

A hybrid PLS-SEM and convolutional neural network analysis of artificial intelligence adoption intention in SMEs

Ayodeji Idowu

Idowu0394@pg.babcock.edu.ng

Babcock University

Yemisi Tomilola Babalola

Babcock University

Yacob Haliso

Babcock University

Oyebayo Ridwan Olaniran

King's College London

Article

Keywords:

Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11254727/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

A hybrid PLS-SEM and convolutional neural network analysis of artificial intelligence adoption intention in SMEs

A. Idowu^{1,*}, Y. T. Babalola¹, Y. Haliso¹, and O. R. Olaniran²

¹Department of Information Resources Management, Babcock University, Ilishan-Remo, Ogun State, Nigeria

²Department of Biostatistics and Health Informatics, Institute of Psychiatry, Psychology and Neuroscience, King's College London, London, United Kingdom

*Corresponding author: Idowu0394@pg.babcock.edu.ng

ABSTRACT

Empirical research on artificial intelligence (AI) adoption relies heavily on linear structural equation modelling (SEM), prioritising in-sample explained variance over out-of-sample predictive validity. Hybrid approaches combining SEM with neural networks are expanding, yet they routinely evaluate modelling stages on separate data splits, rendering claims of mutual validation untestable. This study presents a unified, two-stage evaluation framework. First, Partial Least Squares SEM (PLS-SEM) validates the measurement model and estimates structural relationships. Second, a Convolutional Neural Network (CNN), with an input tensor mapped to the validated measurement model, optimises prediction. Crucially, both architectures are benchmarked using identical resampling folds to guarantee commensurate out-of-sample comparisons. Testing the framework on micro-level data from Nigerian SMEs (N = 1,210), PLS-SEM supported all 15 hypotheses, revealing that AI awareness fully mediates ten of 13 antecedent effects. Nominally, the CNN achieved a 2.06% reduction in out-of-sample RMSE over the structural benchmark ($p = 0.032$).

Introduction

Small and medium-sized enterprises (SMEs) constitute approximately 90% of firms and around 50% of global employment, and they represent the segment in which the distributional implications of artificial intelligence (AI) adoption are likely to be determined. However, adoption across SMEs remains heterogeneous. Recent empirical evidence identifies a persistent disparity between large and small firms in AI adoption in European, Asian, and African economies, attributing this gap primarily to differences in human capital, access to finance, digital and physical infrastructure, and governance conditions, rather than to the mere availability of the underlying technologies themselves¹⁻⁵. With the diffusion of generative AI tools lowering technical complexity and reducing costs previously necessitating dedicated data-science capabilities, the primary constraint has shifted from technological access to *intention*: namely, whether decision-makers with feasible adoption opportunities are willing to adopt^{6,7}. Importantly, the consequences extend beyond the productivity and efficiency of the firm itself. AI is increasingly conceptualised as an enabling input for sustainable business model innovation and to improve enterprise resilience; consequently, differential adoption patterns are expected to shape distributional outcomes that extend beyond the boundaries of adopting firms⁸⁻¹⁰.

Adoption intention is therefore among the most heavily modelled constructs in information systems research. The dominant instrument is partial least squares structural equation modelling (PLS-SEM), typically applied to an integration of the technology–organisation–environment (TOE) framework^{11,12}, diffusion of innovations theory¹³, the technology acceptance model¹⁴ and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)¹⁵. This literature is large, methodologically consistent and, on its own terms, successful: integrated specifications routinely explain between 45% and 65% of the variance in adoption-related outcomes¹⁶⁻¹⁹. The same apparatus is applied across settings as varied as enterprise workforces, professional users and student populations²⁰⁻²⁵, which makes its methodological conventions unusually consequential.

Three recurring characteristics of the extant literature motivate the present investigation. First, model quality is predominantly reported in terms of in-sample explanatory adequacy. The coefficient of determination, R^2 , quantifies fit within the estimation sample rather than predictive performance on previously unseen observations, and these quantities may diverge substantially. Although methodological guidance for PLS-SEM has recommended out-of-sample evaluation for several years^{26,27}, reviews of empirical practice indicate that such assessments remain uncommon in published applications^{28,29}. Consequently, a structural model may be characterised as “substantial” on the basis of a statistic that provides no evidence regarding the transportability of its estimated coefficients.

Second, the conventional linear structural specification constitutes a strong functional-form assumption that is seldom examined empirically. Theoretical accounts of technology adoption frequently imply non-linear relationships—such as capability thresholds, diminishing returns or saturation in perceived usefulness, and trust effects that become consequential only after awareness has been established^{30,31}. A purely linear parameterisation is unable to represent such dynamics and, importantly, cannot adjudicate their absence: if interactions or non-linear terms are not specified and estimated, their potential contribution cannot be evaluated.

Third, a common response to these limitations has been the adoption of hybrid SEM–artificial neural network (SEM–ANN) designs, wherein a neural network is trained subsequent to the structural model and its predictor importance rankings are compared with standardised path coefficients^{32–35}. While this approach represents a substantive conceptual advance, typical implementations do not warrant the inferences often drawn. In many studies, the neural component is trained on construct scores produced by the structural model, evaluated on a data split for which the structural model itself is not evaluated, and summarised via normalised importance rankings. Under this protocol, the claim that “the neural network confirms the structural model” does not constitute a formal test: the two models are not compared on the same folds, uncertainty around their differences is not quantified, and no benchmark is provided to establish whether a non-linear learner yields meaningful incremental predictive value. Moreover, the comparison is frequently conducted in the absence of appropriate baselines—such as a feed-forward network trained directly on the same inputs, a tree-based ensemble, or the structural model used explicitly as a predictive model in its own right.

Accordingly, this study conceptualises explanation and prediction as distinct analytical objectives that require different methodological instruments while being assessed under a shared evaluation protocol. Partial least squares structural equation modelling (PLS-SEM) is employed for its intended purposes: validating the measurement model, estimating latent constructs, and testing hypotheses. Predictive performance is subsequently modelled using a convolutional neural network (CNN). These two stages are integrated, rather than simply sequentially appended, through three explicit coupling points.

First, the measurement model *defines the CNN input representation*. Each respondent is encoded as a two-dimensional construct $\times$ indicator tensor, where rows correspond to the latent constructs validated by the measurement model and columns correspond to their retained indicators. Convolution along the indicator axis enables the model to learn within-construct aggregation of indicators—i.e., a learned analogue of the outer model—whereas convolution along the construct axis facilitates learning of inter-construct relationships—i.e., a learned analogue of the inner model. This structured representation is feasible specifically because the PLS-SEM stage determines indicator-to-construct assignments; it is therefore not equivalent to applying a generic tabular neural network to the same set of observed variables.

Second, the structural model *serves as a benchmark comparator*. Its two-predictor model of adoption intention is evaluated using the identical cross-validation folds applied to the CNN, alongside a feed-forward neural network, a random forest model, and an ordinary least squares regression model estimated on the raw indicators. Consequently, the incremental predictive contribution of the deep learning approach is quantified using paired statistical testing supplemented with an effect-size estimate.

Third, permutation-based importance estimates derived from the CNN are contrasted with standardised PLS-SEM path coefficients, allowing concordance and divergence between explanatory and predictive perspectives to be documented empirically.

Research contributions

This study makes two primary contributions: it formalises a hybrid architecture in which the measurement model determines the input representation of the deep network, making the linkage between confirmatory and predictive stages architectural (i.e., integrated by design) rather than merely sequential; and it evaluates both components under identical cross-validation folds, benchmarking against four alternative approaches and reporting paired statistical tests and effect sizes for each planned contrast, a level of inferential transparency that is seldom provided in the hybrid SEM–ANN literature.

Related work and hypothesis development

Theoretical integration

No single theoretical perspective fully accounts for the determinants of technology adoption; accordingly, recent scholarship has increasingly converged on integrative frameworks^{2,36,37}. The technology–organisation–environment (TOE) framework distinguishes determinants across technological, organisational, and environmental contexts^{11,12}. Diffusion of innovations theory further delineates perceived attributes of the innovation¹³, while the technology acceptance model (TAM)¹⁴ and UTAUT¹⁵ contribute individual-level psychological constructs through which contextual factors influence behavioural outcomes. Meta-analytic findings across sectors support such synthesis: technological, organisational, and environmental determinants each explain unique variance in organisational AI adoption³⁶, and evidence from TAM meta-analyses in AI contexts indicates that the perceived usefulness and perceived ease-of-use pathways remain robust across settings³⁸.

