	Less than 1 year	38	12.9
	1–3 years	112	38.1
	4–6 years	76	25.9
	7–10 years	48	16.3
	Over 10 years	20	6.8
AI usage frequency at work	Daily	128	43.5
	Several times a week	89	30.3
	Occasionally / monthly	58	19.7
	Rarely	16	5.4
	Never	3	1
Industry	Technology, Media & Telecom	78	26.5
	Manufacturing	42	14.3
	Financial Services	48	16.3

	Healthcare	24	8.2
	Professional / Consulting	35	11.9
	Retail / Consumer goods	28	9.5
	Public sector / Education	26	8.8
	Others	13	4.4
Total		**294**	**100**

Results

Common Method Bias Assessment

To assess the quality of the collected data, common method bias was examined through multiple statistical procedures. First, multicollinearity was tested using variance inflation factor (VIF) analysis. The VIF values for all paths in the model ranged from 1.004 to 2.305, considerably lower than the recommended threshold of 5.0 [113,115]. These results suggest the absence of severe multicollinearity problems, indicating that the predictor variables maintain adequate independence in explaining the dependent variable.

Furthermore, Harman's single-factor test was conducted to evaluate potential common method bias. The analysis revealed that the first principal component accounted for 37.6% of the total variance, which is below the critical threshold of 50% [116]. Taken together, these findings provide evidence that common method bias does not pose a significant threat to the validity of the study's results, thereby confirming adequate data quality for subsequent analyses.

Reliability and Validity Analysis

Table 2 presents the reliability and validity analysis of the measurement model. All factor loadings exceeded the recommended threshold of 0.70 [117,118], demonstrating adequate indicator reliability. Cronbach's alpha values ranged from 0.774 to 0.895, and composite reliability (CR) values ranged from 0.868 to 0.923, both exceeding the recommended threshold of 0.70 [113], indicating satisfactory internal consistency. Average variance extracted (AVE) values ranged from 0.675 to 0.773, all surpassing the threshold of 0.50 [119], confirming adequate convergent validity. These results collectively demonstrate that the measurement model exhibits acceptable reliability and convergent validity.

Table 2. Reliability and Validity Analysis of Measurement Model

Construct	Item	Loadings	Cronbach's α	Composite Reliability	AVE
EAC	EAC1	0.812	0.880	0.912	0.675
	EAC2	0.838			
	EAC3	0.823			
	EAC4	0.812			
	EAC5	0.824			
FLE	FLE1	0.869	0.827	0.897	0.743
	FLE2	0.862			
	FLE3	0.855			
INT	INT1	0.859	0.845	0.906	0.763
	INT2	0.887			
	INT3	0.875			
REN	REN1	0.874	0.850	0.909	0.769
	REN2	0.873			
	REN3	0.883			
RES	RES1	0.898	0.853	0.911	0.773
	RES2	0.871			
	RES3	0.868			
SEUA	SEUA1	0.831	0.895	0.923	0.704
	SEUA2	0.838			
	SEUA3	0.851			
	SEUA4	0.853			
	SEUA5	0.823			
SIO	SIO1	0.838	0.774	0.868	0.687
	SIO2	0.799			
	SIO3	0.848			

Descriptive Statistics and Discriminant Validity

Table 3 presents the descriptive statistics, correlation matrix, and discriminant validity assessment based on the Fornell-Larcker criterion.

The results indicate adequate variability in responses, with mean values ranging from 4.230 to 4.757 and standard deviations between 1.597 and 1.799. Regarding discriminant validity, the square root of the AVE for each construct (shown in bold on the diagonal) exceeds the corresponding inter-construct correlations [119]. Furthermore, Table 4 presents the discriminant validity assessment using the Heterotrait-Monotrait (HTMT) ratio. As shown, all HTMT ratios are below the threshold of 0.90 [120]. Collectively, these findings provide robust evidence of discriminant validity in the measurement model.

Table 3. Descriptive statistics, correlations, and discriminant validity using the Fornell-Larcker criterion

Construct	Mean	SD	EAC	FLE	INT	REN	RES	SEUA	SIO
EAC	4.493	1.609	**0.822**						
FLE	4.466	1.650	0.529	**0.862**					
INT	4.611	1.695	0.588	0.313	**0.873**				
REN	4.248	1.740	0.539	0.385	0.372	**0.877**			
RES	4.367	1.799	0.537	0.407	0.418	0.402	**0.879**		
SEUA	4.230	1.687	0.285	0.346	0.276	0.330	0.408	**0.839**	
SIO	4.757	1.597	0.620	0.508	0.468	0.522	0.564	0.357	**0.829**

Table 4. Discriminant validity assessment using the Heterotrait-Monotrait (HTMT) ratio

Construct	EAC	FLE	INT	REN	RES	SEUA	SIO
EAC							
FLE	0.619						
INT	0.682	0.373					
REN	0.623	0.458	0.439				
RES	0.62	0.484	0.492	0.471			
SEUA	0.321	0.399	0.318	0.375	0.467		
SIO	0.741	0.628	0.572	0.636	0.691	0.427	

Structural Model Assessment

The SRMR value of 0.051 was below the 0.08 threshold [121]. However, following PLS-SEM guidelines [98,114], model evaluation prioritized R^2 and Q^2. R^2 values ranged from 0.325 to 0.376 for SC dimensions, with SIO achieving 0.521. All Q^2 values exceeded zero, ranging from 0.237 to 0.347, confirming predictive relevance. The structural model assessment results, including path coefficients and explanatory power, are illustrated in Figure 2.

