



Research article

AI-enabled CRM capability, service innovation, and sustainable banking outcomes: A digital green-finance perspective from Taiwan

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Abstract: Digital transformation and the green-finance agenda are increasingly intertwined, yet the organizational mechanism connecting digital capability to sustainability-oriented banking practice remains under-specified. Drawing on dynamic-capabilities and sustainable-banking research, we analyzed a pooled sample of 800 financial-services practitioners in Taiwan. Partial least squares structural equation modeling showed a strong positive association between perceived AI-enabled customer relationship management (CRM) capability and service innovation; service innovation was positively associated with perceived organizational resilience and organizational sustainability. After service innovation entered the model, the direct effects of AI-CRM capability for both outcomes were non-significant, yielding an indirect-only mediation pattern. The results therefore located the estimated organizational association of AI-CRM with resilience and sustainability in service innovation rather than in the technology. We did not establish temporal causality and did not measure carbon emissions, energy use, or ESG-disclosure quality. Our contribution is correspondingly specific: We identified an organizational micro-foundation through which responsible AI-CRM use is associated with sustainability-oriented financial-service practice. In green-finance terms, the argument is positioned at the level of organizational micro-foundations rather than measured environmental outcomes.

Keywords: green finance; digital green finance; sustainable banking; AI-enabled CRM; service innovation; organizational sustainability; organizational resilience

JEL Codes: G21, G23, O33, Q56

1. Introduction

1.1. Background and context

Green finance has moved from a specialist policy concern to a central issue in banking strategy. For financial institutions, the transition is not limited to green bonds, sustainable lending, or climate-risk disclosure. It also reaches ordinary service operations: How customers are advised, how transactions are completed, and how information is generated and documented (Khan et al., 2024; Hussain et al., 2024). Digital channels and artificial intelligence now shape many of these activities. They can reduce reliance on paper and branch-based interactions and create new questions about transparency, accountability, and customer trust (Islam et al., 2023).

AI-enabled CRM is particularly important in this setting because it sits at the point where data-intensive decision making meets the customer relationship. Banks use such systems for credit assessment, fraud detection, chat-based service, and product recommendations (Königstorfer & Thalmann, 2020; Mogaji et al., 2021; Manser Payne et al., 2021). Unlike conventional CRM, however, AI-based recommendations are probabilistic and may be difficult for staff or customers to interpret. Their usefulness therefore depends not only on predictive accuracy but also on whether users can understand, question, and appropriately rely on the output. Regulatory guidance in banking increasingly reflects this concern by emphasizing explainability, fairness, and human oversight (BIS, 2021; FSC, 2023).

This combination of technical capability and relational accountability makes AI-CRM a useful setting for examining the micro-foundations of digital green finance. Prior work has documented adoption, customer acceptance, and performance effects, but it has said less about the organizational process that connects AI-CRM to broader outcomes. We focus on service innovation because employees must convert system outputs into new or improved customer-facing routines before any organizational benefit can emerge. In that sense, service innovation is not a peripheral outcome; it is the point at which digital capability is enacted.

1.2. Research motivation

Three gaps motivate the study. First, much of the banking literature treats AI-CRM mainly as an analytical or automation technology, leaving the quality of the surrounding interaction underexamined: Whether explanations are intelligible and whether staff can override a recommendation they judge wrong. Sustainable-finance research has the opposite emphasis. It tends to remain at the level of products, regulation, or capital allocation and rarely examines how a firm's internal service routines support or constrain sustainability-oriented practice. Asian financial markets sharpen both gaps because evidence from them remains limited despite rapid digital adoption and strong regulatory

oversight. Taiwan provides a suitable setting because its banking, insurance, securities, and fintech firms operate within a dense and technologically advanced ecosystem.

AI-CRM research in banking has looked at technological adoption (Königstorfer & Thalmann, 2020; Mogaji et al., 2021; Ozay et al., 2024), at customer acceptance of AI-driven banking services (Hoehle et al., 2012; Manser Payne et al., 2021; Shankar & Rishi, 2020), and at the broader effect of CRM on bank performance (Padmavathy et al., 2012; Berraies et al., 2020). Several gaps survive this work. Prior treatments of AI-CRM capability have tended to privilege the technical-functional side, meaning analytics, automation, and personalization, while saying much less about the relational and transparency-oriented features that, in trust-intensive banking, actually decide whether customers accept AI-mediated service and whether staff use it well (Bharti et al., 2023; Roy et al., 2025). A second gap concerns outcomes. Banks are now judged on environmental and ESG performance, but the behavioral mechanism that links AI-CRM capability to bank-level outcomes such as resilience and environmental sustainability, namely service innovation, is seldom modeled in explicit terms; the organizational micro-foundations of digital green finance are left underspecified (Mainardes et al., 2023; Garrido-Moreno et al., 2024; Hussain et al., 2024). Evidence from Asian banking markets is also thin next to the Western literature, even though Asia hosts some of the most digitally advanced banking ecosystems anywhere. Taiwan is well suited on this count. Its financial sector combines mature retail banking with established insurance and security subsectors and an active digital-banking and fintech ecosystem, which makes it an apt empirical context for these questions, banking being the focal industry.

Grounded in the dynamic capability perspective and the green-finance and sustainable-banking literatures, we examine a pooled sample of financial-services practitioners in Taiwan. We have four objectives:

- (1) To conceptualize an overall AI-CRM capability measure that represents analytical intelligence, automation, personalization, and customer interaction quality.
- (2) To estimate the associations between AI-CRM capability, service innovation, organizational resilience, and organizational sustainability.
- (3) To assess whether service innovation carries the indirect relationships between AI-CRM capability and the two organizational outcomes.
- (4) To derive practical implications for responsible AI-CRM design and sustainability-oriented service governance.

We address three research questions:

RQ1: How is perceived AI-CRM capability related to service innovation in the pooled financial-services sample?

RQ2: How is service innovation related to organizational resilience and organizational sustainability?

RQ3: Do the estimated indirect effects through service innovation account for the associations between AI-CRM capability and the two organizational outcomes?

2. Theoretical background and hypotheses development

2.1. *Digital green finance and the organizational micro-foundations of sustainable banking*

Green-finance research has traditionally emphasized instruments and allocation mechanisms, including green lending, green bonds, and carbon disclosure (Zhou et al., 2020). That focus is necessary but incomplete. Environmental and social performance is also shaped by what happens inside financial institutions: The routines through which information is produced, services are delivered, and customer decisions are supported (Hussain et al., 2024; Islam et al., 2023; Nizam et al., 2019). This organizational perspective directs attention to the capabilities that make sustainability commitments operational.