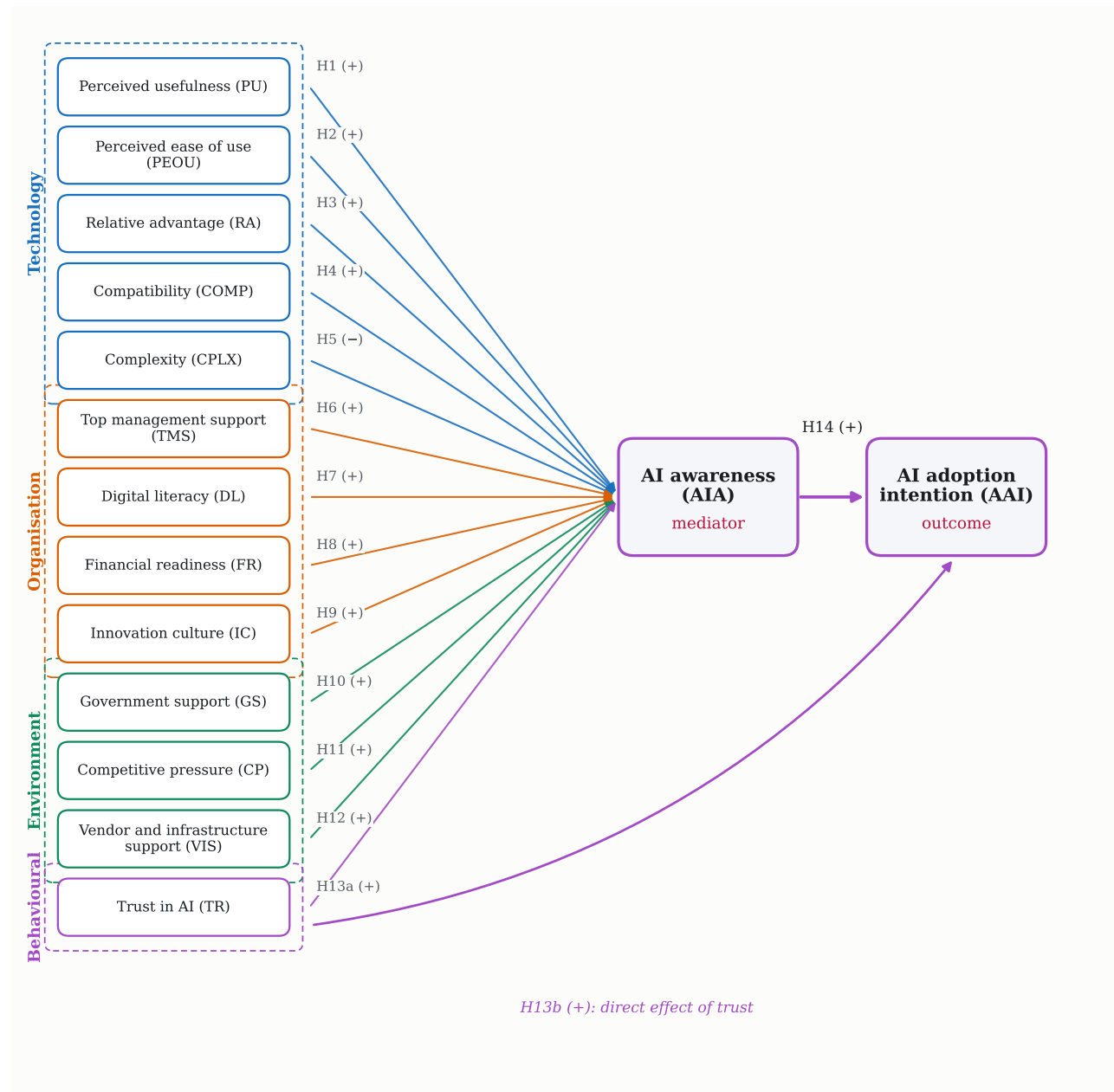


Figure 1. Conceptual model and hypotheses. Thirteen antecedent constructs, organised into the technological, organisational, environmental, and behavioural domains of the integrated TOE–DOI–behavioural framework, are hypothesised to influence AI awareness, which is posited to mediate their effects on intention to adopt AI. Each directed path is annotated with the corresponding hypothesis identifier and the expected sign of the relationship. Trust in AI is further hypothesised to exert a direct effect on adoption intention (H13b; curved path). Colours denote the associated theoretical domain, and all constructs are explicitly labelled to ensure identifiability independent of colour coding.

Building on this integrated view, we operationalise fifteen constructs organised into four domains. *Technology*: perceived usefulness (PU), perceived ease of use (PEOU), relative advantage (RA), compatibility (COMP), and complexity (CPLX). *Organisation*: top management support (TMS), digital literacy (DL), financial readiness (FR), and innovation culture (IC). *Environment*: government support (GS), competitive pressure (CP), and vendor and infrastructure support (VIS). *Behavioural*: trust in AI (TR), AI awareness (AIA), and AI adoption intention (AAI). AI awareness is modelled as a mediating construct, consistent with the staged decision logic in diffusion theory—where knowledge precedes persuasion and adoption decisions¹³—and with empirical evidence indicating that awareness and perceived usefulness are distinct constructs that occur in a sequential order^{39,40}. The complete hypothesised model, including all proposed paths and corresponding hypothesis labels, is presented in

Fig. 1.

Technological antecedents

Perceived usefulness constitutes the most consistently replicated antecedent of technology acceptance and continues to do so in the context of AI adoption specifically^{38,41,42}. Perceived ease of use is typically the weaker of the two canonical TAM pathways in mature markets; however, it remains substantively influential in contexts where digital competencies are unevenly distributed^{43,44}. Relative advantage is conceptually distinct from perceived usefulness insofar as it is inherently comparative rather than absolute, and it is repeatedly identified as among the strongest diffusion-theoretic predictors of organisational adoption^{36,45}. Evidence from adopter-segmentation analyses further indicates that the salience of these perceptions varies systematically across subgroups within the same population⁴⁶. Compatibility reflects the degree of congruence between the innovation and existing workflows and systems, representing a non-trivial constraint in settings characterised by heterogeneous or partially manual processes^{7,47}. Complexity denotes the perceived difficulty associated with understanding and using the innovation and is therefore expected to inhibit adoption-related cognitions^{2,13}.

H1–H4

Perceived usefulness, perceived ease of use, relative advantage, and compatibility each exert a positive effect on AI awareness.

H5 Complexity exerts a negative effect on AI awareness.

Organisational antecedents

Leadership commitment is consistently identified as a decisive organisational determinant: internal enabling conditions, particularly senior sponsorship, shape whether AI initiatives secure resources and persist through the implementation phase^{48–50}. Digital literacy constitutes the organisational analogue of the international adoption divide; analyses of Eurobarometer data indicate that digital skills and prior experience are the primary predictors of AI acceptance⁵¹, a finding corroborated by a decade of AI-literacy research in educational contexts⁵². Financial readiness is the most frequently reported constraint in SME surveys; however, its influence on *awareness* as opposed to implementation is anticipated to be comparatively limited^{3,53}. Innovation culture determines whether firms engage in experimentation and moderates digital adoption processes in emerging economies^{50,54}. Firm-level evidence further suggests that employees' adoption intentions are associated with subsequent operational performance, while organisational adoption reciprocally alters how employees enact job crafting; accordingly, the organisational block functions both as an antecedent and an outcome of adoption^{55–57}.

H6–H9

Top management support, digital literacy, financial readiness, and innovation culture each positively affect AI awareness.

Environmental antecedents

Government support encompassing grant provision, tax treatment, skills development programmes, and the regulatory environment conditions the set of opportunities available to small firms^{4,58}. Competitive pressure constitutes a canonical environmental driver within technology–organisation–environment (TOE) applications and continues to be empirically salient in recent evidence on small and medium-sized enterprises (SMEs)^{59,60}. Vendor and infrastructure support can partially compensate for the limited internal capabilities typical of small firms and is repeatedly identified as a determinant of technology-related outcomes in resource-constrained contexts^{17,61,62}.