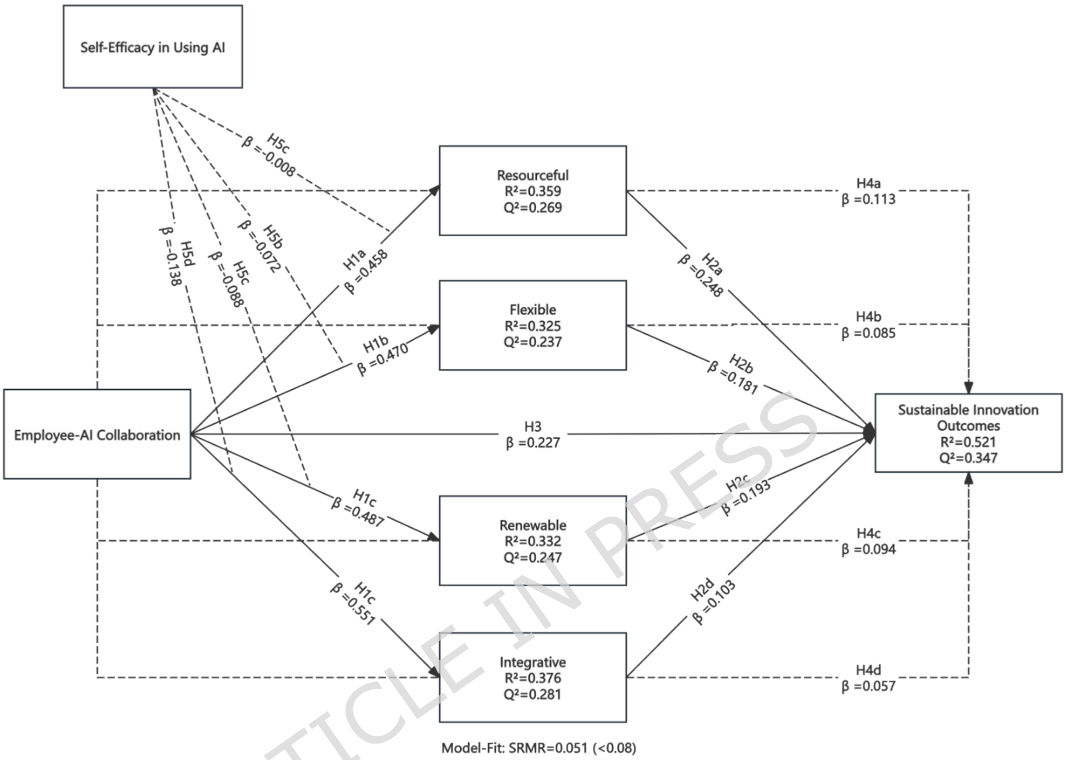

Figure 2. Structural model assessment results

Hypothesis Testing

Table 5 presents the results of the structural model assessment. All hypothesized direct relationships were supported. Specifically, EAC significantly enhanced all four SC dimensions (H1a–H1d: $\beta = 0.458$–0.551, $p < 0.001$), which in turn positively influenced SIO (H2a–H2d: $\beta = 0.103$–0.248, $p < 0.05$). Notably, the direct effect of EAC on SIO was also significant (H3: $\beta = 0.227$, $p = 0.001$).

Regarding mediation, the indirect effects of EAC on SIO via the four SC dimensions were statistically significant, supporting H4a–H4d. Crucially, since the direct effect of EAC on SIO (H3) remained significant in the presence of the mediators, it is concluded that the SC dimensions play a partial mediating role (specifically, complementary mediation) rather than full mediation [113].

In terms of moderation, only H5d was supported: SEUA negatively moderated the relationship between EAC and the Integrative dimension (β = -0.138, p = 0.004). This indicates that higher SEUA dampens the positive influence of EAC on integrative capacity, a finding discussed further below. The remaining interaction effects were nonsignificant (H5a–H5c).