Digitalization is one such capability domain (Proksch et al., 2024), though its environmental value should not be taken for granted. Moving transactions online can cut paper use and customer travel, and better data systems can improve the traceability of ESG-related information (Islam et al., 2023; Khan et al., 2024). Digital systems also consume resources, and they can reproduce opaque or biased decisions. Thus, the useful theoretical question is not whether digitalization is inherently green. It is under what organizational conditions digitalization becomes compatible with sustainability goals. We pursue that question at the customer interface, through AI-CRM capability and the service-innovation routines that put it to use.

2.2. *AI-enabled CRM as a digital banking capability*

CRM has evolved from a record-keeping system into an infrastructure for prediction, automation, and customer engagement. In banking, AI extends this infrastructure into credit scoring, fraud monitoring, anti-money-laundering checks, conversational service, and personalized recommendations (Königstorfer & Thalmann, 2020; Mogaji et al., 2021; Mainardes et al., 2023). These applications make AI-CRM strategically important, but they also expose limitations in purely technical accounts of capability.

The dynamic capabilities perspective helps explain why. AI-CRM can support sensing, by flagging changes in customer behavior; seizing, by helping a firm respond with tailored services; and reconfiguring, by enabling the redesign of service processes (Teece, 2007); all three depend on use. A technically sophisticated system delivers little organizational value if employees distrust its recommendations, cannot interpret them, or cannot adapt them to a particular customer's situation. That is why customer interaction quality belongs to the capability, not to an optional layer of design.

The dynamic capabilities perspective, an extension of the resource-based view (Barney, 1991; Teece, 2007), offers a useful lens for reading AI-CRM as a strategic digital banking capability. Following Akter et al. (2021), AI-CRM feeds three classes of dynamic capability in banking. Sensing covers the detection of shifts in customer preferences, risk profiles, and competitive threats from fintech entrants. Seizing covers the mobilization of personalized offerings, service innovations, and relationship interventions once those signals appear. Reconfiguring covers the continuous adaptation of service routines, branch-digital channel mixes, and customer-engagement processes that keeps a competitive edge (Mainardes et al., 2023; Berraies et al., 2020). The first two, sensing and seizing,

turn on more than the technical sophistication of the AI. They also turn on whether bank staff trust the recommendations enough to act on them, and whether customers accept AI-driven personalization instead of reading it as opaque or intrusive (Manser Payne et al., 2021; Bharti et al., 2023). This is where relational and transparency features become pivotal: The explainability of recommendations, the controllability of AI outputs, and the consistency of service delivery all bear on whether AI capability is associated with customer-facing banking innovation.

For this reason, we treat AI-CRM as a global digital capability construct represented by four theoretical facets: analytical intelligence, automation, personalization, and customer interaction quality. The empirical model does not estimate four separate first-order dimensions. Instead, it asks whether a concise overall measure of these complementary features is associated with innovation-oriented service practice.

2.3. AI-enabled CRM capability as a global construct

The measurement choice deserves explicit qualification. Each facet is represented by a single item, producing a four-item reflective global measure. This design is parsimonious, but it does not establish a validated higher-order structure. The construct is therefore interpreted as an overall perception of AI-CRM capability rather than as evidence that four distinct subdimensions have been independently confirmed. A fuller scale-development study remains necessary.

Two specification alternatives deserve mention, and we acknowledge rather than resolve them. A formative specification would treat the four facets as distinct, non-interchangeable causes of an overall capability index. A reflective higher-order specification would instead need several indicators per facet to identify each first-order dimension. The present design fits neither. With a single indicator per facet, the four items are modelled as reflective manifestations of one global perception, so the data can speak only to that overall construct, and not to the relative pull of analytical intelligence, automation, personalization, or interaction quality. We treat this single-indicator-per-facet structure as a central measurement limitation, not a minor caveat, and readers should not infer that any one facet drives the reported associations.

For sustainable-banking research, the key point is that AI-enabled CRM capability is not treated here as a purely technological asset. The instrument operationalizes AICRM as a parsimonious four-item reflective construct, one indicator standing for each theoretically specified facet: analytical intelligence, automation, personalization, and customer interaction quality. We therefore evaluate an overall AI-CRM capability construct rather than four separately validated first-order subdimensions. Customer interaction quality captures the transparency, explainability, and relational responsiveness of AI-mediated banking service. It matters most in banking, where regulatory transparency requirements and customer trust make it necessary for AI-driven recommendations to be understood, evaluated, and acted on appropriately. Future scale-development work should validate each facet with multiple indicators and test a higher-order measurement model.

2.4. *AI-enabled CRM capability and service innovation*

Service innovation in financial services includes more than the launch of new products. It also involves changes to onboarding, advisory work, channel coordination, and the way employees use customer information. AI-CRM supports these changes by making patterns more visible, automating routine tasks, and enabling faster adaptation of service responses (Akter et al., 2023; Blommerde, 2023; Mainardes et al., 2023; Zia & Alotaibi, 2024).

AI can also read behavioral data and surface actionable insights through interfaces that practitioners interpret and act on quickly, letting service be tailored in real time (Kumar et al., 2023).

Three mechanisms are especially relevant here. Analytical tools can turn dispersed customer data into interpretable cues for service decisions; automation can free time from repetitive work, though only where workflows are well designed; and feedback functions help employees refine system outputs and the routines around them. What the mechanisms share is a common implication, the contribution of AI-CRM lies in how it reshapes work, not in the mere presence of the technology.

Interfaces that visualize AI performance feedback and let practitioners feed corrections back support iterative refinement, embedding organizational learning into AI-mediated service routines (Bu et al., 2022).

The relational dimension of AI-CRM capability, transparency, explainability, and controllability of AI-driven recommendations, further supports service innovation in banking by enabling staff to evaluate AI outputs critically, contextualize them within client relationships, and adapt them to specific customer situations rather than applying them mechanically (Berraies et al., 2020; Levy & Hino, 2016; Manser Payne et al., 2021). On this basis, the following hypothesis is advanced:

H₁: AI-enabled CRM capability is positively associated with service innovation in financial services.

2.5. *Service innovation and organizational resilience*

Organizational resilience concerns the capacity to absorb disruption, adapt to changing conditions, and recover without losing core functioning (Lengnick-Hall et al., 2011). Service innovation contributes to resilience by enabling organizations to revise customer-facing processes as markets, regulations, and customer needs change. In financial services, such adaptation includes revised credit procedures, new digital channels, and more responsive communication during service failures.

H₂: Service innovation is positively associated with organizational resilience.

2.6. *Service innovation and organizational sustainability*

Organizational sustainability refers here to the perceived alignment of economic viability, social responsibility, and environmental considerations. In financial services, digital service innovations provide an organizational mechanism for lowering transaction friction, broadening access, and reducing dependence on paper-intensive or branch-intensive processes. These mechanisms are theoretically relevant, while the present measures capture perceptions of sustainability rather than audited environmental performance.

