

Human–AI Collaboration and Employee Service Innovation in Tourism Services: The Mediating Role of AI-Enabled Knowledge Integration and the Moderating Role of Organisational Support

Ambili G. R. Kuniyel¹, Dr. N. Uma Devi²

¹Ph.D. Research Scholar, Bharathiar School of Management and Entrepreneur Development (BSMED),
Bharathiar University

²Associate Professor, Bharathiar School of Management and Entrepreneur Development (BSMED),
Bharathiar University

Abstract

Artificial intelligence (AI) is increasingly embedded in tourism service work, yet the presence or use of AI does not by itself explain how employees convert machine-generated information into innovative service responses. This study develops and tests a conditional-process model in which Human–AI Collaboration (HAIC) is associated with Employee Service Innovation Behaviour (SIB) through AI-enabled Knowledge Integration (AIKI), while Organisational Support for Human–AI Collaboration (AISUP) conditions the HAIC–AIKI relationship. Drawing on dynamic capabilities theory and sociotechnical systems theory, the study conceptualises employee–AI collaboration as an enacted work process and AI-enabled knowledge integration as a micro-level transformation mechanism through which AI information is evaluated, combined with professional and customer knowledge, and translated into service action. The empirical analysis uses 450 complete employee records containing 19 focal indicators measured on five-point Likert scales. The four-factor measurement model showed very good fit, $\chi^2(146) = 166.07$, $p = 0.122$, CFI = 0.997, TLI = 0.996, RMSEA = 0.017, and SRMR = 0.025. HAIC was positively associated with AIKI ($B = 0.558$, $p < 0.001$), AIKI was positively associated with SIB ($B = 0.422$, $p < 0.001$), and HAIC remained positively associated with SIB ($B = 0.320$, $p < 0.001$). The HAIC $\times$ AISUP interaction was positive and statistically significant ($B = 0.122$, SE = 0.060, $p = 0.044$). A 5,000-resample bootstrap indicated a positive indirect association through AIKI ($B = 0.236$, 95% CI [0.184, 0.288]) and a significant index of moderated mediation ($B = 0.051$, 95% CI [0.008, 0.097]). Conditional indirect effects were 0.201 at low AISUP and 0.270 at high AISUP. The findings position AI-enabled knowledge integration as the central conversion mechanism linking employee–AI collaboration with service innovation and show that organisational support changes the strength of this conversion process. Given the cross-sectional, single-source design, the results are interpreted as associational rather than causal.

Keywords: human–AI collaboration; AI-enabled knowledge integration; employee service innovation behaviour; organisational support; tourism services; dynamic capabilities; sociotechnical systems; conditional process analysis

1. Introduction

Artificial intelligence (AI) is reshaping service work by introducing recommendation systems, predictive analytics, conversational agents, generative systems, intelligent scheduling, decision-support tools and service robots into activities previously dependent primarily on employee judgement. The strategic question has therefore moved beyond whether organisations adopt AI towards how employees and organisations organise work so that machine-generated information complements professional expertise, contextual judgement and customer knowledge. This question is particularly important in tourism services because service value is created through interaction, interpretation and adaptation close to the customer. Employees encounter service failures, detect emerging needs, improvise responses and convert experiential knowledge into changes in service delivery.

Recent research reinforces the need to move beyond a simple adoption perspective. Kumawat et al. (2025) systematically reviewed 80 empirical studies focused on hospitality employees and found a rapidly expanding but fragmented literature spanning antecedents, mediators, moderators and outcomes of employee–AI interaction. Wu et al. (2025), using two-wave data from 475 hotel employees, reported positive associations between human–AI collaboration and work engagement through quality-of-work-life mechanisms. By contrast, Li et al. (2025) found that AI usage can reduce employee–customer information exchange and thereby constrain employee service innovation, although job autonomy can mitigate this pathway. Li and Ding (2026) further demonstrated that the consequences of employee–AI collaboration vary by AI type, with mechanical AI associated with innovation deterioration through identity-related processes and thinking and feeling AI associated with reinforcement. Together, these studies suggest that AI does not have a uniform innovation effect.

This study addresses that problem by positioning Human–AI Collaboration (HAIC) as an enacted employee–technology work process rather than as a proxy for adoption, frequency of use or generic AI capability. The operationalisation is grounded in the five-item employee–AI collaboration measure developed by Kong et al. (2023), which conceptualises employee–AI collaboration as proactive behaviour. The present model then asks what happens to the information generated through that collaboration. We propose AI-enabled Knowledge Integration (AIKI) as the central mechanism: employees critically evaluate AI outputs, combine them with professional and customer knowledge, and translate them into contextually appropriate service improvements.

The second theoretical move concerns organisational context. AI-enabled knowledge integration does not occur in a social vacuum. Resources, managerial encouragement, training and guidance can provide employees with the competence, authority and legitimacy to question, adapt and experiment with AI outputs. This proposition is consistent with sociotechnical systems reasoning, which treats technological and social arrangements as interdependent components of work-system design (Makarius et al., 2020).

The study therefore examines a conditional process in which HAIC is associated with AIKI, AIKI is associated with Employee Service Innovation Behaviour (SIB), and Organisational Support for Human–AI Collaboration (AISUP) moderates the HAIC–AIKI association. The contribution is consequently narrower and more defensible than a generic claim that AI collaboration produces innovation: the study specifies a knowledge-conversion mechanism and an organisational boundary condition.

Three research questions guide the study: (1) Is employee-level human–AI collaboration positively associated with AI-enabled knowledge integration? (2) Does AI-enabled knowledge integration account for part of the association between human–AI collaboration and employee service innovation behaviour?

and (3) Does organisational support strengthen the association between human–AI collaboration and AI-enabled knowledge integration and, consequently, the indirect association with service innovation?