Table 5. Hypothesis Testing Results

Hypothesis	**Path**	**Beta**	**t-value**	**p-value**	**95% CI**	**Result**
Direct Effects						
H1a	EAC → RES	0.458	9.879	0.000	[0.366, 0.545]	Supported
H1b	EAC → FLE	0.470	10.223	0.000	[0.378, 0.556]	Supported
H1c	EAC → REN	0.487	10.435	0.000	[0.397, 0.578]	Supported
H1d	EAC → INT	0.551	13.243	0.000	[0.466, 0.630]	Supported
H2a	RES → SIO	0.248	4.664	0.000	[0.143, 0.355]	Supported
H2b	FLE → SIO	0.181	3.545	0.000	[0.080, 0.283]	Supported
H2c	REN → SIO	0.193	3.877	0.000	[0.097, 0.289]	Supported
H2d	INT → SIO	0.103	2.043	0.041	[0.002, 0.200]	Supported
H3	EAC → SIO	0.227	3.479	0.001	[0.102, 0.353]	Supported
Mediation Effects						
H4a	EAC → RES → SIO	0.113	4.199	0.000	[0.064, 0.170]	Supported
H4b	EAC → FLE → SIO	0.085	3.473	0.001	[0.039, 0.134]	Supported
H4c	EAC → REN → SIO	0.094	3.483	0.001	[0.045, 0.150]	Supported
H4d	EAC → INT → SIO	0.057	1.984	0.047	[0.001, 0.114]	Supported
Moderation Effects						

H5a	SEUA x EAC → RES	-0.008	0.170	0.865	[-0.106, 0.091]	Not Supported
H5b	SEUA x EAC → FLE	0.072	1.560	0.119	[-0.017, 0.160]	Not Supported
H5c	SEUA x EAC → REN	0.088	1.696	0.090	[-0.014, 0.191]	Not Supported
H5d	SEUA x EAC → INT	-0.138	2.866	0.004	[-0.235, -0.044]	Supported

Slope Analysis

Figure 3 illustrates the moderating effect of SEUA on the relationship between EAC and the Integrative dimension of SC. The plot demonstrates that as SEUA increases from low (-1 SD) to high (+1 SD), the positive slope of the relationship between EAC and Integrative capacity decreases, confirming the negative moderation effect. This unexpected pattern will be further explored in the discussion section.

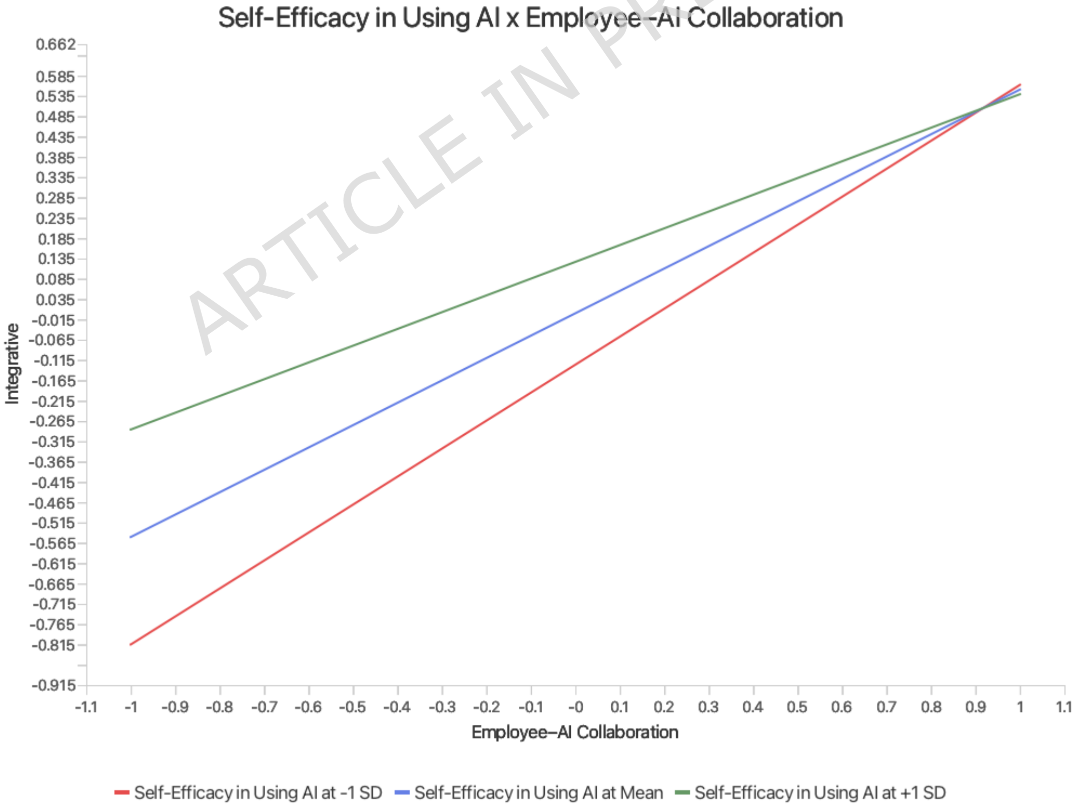

Figure 3. Moderating Effect of SEUA on the Relationship between EAC and INT

Alternative Model Analysis

To address potential reverse causality inherent in cross-sectional designs, the study tested an alternative model specifying SIO as an antecedent of the four SC dimensions, following structural model assessment guidelines [98,114]. Results revealed that although all paths in the alternative model reached significance, the hypothesized model demonstrated substantially stronger explanatory power for the focal dependent variable SIO (R^2 = 0.521) compared to the alternative model (R^2 = 0.384), a difference of 13.7 percentage points. Meanwhile, the alternative model yielded higher R^2 values for all SC dimensions, suggesting that innovation achievements also contribute to career sustainability. However, the gap in explanatory power for SIO was considerably larger than that for SC dimensions, indicating that the pathway from career sustainability to innovation outcomes remains the dominant direction. Overall, the superior explanatory power for SIO in the hypothesized model provides robust support for our proposed causal direction.