Economically, AI-CRM-enabled service innovations can raise practitioner productivity and digital-channel efficiency, lifting customer lifetime value while holding down interaction costs.

On the social side, innovations that draw on AI-CRM transparency and explainability provide a mechanism for widening access to underserved customers and building trust through more comprehensible, ethically governed interactions.

Environmentally, AI-enabled digital service innovation provides a mechanism for dematerialized banking through paperless transactions, remote access, and leaner use of physical infrastructure (Islam et al., 2023). We gauge this mechanism through respondents' perceptions of organizational sustainability rather than direct measures of energy use, resource consumption, or carbon emissions; digital channel migration is therefore theorized as a green-banking mechanism rather than treated as an objectively verified environmental outcome.

Prior research links the embedding of AI in service processes with sustainability-related outcomes through knowledge sharing, stakeholder alignment, and resource reconfiguration (Forcadell et al., 2019; Allui & Rawshdeh, 2024). Interaction quality is central here. When AI-CRM is transparent and its recommendations explainable, practitioners and customers can evaluate AI-mediated decisions for ethical and environmental fit, and the information feeding ESG governance becomes more traceable. Credible green finance rests on transparent, verifiable disclosure, which is increasingly tied to firm performance (Khan et al., 2024; Mohammad & Wasiuzzaman, 2021), so the transparency-oriented side of AI-CRM supplies a theoretical bridge between customer-interface digitalization and green-finance governance. Our data establish associations with perceived organizational sustainability; they do not independently verify ESG-disclosure quality or environmental performance.

H₃: Service innovation is positively associated with organizational sustainability.

2.7. *The mediating role of service innovation*

AI-CRM capability alone does not redesign a service. Employees must interpret the information, decide whether it is appropriate, and incorporate it into work routines. This distinction separates a technological resource from its organizational use. From a resource-based and dynamic-capabilities perspective, service innovation is the process through which analytical and relational features are combined with employee judgment.

Dynamic capabilities theory reinforces this mediating logic. AI-driven sensing and analytics have to be coupled with the seizing of innovation opportunities, through service redesign, before they yield sustainable banking outcomes (Teece, 2007). Service innovation is thus the behavioral pathway that statistically links AI-CRM capability to adaptive bank-level practice. Moreover, where staff keep drawing on AI-CRM insights to rework how service is delivered, banks accumulate routines that are at once resilient, in that they adapt quickly to disruption, and sustainable, in that they stay aligned with long-term strategic, regulatory, and ethical commitments (Berraies et al., 2020; Mainardes et al., 2023).

The mediation argument is therefore procedural rather than deterministic. AI-CRM expands the range of information and options available to employees, while service innovation captures whether those resources are translated into changed practice. The model specifies resilience and sustainability as outcomes associated with that changed practice rather than with the technology by itself.

H_{4a/b}: Service innovation mediates the associations between AI-enabled CRM capability and organizational resilience (H_{4a}) and organizational sustainability (H_{4b}).

2.8. Conceptual framework

Figure 1 summarizes the pooled structural model. AI-CRM capability is specified as an antecedent of service innovation, and service innovation is linked to organizational resilience and organizational sustainability. The direct paths from AI-CRM capability to both outcomes are retained to classify the mediation pattern. Because the data are cross-sectional, the arrows represent hypothesized directional associations rather than demonstrated temporal causation.

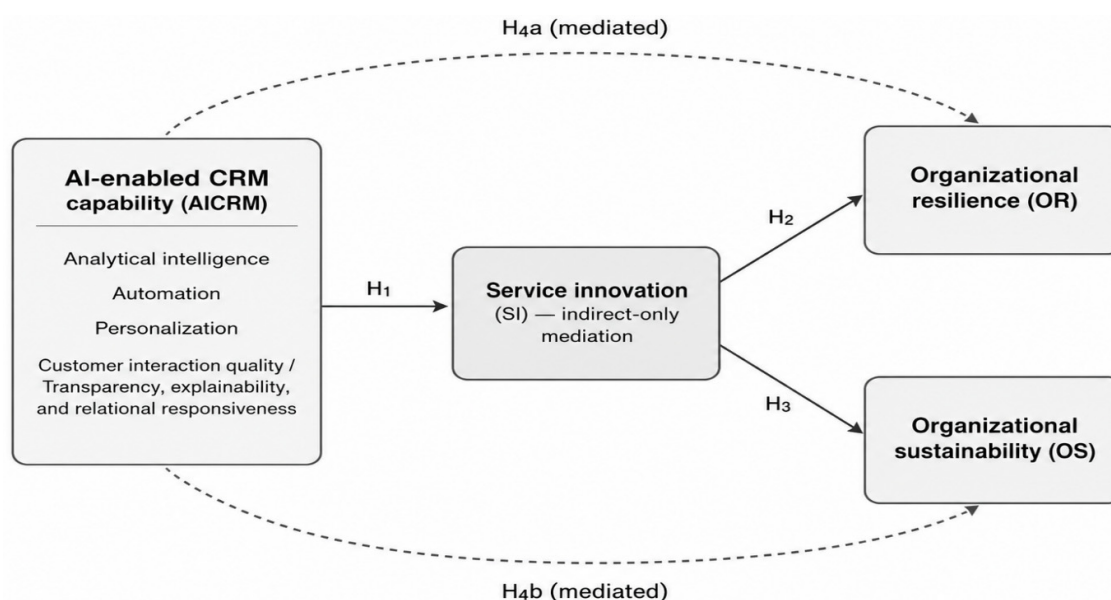


Figure 1. Conceptual framework.

3. Methodology

3.1. Research design and context

In this study, we used a quantitative, cross-sectional design to estimate the proposed model in Taiwan's financial-services sector. The pooled sample included practitioners from banking, insurance, securities, and fintech. Including these settings broadens the range of organizational contexts represented in the analysis, but we did not test sector differences. Retail banking provided the main substantive application because AI-CRM was especially visible in customer-facing banking work.

Pooling the four subsectors rests on an assumption of theoretical equivalence rather than a demonstrated one. Banking, insurance, securities, and fintech differ in products, regulation, and AI-adoption maturity. The hypothesized relationships operate at the level of a generic customer-facing mechanism: AI-CRM capability informs service-innovation routines, and those routines in turn relate to resilience and sustainability. The pooled specification assumes that this mechanism operates comparably across knowledge-intensive, trust-dependent financial services. That assumption was not tested: We did not assess measurement invariance across subsectors and reported no subgroup or multi-group

analysis. The study was accordingly framed as a pooled financial-services investigation with retail banking as the focal illustrative context; between-sector differences were reserved for adequately powered future research.