H10–H12

Government support, competitive pressure, and vendor and infrastructure support each positively affect AI awareness.

Trust, awareness and intention

Trust assumes a distinctive role in the adoption of artificial intelligence (AI) because the technology and its decision processes remain largely non-transparent to many actors responsible for adoption decisions. Recent research conceptualizes trust both as an antecedent of engagement and as an outcome of use experience, with cross-cultural heterogeneity in its determinants^{63,64}. Moreover, empirical evidence indicates that trust operates in parallel with perceived risk rather than solely through it^{65,66}. Several studies further report a direct effect of trust on adoption intention that is not fully mediated by cognitive appraisal mechanisms^{40,44}; accordingly, we specify both mediated and direct pathways. An analogous dual-path structure is evident in the conversational-agent literature, where trust and perceived service quality independently predict continuance intentions beyond usefulness-based evaluations^{67–69}. Within staged adoption models, awareness constitutes the most proximal determinant of intention, and the awareness–implementation gap represents a robust empirical regularity in the small and medium-sized enterprise (SME) literature^{6,7}.

H13a, H13b

Trust in AI positively affects AI awareness and exerts a positive direct effect on AI adoption intention.

H14

AI awareness positively affects AI adoption intention and mediates the effects of contextual antecedents on AI adoption intention.

Hybrid structural and machine-learning designs

Machine learning has been incorporated into this body of work to relax the linearity assumptions implicit in conventional structural models³⁰. The hybrid SEM–ANN paradigm is now well established, with applications reported across e-learning continuance³³, whistleblowing-application adoption³⁴, adaptive supply-chain contexts³⁵, and AI adoption among SMEs³². Related configurational approaches, such as PLS–fsQCA, pursue an analogous objective via an alternative methodological route^{18,70}. In addition, hybrid structural and review-based frameworks have been proposed to support adoption forecasting in research settings⁷¹.

Three methodological limitations recur in this stream. First, the neural component is commonly trained on construct scores rather than on the original indicators; consequently, it inherits the measurement model's linear aggregation and can only identify interactions *between* constructs, not within-construct patterns at the indicator level. Second, evaluation procedures typically differ between the SEM and neural stages, such that reported performance comparisons are often based on metrics computed on non-identical data or under non-equivalent validation protocols. Third, benchmarking is frequently insufficient: absent a consistently evaluated linear baseline and a non-neural non-linear comparator, observed improvements cannot be clearly attributed to depth, non-linearity, or the increased parameterization of neural architectures. Broader reviews of machine learning applications in the social sciences converge on the same conclusion: predictive gains over well-specified linear models are often modest and are frequently matched by tree-based ensembles^{30,72}. When interpretability is required, permutation-based importance measures and Shapley-type attribution methods are commonly used to reconnect predictive models to explanatory accounts^{31,73,74}.

Convolutional architectures are relevant in this context for structural rather than stylistic reasons. Convolution implements a weight-sharing operator along an axis for which the same functional relationship is assumed to hold across positions^{75–77}. A reflective measurement block exhibits precisely this property: each indicator can be treated as an exchangeable manifestation of the same latent construct. Accordingly, representing respondents as construct $\times$ indicator matrices embeds the measurement model's exchangeability assumption as an inductive bias of the network, thereby allowing an initial convolutional stage to learn the aggregation that is otherwise imposed exogenously by the outer model.

Methods

Research design

The present study employed a quantitative, cross-sectional survey design grounded in a post-positivist epistemological orientation. This approach was deemed appropriate given the confirmatory nature of the research questions, the derivation of hypotheses from established theoretical frameworks (TOE, DOI, TAM, UTAUT2), and the requirement for an analytical strategy capable of estimating standardised effects at the national level^{78,79}. Comparable research designs have been utilised to examine AI acceptance within the governmental sector⁸⁰, as well as AI adoption among SMEs in Saudi Arabia⁸¹, Pakistan³², and related contexts.

Study population and sampling

The target population consisted of owners, managers, and senior decision-makers of small and medium-sized enterprises (SMEs) across Nigeria's 36 states and the Federal Capital Territory (FCT). Based on the latest NBS/SMEDAN MSME Survey^{82,83}, Nigeria has 73,081 SMEs defined as enterprises employing 10–199 individuals distributed across the six geopolitical zones. Table 1 presents the corresponding zonal distribution used to define the sampling frame.

Table 1. Population of SMEs and proportional sample allocation across Nigeria’s six geopolitical zones.

Geopolitical Zone	Population (SMEs)	Proportional Sample	Valid Responses
South-West	23,290	478	387
South-South	14,820	304	252
South-East	11,460	235	190
North-Central	9,870	203	165
North-West	8,730	179	144
North-East	4,911	101	72
Total	73,081	1,500	1,210

Source: Population data derived from⁸² and⁸³.

Sample size determination

The minimum required sample size was determined using Yamane’s⁸⁴ formula:

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

where $N = 73,081$ denotes the total population of SMEs and $e = 0.05$ specifies the desired precision level. This computation produced an initial estimate of $n \approx 398$. Given the analytical demands of a 15-construct PLS-SEM model and to comply with the “ten-times rule”²⁷, which stipulates a minimum of ten observations per indicator associated with the most complex construct, the planned sample size was increased to 1,500. Bowley’s⁸⁵ proportionate allocation method was subsequently applied to apportion the sample across zones:

$$n_h = \frac{n \cdot N_h}{N} \quad (2)$$

where N_h represents the SME population in zone h . In total, 1,500 questionnaires were administered between September 2024 and February 2025, of which 1,210 were returned and deemed valid (response rate = 80.7%). This achieved sample size exceeds the Krejcie and Morgan benchmark⁸⁶ for populations of comparable magnitude and meets the minimum bootstrap-related requirements for PLS-SEM.

Data collection

Primary data were collected between September 2024 and February 2025 by twelve trained research assistants (two per zone). A hybrid survey administration strategy was implemented, comprising (i) in-person, paper-based questionnaires administered in markets, industrial clusters, and SMEDAN-affiliated business hubs, and (ii) an online questionnaire deployed via Google Forms and disseminated through state Chambers of Commerce and Industry, the FATE Foundation alumni network, and the Nigerian Association of Small and Medium Enterprises (NASME) mailing list. Written informed consent was obtained from all participants. Participation was voluntary, anonymous, and uncompensated. The study protocol received ethical approval from the Babcock University Research Ethics Committee (Approval No. BUHREC 292/25).

Data preparation

All returned questionnaires were screened for completeness. Responses exhibiting >10% missing data were excluded from further analysis. For the retained cases, the residual missingness (1.4%) was addressed via within-construct mean imputation. Potential common-method variance was evaluated using Harman’s single-factor test; the first unrotated factor explained 26.3% of the total variance, which is below the conventional 50% criterion, suggesting that common-method bias is unlikely to substantively affect the estimated structural relationships⁸⁷.

Instrument development and operationalisation of constructs

The research instrument was a structured, self-administered questionnaire comprising four sections: (i) demographic and firm-level characteristics; (ii) awareness of specific AI tools across eleven functional categories (customer relationship management, marketing automation, scheduling and project management, accounting and financial management, human resources and recruitment, chatbots and customer interaction, email personalisation, meeting management, design and app builders, content creation, social media management); (iii) reflective items measuring each of the 15 latent constructs of the structural model on five-point Likert scales (1 = strongly disagree to 5 = strongly agree); and (iv) self-reported AI adoption intention.

Items were adapted from validated published scales. The TAM constructs (PU, PEOU) drew on¹⁴ and⁴⁶. The DOI constructs (RA, COMP, CPLX) drew on¹³, and the operationalisations of³² and⁸¹. Organisational constructs (TMS, DL, FR, IC) drew

on^{32, 88} and¹⁶. Environmental constructs (GS, CP, VIS) followed⁵⁹. Trust was operationalised from⁶⁵ and¹⁶. AI adoption intention used the UTAUT2 behavioural-intention items of¹⁵.