Discussion

This study confirms EAC significantly enhances all four SC dimensions: Resourceful, Flexible, Renewable, and Integrative. While prior research established the general link between EAC and SC [21] and theoretically proposed that AI creates opportunities for career flexibility [28], the study extends this line of inquiry by empirically demonstrating how EAC differentially enhances each of the four SC dimensions. Results also validate the human-machine complementary perspective where AI improves task efficiency and career capabilities [122]. Unlike concerns that AI convenience reduces effort [123,124], the findings emphasize AI's augmenting effect on career adaptability. This difference stems from different research foci: previous work examined immediate effort while this study addresses long-term capability development. Per COR theory's reinvestment principle, AI-released resources are strategically invested in skill renewal and opportunity exploration rather than wasted.

Second, this study finds that the four SC dimensions positively predict SIO and constitute significant mediating paths between EAC and SIO. Prior research has demonstrated direct associations between SC and innovative work behavior [125,126]. The study extends these findings in two ways: first, by identifying SC as the mediating mechanism through which EAC translates into innovation outcomes, revealing the transformation pathway that prior direct-effect studies did not examine; second, by shifting the outcome from general innovative work behavior to SIO, namely successful implementation and sustained organizational adoption of innovation, a perspective that has received limited attention in prior research [19,31]. These findings provide empirical support for COR theory's resource investment principle in AI-enabled contexts [36,50,127]: employees who accumulate career resources through AI collaboration possess the material foundation, psychological safety, and cognitive capabilities necessary for successful implementation and sustained application of innovation.

Third, this study reveals that EAC is also directly associated with SIO beyond the mediating pathway, suggesting that AI systems may help employees identify innovation opportunities, optimize solutions, and reduce implementation risks through data-driven decision support [29,90,92]. Notably, Zhang and Chin [126] found an inverted U-shaped relationship between career resourcefulness and innovative work behavior, where employees with abundant resources tend to adopt conservative strategies. In contrast, the results reveal a linear positive relationship between the Resourceful dimension and SIO, and the other three SC dimensions demonstrate consistent linear positive relationships as well. This pattern may reflect the unique characteristics of sustainable innovation outcomes as an outcome variable: employees who perceive higher career sustainability may be more motivated to engage in sustainable innovation because such innovation can in turn conserve their resources and reduce long-term workload [128]. The alternative model analysis provides additional insight: results suggest that SIO may also contribute to SC development, indicating a potential mutually reinforcing relationship between SC and SIO. Unlike general innovative work behavior that may be perceived as risky or resource-depleting, SIO emphasizes successful implementation and sustained application, which aligns with employees' interest in maintaining career stability, AI collaboration may further reinforce this pattern by reducing cognitive costs and innovation risks [129-131].

However, the most striking finding lies in the moderating role of SEUA. This study finds that SEUA only significantly and negatively moderates the relationship between EAC and the Integrative dimension, while no significant moderating effects were found on the other three dimensions. This finding contrasts with prior research that has predominantly documented positive effects of AI self-efficacy, where studies have shown that AI self-efficacy buffers workplace stressors and facilitates positive outcomes [17,35,132]. However, the results reveal a counterintuitive pattern: higher SEUA diminishes the positive effect of EAC on integrative capacity. This may be explained through attribution mechanisms [133,134]. The Integrative dimension involves cognitively intensive tasks such as synthesizing diverse information, critical evaluation, and knowledge absorption, which are highly aligned with AI's information processing capabilities [135]. When employees possess high confidence in AI usage, they may attribute integrative task success to AI rather than to their own capability development [136], thereby reducing their perceived growth in this dimension.

Theoretical Implications

This study makes the following theoretical contributions to the literature on AI-enabled work, career sustainability, and sustainable innovation.

First, this study expands the application of COR theory in technology-enabled contexts by constructing a complete theoretical chain of AI collaboration, career sustainability, and sustainable innovation. Although existing research has explored the associations between EAC and SC [21,28,32], the mechanism by which career sustainability further relates to innovation outcomes remains unclear. Based on COR theory, this study positions the four dimensions of SC as resource transformation mechanisms linking EAC and SIO. Notably, unlike the inverted U-shaped relationship between career resource abundance and innovation in traditional contexts [126,137], this study finds that this relationship exhibits linear positive characteristics in AI collaboration contexts, suggesting that technological collaboration may be associated with altered decision logic of resource investment through reduced innovation risks. This provides new evidence for understanding the boundary conditions of the resource investment principle of COR theory in different technological contexts.