The research model integrated the dynamic capabilities perspective (Teece, 2007) with the banking and sustainable-banking literatures (Padmavathy et al., 2012; Mainardes et al., 2020; Mainardes et al., 2023) and the service-innovation literature (Blommerde, 2023; Wu & Nguyen, 2019; Berraies et al., 2020), enabling examination of bank-level capability mechanisms and the behavioral routines through which capability is converted into customer-facing innovation. This theoretical integration addressed a recognized gap between macro-level CRM capability studies in banking and behavior-level service-innovation research.

3.2. Sampling and data collection

A stratified purposive quota strategy was used to recruit practitioners with relevant experience in AI-CRM, customer service, digital transformation, or service innovation. Firms were identified through professional networks, industry associations, and financial-sector listings. Because individual selection probabilities were unknown, the sample is non-probability based. The findings were therefore intended to support analytical generalization to the proposed mechanism rather than population estimates for all financial employees in Taiwan.

A total of 850 questionnaires were distributed between May and August 2025, and 800 usable responses were retained. The pooled sample included banking ($n = 336$), insurance ($n = 224$), securities ($n = 144$), and fintech ($n = 96$) practitioners. No subgroup comparison was reported. Most respondents held supervisory or specialist roles, 71% had at least two years of direct AI-CRM experience, and 63% had received formal training.

A formal a priori power-analysis record was not retained. Accordingly, sample adequacy was supported conservatively by the large pooled sample ($n = 800$), the parsimonious structural model, and the stability of the reported bootstrap estimates. This absence was acknowledged as a design limitation, and future replications should document an a priori minimum-sample calculation based on the smallest expected structural effect.

To mitigate common method bias (CMB), procedural remedies included anonymity assurance, separation of predictor and criterion sections, and counterbalancing of selected item blocks. The statistical diagnostics for common method bias, namely Harman's single-factor test and a full-collinearity assessment, were reported with the data-analysis procedures in Section 3.4.

3.3. Measurement and instrument development

All constructs were measured as reflective latent variables using validated multi-item scales adopted and refined from prior banking and service-innovation studies, supplemented by newly developed items for the customer interaction quality dimension. Items were rated on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). The instrument was reviewed by three domain experts in digital banking and AI-CRM, and two industry practitioners (one bank CMO and one bank Head of Digital) to confirm content validity, construct coverage, and contextual suitability for banking.

AI-Enabled CRM Capability (AICRM): Operationalized in this study as a four-item global reflective construct whose items represent four complementary capability domains; analytical intelligence, automation, personalization, and interaction quality. The model therefore evaluated an overall practitioner-perceived AI-CRM capability rather than estimating four separate first-order dimensions. Sample items included: “Our CRM system uses AI algorithms to predict customer preferences”; “AI tools help automate customer service decisions”; “The AI-CRM interface clearly explains the basis for its recommendations (AI transparency)”; and “I can understand and correct AI-CRM outputs when they are inaccurate (AI controllability)”. The interaction-quality item content was informed by other work on AI transparency in banking (Königstorfer & Thalmann, 2020; Manser Payne et al., 2021), trust in digital banking (van Esterik-Plasmeijer & van Raaij, 2017; Sekhon et al., 2014), and AI-mediated relationship quality (Roy et al., 2025). The four-item global specification was reviewed by domain experts and evaluated in the pilot study. Future research should develop multi-item first-order scales for each capability domain and test a higher-order measurement model.

Service Innovation (SI): Captures the practitioner’s and organization’s ability to create new service concepts and delivery mechanisms through AI-CRM-mediated workflows. Items include: “Our organization regularly introduces innovative service processes enabled by AI-CRM tools”; and “We utilize AI-mediated digital platforms to co-create value with customers” (Wu & Nguyen, 2019; Blommerde, 2023).

Organizational Resilience (OR): Reflects adaptability and responsiveness to disruptions, enabled by AI-CRM interaction capabilities. Sample items: “Our organization quickly adjusts to sudden market changes using AI-generated insights”; “AI-CRM-driven intelligence enhances our capacity to recover from service failures” (Garrido-Moreno et al., 2024; Feliciano-Cestero, 2023).

Organizational Sustainability (OS): Measures long-term strategic balance between economic, social, and environmental goals, enabled through AI-mediated service innovation. Example items: “Our company integrates social and environmental considerations into AI-driven innovation decisions”; “AI-CRM solutions contribute to sustainable and ethically governed financial performance” (Prieto-Sandoval et al., 2019; Li & Jin, 2024).

The original questionnaire was prepared in English and translated into Mandarin Chinese using Brislin’s (1986) back-translation procedure to ensure conceptual equivalence. A pilot test with 30 respondents drawn proportionally from the four subsectors showed satisfactory internal consistency (Cronbach’s $\alpha > 0.80$ for all constructs) and satisfactory loading of the new customer interaction quality items on the AICRM factor.

3.4. Data analysis technique

Data were analyzed in SmartPLS 4.0 over three stages. We first assessed the measurement model for internal consistency reliability (Cronbach’s alpha and composite reliability), convergent validity (average variance extracted), collinearity (variance inflation factors), indicator outer loadings, ρ_A , and discriminant validity via the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT); full diagnostics appear in Tables 1a-1d. We then estimated the pooled structural model with 5,000 bootstrap subsamples. Direct and indirect effects were finally interpreted using the classification

logic of Zhao et al. (2010), which identifies the observed statistical pattern without asserting temporal mediation.

(1). Measurement model assessment: Internal consistency was evaluated using Cronbach's alpha and composite reliability, convergent validity using average variance extracted (AVE), and collinearity using variance inflation factors (VIF). Indicator outer loadings, rho_A, and discriminant validity (the Fornell-Larcker criterion and HTMT) are reported in Tables 1b–1d.

(2). Structural model assessment: Standardized path coefficients, t-values, and p-values were estimated using bootstrapping with 5,000 subsamples (Hair et al., 2021) for hypotheses H₁–H₄ in the pooled sample (n = 800). Model fit and explanatory performance were evaluated using SRMR, NFI, R², Q², and path-specific f² values.

(3). Indirect-effect assessment: direct and indirect effects were evaluated using Zhao et al.'s (2010) classification logic to identify the observed mediation pattern without implying temporal or causal mediation.

Predictive relevance was assessed using Stone-Geisser Q², and path-specific effect sizes were evaluated using Cohen's f². Indicator-level PLSpredict benchmarking was not reported and was therefore not used to support claims of out-of-sample predictive superiority.