2. Theoretical Background and Hypothesis Development

2.1 Human–AI collaboration as an enacted work relationship

AI adoption, AI use and human–AI collaboration describe different phenomena. Adoption refers primarily to an organisation's implementation of a technology; use refers to employees' interaction with that technology; collaboration refers to an interdependent work arrangement in which human and AI capabilities jointly participate in task execution and decision processes. Kong et al. (2023) conceptualised employee–AI collaboration as proactive behaviour and developed a five-item measure. The present study follows that behavioural interpretation.

HAIC is operationalised through employee reports of AI participation in decision making, forecasting or prediction, problem solving, information identification and evaluation, and recognition of problems, opportunities or risks. This formulation is important because it treats collaboration as an enacted work process rather than assuming that access to AI automatically creates collaboration.

H1. Human–AI Collaboration is positively associated with AI-enabled Knowledge Integration.

2.2 Dynamic capabilities as a micro foundational lens for human–AI collaboration

Dynamic capabilities theory explains how organisations purposefully renew and reconfigure resources and competences in changing environments (Teece et al., 1997; Teece, 2007). A potential level-of-analysis problem arises because the present constructs are measured at the employee level, whereas dynamic capabilities are generally theorised as organisational capabilities. A micro foundational perspective addresses this issue by examining how individual actions, social processes and structures provide lower-level mechanisms underlying organisational routines and capabilities (Felin et al., 2012).

Within the present model, HAIC represents an employee-level sensing and interpreting interface: employees encounter AI-generated signals, predictions and recommendations and decide how those outputs should be interpreted in relation to service problems and opportunities. AIKI represents the next micro-level process, in which machine-generated information is evaluated and combined with professional and customer knowledge. SIB represents the behavioural expression of this integrated knowledge through searching for, generating, promoting, planning and implementing new service solutions.

This framing does not claim that the present employee survey directly measures an organisational dynamic capability. Instead, the constructs represent plausible micro-level processes through which adaptive capacity can be enacted and potentially aggregated into organisational routines. This distinction is consistent with micro foundations research, which treats individuals, interactions and structures as lower-level components whose aggregation can contribute to higher-level capabilities (Felin et al., 2012; Helfat & Peteraf, 2015). The theoretical sequence is therefore: employee–AI collaboration → sensing and interpreting machine-generated information → knowledge integration → innovative service behaviour → potential contribution to organisational adaptation.

Recent hospitality research similarly portrays employee–AI interaction as a knowledge process. Si et al. (2026) describe employee–AI co-evolution in hospitality in terms of knowledge sourcing, internalisation and creation, suggesting that AI can become part of organisational knowledge development rather than merely a technical input. The present study complements that perspective by testing an employee-level knowledge-integration mechanism quantitatively.

2.3 AI-enabled knowledge integration and employee service innovation

Knowledge integration involves combining heterogeneous knowledge resources into actionable understanding. In tourism services, relevant knowledge includes customer information, professional experience, service standards, local context, organisational procedures and operational information. AI adds another information stream through prediction, pattern recognition, recommendation and generative output. However, machine-generated information becomes useful for service innovation only when employees evaluate its relevance, reconcile it with contextual knowledge and translate it into action.

AIKI is therefore defined as the employee's capability/behaviour of critically evaluating, combining and translating AI-generated information with professional, organisational and customer knowledge to produce contextually appropriate service action. This definition distinguishes AIKI from AI adoption, frequency of AI use, AI literacy, AI self-efficacy, knowledge sharing and generic knowledge integration.

H2. AI-enabled Knowledge Integration is positively associated with Employee Service Innovation Behaviour.

2.4 Human–AI collaboration and employee service innovation

HAIC can also be associated directly with service innovation because AI may reduce information-processing demands and expand employees' opportunity to search, compare, experiment and solve customer problems. Nevertheless, this is an augmentation proposition rather than a technology-deterministic claim. Recent evidence shows that AI can simultaneously support and constrain innovation depending on AI configuration, information exchange and work design (Li et al., 2025; Li & Ding, 2026).

H3. Human–AI Collaboration is positively associated with Employee Service Innovation Behaviour.

2.5 AI-enabled knowledge integration as a mediating mechanism

The central process proposition is that collaboration becomes innovation partly through knowledge integration. HAIC creates an employee–AI interface; AIKI captures the transformation of machine-generated information into integrated, contextually meaningful knowledge; and SIB captures the behavioural expression of that knowledge. The logic extends hospitality research linking knowledge sharing and service innovation (Hu et al., 2009) into an AI-mediated environment.

The proposed mediation is therefore not simply that AI is useful, but that employees' ability to evaluate and recombine AI information is part of the pathway through which collaboration is associated with innovative service behaviour.

H4. AI-enabled Knowledge Integration mediates the positive association between Human–AI Collaboration and Employee Service Innovation Behaviour.

2.6 Sociotechnical systems theory and organisational support as a boundary condition

Sociotechnical systems theory emphasises that technology is embedded in social structures, roles, relationships, skills and work processes rather than operating independently of them. In AI implementation, employees require more than technical access: they need socialisation, guidance and work arrangements that allow them to understand, challenge and appropriately incorporate AI outputs (Makarius et al., 2020).

AISUP captures four organisational conditions relevant to that process: resources, managerial encouragement, training and clear guidance. These conditions should matter specifically for the HAIC–AIKI relationship because collaboration provides access to AI-generated information, whereas support determines whether employees have the capability and organisational legitimacy to evaluate, contextualise and use that information. Without support, collaboration may remain a transactional interaction with a tool. With support, employees may be better positioned to exercise judgement, challenge erroneous

recommendations, experiment with alternative uses and connect AI outputs to customer and professional knowledge. AISUP is therefore theorised as a conversion condition rather than simply a general organisational resource.

H5. Organisational Support for Human–AI Collaboration positively moderates the relationship between Human–AI Collaboration and AI-enabled Knowledge Integration, such that the relationship is stronger when support is high.

If AISUP strengthens the first stage of the indirect pathway, the indirect association between HAIC and SIB through AIKI should vary as organisational support changes. Conditional-process analysis provides a formal test of this proposition (Preacher et al., 2007; Hayes, 2018).