Second, this study reveals the dual-pathway mechanism linking EAC and innovation, enriching theoretical understanding of the multi-level effects of technology empowerment. Existing research mostly focuses on single-path associations between AI and performance or innovation, rarely examining mediating mechanisms and direct effects simultaneously [26,91,138]. This study finds that EAC is not only indirectly associated with innovation through the long-term capability development path of cultivating SC but also directly related to SIO by providing immediate intelligent support. This dual-pathway framework reveals the temporal dimension differences of technology empowerment: short-term intelligent assistance and long-term capability cultivation may work synergistically to jointly relate to innovation output. This provides a theoretical framework for understanding how AI collaboration operates across different time scales.

Third, this study advances the theorization process of sustainable innovation by focusing on SIO. Previous research mostly focused on the associations between career sustainability and general employee innovation behavior or intention, with less exploration of the mechanisms relating to sustainable innovation output [19,31]. This study extends the research perspective from the generation of innovation behavior to the implementation and sustained application of innovation outcomes, revealing how career sustainability may provide support for the long-term value of innovation. Moreover, the alternative model analysis in the study suggests that SIO may also contribute to SC development, indicating a potential mutually reinforcing relationship between sustainable careers and sustainable innovation outcomes. This provides a new perspective for understanding the theoretical linkage between individual-level and organizational-level sustainability.

Finally, this study reveals important boundary conditions of SCT in EAC contexts by discovering the selective negative moderating effect of SEUA. Existing research generally assumes based on SCT that technology self-efficacy is associated with positive outcomes, such as buffering workplace stressors and facilitating innovation [17,35,63,132], but this study finds that SEUA exhibits a negative moderating effect on the Integrative dimension. This counterintuitive finding challenges the traditional assumption that self-efficacy is universally beneficial, revealing that the effects of technology self-efficacy have task specificity, and expands the applicability boundaries of SCT in Employee-AI Collaboration contexts.

Practical Implications

This study explores career sustainability and innovation mechanisms in the context of AI collaboration, providing actionable practical implications at the individual, organizational, and policy levels.

At the individual level, employees should leverage AI-released time for professional learning, cross-domain exploration, and innovation projects, transforming efficiency gains into career development. When using AI for cognitive tasks like information integration, employees should regularly reflect on their independent capability development, reviewing performance on similar tasks and summarizing analytical methods learned from AI assistance [139,140].

At the organizational level, when implementing AI tools, managers should not only focus on short-term efficiency improvements but also incorporate employee SC development into the AI project evaluation system [141]. Specifically, HR departments can regularly measure employee career resource abundance, work flexibility, skill renewal opportunities, and information integration capabilities after AI tool introduction, using these indicators as key performance metrics for AI empowerment effects. Organizations should design human-AI collaboration capability development programs that clearly distinguish which tasks are suitable for AI and which capabilities need continuous employee development, such as helping employees establish reasonable task allocation awareness and capability development plans through workshops [75].

At the policy level, this study finds significant associations among AI collaboration, employee SC development, and innovation outcomes, suggesting that policymakers need to pay attention to the potential associations between technology application and the long-term development capabilities of the workforce when promoting AI technology adoption. Policy level considerations could include incorporating employee career development indicators into the evaluation system of AI application effects, rather than focusing solely on productivity indicators. Additionally, when designing AI-related courses, vocational training and re-education programs could consider helping learners establish correct perceptions of their own capability development beyond technical skills training, avoiding overdependence on technological tools while neglecting the cultivation of their own capabilities [142,143].

Limitations and Future Recommendations

This study has the following limitations. First, the cross-sectional design limits the ability to make causal inferences. Second, complete reliance on self-reports may introduce common method bias. Third, the sample predominantly consists of highly educated young employees with high AI usage frequency, which may affect the generalizability of results. Fourth, the research context mainly comes from Chinese enterprise environments, and cultural and institutional differences may affect cross-cultural applicability. Finally, the attribution mechanism explanation for the negative moderating effect of SEUA has not been directly verified.

Future research can improve in the following directions. First, adopting a three-wave time-lagged design, such as measuring baseline career capabilities and SEUA before AI tool introduction, measuring AI collaboration levels and career sustainability 3 months after introduction, and measuring innovation outcomes after 6 months, to better establish temporal precedence and strengthen causal inference. Second, combining objective data validation, such as obtaining employee skill training records and work flexibility arrangement records from enterprise human resource systems, or obtaining innovation project implementation data from project management systems, for triangulation with self-reports. Third, purposively recruiting low digital literacy groups and older employees, through offline questionnaires or cooperation with traditional industry enterprises, to test the robustness of the model across different digital capability groups. Fourth, replicating the study in individualistic cultural contexts to examine whether cultural differences exist in the moderating effect of SEUA. Finally, directly measuring employee attribution tendencies for AI collaboration success and measuring actual information integration capability performance to verify the attribution mechanism hypothesis.