As a statistical diagnostic of common method bias, Harman's single-factor test showed that the largest unrotated factor accounted for 31.4% of total variance. This finding does not establish the absence of CMB, but it does not indicate that a single general factor dominates the covariance structure. The possibility of residual same-source bias is therefore retained as a limitation.

We complemented these procedural remedies with a full-collinearity test following Kock (2015). This test was distinct from the standard collinearity check summarized in Table 1a, whose reported VIF ranges were indicator-level collinearity diagnostics obtained in the measurement assessment; the full-collinearity test instead regressed each construct on all others to obtain a single construct-level full-collinearity VIF for each construct. The resulting construct-level values are reported in Section 4.2. Because all constructs were measured from the same respondents at a single point in time, the diagnostic could not rule out same-source inflation; we therefore recommend a marker-variable or common-latent-factor design for replication and retain residual common method bias as a limitation.

3.5. *Ethical considerations*

Participation was voluntary. Respondents were adults acting in a professional capacity, and the questionnaire collected no directly identifying or sensitive personal information. The survey introduction explained the purpose of the study, anonymity protections, and the intended use of the data. Respondents continued only after providing electronic consent. Under the applicable institutional rules governing human-subjects research, anonymous survey studies of adult professionals acting in their occupational capacity that collect no sensitive or directly identifying personal data do not require formal ethics-committee review; the study proceeded under this exemption, and no approval or exemption number was issued.

4. Results

4.1. Respondent profile and data screening

The dataset contained 800 usable responses. Missing values represented less than 1.8% of observations and were handled with the expectation-maximization procedure. Maximum absolute skewness was 1.63 and maximum absolute kurtosis was 3.42. These values indicated no severe univariate distributional problem for descriptive interpretation or bootstrap estimation; PLS-SEM does not require multivariate normality.

The sample included 336 banking, 224 insurance, 144 securities, and 96 fintech practitioners. Respondents had a mean age of 38.6 years and a mean organizational tenure of 9.3 years. Early-versus-late response comparisons produced no statistically significant differences at the 0.05 level.

4.2. Measurement model evaluation

The psychometric properties of the global constructs are summarized in Table 1a. Internal consistency and convergent validity were satisfactory for the four-item AICRM measure and the three outcome constructs. Discriminant validity was also supported: Each construct's square root of AVE exceeded its correlations with the other constructs (Fornell-Larcker; Table 1c) and all HTMT ratios fell below the 0.85 threshold (Table 1d), with indicator loadings and ρ_A reported in Tables 1b–1c. The VIF ranges in Table 1 were indicator-level collinearity diagnostics obtained in the measurement assessment. Using the construct-correlation matrix reported in Table 1c, the corresponding construct-level full-collinearity VIFs were AICRM = 1.87, SI = 2.96, OR = 1.89, and OS = 2.02. All four values were below the conservative 3.3 threshold, indicating no severe full-collinearity under Kock's (2015) diagnostic; residual same-source bias remains a design limitation.

The four-item global AICRM construct showed satisfactory internal consistency and convergent validity. Because each theoretically specified capability facet was represented by a single indicator, these results support the reliability of the global measure but do not establish separate first-order dimensions.

Table 1a. Reliability and validity of constructs.

Construct	Items	Cronbach's α	CR	AVE	VIF Range
AI-Enabled CRM Capability (AICRM)	4	0.91	0.94	0.79	1.28–2.01
Service Innovation (SI)	3	0.88	0.90	0.75	1.32–2.06
Organizational Resilience (OR)	3	0.90	0.91	0.78	1.24–1.96
Organizational Sustainability (OS)	3	0.92	0.93	0.81	1.19–1.84

Table 1b. Indicator loadings.

Construct	Indicator	Loading
AICRM	AICRM1	0.88
	AICRM2	0.90
	AICRM3	0.89
	AICRM4	0.88
SI	SI1	0.84
	SI2	0.88
	SI3	0.87
OR	OR1	0.87
	OR2	0.89
	OR3	0.89
OS	OS1	0.89
	OS2	0.91
	OS3	0.90

Table 1c. Construct reliability (rho_A) and Fornell-Larcker criterion.

Construct	rho_A	AICRM	SI	OR	OS
AICRM	0.918	0.888			
SI	0.885	0.68	0.863		
OR	0.904	0.47	0.64	0.883	
OS	0.923	0.45	0.67	0.61	0.900

Note: Diagonal values (bold positions) are the square root of AVE; off-diagonal values are inter-construct correlations. Each square root of AVE exceeds the corresponding correlations, supporting discriminant validity.

Table 1d. Heterotrait-Monotrait ratio (HTMT).

Construct	AICRM	SI	OR	OS
AICRM	—			
SI	0.74	—		
OR	0.52	0.69	—	
OS	0.49	0.71	0.66	—

Note: All HTMT values are below the 0.85 threshold, supporting discriminant validity. Loadings exceed 0.708; Cronbach's alpha, rho_A, and CR exceed 0.70 with CR below 0.95; AVE exceeds 0.50.

4.3. Structural model evaluation

The structural model was estimated with 5,000 bootstrap resamples. SRMR was 0.046 and NFI was 0.93. The model explained 47% of the variance in service innovation, 56% in organizational resilience, and 59% in organizational sustainability. Table 2 reports the path estimates, and Figure 2 presents the same results graphically.

The reported R^2 values were 0.47 for service innovation, 0.56 for organizational resilience, and 0.59 for organizational sustainability. Within the specified model, the direct AICRM→OR and AICRM→OS coefficients were negligible once service innovation was included, so the substantive explanatory pattern was concentrated in the service-innovation pathway. Direct magnitude comparisons with prior AI-CRM studies were not made because differences in constructs, samples, and contexts precluded reliable one-to-one comparison.

Table 2. Hypothesis testing results.

Hyp.	Path	β	t-value	p-value	Result
H ₁	AICRM → SI	0.68	14.72	< 0.001	Supported
H ₂	SI → OR	0.62	11.45	< 0.001	Supported
H ₃	SI → OS	0.65	12.18	< 0.001	Supported
H _{4a}	AICRM → SI → OR (Mediation)	0.42	8.37	< 0.001	Supported
H _{4b}	AICRM → SI → OS (Mediation)	0.44	8.81	< 0.001	Supported

All three hypothesized structural paths were statistically significant. AI-CRM capability was positively associated with service innovation ($\beta = 0.68$, $p < 0.001$), and service innovation was positively associated with organizational resilience ($\beta = 0.62$, $p < 0.001$) and organizational sustainability ($\beta = 0.65$, $p < 0.001$). The two hypothesized indirect effects were also statistically significant.