H6. The indirect association between Human–AI Collaboration and Employee Service Innovation Behaviour through AI-enabled Knowledge Integration is stronger when Organisational Support for Human–AI Collaboration is high.

2.7 Research gap and contribution positioning

The broad relationship between AI and employee service innovation is no longer an unexplored question. Recent studies have examined human–AI collaboration and employee outcomes, AI usage and employee–customer information exchange, AI type and service innovation, explainable AI and frontline service innovation, responsible AI and service innovation, and employee–AI knowledge co-evolution (Kumawat et al., 2025; Li et al., 2025; Li & Ding, 2026; Li & Zong, 2026; Si et al., 2026; Xu et al., 2026).

The present contribution is consequently positioned at three levels. First, it distinguishes enacted collaboration from adoption or use. Second, it identifies AI-enabled knowledge integration as the transformation mechanism connecting collaboration with service innovation. Third, it treats organisational support as a sociotechnical boundary condition that changes the strength of the collaboration-to-knowledge conversion. The resulting proposition is that AI collaboration is associated with service innovation when employees can critically integrate machine-generated information with professional and customer knowledge within a supportive work environment.

3. Methodology

3.1 Research design and unit of analysis

The study uses a quantitative, cross-sectional employee survey design. The unit of analysis is the individual employee. The analytical dataset contains 450 unique respondent records and 19 focal indicators: five HAIC indicators, four AIKI indicators, six SIB indicators and four AISUP indicators. All focal indicators are measured on five-point Likert scales from 1 = strongly disagree to 5 = strongly agree. The workbook also contains demographic and organisational descriptors.

3.2 Research Context, Population, Sampling and Data Collection

3.2.1 Study Setting

The study was conducted in Kerala, India. Kerala was selected because its tourism economy encompasses diverse service activities, providing an appropriate setting for examining Human–AI Collaboration across heterogeneous tourism work environments rather than within a single hospitality subsector. The state government's tourism documentation identifies tourism as a major employment-generating sector and reports substantial employment associated with tourism-related activities (Kerala State Planning Board, 2016, 2021).

The study covered accommodation, food and beverage, travel and tours, transportation, adventure/other tourism services, and cultural/heritage services, consistent with the sectors represented in the final dataset.

3.2.2 Target Population and Sampling Frame

The target population comprised employees aged 18 years or above working in tourism-oriented service organisations in Kerala across the six study sectors, whose roles provided sufficient exposure to tourism-service operations to report meaningfully on Human–AI Collaboration and related workplace practices. Kerala's tourism sector is a major employment-generating component of the state economy, with official state planning documents reporting substantial tourism-related employment (Kerala State Planning Board, 2016, 2021). Accordingly, no precise employee-level population count was assumed for the present study. Because a comprehensive employee-level sampling list covering all eligible tourism workers in Kerala was not available, the sampling frame comprised identifiable tourism-service establishments and their eligible employees within the defined sectors. This establishment-based frame was appropriate because tourism employment is distributed across numerous types and sizes of service organisations rather than concentrated in a single industry category.

3.2.3 Sampling Technique and Sample Size

A multistage stratified sampling approach was used. First, Kerala was defined as the geographical population boundary. Second, tourism-service establishments were organised into the six study sectors. Third, eligible employees within the selected establishments constituted the final sampling units. Stratification was used to ensure coverage of the heterogeneous tourism-service environment rather than allowing the sample to be dominated by one subsector.

The minimum sample requirement was assessed using Cochran's formula for a large population (Cochran, 1977):

$$n_0 = \frac{Z^2 pq}{e^2}$$

Using a 95% confidence level ($Z = 1.96$), maximum variability ($p = 0.50$, $q = 0.50$) and 5% precision ($e = 0.05$):

$$n_0 = \frac{(1.96)^2 (0.50)(0.50)}{(0.05)^2} = 384.16$$

Thus, approximately 384 completed responses represent the minimum benchmark, with the exact value conventionally rounded upward to 385 for whole respondents. The final analytical sample of 450 complete responses exceeded this benchmark by 65.84 cases (17.1%). At $N = 450$, the corresponding approximate 95% margin of error under the same maximum-variability assumption is ± 4.62 percentage points.

The achieved sample was also appropriate for the study's analytical model, which comprised 19 observed indicators across four constructs, followed by item-level CFA and composite-score conditional-process analysis. The dataset contained 450 unique records with complete responses on all focal indicators, and the conditional-process analysis used 5,000 bootstrap resamples.

3.2.4 Eligibility Criteria

Participants were eligible if they were adults employed in a tourism-service organisation in Kerala, worked within one of the six defined tourism-service sectors, understood the questionnaire and voluntarily agreed to participate. Responses were retained when eligibility requirements were satisfied and all 19 focal indicators were completed.

Responses were excluded when participants were outside the target population or when responses were duplicated, incomplete or invalid. The final dataset comprised 450 unique and complete records, with all focal-item responses within the prescribed five-point scale.

3.2.5 Recruitment and Data Collection

Eligible employees were approached through tourism-service establishments represented within the sampling frame and invited to complete the structured questionnaire. Participants received information concerning the study purpose and voluntary nature of participation before responding. Data collection was conducted from March 2024 to March 2026. The final analytical dataset comprised 450 usable responses.

3.2.6 Confidentiality and Data Protection

Participation was voluntary, and responses were treated confidentially and analysed in aggregate form. The analytical dataset contained no respondent names or direct identifiers, and the 450 records were unique. Access to the research data was restricted to the research purposes of the study, with individual responses not reported separately.

3.3 Respondent profile

Table 1. Respondent profile of the analytical sample (N = 450).