The 15 reflective constructs were measured by 68 indicators on five-point agreement scales (Supplementary Table S1). Block sizes ranged from four to six indicators. The complexity block is reverse-keyed. Eleven binary items recorded awareness of AI tools in the same eleven functional categories listed above. Demographic and firm characteristics comprised gender, age band, highest qualification, years in operation, sector, firm size and sampling stratum.

A pilot study was conducted with 60 SMEs across Lagos, Abuja and Kano in August 2024. Cronbach's alpha for each construct exceeded 0.70, item-total correlations exceeded 0.50, and the questionnaire was refined for clarity following the pilot. Three subject-matter experts (two academics in Information Systems and one digital-economy policy analyst) reviewed the instrument for content and face validity prior to deployment.

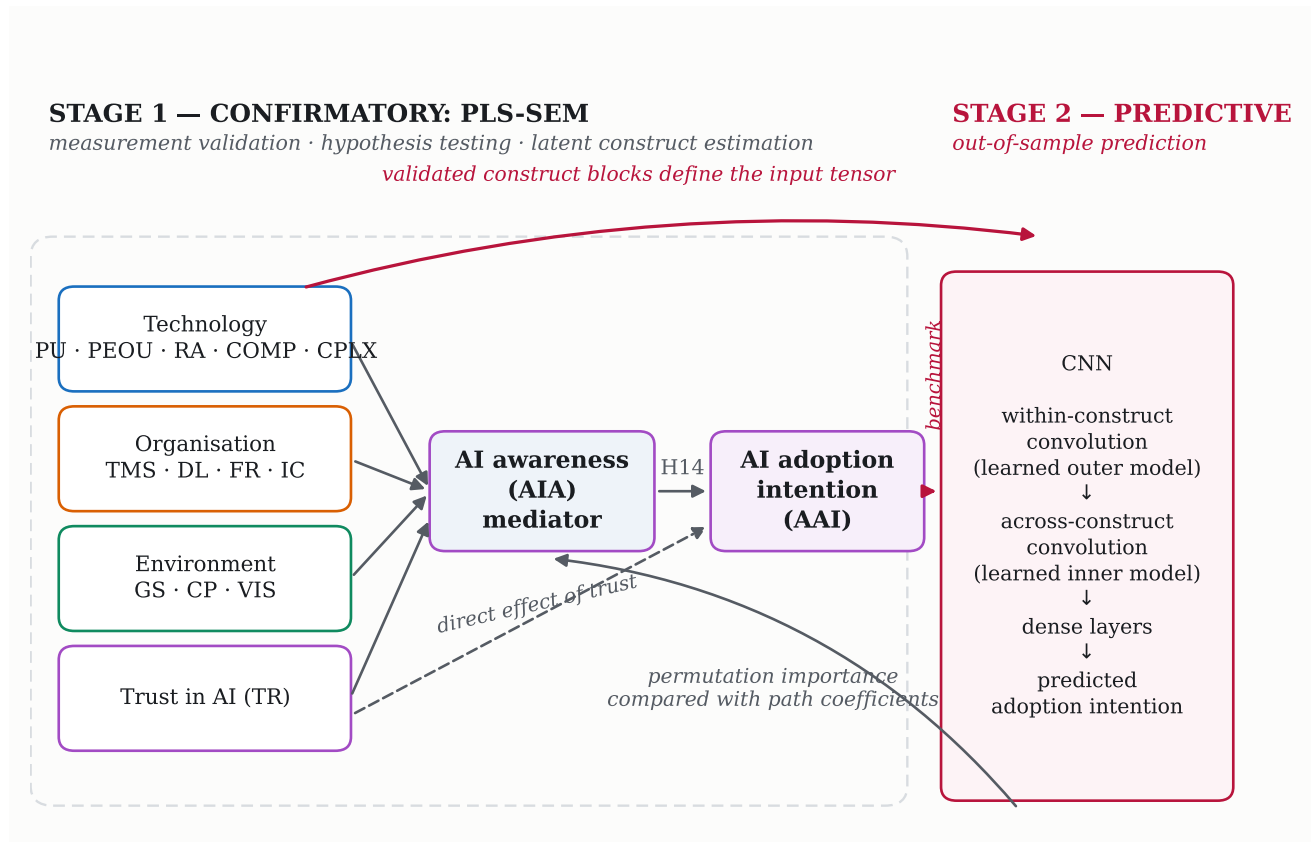


Figure 2. The two-stage hybrid design. Stage 1 (PLS-SEM) validates the measurement model, estimates the latent constructs and tests the hypotheses. Stage 2 (CNN) performs prediction. The coupling is architectural: the construct blocks validated in Stage 1 define the rows of the network's input tensor, so the first convolutional stage learns an aggregation of indicators within a construct (the learned outer model) and the second learns interactions between constructs (the learned inner model). The structural model is also used as a predictive benchmark on the same folds, and construct-level permutation importance in the network is compared with the standardised path coefficients.

Analytical strategy

The two-stage analytical workflow followed⁸⁹:

Stage 1: PLS-SEM

The structural model was estimated by partial least squares structural equation modelling using Mode A (correlation) outer weights and the path-weighting inner scheme⁸⁹. PLS-SEM was selected because the model is complex (fifteen constructs, thirteen paths into a single mediator), because the objective is predictive as well as explanatory, and because the indicators are ordinal.

The measurement model was assessed on indicator reliability (outer loadings), internal consistency (Cronbach's α , ρ_A and composite reliability ρ_c), convergent validity ($AVE \geq 0.50$) and discriminant validity (HTMT and the Fornell–Larcker

criterion), following current best-practice guidance^{90,91}. Common-method variance was assessed with Harman’s single-factor test and with full-collinearity VIF across all construct scores^{92–95}.

The structural model was assessed on standardised path coefficients with percentile bootstrap inference (5,000 subsamples, each re-estimating the complete measurement and structural model), inner VIF, effect size f^2 ⁹⁶ and R^2 ⁹⁷. Mediation followed the typology of Zhao et al.⁹⁸: indirect effects were estimated as $a \times b$ with bootstrap intervals, and direct effects were taken from a saturated outcome model in which every antecedent enters alongside the mediator. Predictive relevance was assessed by $Q^2_{predict}$ from 10-fold cross-validation against a naïve linear-regression benchmark, as specified by PLSpredict²⁶.

Stage 2: convolutional neural network

Input representation

Each respondent is encoded as a $14 \times 6 \times 1$ tensor. The row dimension corresponds to the fourteen constructs hypothesised to predict adoption intention (thirteen antecedent variables plus the mediator), whereas the column dimension comprises the retained indicators. Indicator values are standardised and zero-padded to match the maximum number of indicators observed across construct-specific blocks. This representation constitutes the interface between the two analytical stages: it is determined by the measurement model validated in Stage 1 and operationalises the reflective measurement assumption. Specifically, convolutional kernels that translate along the indicator axis impose weight sharing across indicator positions, consistent with the measurement model’s treatment of indicators as exchangeable manifestations of the same latent construct.

Architecture

The architecture comprises two convolutional stages (Table 2). In the first stage, 1×3 kernels are applied by sliding exclusively along the indicator axis, followed by pooling across indicators. This operation yields a single embedding for each construct and can be interpreted as a learned analogue of the outer model. In the second stage, 3×1 kernels are applied along the construct axis to capture inter-construct dependencies, constituting a learned analogue of the inner model. The construct axis is retained (i.e., no global pooling is applied over constructs), such that the subsequent dense head is provided with a feature representation for each construct. A schematic overview of the complete design is shown in Fig. 2, and a machine-readable model specification is provided in the reproduction package.

Table 2. Architecture of the item-tensor convolutional neural network.