4.4. Mediation analysis

The direct and indirect effects were examined jointly. The indirect effects from AI-CRM capability through service innovation were 0.42 for resilience and 0.44 for sustainability, both at $p < 0.001$. With service innovation in the model, the direct effects from AI-CRM capability to resilience and sustainability were 0.04 and 0.03, respectively, and were not statistically significant. Under Zhao et al.'s (2010) classification, both outcomes showed an indirect-only mediation pattern. Bootstrap 95% confidence intervals for the direct, indirect, and total effects are reported in Supplementary Table S3. Because the data were collected at one point in time, this result is a statistical decomposition rather than evidence of a causal temporal sequence.

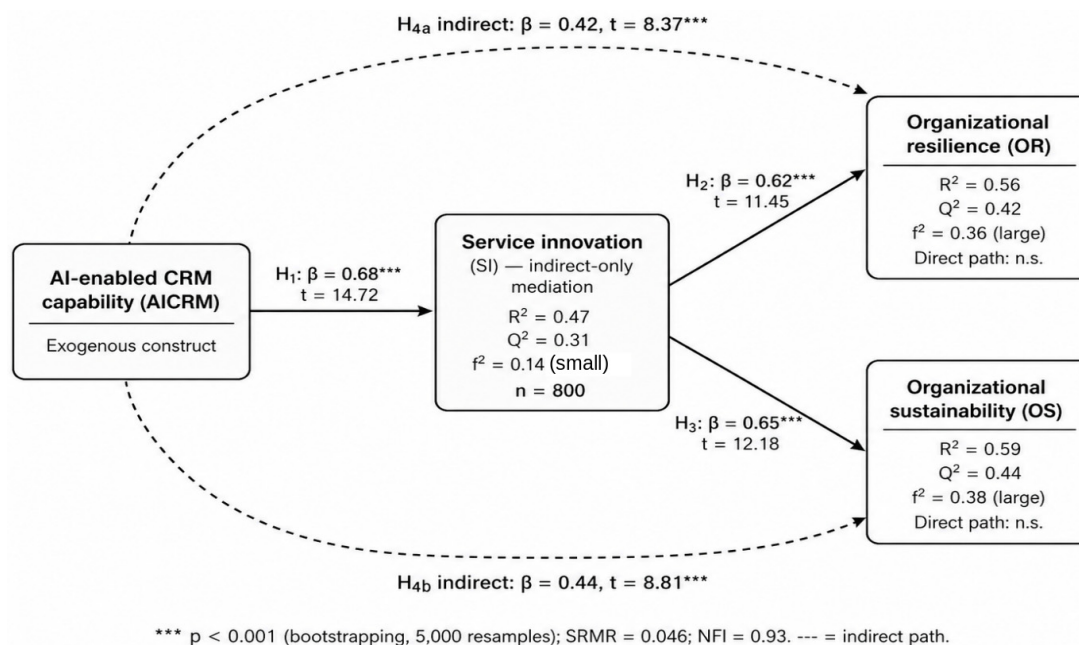


Figure 2. Structural model results with standardized path coefficients.

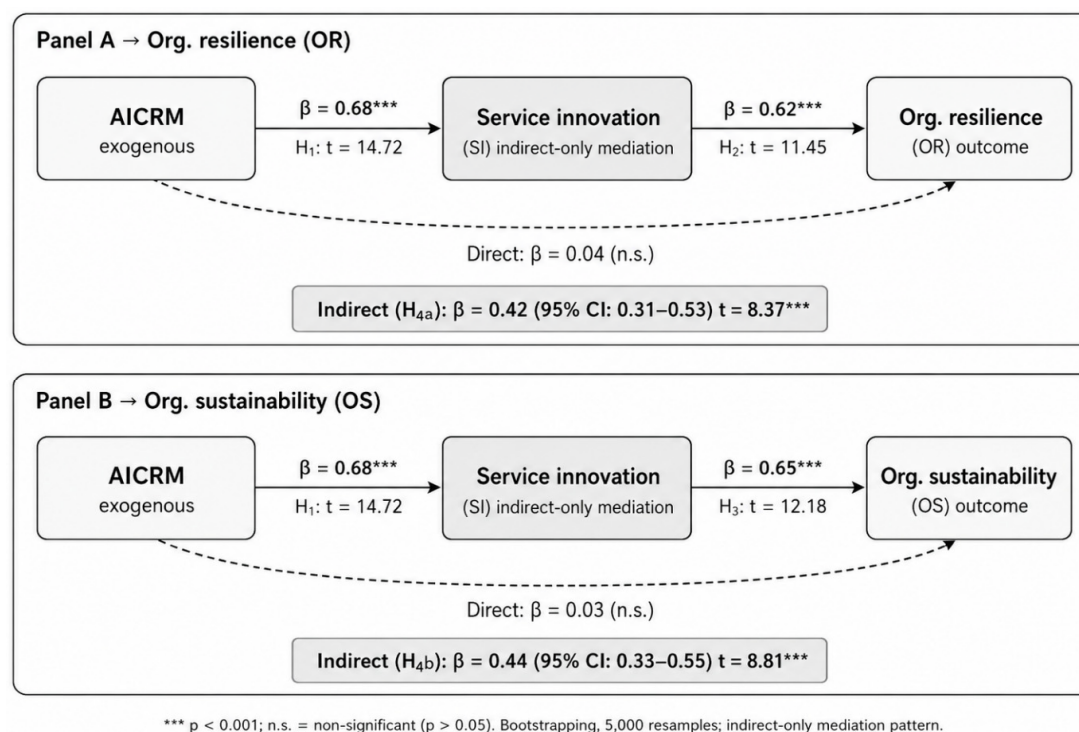


Figure 3. Mediation analysis: decomposition of direct and indirect effects.

4.5. Predictive relevance and effect sizes

Model predictive validity was assessed via Stone–Geisser Q^2 and Cohen's f^2 statistics, summarized in Table 3.

Table 3. Predictive relevance of endogenous constructs and path-specific effect sizes.

Endogenous construct	Q^2	Structural path and f^2	Interpretation
Service Innovation (SI)	0.31	AICRM $\rightarrow$ SI: 0.14	Q^2 indicates predictive relevance; f^2 indicates a small path contribution (approaching medium).
Organizational Resilience (OR)	0.42	SI $\rightarrow$ OR: 0.36	Q^2 indicates predictive relevance; f^2 indicates a large path contribution.
Organizational Sustainability (OS)	0.44	SI $\rightarrow$ OS: 0.38	Q^2 indicates predictive relevance; f^2 indicates a large path contribution.

All Q^2 values exceeded zero, indicating predictive relevance for the endogenous constructs under the blindfolding procedure. The reported f^2 statistics indicate a small contribution for AICRM $\rightarrow$ SI ($f^2 = 0.14$, approaching the 0.15 medium threshold) and large contributions for SI $\rightarrow$ OR ($f^2 = 0.36$) and SI $\rightarrow$ OS ($f^2 = 0.38$). Because indicator-level PLSpredict results and linear-model benchmark errors are not reported in this manuscript, no claim of superior out-of-sample prediction is made.