Variable	Category	N	%
Gender	Male	225	50.0
Gender	Female	214	47.6
Gender	Other/Prefer not to say	11	2.4
Age	18–25	78	17.3
Age	26–35	139	30.9
Age	36–45	117	26.0
Age	46–55	95	21.1
Age	56+	21	4.7
Education	Bachelor's	205	45.6
Education	Master's	158	35.1
Education	Diploma	65	14.4
Education	Doctorate/Other	22	4.9
Experience	<3 years	85	18.9
Experience	3–5 years	105	23.3
Experience	6–10 years	128	28.4
Experience	11–15 years	85	18.9
Experience	>15 years	47	10.4
Job level	Frontline/Operational	234	52.0
Job level	Supervisory	88	19.6
Job level	Managerial	107	23.8
Job level	Senior management	21	4.7
Organisation type	Independent	192	42.7
Organisation type	Chain/Branded	169	37.6
Organisation type	Group/Corporate	89	19.8
Tourism activity	Accommodation	139	30.9

Tourism activity	Food & Beverage	109	24.2
Tourism activity	Travel/Tours	89	19.8
Tourism activity	Transportation	39	8.7
Tourism activity	Adventure/Other	38	8.4
Tourism activity	Cultural/Heritage	36	8.0

Source: Authors' analysis of the survey dataset.

Note. Percentages are based on N = 450. The sample is heterogeneous across tourism activity, organisational form, job level and demographic characteristics.

3.4 Measurement and construct operationalisation

Table 2. Construct operationalisation and measurement provenance.

Construct	Items	Measurement provenance	Scale
Human–AI Collaboration (HAIC)	5	Adapted from Kong et al. (2023), retaining the five employee–AI collaboration work processes	1–5 Likert
AI-enabled Knowledge Integration (AIKI)	4	Study-developed contextual measure focused on critical evaluation and integration of AI, professional and customer knowledge	1–5 Likert
Employee Service Innovation Behaviour (SIB)	6	Service-specific adaptation of the innovative-work-behaviour tradition of Scott and Bruce (1994)	1–5 Likert
Organisational Support for HAIC (AISUP)	4	Study-developed contextual measure covering resources, managerial encouragement, training and guidance	1–5 Likert

Source: Authors' compilation based on Kong et al. (2023) and the study's contextualised measures.

HAIC items assess AI participation in decision making, forecasting/prediction, problem solving, information identification/evaluation, and recognition of problems, opportunities or risks. SIB items cover searching for new methods, generating ideas, promoting ideas, planning implementation, seeking resources and introducing new approaches to customer or service problems.

AIKI is deliberately treated as a study-developed measure. Its four items assess combining AI-generated information with professional knowledge, critically evaluating AI outputs before integration, integrating AI insights with customer knowledge, and translating AI-generated information into contextually appropriate service improvements. AISUP captures resources, managerial encouragement, training and clear guidance for human–AI collaboration.

3.5 Data screening and analytical procedure

All 450 respondent identifiers are unique. No missing observations occur on the 19 focal indicators, and all focal item responses fall within the intended 1–5 range. Composite scores were calculated as arithmetic means of their respective indicators. Internal consistency was assessed using Cronbach's alpha.

The item-level confirmatory factor analysis (CFA) was estimated using maximum likelihood in IBM SPSS Amos. Standardised loadings, composite reliability (CR), average variance extracted (AVE), latent

correlations and HTMT ratios were examined. For the conditional-process analysis, composite scores were analysed using IBM SPSS Statistics with the PROCESS macro. HAIC and AISUP were mean-centred and their product were entered as the interaction term predicting AIKI. SIB was regressed on HAIC, AIKI and AISUP. Mediation and conditional indirect effects were evaluated using 5,000 nonparametric bootstrap resamples. The index of moderated mediation was estimated from the interaction coefficient in the mediator equation multiplied by the AIKI-to-SIB coefficient.

Model-fit statistics reported in this article are from the actual item-level CFA. The structural analysis is based on composite scores. Accordingly, the study is described as CFA followed by composite-score regression and bootstrapped conditional-process analysis, not as a full latent-variable SEM.

3.6 Common-method variance and causal inference

All focal variables are employee-reported and measured within the same cross-sectional dataset. Common-method variance is therefore a plausible alternative explanation for part of the observed covariance. The four-factor CFA is substantially better fitting than a one-factor model, which provides evidence against a single-factor representation but does not establish that common-method variance is absent. This distinction is consistent with Podsakoff et al. (2003), who emphasise the importance of procedural and statistical remedies.

The cross-sectional design also does not establish temporal precedence. Accordingly, the structural interpretation is explanatory and associational. Future research should measure HAIC and AISUP at Time 1, AIKI at Time 2, and SIB at Time 3, with supervisor-rated SIB where feasible.

3.7 Sample-size justification and sensitivity

The analytical sample of 450 is substantial for the reported measurement model and conditional-process analysis, but sample-size adequacy should not be justified by a simple observations-per-parameter rule. Simulation evidence shows that SEM sample requirements depend on model complexity, loading magnitude, path strength, missingness and solution characteristics (Wolf et al., 2013).

A sensitivity calculation for the present interaction test indicates that, with $N = 450$ and one degree of freedom for the incremental interaction effect, an incremental f^2 of approximately 0.018 corresponds to 80% power at $\alpha = 0.05$. The observed HAIC $\times$ AISUP interaction has an incremental f^2 of approximately 0.009, indicating a modest effect and reinforcing the need for replication in larger and/or longitudinal samples. This is a sensitivity analysis rather than an a priori power calculation and should not be represented as the latter.

4. Results

4.1 Data quality and descriptive statistics

The analytical file contains 450 unique records with complete responses on all 19 focal indicators. The composite means are close to the scale midpoint: HAIC $M = 2.998$ ($SD = 0.660$), AIKI $M = 2.999$ ($SD = 0.674$), SIB $M = 3.002$ ($SD = 0.654$), and AISUP $M = 2.995$ ($SD = 0.678$). No pronounced composite-level floor or ceiling pattern is evident.

4.2 Reliability and convergent validity

Table 3. Reliability and convergent validity of the measurement model.

Construct	Items	Standardised loading range	Cronbach's α	CR	AVE
HAIC	5	0.811–0.843	0.913	0.913	0.677
AIKI	4	0.803–0.838	0.887	0.887	0.662

SIB	6	0.787–0.854	0.926	0.926	0.677
AI SUP	4	0.795–0.890	0.890	0.890	0.669

Source: Authors' analysis of survey data.