Layer	Configuration	Output shape
Input	$14 \times 6 \times 1$ tensor: rows are validated constructs, columns are their standardised indicators, zero-padded	$1 \times 14 \times 6$
Conv2D-1 (within-construct)	32 filters, kernel 1×3 , padding (0,1), BatchNorm, ReLU	$32 \times 14 \times 6$
Conv2D-2 (within-construct)	32 filters, kernel 1×3 , padding (0,1), BatchNorm, ReLU	$32 \times 14 \times 6$
Pool (indicator axis)	adaptive average pool over indicators only; the construct axis is preserved (learned outer model)	$32 \times 14 \times 1$
Conv2D-3 (across-construct)	64 filters, kernel 3×1 , padding (1,0), BatchNorm, ReLU	$64 \times 14 \times 1$
Conv2D-4 (across-construct)	64 filters, kernel 3×1 , padding (1,0), BatchNorm, ReLU (learned inner model)	$64 \times 14 \times 1$
Flatten + Dropout + Dense	flatten to 896, dropout 0.3, 64 units, ReLU	64
Dropout + Output	dropout 0.3, 1 linear unit	1

Trainable parameters: 79,649. The first convolutional stage slides along the indicator axis only and is the learned analogue of the outer (measurement) model; the second slides along the construct axis and is the learned analogue of the inner (structural) model.

Training and hyperparameter selection

Hyperparameters were determined via an exhaustive grid search over learning rate, dropout probability, weight decay, and filter width. Candidate configurations were evaluated using the mean validation RMSE averaged across three random seeds on a validation split that was strictly disjoint from the held-out test split; consequently, no test data were used during model selection (Supplementary Table S4). The optimal setting employed the Adam optimiser with a learning rate of 3×10^{-4} , weight decay of 1×10^{-4} , and dropout of 0.30; the convolutional backbone used 32 and 64 filters in the first and second stages, respectively. Training was conducted with batch size 64 using mean squared error as the objective, with learning-rate reduction on plateau and early stopping based on validation loss (patience = 40) for up to 400 epochs. The resulting model comprised 79,649 trainable parameters.

Benchmarks and evaluation protocol

Five predictive models were assessed using identical data partitions: (i) the item-tensor convolutional neural network (CNN); (ii) a one-dimensional CNN applied to construct-level scores to isolate the incremental contribution of the item-level representation; (iii) a feed-forward neural network trained on construct scores, consistent with architectures commonly employed in the

SEM–ANN literature; (iv) a random forest trained on construct scores, serving as a non-neural nonlinear benchmark; and (v) ordinary least squares regression using all indicator variables. The PLS–SEM structural model, specified with two predictors of adoption intention, served as a sixth model and reference baseline. Model performance was estimated via 10-fold cross-validation repeated twice (20 total folds). Between-model performance differences were evaluated using paired *t*-tests and Wilcoxon signed-rank tests computed across folds, and effect sizes were quantified using Cohen’s *d* for paired differences.

Importance

Construct-level permutation importance was estimated on the held-out test partition as the mean increase in RMSE induced by permuting, across respondents, the complete indicator block associated with each construct, with results averaged over 50 Monte Carlo repetitions. The resulting importance scores were compared with the absolute standardised path coefficients using Spearman’s rank correlation.

Results

Sample and awareness profile

The analysed sample comprised 1,210 observations (Table 3). Awareness of AI tools varied markedly by functional category (Table 4, Fig. 3), ranging from 85.0% for content-creation tools and 83.6% for design and app builders to 62.7% for human-resources and recruitment tools, yielding an absolute difference of 22.3 percentage points. Cochran’s *Q* test rejected the null hypothesis of equal awareness across the eleven categories ($Q = 526.37$, $df = 10$, $p < 0.001$). Among the 55 pairwise McNemar comparisons, 18 remained statistically significant following Bonferroni correction. These significant contrasts primarily differentiated the two customer-facing categories from the back-office categories, whereas adjacent mid-ranked categories were not statistically distinguishable. Overall, the results indicate a front-office/back-office asymmetry in awareness rather than a monotonic gradient across categories.

Table 3. Profile of the analysed sample ($N = 1,210$).

Characteristic	Category	<i>n</i>	%
Gender	Male	791	65.4
	Female	419	34.6
Age	18-28	447	36.9
	29-39	513	42.4
	40-50	160	13.2
	51-60	56	4.6
	61-70	24	2.0
	>70	10	0.8
Highest qualification	Secondary or below	124	10.2
	Diploma/NCE	201	16.6
	Bachelor	587	48.5
	Master	251	20.7
	Doctorate	47	3.9
Years in operation	<=3 years	361	29.8
	4-6 years	364	30.1
	7-10 years	276	22.8
	11-15 years	146	12.1
	>15 years	63	5.2
Sector	Trade & retail	354	29.3
	ICT & professional services	222	18.3
	Other services	180	14.9
	Agriculture & agro-processing	170	14.0
	Manufacturing	157	13.0
	Hospitality & food	127	10.5
Firm size	10-49 employees	732	60.5
	50-99 employees	315	26.0
	100-199 employees	163	13.5

Table 4. Awareness of AI tools by functional category ($N = 1,210$).

Rank	Functional category	Aware	Not aware
1	Content creation	1,028 (85.0%)	182 (15.0%)
2	Design and app builders	1,012 (83.6%)	198 (16.4%)
3	Chatbots and customer interaction	818 (67.6%)	392 (32.4%)
4	Marketing automation	807 (66.7%)	403 (33.3%)
5	Scheduling and project management	802 (66.3%)	408 (33.7%)
6	Customer relationship management	802 (66.3%)	408 (33.7%)
7	Social media management	795 (65.7%)	415 (34.3%)
8	Meeting management	775 (64.0%)	435 (36.0%)
9	Email personalisation	771 (63.7%)	439 (36.3%)
10	Accounting and financial management	771 (63.7%)	439 (36.3%)
11	Human resources and recruitment	759 (62.7%)	451 (37.3%)

Cochran's $Q = 526.37$, $df = 10$, $p < 0.001$. Of the 55 pairwise McNemar contrasts, 18 remained significant after Bonferroni adjustment (Supplementary Table S2).

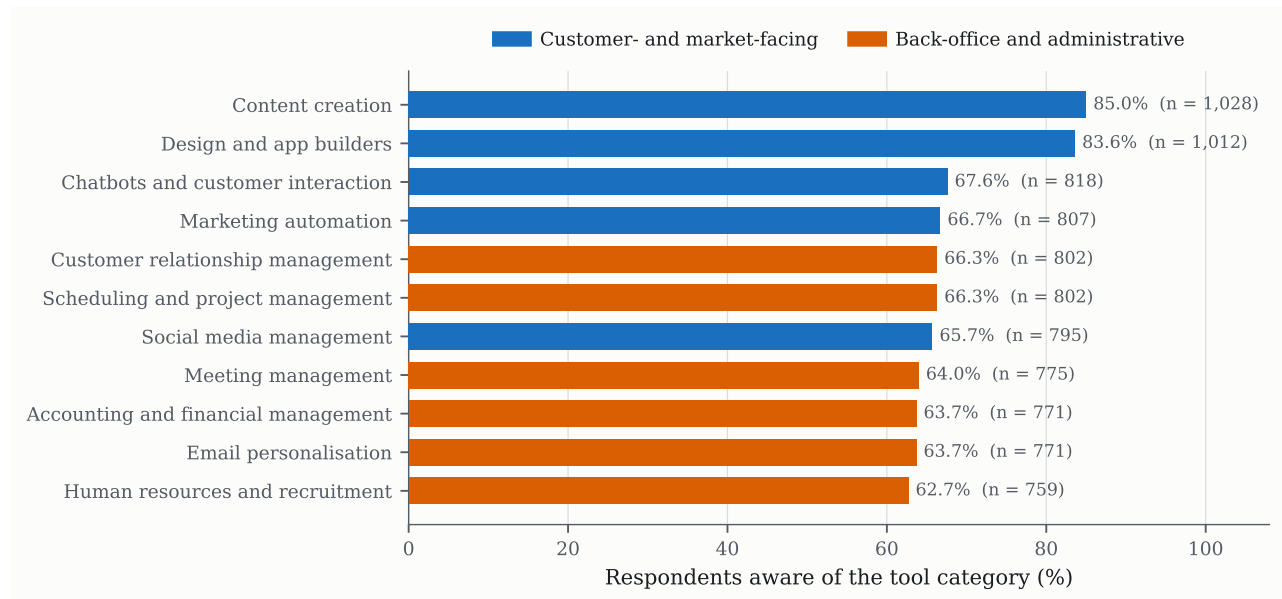


Figure 3. Awareness of AI tools by functional category ($N = 1,210$). The bars report the proportion of respondents indicating awareness of each category, with the corresponding counts displayed. Awareness is predominantly concentrated in customer- and market-facing categories and is consistently lower across back-office functions, yielding a 22.3 percentage-point range between the most and least recognised categories. Cochran's Q test rejects the null hypothesis of equal awareness proportions across the eleven categories.