Conclusion

This study investigates how EAC influences SIO through SC capacities and the moderating effect of SEUA, addressing three research gaps in the literature. First, SC is identified as the resource transformation mechanism linking AI collaboration and innovation outcomes, revealing how AI-released resources translate into career capability development and subsequently into innovation. Second, it's found that SEUA exhibits a selective negative moderating effect on the Integrative dimension, suggesting potential attribution bias in technology empowerment processes. Third, by focusing on SIO rather than general innovative work behavior, the study captures successful implementation and sustained organizational adoption, and further reveals a potential mutually reinforcing relationship between SC and SIO. These findings extend COR theory's resource investment principle to AI-enabled contexts, reveal dual-pathway mechanisms linking EAC and innovation, and identify boundary conditions of SCT in human-AI collaboration. Practically, organizations should incorporate career sustainability development into AI implementation strategies and help employees maintain independent capability growth alongside AI usage. Given the counterintuitive finding on SEUA, particular attention should be paid to ensuring employees recognize their own capability development rather than over-attributing success to AI assistance. Future research should employ longitudinal designs to validate causal relationships and examine cross-cultural applicability.

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Declarations

Declaration of conflicting interests

The authors declare that there is no conflict of interest.

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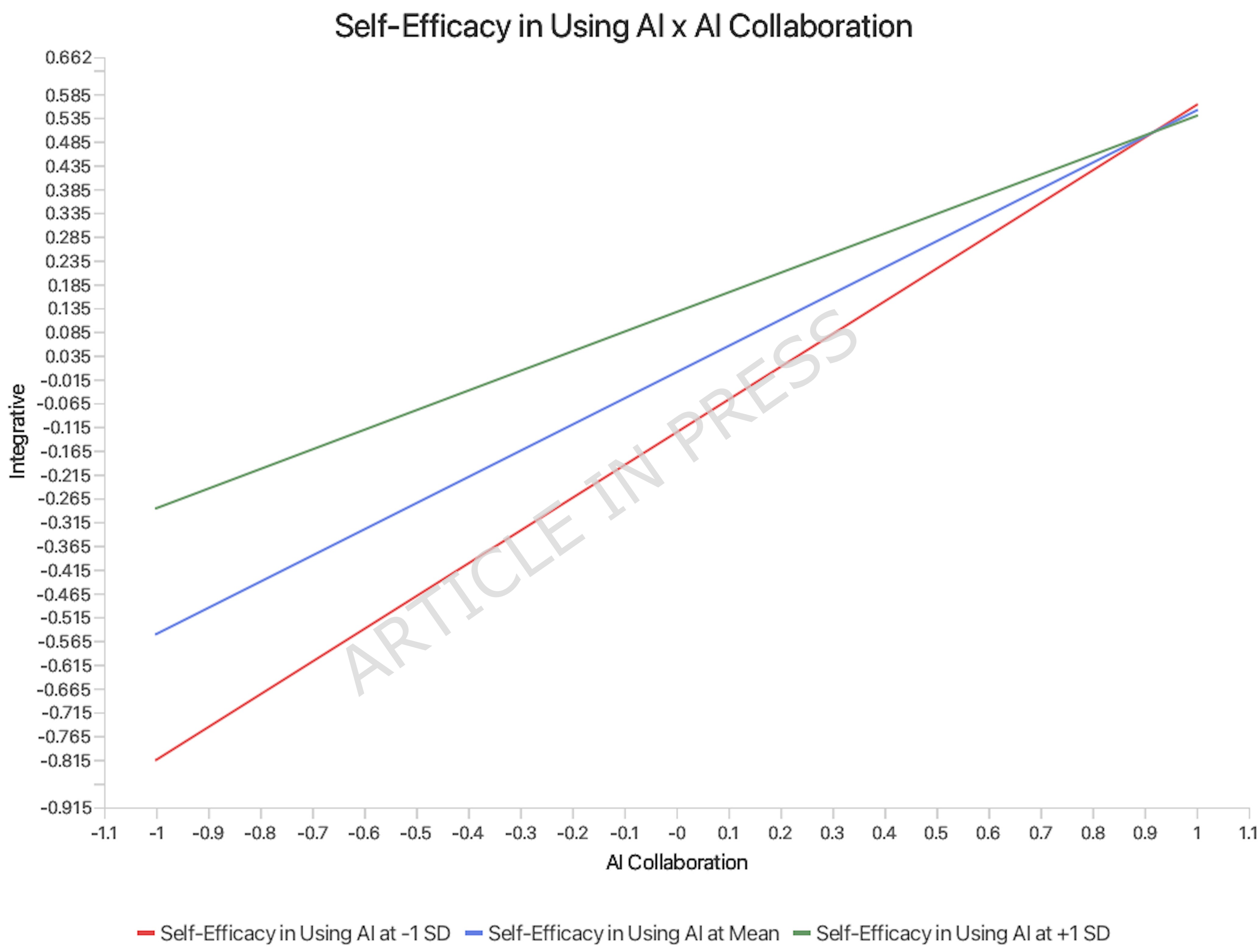
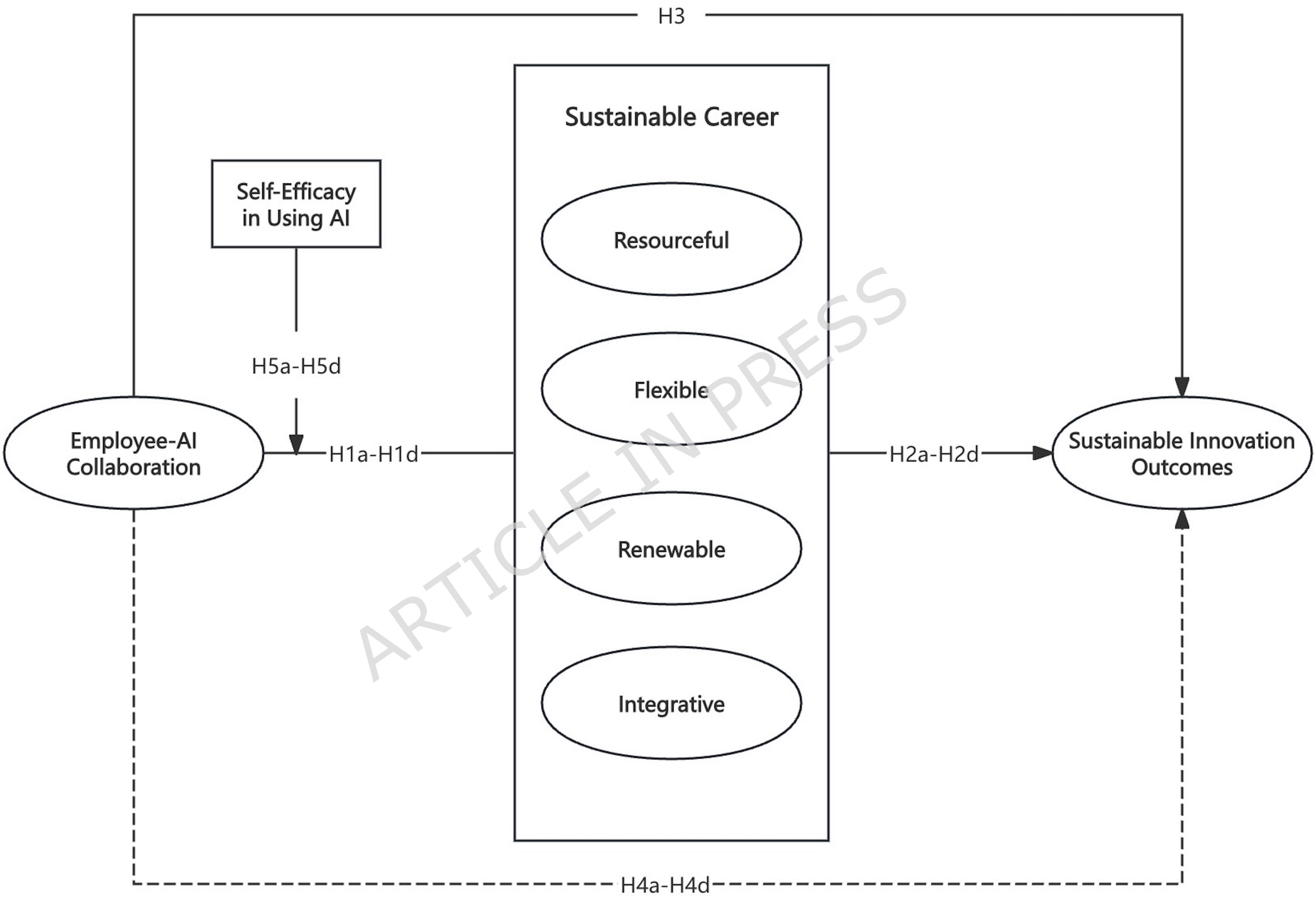
Data availability