All standardised factor loadings exceed 0.78. Cronbach's alpha ranges from 0.887 to 0.926, CR ranges from 0.887 to 0.926, and AVE ranges from 0.662 to 0.677. These results support internal consistency and convergent validity.

4.3 Measurement-model fit and discriminant validity

Table 4. Measurement-model fit and one-factor comparison.

Model	χ^2	Df	CFI	TLI	RMSEA	SRMR
Four-factor CFA	166.07	146	0.997	0.996	0.017	0.025
One-factor CFA	2582.16	153	0.577	0.527	0.188	0.198

Source: Authors' CFA results.

The four-factor measurement model demonstrated very good fit to the observed item covariance structure, $\chi^2(146) = 166.07$, $p = 0.122$, CFI = 0.997, TLI = 0.996, RMSEA = 0.017, and SRMR = .025. The one-factor model fit poorly, $\chi^2(153) = 2582.16$, CFI = 0.577, TLI = 0.527, RMSEA = 0.188, and SRMR = 0.198. The substantial deterioration supports the empirical distinctiveness of HAIC, AIKI, SIB and AISUP.

The reported three-factor alternatives also fit materially worse than the four-factor model.

Table 5. Alternative three-factor measurement models.

Alternative model	χ^2	Df	CFI	TLI	RMSEA
HAIC + AIKI combined	773.50	149	0.891	0.875	0.097
HAIC + SIB combined	1034.79	149	0.846	0.823	0.115
AIKI + SIB combined	676.68	149	0.908	0.895	0.089

Source: Authors' CFA results.

The strongest reported three-factor alternative, combining AIKI and SIB, produced CFI = 0.908 and RMSEA = 0.089, compared with CFI = 0.997 and RMSEA = 0.017 for the four-factor model. Taken together, the reported comparisons support the distinctiveness of the four-factor measurement specification.

Table 6. Heterotrait–monotrait (HTMT) ratios for discriminant validity.

Construct pair	HTMT
HAIC–AIKI	0.606
HAIC–SIB	0.607
AIKI–SIB	0.677
HAIC–AISUP	0.032
AIKI–AISUP	0.029
SIB–AISUP	0.176

Source: Authors' analysis of survey data.

All reported HTMT ratios are below 0.70, with a maximum of 0.677 for AIKI–SIB. The results support discriminant validity and are below the commonly used 0.85 HTMT threshold (Henseler et al., 2015). AISUP is notably distinct from HAIC and AIKI at the zero-order measurement level. This is not incompatible with moderation: a variable can have weak marginal association with two variables while changing the slope of their conditional relationship.

4.4 Structural relationships

Table 7. Structural relationships in the composite-score conditional-process model.

Path	B	SE	T	P	Conclusion
HAIC → AIKI	0.558	0.040	13.81	< 0.001	H1 supported in the hypothesised direction
AISUP → AIKI	0.020	0.039	0.50	0.618	AISUP main effect
HAIC × AISUP → AIKI	0.122	0.060	2.02	0.044	H5 supported in the hypothesised direction
AIKI → SIB	0.422	0.040	10.62	<0 .001	H2 supported in the hypothesised direction
HAIC → SIB	0.320	0.041	7.88	< 0.001	H3 supported in the hypothesised direction
AISUP → SIB	0.153	0.033	4.63	< 0.001	Additional direct estimate

Source: Authors' conditional-process analysis.

The mediator equation explains $R^2 = 0.303$ of AIKI variance, while the SIB equation explains $R^2 = 0.473$. HAIC was positively associated with AIKI ($B = 0.558$, $p < 0.001$), AIKI was positively associated with SIB ($B = 0.422$, $p < 0.001$), and HAIC remained positively associated with SIB after AIKI was included ($B = 0.320$, $p < 0.001$). AISUP also showed a positive direct association with SIB ($B = 0.153$, $p < 0.001$). Because AISUP is theorised primarily as a moderator, the AISUP → AIKI coefficient is best labelled the AISUP main effect rather than a “control estimate.”

The HAIC × AISUP interaction was positive and significant ($B = 0.122$, $SE = 0.060$, $t = 2.02$, $p = 0.044$). The simple slopes were approximately 0.475 at low AISUP (−1 SD), 0.558 at the mean, and 0.641 at high AISUP (+1 SD). A Johnson–Neyman calculation placed the lower significance boundary at approximately AISUP = 0.72; because the observed scale begins at 1, the HAIC slope was significant throughout the observed AISUP range while increasing in magnitude as support rose.