Measurement model

All fifteen latent constructs met established benchmarks for measurement reliability and validity (Table 5, Supplementary Figure S1). Internal consistency was satisfactory across constructs, with Cronbach's α ranging from 0.793 to 0.943, ρ_A from 0.793 to 0.954, and composite reliability from 0.866 to 0.956, thereby falling within the recommended interval of $[0.70, 0.95]$. Convergent validity was also supported: AVE values ranged from 0.617 to 0.783, exceeding the conventional 0.50 criterion for all constructs. Indicator outer loadings spanned 0.625 to 0.946; although six of the 68 indicators loaded below 0.70, they were retained because a sensitivity analysis excluding these indicators did not alter any structural path coefficient by more than 0.009 (see robustness analysis below). Evidence for discriminant validity was likewise obtained: the maximum HTMT ratio was 0.779, below the conservative 0.85 threshold, and the Fornell–Larcker criterion was satisfied for all construct pairs without violations.

No substantive evidence of common-method variance was observed. Harman's single-factor test indicated that the first factor explained 29.2% of the variance, well below the 50% cutoff. The full-collinearity VIF reached 3.369, slightly exceeding Kock's 3.3 guideline; this peak occurred for the mediator, which is expected to covary with all thirteen antecedents and the

Table 5. Measurement model: reliability and convergent validity.

Construct	Block	Items	Loadings	α	ρ_A	ρ_c	AVE
Perceived usefulness (PU)	Technology	5	0.693–0.937	0.902	0.932	0.929	0.725
Perceived ease of use (PEOU)	Technology	4	0.803–0.818	0.829	0.83	0.886	0.661
Relative advantage (RA)	Technology	5	0.632–0.930	0.895	0.921	0.924	0.713
Compatibility (COMP)	Technology	4	0.784–0.820	0.811	0.813	0.876	0.638
Complexity (CPLX)	Technology	4	0.778–0.792	0.793	0.793	0.866	0.617
Top management support (TMS)	Organisation	5	0.690–0.939	0.908	0.934	0.933	0.738
Digital literacy (DL)	Organisation	5	0.710–0.939	0.919	0.937	0.941	0.762
Financial readiness (FR)	Organisation	4	0.793–0.818	0.822	0.823	0.882	0.652
Innovation culture (IC)	Organisation	4	0.625–0.940	0.846	0.91	0.897	0.69
Government support (GS)	Environment	4	0.786–0.822	0.813	0.815	0.877	0.641
Competitive pressure (CP)	Environment	4	0.708–0.927	0.851	0.886	0.9	0.695
Vendor and infrastructure support (VIS)	Environment	4	0.639–0.926	0.834	0.882	0.89	0.672
Trust in AI (TR)	Behavioural	5	0.677–0.933	0.904	0.926	0.931	0.731
AI awareness (AIA)	Behavioural	6	0.749–0.946	0.943	0.954	0.956	0.784
AI adoption intention (AAI)	Behavioural	5	0.735–0.934	0.919	0.932	0.94	0.759

Thresholds: $\alpha \geq 0.70$, $\rho_A \geq 0.70$, $\rho_c \in [0.70, 0.95]$, $AVE \geq 0.50$. All 15 constructs met every threshold. Outer loadings ranged from 0.625 to 0.946 (Supplementary Table S3).

outcome by design. Importantly, the inner-model VIFs used for estimating the structural relations were substantially lower (maximum 2.204), remaining comfortably below the threshold of 5.

Structural model and hypothesis tests

All fifteen structural hypotheses were supported. The estimated model is shown in Fig. 4, which carries every coefficient and its p -value on the corresponding path of the conceptual model of Fig. 1; Table 6 reports the same estimates with their standard errors, intervals and effect sizes, and Fig. 5 shows the thirteen effects on awareness with their confidence intervals. The strongest predictors of AI awareness were trust in AI ($\beta = 0.173$, $t = 7.09$, $p < 0.001$, $f^2 = 0.046$), digital literacy ($\beta = 0.155$, $t = 6.67$, $p < 0.001$, $f^2 = 0.040$) and top management support ($\beta = 0.133$, $t = 5.67$, $p < 0.001$, $f^2 = 0.030$), followed by perceived usefulness ($\beta = 0.122$) and relative advantage ($\beta = 0.102$). Complexity exerted the hypothesised negative effect ($\beta = -0.051$, $t = -2.55$, $p = 0.011$). Effect sizes were small throughout, between $f^2 = 0.005$ and $f^2 = 0.046$: with thirteen correlated predictors entering one mediator, explanatory weight is distributed rather than concentrated, and no single antecedent is individually decisive.

The mediator-to-outcome path was by far the largest in the model ($\beta = 0.651$, $t = 30.61$, $p < 0.001$, $f^2 = 0.618$), and trust retained a direct effect on intention alongside it ($\beta = 0.137$, $t = 5.53$, $p < 0.001$). The model explained 61.1% of the variance in AI awareness (adjusted $R^2 = 0.607$) and 54.7% in adoption intention (adjusted $R^2 = 0.547$).

Table 6. Structural model: standardised path coefficients and bootstrap inference.

H	Path	β	SE	95% CI	t	p	f^2	VIF	Decision
H1	PU $\rightarrow$ AIA	0.122	0.027	[0.071, 0.177]	4.54	<0.001	0.018	2.15	Supported
H2	PEOU $\rightarrow$ AIA	0.082	0.023	[0.037, 0.125]	3.61	<0.001	0.012	1.46	Supported
H3	RA $\rightarrow$ AIA	0.102	0.027	[0.047, 0.154]	3.75	<0.001	0.012	2.20	Supported
H4	COMP $\rightarrow$ AIA	0.063	0.023	[0.019, 0.109]	2.72	0.007	0.007	1.52	Supported
H5	CPLX $\rightarrow$ AIA	-0.051	0.020	[-0.092, -0.012]	-2.55	0.011	0.005	1.29	Supported
H6	TMS $\rightarrow$ AIA	0.133	0.023	[0.087, 0.178]	5.67	<0.001	0.030	1.52	Supported
H7	DL $\rightarrow$ AIA	0.155	0.023	[0.109, 0.201]	6.67	<0.001	0.040	1.54	Supported
H8	FR $\rightarrow$ AIA	0.058	0.022	[0.017, 0.103]	2.69	0.007	0.006	1.43	Supported
H9	IC $\rightarrow$ AIA	0.093	0.023	[0.048, 0.139]	4.03	<0.001	0.015	1.51	Supported
H10	GS $\rightarrow$ AIA	0.069	0.022	[0.026, 0.112]	3.15	0.002	0.009	1.38	Supported
H11	CP $\rightarrow$ AIA	0.075	0.022	[0.032, 0.118]	3.37	<0.001	0.010	1.46	Supported
H12	VIS $\rightarrow$ AIA	0.086	0.021	[0.043, 0.127]	4.01	<0.001	0.013	1.47	Supported
H13a	TR $\rightarrow$ AIA	0.173	0.024	[0.126, 0.220]	7.09	<0.001	0.046	1.66	Supported
H14	AIA $\rightarrow$ AAI	0.651	0.021	[0.609, 0.692]	30.61	<0.001	0.618	1.52	Supported
H13b	TR $\rightarrow$ AAI	0.137	0.025	[0.090, 0.185]	5.53	<0.001	0.028	1.52	Supported

Percentile bootstrap, 5,000 subsamples. f^2 : 0.02 small, 0.15 medium, 0.35 large. AIA, AI awareness; AAI, AI adoption intention. All inner VIF values were below the 5.0 threshold (maximum 2.20).