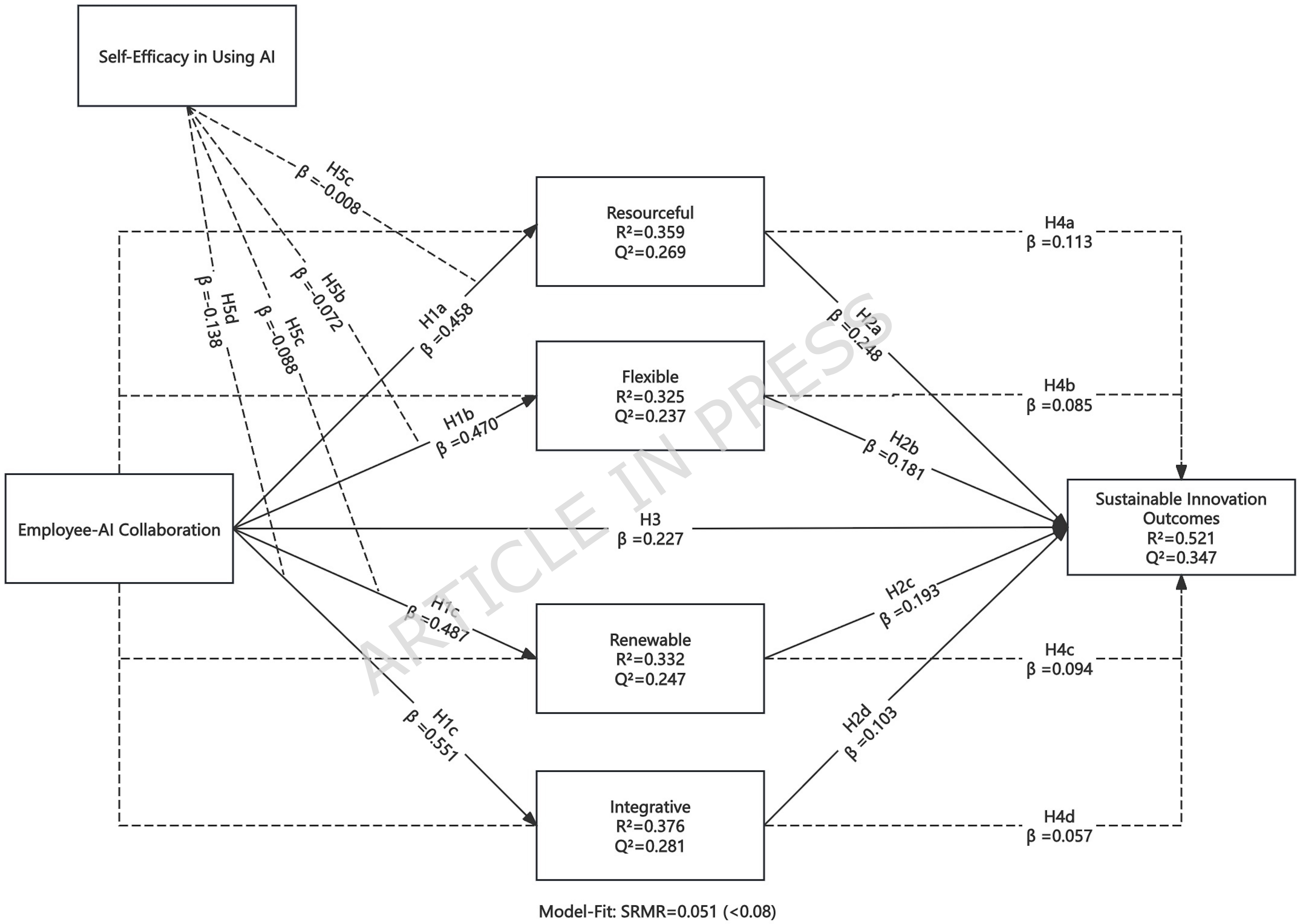
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Author Contributions