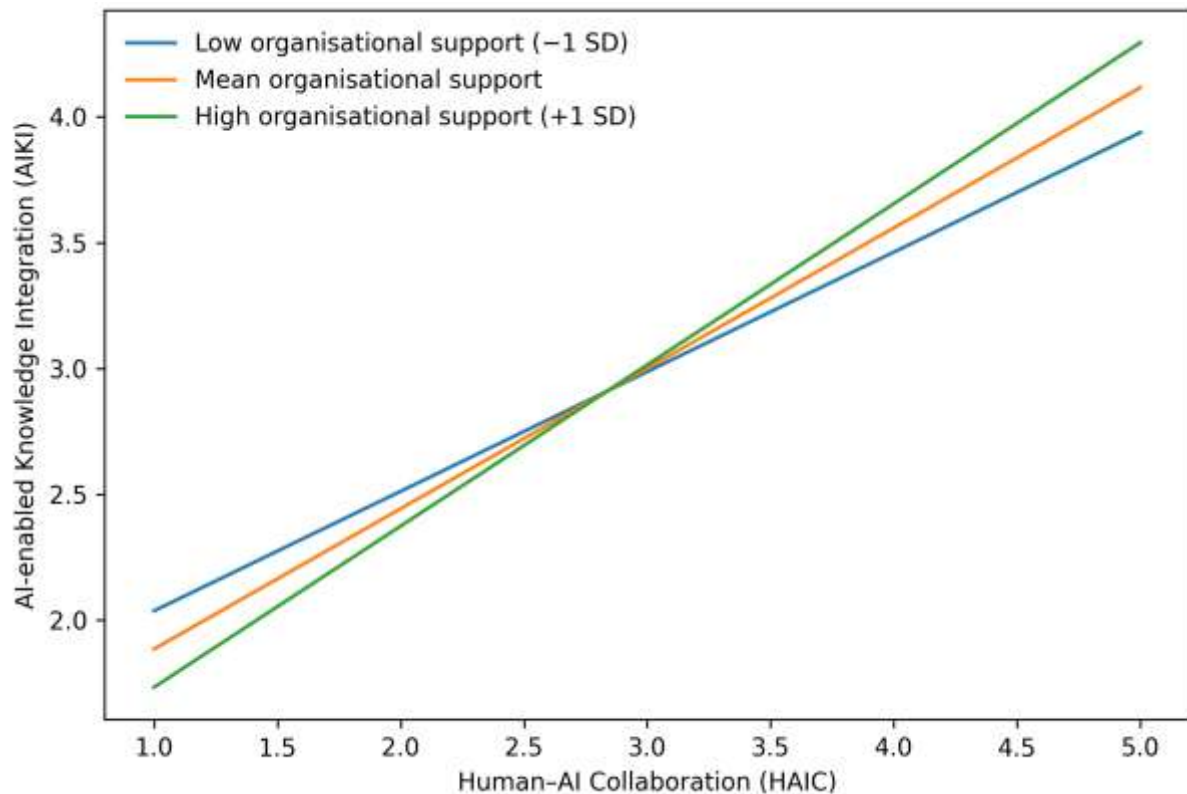


Figure 1. Simple-slope representation of the Human–AI Collaboration × Organisational Support interaction predicting AI-enabled Knowledge Integration.

Source: Authors' conditional-process analysis of the survey data.

4.5 Mediation and moderated mediation

Table 8. Mediation and moderated-mediation effects.

Effect	Estimate	Boot SE	95% CI
HAIC → AIKI → SIB	0.236	0.026	[0.184, 0.288]
Index of moderated mediation	0.051	0.023	[0.008, 0.097]
Conditional indirect: low AISUP (–1 SD)	0.201	0.027	[0.150, 0.256]
Conditional indirect: high AISUP (+1 SD)	0.270	0.033	[0.208, 0.340]

Source: Authors' bootstrapped conditional-process analysis (5,000 resamples).

The indirect association of HAIC with SIB through AIKI was 0.236, with a bootstrap 95% CI of [0.184, 0.288]. Because the interval excludes zero, H4 is supported. HAIC also retained a positive direct association with SIB, indicating complementary rather than full mediation within this cross-sectional conditional-process model.

The conditional indirect association was 0.201 at low AISUP and 0.270 at high AISUP. More importantly, the formal index of moderated mediation was .051, with a bootstrap 95% CI of [0.008, 0.097]. Because the interval excludes zero, H6 is supported. The conclusion therefore rests on the index of moderated mediation rather than merely on the difference between conditional indirect effects (Preacher et al., 2007; Hayes, 2018).

4.6 Hypothesis summary

Table 9. Summary of hypotheses and empirical results.

Hypothesis	Prediction	Result
H1	HAIC → AIKI positive	Supported
H2	AIKI → SIB positive	Supported
H3	HAIC → SIB positive	Supported
H4	AIKI mediates HAIC → SIB	Supported; complementary indirect and direct associations
H5	AISUP strengthens HAIC → AIKI	Supported
H6	Conditional indirect effect stronger at high AISUP	Supported; index significant

Source: Authors' analysis of survey data.

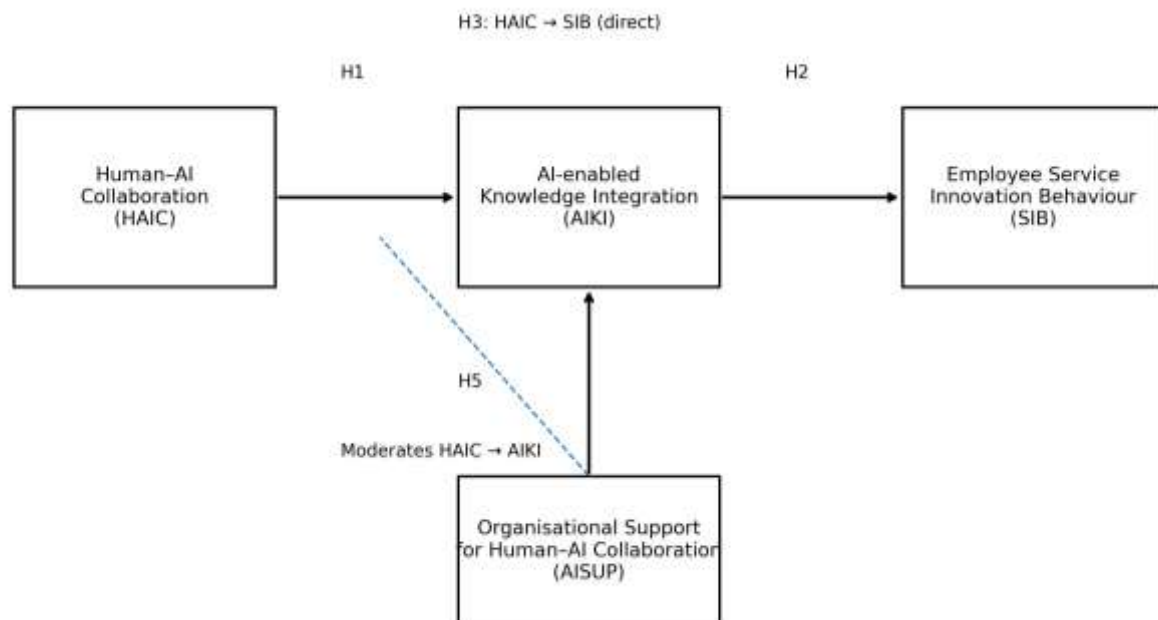


Figure 2. Conditional-process model tested in the study, linking Human–AI Collaboration, AI-enabled Knowledge Integration, Organisational Support for Human–AI Collaboration and Employee Service Innovation Behaviour.