4.6. Summary of findings

Taken as a whole, the pooled model shows a consistent pattern: Higher perceived AI-CRM capability is associated with more service innovation, and service innovation is associated with stronger perceived resilience and sustainability. The direct effects from AI-CRM capability to the two outcomes are negligible once service innovation is included.

5. Discussion

5.1. Overview of findings

The results support the hypothesized associations within the stated design boundaries. The four constructs covary in the expected direction, and service innovation accounts for the statistically significant indirect associations. The data do not establish that AI-CRM adoption causes resilience or sustainability; they show that the estimated associations with those outcomes are concentrated in the service-innovation pathway.

5.2. *Theoretical contributions*

The study makes four contributions. It adds customer interaction quality to an otherwise technical account of AI-CRM capability; it identifies service innovation as the empirical link between that capability and organizational outcomes; it brings resilience and sustainability into one model without conflating them; and it draws its evidence from a pooled Taiwanese financial-services sample.

5.2.1. Extending bank AI-CRM capability with customer interaction quality

The construct-content contribution is the most direct. Existing accounts tend to emphasize analytics, automation, and personalization, whereas the present measure also asks whether AI-mediated recommendations are understandable and correctable. That distinction matters in financial services, where a recommendation that cannot be explained may be unusable even when it is statistically accurate. The evidence supports the reliability of the global four-item measure, not four separate latent dimensions.

5.2.2. Establishing service innovation as the organizational mechanism

A second contribution concerns mechanism. Non-significant direct effects alongside significant indirect effects locate the association between AI-CRM capability and the two outcomes in service innovation rather than in the technology. This gives a more precise account than a generic technology-performance link, tying organizational benefit to changes in service practice.

The practical reading is pointed. Since the direct paths are negligible once service innovation enters, acquiring AI-CRM capability on its own is unlikely to be associated with better resilience or sustainability unless a firm also redesigns the service routines through which the capability gets used. That moves the account away from the familiar claim that AI improves performance and toward a conditional one: AI-CRM capability relates to organizational outcomes through service innovation, or barely at all.

5.2.3. Linking AI capability to sustainability and resilience

Modeling resilience and sustainability jointly is a third contribution. Resilience concerns adaptation to disruption, while sustainability concerns longer-term alignment with economic, social, and environmental priorities. Their coefficients are similar, yet the constructs remain conceptually distinct, and the model shows that service innovation is associated with both short-term adaptability and longer-term orientation.

Throughout, sustainability refers to respondents' perceptions of organizational sustainability, not to audited environmental performance, emissions, energy use, or ESG-disclosure quality. The contribution is bounded by that operationalization.

5.2.4. Contextually diverse evidence from Taiwan's financial sector

The contextual contribution is deliberately modest. The pooled sample spans banking, insurance, securities, and fintech but does not estimate between-sector differences. Its value lies in demonstrating the proposed associations in a heterogeneous Taiwanese financial-services workforce. Sector-specific claims require future work with measurement-invariance tests and adequately powered subgroup analyses.

5.3. *Implications for AI-CRM design and deployment in banking*

The practical implications follow from the central result: AI-CRM capability matters when it changes service work. Recommendations therefore concern the design and governance of use rather than technology acquisition alone.

5.3.1. Prioritize AI transparency and explainability

Transparency and explainability are operating requirements for responsible AI-CRM deployment in banking. Frontline staff need to know why a recommendation was produced, what information it used, and when it is unreliable. This is especially important in lending, investment, and other high-stakes interactions. We not isolate individual design features, but the interaction-quality item establishes their relevance within the global AICRM measure.

5.3.2. Design for appropriate staff reliance and customer trust

Appropriate reliance is equally important. Confidence indicators, escalation rules, and correction mechanisms help employees avoid blind acceptance and routine rejection of AI advice. These features should be embedded in workflows and training rather than added as afterthoughts.

5.3.3. Reduce staff effort to enable service innovation

Automation should be assessed in terms of the work it removes and the work it creates. When opaque review requirements offset time saved on routine processing, automation does not expand innovation capacity. Managers should therefore verify whether AI-CRM reduces cognitive and administrative load in practice.

5.3.4. Design hybrid human-AI banking service architectures

Finally, AI-CRM should be designed as part of a human-AI service system. Employee judgment remains necessary when customer circumstances are unusual, ethically sensitive, or poorly represented in historical data. Hybrid workflows make this judgment explicit and create channels for feedback to improve the system and the service process.

5.4. Managerial and practical implications

Three priorities follow for senior managers. Marketing leaders need to build staff competence in interpreting and communicating AI-assisted recommendations. Information leaders, by contrast, should track how systems are used rather than whether they are merely available. Moreover, risk and sustainability leaders should fold model governance, explainability, and customer protection into existing ESG and risk-management processes.

Marketing leaders carry the first set of tasks. Building customer-centric AI-CRM competence requires structured AI-literacy programs so that frontline staff can read system capabilities and limitations, recognize uncertainty indicators, judge recommendation quality, and feed problems back. These are digital-banking capabilities rather than purely technical skills, and they support the service-innovation behavior through which AI-CRM capability is associated with resilience and sustainability (AICRM $\rightarrow$ SI: $\beta = 0.68$, Table 2). For digital-native customers, marketing leaders should also redesign engagement journeys so that AI-driven personalization is surfaced transparently as a value-add rather than concealed.

Information leaders face a different task: Institutionalizing the AI-mediated learning loops that underpin resilience. Because the path from service innovation to resilience is significant, AI-CRM capability, once expressed through service innovation, is associated with a bank's adaptive capacity. The practical step is to stand up feedback systems that capture staff usage patterns, service-innovation outcomes, and customer responses in real time, so that the loops continuously sharpen system performance and staff capability. Sustaining that value over time depends on investment in MLOps, model-monitoring, and explainability tooling built for retail-banking workflows.

For risk and sustainability officers, the first task is to align AI-CRM governance with ESG and green-finance commitments. The positive association between innovation and sustainability implies that perceived organizational sustainability, environmental dimension included, is linked to AI-mediated service innovation, which turns AI-CRM governance into a green-finance and ESG matter as much as a regulatory one. Practically, that calls for governance frameworks that write transparency requirements, bias auditing, model-risk management, and explainability standards into CRM procurement, model approval, and ongoing monitoring (BIS, 2021; FSC, 2023). It also calls for tying the transparency and explainability features of AI-CRM to the bank's ESG and sustainability disclosure, so that customer-interface digitalization produces auditable evidence of responsible, environmentally aligned practice (Khan et al., 2024). Handled this way, AI-CRM lines up with the bank's risk-appetite statement, its ESG commitments, and its consumer-protection obligations, and responsible AI reads as a strategic green-finance asset rather than a compliance cost.