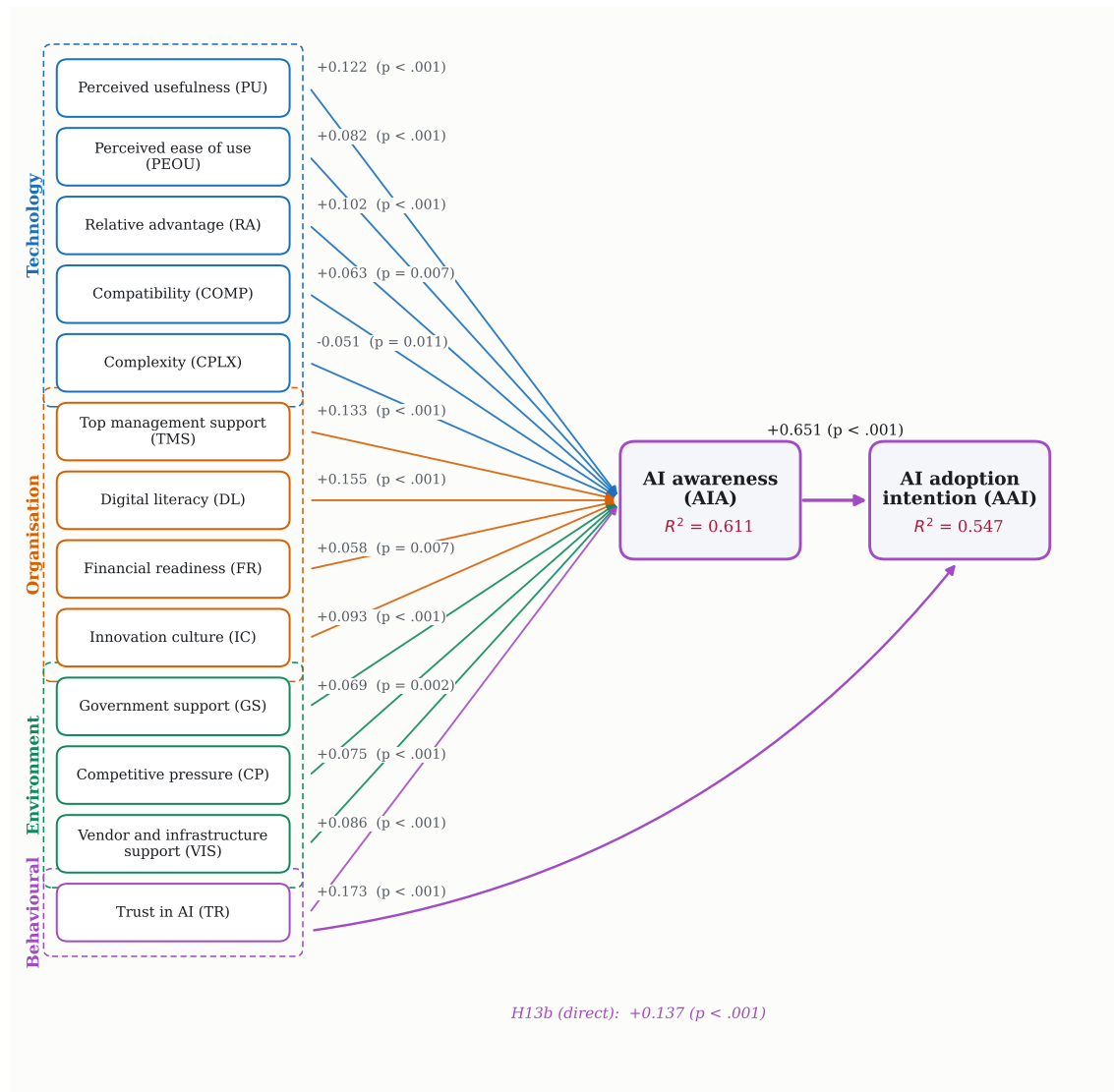


Figure 4. Estimated structural model. The model of Figure 1 reports the recovered parameter estimates, including standardised path coefficients with associated p -values obtained from 5,000 bootstrap resamples, as well as the coefficients of determination (R^2) for each endogenous construct. All fifteen structural paths are statistically significant at the 5% level and are therefore depicted with solid lines; the effect of complexity exhibits the hypothesised negative sign. Notably, the mediator-to-outcome coefficient (+0.651) is approximately an order of magnitude larger than any individual antecedent effect, constituting the model's primary structural characteristic.

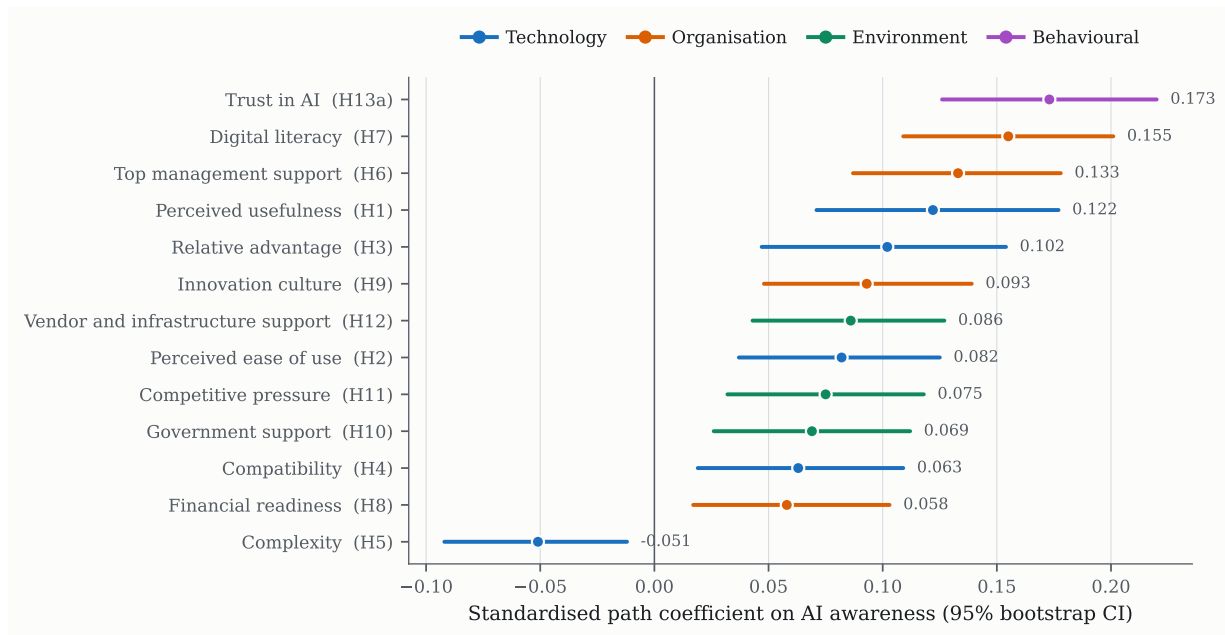


Figure 5. Standardised path coefficients on AI awareness with 95% bootstrap confidence intervals. Points are point estimates and horizontal bars are percentile intervals from 5,000 bootstrap subsamples, each re-estimating the complete measurement and structural model. Colour identifies the theoretical block; every predictor is also labelled, so identity does not depend on colour. All thirteen effects are distinguishable from zero, and complexity carries the expected negative sign.

Mediation

Awareness mediated the antecedent effects almost uniformly (Table 7, Fig. 6). Twelve of the thirteen antecedents showed indirect-only (full) mediation: the indirect effect through awareness was significant while the direct effect on intention was not. Trust was the single exception, showing complementary partial mediation with same-signed indirect ($\beta = 0.113$, $p < 0.001$) and direct ($\beta = 0.114$, $p < 0.001$) components of almost identical magnitude. The largest indirect effects were those of trust (0.113), digital literacy (0.101) and top management support (0.087).

This is the model's clearest substantive structure: contextual factors do not reach intention directly but through awareness, whereas trust operates on both routes at once; it raises awareness and, independently, raises willingness to adopt.

Table 7. Mediation of antecedent effects on AI adoption intention through AI awareness.