ZLW— Conceptualization, Methodology, Data Curation, Formal Analysis, and Writing—Original Draft.
LXZ —Supervision, Conceptualization, Validation, Investigation, and Writing—Review & Editing.
HG — Data Curation, Resources, and Writing—Review & Editing.
WMHWH—Methodology, Data Curation, and Conceptualization
SHMA—Validation and Data Curation.
All authors have read and agreed to the published version of the manuscript.


Self-Efficacy in Using AI x AI Collaboration
Integrative
0.662
0.585
0.535
0.485
0.435
0.385
0.335
0.285
0.235
0.185
0.135
0.085
0.035
-0.015
-0.065
-0.115
-0.165
-0.215
-0.265
-0.315
-0.365
-0.415
-0.465
-0.515
-0.565
-0.615
-0.665
-0.715
-0.765
-0.815
-0.915
-1.1
-1
-0.9
-0.8
-0.7
-0.6
-0.5
-0.4
-0.3
-0.2
-0.1
-0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
1.1
AI Collaboration
Self-Efficacy in Using AI at -1 SD
Self-Efficacy in Using AI at Mean
Self-Efficacy in Using AI at +1 SD


H3
Sustainable Career
Self-Efficacy in Using AI
Resourceful
H5a-H5d
Flexible
Employee-AI Collaboration
H1a-H1d
H2a-H2d
Sustainable Innovation Outcomes
Renewable
Integrative
H4a-H4d


Self-Efficacy in Using AI
H5c
β =-0.008
H5b
β =-0.072
H5c
β =-0.088
H5d
β =-0.138
Resourceful
R²=0.359
Q²=0.269
Flexible
R²=0.325
Q²=0.237
Renewable
R²=0.332
Q²=0.247
Integrative
R²=0.376
Q²=0.281
Employee-AI Collaboration
H1a
β =0.458
H1b
β =0.470
H1c
β =0.487
H1c
β =0.551
H3
β =0.227
H2a
β =0.248
H2b
β =0.181
H2c
β =0.193
H2d
β =0.103
H4a
β =0.113
H4b
β =0.085
H4c
β =0.094
H4d
β =0.057
Sustainable Innovation Outcomes
R²=0.521
Q²=0.347
Model-Fit: SRMR=0.051 (<0.08)