These recommendations come with an explicit evidentiary boundary. What we tested were the associations among AI-CRM capability, service innovation, resilience, and perceived sustainability. The more specific prescriptions, including MLOps and model monitoring, bias auditing, ESG-disclosure integration, procurement governance, and risk-appetite alignment, were not directly modeled; we advance them as reasoned extensions grounded in prior literature and professional practice. They also point to something the present model does not measure. Technology is only one input to a successful AI transformation, which further depends on complementary organizational resources, employee readiness,

governance structures, and resource allocation (Ozay et al., 2025). Firms that acquire AI-CRM capability without these complements should not expect the service-innovation pathway to appear on its own.

5.5. *Comparison with other studies*

The findings are consistent with research showing that AI-related capabilities are associated with service innovation and customer-facing value (Kumar et al., 2023; Bharti et al., 2023). They also extend banking studies focused on adoption or broad performance outcomes by specifying service innovation as the intervening organizational process (Königstorfer & Thalmann, 2020; Mainardes et al., 2023). Direct comparison with earlier studies remains limited because the present measures, sample, and cross-sectional design differ from those used in other research.

The pooled design broadens contextual coverage but does not provide comparative evidence across subsectors. In future studies, researchers should test sector differences directly after establishing measurement invariance (Henseler et al., 2016) and retaining complete subgroup outputs.

5.6. *Summary of discussion*

In summary, the results point to a simple but consequential distinction: Possessing AI-CRM capability is not the same as using it to change service practice. The estimated benefits are concentrated in the service-innovation pathway. This interpretation connects digital capability with green-finance governance while remaining within the limits of perceptual, cross-sectional data.

6. **Conclusions**

6.1. *Summary of key findings*

In this study, we estimated a pooled PLS-SEM model of AI-CRM capability, service innovation, organizational resilience, and organizational sustainability among 800 financial-services practitioners in Taiwan. AI-CRM capability was strongly associated with service innovation. Service innovation, in turn, was associated with both organizational outcomes. The direct paths from AI-CRM capability to resilience and sustainability were not statistically significant once service innovation was included, yielding an indirect-only mediation pattern.

(1) AI-enabled CRM capability was positively associated with service innovation ($\beta = 0.68$), consistent with the idea that analytical intelligence, automation, personalization, and interaction quality jointly support innovation-oriented banking practice.

(2) Service innovation, in turn, related positively to organizational resilience ($\beta = 0.62$) and perceived organizational sustainability ($\beta = 0.65$), a pattern that fits its proposed adaptive and longer-term strategic roles.

(3) For both outcomes, the mediation was indirect-only and statistically significant, though the cross-sectional design rules out a causal interpretation.

6.2. Theoretical implications

The theoretical implication is not that AI-CRM directly produces sustainability. Rather, digital capability is organizationally consequential mainly where it is associated with changes in service routines. Customer interaction quality is part of that capability context because explainability and correctability influence whether AI outputs can be responsibly used. The pooled sample adds contextual breadth, not evidence of sector differences.

6.3. Managerial implications

The managerial message is similarly focused. Financial institutions should evaluate AI-CRM investments in terms of whether they improve employees' ability to redesign service, exercise judgment, and communicate recommendations transparently. Governance should connect model oversight with customer protection and sustainability reporting. Training should address technical use and the limits of algorithmic recommendations.

(1) Invest in customer-centric AI-CRM design for retail banking: Prioritize transparency, explainability, and relational responsiveness as core capability requirements aligned with regulatory and customer-trust expectations.

(2) Develop bank staff AI-CRM competencies: Structured AI literacy programs that build skills in evaluating, correcting, and creatively leveraging AI-CRM outputs are critical digital banking capability investments.

(3) Design hybrid human–AI banking service workflows: Organizational structures that explicitly combine AI analytical capability with staff relational and contextual judgment support the innovation behaviors through which bank resilience and sustainability are built.

(4) Align AI-CRM governance with sustainability: embed ethical AI, bias auditing, and explainability requirements into AI-CRM procurement and deployment governance frameworks.

6.4. Limitations

Several limitations qualify the findings. The cross-sectional design establishes no temporal order. The non-probability sample limits population inference. Because all focal variables were reported by the same respondents, residual common method bias cannot be excluded. The four-item AICRM measure is a global measure and does not validate separate subdimensions. Full measurement diagnostics, including item loadings, ρ_A , HTMT, and the Fornell-Larcker matrix, appear in Tables 1b–1d, and the complete measurement and structural-model outputs are provided as Supplementary Material for transparency and reproducibility. Sustainability was measured perceptually rather than through audited environmental indicators. Replication should address these limitations with longitudinal data, fuller measurement models, multi-source designs, and objective operational outcomes.

6.5. *Directions for future research*

Future work should proceed in six directions.

- (1) Field experiments should manipulate explanation depth, uncertainty displays, or correction options and observe how employees use AI-CRM in real service decisions.
- (2) Longitudinal studies should examine whether changes in AI-CRM capability precede changes in service innovation and organizational outcomes.
- (3) Scale-development research should create multiple indicators for each capability facet and compare global, formative, and higher-order specifications.
- (4) Sector comparisons should be undertaken only after establishing measurement invariance and adequate subgroup power.
- (5) Governance research should test whether regulatory pressure, model-risk practices, or ethical climate alter the AI-CRM-service innovation relationship.
- (6) Sustainability research should add objective indicators such as paper use per transaction, digital-channel migration, energy intensity, operational emissions, and independently assessed ESG disclosure.

Author contributions

Kuo Ming Chu: Conceptualization; Methodology; Writing—original draft; Supervision; Funding acquisition; Project administration.

Hui Chun Chan: Conceptualization; Methodology; Investigation (planned); Data curation (planned); Writing—review & editing; Project administration.

All authors have read and approved the final version of the manuscript.

Use of generative AI tools

Generative AI tools were used to support language editing, structural refinement, and consistency checking. The authors retained responsibility for the theoretical argument, research design, measurement decisions, data collection, statistical analysis, interpretation, and final wording. All AI-assisted revisions were reviewed and verified by the authors. No AI system was used to fabricate data or results, and no AI tool is listed as an author.

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Conflict of interest

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

Data availability

De-identified data, the item codebook, and analysis documentation may be made available by the corresponding author upon reasonable request, subject to participant-confidentiality commitments and applicable institutional requirements. Any shared materials will exclude information that could enable the identification of individuals or participating organizations.

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