Note. Structural paths were estimated using composite scores following item-level CFA.

Source: Authors' conceptualisation based on dynamic capabilities theory (Teece et al., 1997, 2007), micro foundations research (Felin et al., 2012), sociotechnical systems theory (Makarius et al., 2020), and conditional-process logic (Preacher et al., 2007; Hayes, 2018).

5. Discussion

5.1 Human–AI collaboration is associated with knowledge integration

The first finding is a strong positive association between HAIC and AIKI. Employees who report greater AI participation in decision making, forecasting, problem solving and information evaluation also report greater integration of AI-generated information with professional and customer knowledge. This extends the employee–AI collaboration literature by moving the question from whether employees collaborate with AI to what employees do with the information produced through that collaboration. The result is

consistent with the proactive behavioural interpretation of employee–AI collaboration developed by Kong et al. (2023).

5.2 Knowledge integration is the central transformation mechanism

The mediation result provides the central process contribution. AIKI accounts for part of the association between HAIC and SIB, while the direct HAIC–SIB association remains significant. This complementary pattern indicates that knowledge integration is an important pathway but not the only pathway connecting collaboration with innovative service behaviour. Other mechanisms may include cognitive resource redistribution, experimentation, solution search and changes in employees' perceived opportunity to improve service processes.

5.3 The finding complements rather than contradicts negative AI–innovation evidence

Li et al. (2025) show that AI usage can reduce employee–customer information exchange and thereby constrain service innovation. The present model does not contradict that possibility. Instead, it specifies a different conversion process: when employees critically evaluate and integrate AI outputs with customer and professional knowledge, AI-generated information may become an additional input to innovation. The theoretical message is therefore not “AI causes innovation”, but “AI-enabled collaboration is associated with innovation when knowledge integration is enacted within a supportive work system.”

5.4 Organisational support is a conversion condition

The interaction result indicates that organisational context changes the strength of the HAIC–AIKI association. The simple slopes rise from approximately 0.475 at low AISUP to 0.641 at high AISUP. This pattern is consistent with a sociotechnical interpretation: access to AI is insufficient if employees lack resources, training, managerial permission or clear guidance for evaluating and adapting AI outputs. Organisational support therefore operates as a conversion condition that affects whether employee–AI interaction becomes integrated knowledge.

5.5 Micro foundations of adaptive capability

The findings provide a cautious micro foundational extension of dynamic capabilities theory. HAIC can be interpreted as an employee-level process for sensing and interpreting machine-generated information; AIKI represents an integration process; and SIB represents an adaptive behavioural response. These are not equivalent to a firm-level dynamic capability. Rather, repeated and socially embedded employee processes can provide lower-level mechanisms through which organisations develop learning and reconfiguration capacity (Felin et al., 2012; Helfat & Peteraf, 2015).

5.6 AI heterogeneity and the limits of the present construct

Recent research indicates that AI effects are heterogeneous. Li and Ding (2026) show that different AI configurations can have different implications for service innovation, while Yang and Wu (2026) identify simultaneous autonomy-enhancing and insecurity-enhancing pathways of human–robot collaboration. The present questionnaire does not distinguish generative, predictive, conversational, robotic, recommendation or decision-support AI. The observed relationships should therefore be interpreted at the process level rather than as evidence that every type of AI produces the same pattern.

6. Theoretical Contributions

- Construct-level contribution: The study distinguishes enacted Human–AI Collaboration from broad AI adoption or use, moving the explanation toward the employee–technology interface.
- Process-level contribution: The study identifies AI-enabled Knowledge Integration as a distinct transformation mechanism connecting collaboration with service innovation.

- Boundary-condition contribution: The study identifies organisational support as a sociotechnical boundary condition that changes the strength of the collaboration-to-knowledge relationship.
- Micro foundational contribution: The study connects employee sensing, interpretation, integration and innovative action with dynamic-capability reasoning without conflating individual and organisational levels.

7. Implications for HRM and Tourism Management

- Develop AI collaboration capability, not only software proficiency. Training should cover critical evaluation of AI outputs, verification, escalation, human override, bias awareness, data protection and translation of AI information into customer-relevant action.
- Redesign jobs around complementarity. AI can support information processing while employees retain responsibility for contextual judgement, empathy, exception handling and customer-facing service design.
- Create organisational learning loops. Employees should capture successful AI applications, errors, customer reactions and service experiments so that individual learning becomes collective knowledge.
- Strengthen managerial support. Managers should legitimise responsible experimentation and constructive challenge of AI recommendations; the interaction result indicates that support is associated with the strength of the collaboration-to-knowledge pathway.
- Clarify accountability. HR policies should specify responsibility when AI recommendations are inaccurate, biased, inappropriate or inconsistent with service standards.
- Protect customer knowledge. AI implementation should not unintentionally remove employee–customer interaction that supplies contextual information required for service innovation.
- Measure innovation rather than adoption alone. AI governance dashboards should monitor implemented service improvements, learning from AI errors and customer-value outcomes, not merely frequency of AI use.
- Align recruitment and development with hybrid capabilities: critical digital judgement, learning agility, customer empathy, collaboration, problem solving and the ability to combine analytical and relational knowledge.

8. Limitations and Future Research

- Cross-sectional design. The proposed HAIC → AIKI → SIB sequence is theoretically motivated, but the data do not establish temporal precedence. A three-wave design should measure HAIC/AISUP at Time 1, AIKI at Time 2 and SIB at Time 3.
- Single-source measurement. All focal variables are employee-reported. Future studies should combine employee and supervisor ratings and introduce temporal or psychological separation to reduce common-method concerns.
- Study-developed measures. AIKI and AISUP show strong main-study psychometric properties, but independent content validation, cognitive pretesting, pilot testing and replication are required before these measures can be treated as broadly validated scales.
- AI heterogeneity. The questionnaire does not distinguish AI types. Future research should compare generative, predictive, conversational, robotic and decision-support systems and test whether the knowledge-integration mechanism varies by task and technology.

- Sample heterogeneity. The dataset spans six tourism activity categories. Future studies should test measurement invariance before comparing structural relationships across activity, organisational and demographic groups.
- Interaction magnitude. The interaction is statistically significant but modest; the sensitivity analysis indicates that replication with larger samples is warranted.

9. Conclusion

This study advances a process-oriented account of how employee–AI collaboration is associated with service innovation in tourism services. The central empirical pattern is HAIC → AIKI → SIB, with organisational support strengthening the first stage of that pathway. HAIC is positively associated with AIKI, AIKI is positively associated with SIB, HAIC retains a direct association with SIB, and the formal index of moderated mediation is positive. These findings position AI-enabled knowledge integration as the central conversion mechanism through which employees can turn machine-generated information into contextually meaningful service knowledge.

The theoretical implication is deliberately bounded. The study does not claim that an employee-level survey directly measures an organisational dynamic capability. Instead, it identifies employee-level sensing, interpretation, knowledge integration and innovative action as plausible micro-level mechanisms through which adaptive capacity can be enacted and potentially aggregated. The sociotechnical implication is similarly clear: technology and social arrangements must be designed together.

For tourism organisations, the practical message is to invest not only in AI technologies but also in collaboration capability, critical evaluation, training, managerial support, job design, accountability, learning systems and employee discretion. Future longitudinal, multisource and AI-type-specific research can determine how stable these associations are and how they vary across tourism contexts.

References

1. Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quinonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health*, 6, 149. <https://doi.org/10.3389/fpubh.2018.00149>
2. Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.
3. Felin, T., Foss, N. J., Heimeriks, K. H., & Madsen, T. L. (2012). Microfoundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies*, 49(8), 1351–1374. <https://doi.org/10.1111/j.1467-6486.2012.01052.x>
4. Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). Guilford Press.
5. Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal*, 36(6), 831–850. <https://doi.org/10.1002/smj.2247>
6. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
7. Hu, M. L. M., Horng, J. S., & Sun, Y. H. C. (2009). Hospitality teams: Knowledge sharing and service innovation performance. *Tourism Management*, 30(1), 41–50. <https://doi.org/10.1016/j.tourman.2008.04.009>

8. Kerala State Planning Board. (2016). Economic review 2016. <https://spb.kerala.gov.in/economic-review/ER2016/chapter09.php>
9. Kerala State Planning Board. (2021). Kerala development report: Initiatives, achievements, and challenges. <https://spb.kerala.gov.in/sites/default/files/2022-10/Kerala-Development-Report-2021.pdf>
10. Kong, H., Yin, Z., Baruch, Y., & Yuan, Y. (2023). The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation. *Journal of Vocational Behavior*, 146, 103928. <https://doi.org/10.1016/j.jvb.2023.103928>
11. Kumawat, E., Datta, A., Prentice, C., & Leung, R. (2025). Artificial intelligence through the lens of hospitality employees: A systematic review. *International Journal of Hospitality Management*, 124, 103986. <https://doi.org/10.1016/j.ijhm.2024.103986>
12. Li, J., & Ding, D. (2026). Reinforcement or deterioration? Unraveling how employee and AI collaboration impacts service innovation. *International Journal of Information Management*, 87, 103018. <https://doi.org/10.1016/j.ijinfomgt.2025.103018>
13. Li, X., Wei, X., Tian, G., Cui, M., & He, Y. (2025). The effect of artificial intelligence usage on employee service innovation behavior: An information exchange perspective. *Asia Pacific Journal of Human Resources*, 63(4), e70032. <https://doi.org/10.1111/1744-7941.70032>
14. Li, X., & Zong, Q. (2026). How does explainable AI affect service innovation of frontline employees? A moderated chain mediation model. *International Journal of Contemporary Hospitality Management*, 38(4), 1172–1191. <https://doi.org/10.1108/IJCHM-01-2025-0164>
15. Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, 120, 262–273. <https://doi.org/10.1016/j.jbusres.2020.07.045>
16. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
17. Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, 42(1), 185–227. <https://doi.org/10.1080/00273170701341316>
18. Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior: A path model of individual innovation in the workplace. *Academy of Management Journal*, 37(3), 580–607. <https://doi.org/10.5465/256701>
19. Si, Y., Chen, M., & Xiao, H. (2026). Nudging employee–AI co-evolution through the enhancement of knowledge capital in the hospitality industry. *International Journal of Hospitality Management*, 134, 104534. <https://doi.org/10.1016/j.ijhm.2025.104534>
20. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
21. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)

22. Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, 73(6), 913–934. <https://doi.org/10.1177/0013164413495237>
23. Wu, T.-J., Zhang, R.-X., & Zhang, Z. (2025). Navigating the human-artificial intelligence collaboration landscape: Impact on quality of work life and work engagement. *Journal of Hospitality and Tourism Management*, 62, 276–283. <https://doi.org/10.1016/j.jhtm.2025.02.005>
24. Xu, Y., Xie, P., Naeem, R. M., Almugren, I., Hameed, Z., & Agarwal, S. (2026). Responsible AI and employee service innovation behavior: A sequential mediation model of AI self-efficacy and AI crafting. *Technological Forecasting and Social Change*, 224, 124470. <https://doi.org/10.1016/j.techfore.2025.124470>
25. Yang, X., & Wu, W. (2026). The double-edged sword effect of human-robot collaboration on hospitality employees' service innovation behavior. *Journal of Hospitality Marketing & Management*, 35(4), 494–517. <https://doi.org/10.1080/19368623.2026.2614411>
26. Yin, Z., Kong, H., Baruch, Y., L'Esper Decosta, P., & Yuan, Y. (2024). Interactive effects of AI awareness and change-oriented leadership on employee-AI collaboration: The role of approach and avoidance motivation. *Tourism Management*, 105, 104966. <https://doi.org/10.1016/j.tourman.2024.104966>