Antecedent	Indirect	95% CI	<i>p</i>	Direct	<i>p</i>	Type
Perceived usefulness (PU)	0.080	[0.046, 0.116]	<0.001	0.051	0.068	Full (indirect-only)
Perceived ease of use (PEOU)	0.053	[0.025, 0.082]	<0.001	-0.012	0.609	Full (indirect-only)
Relative advantage (RA)	0.067	[0.031, 0.101]	<0.001	0.016	0.601	Full (indirect-only)
Compatibility (COMP)	0.041	[0.012, 0.071]	0.007	-0.018	0.446	Full (indirect-only)
Complexity (CPLX)	-0.033	[-0.060, -0.008]	0.011	-0.012	0.583	Full (indirect-only)
Top management support (TMS)	0.087	[0.057, 0.117]	<0.001	-0.005	0.855	Full (indirect-only)
Digital literacy (DL)	0.101	[0.070, 0.132]	<0.001	-0.000	0.992	Full (indirect-only)
Financial readiness (FR)	0.038	[0.011, 0.067]	0.008	0.028	0.250	Full (indirect-only)
Innovation culture (IC)	0.061	[0.031, 0.091]	<0.001	0.047	0.067	Full (indirect-only)
Government support (GS)	0.045	[0.017, 0.074]	0.002	-0.008	0.719	Full (indirect-only)
Competitive pressure (CP)	0.049	[0.020, 0.078]	<0.001	0.016	0.491	Full (indirect-only)
Vendor and infrastructure support (VIS)	0.056	[0.028, 0.084]	<0.001	0.018	0.456	Full (indirect-only)
Trust in AI (TR)	0.113	[0.082, 0.145]	<0.001	0.114	<0.001	Complementary partial

Indirect effects estimated as $a \times b$ with 5,000 bootstrap subsamples; direct effects from the saturated outcome model. Typology follows Zhao et al.

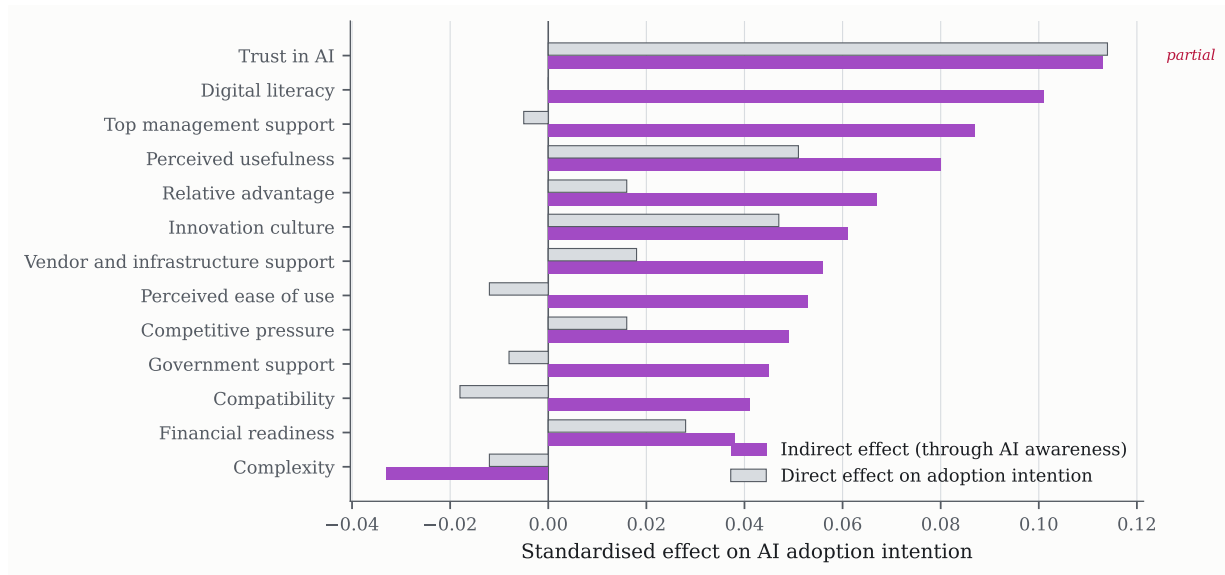


Figure 6. Indirect and direct effects on AI adoption intention. Indirect effects operate through AI awareness; direct effects are taken from the saturated outcome model. Twelve of thirteen antecedents show indirect-only (full) mediation, with direct effects indistinguishable from zero. Trust in AI is the single exception, carrying indirect and direct components of almost identical magnitude (complementary partial mediation, marked).

Predictive relevance of the structural model

Cross-validated predictive relevance was positive for both endogenous constructs (Table 8), with $Q^2_{predict} = 0.602$ for awareness and 0.546 for adoption intention. However, relative to the naïve linear benchmark, predictive performance differed across the two constructs. For awareness, the PLS model yielded lower prediction error on both metrics (RMSE 0.6316 vs. 0.6407; MAE 0.5034 vs. 0.5063). In contrast, for adoption intention the PLS model did not outperform the benchmark (RMSE 0.6748 vs. 0.6738; MAE 0.5360 vs. 0.5346). Accordingly, the two-predictor structural model cannot be considered superior to the naïve linear model with respect to the outcome variable. This result is reported explicitly because reliance on the common practice of deeming PLSpredict results “supportive” based solely on the mediator would have concealed this limitation.

Table 8. In-sample explanation and out-of-sample predictive relevance.

Construct	R^2	R^2_{adj}	95% CI	$Q^2_{predict}$	RMSE	RMSE _{LM}	MAE	MAE _{LM}
AI awareness (AIA)	0.611	0.607	[0.582, 0.648]	0.602	0.6316	0.6407	0.5034	0.5063
AI adoption intention (AAI)	0.547	0.547	[0.512, 0.585]	0.546	0.6748	0.6738	0.5360	0.5346

$Q^2_{predict}$ from 10-fold cross-validation. LM denotes the naïve linear-regression benchmark on the raw indicators. R^2 confidence intervals are percentile bootstrap intervals.

Predictive stage: the convolutional network

Training of the final neural network terminated after 46 epochs (Fig. 7). On the held-out test partition, performance was RMSE = 0.6888 with $R^2 = 0.560$, compared with RMSE = 0.5560 and $R^2 = 0.695$ on the training partition. This generalisation gap is consistent with moderate overfitting that dropout, weight decay, and early stopping attenuated but did not fully remove.

Over 20 cross-validation folds (Table 9, Fig. 8), mean predictive accuracy ranked as follows: random forest (RMSE 0.6525 ± 0.0500), feed-forward network (0.6541 ± 0.0488), item-tensor CNN (0.6580 ± 0.0533), construct-score CNN (0.6631 ± 0.0501), the PLS-SEM structural model (0.6718 ± 0.0586), and ordinary least squares using all indicators (0.6918 ± 0.0579).

Three planned contrasts inform the substantive interpretation. First, the CNN outperformed the structural benchmark. The paired cross-validation comparison indicated a 2.06% reduction in RMSE relative to the structural model; this difference was statistically supported: $t(19) = -2.31$, $p = 0.032$, Wilcoxon $p = 0.007$, Cohen’s $d = 0.52$. Analogous improvements were observed for the feed-forward network (2.64%, $p = 0.001$) and the random forest (2.88%, $p = 0.010$).

Second, the CNN did not outperform the two strongest non-SEM baselines. Relative to the feed-forward network, the estimated difference was -0.59% ($p = 0.349$), and relative to the random forest it was -0.85% ($p = 0.295$); neither

contrast approached statistical significance, and the point estimates favoured the simpler models. Accordingly, the predictive advantage over the structural model appears attributable primarily to relaxing linear functional form assumptions, rather than to convolutional inductive biases or increased depth. Although the item-tensor CNN yielded a 0.76% lower RMSE than the construct-score CNN, this difference was not significant ($p = 0.164$), suggesting that—at the present sample size—learning the measurement aggregation directly from indicators provides, at most, a modest incremental benefit over using inherited construct scores.

Third, the measurement model provided clear practical value. Ordinary least squares regression using all 68 raw indicators performed significantly worse than the two-predictor structural model (2.97% higher RMSE, $p < 0.001$, $d = 1.43$). Thus, dimensionality reduction via a validated measurement model is not merely an interpretive convenience; under the current sample size constraints, it appears necessary to obtain usable predictive performance.

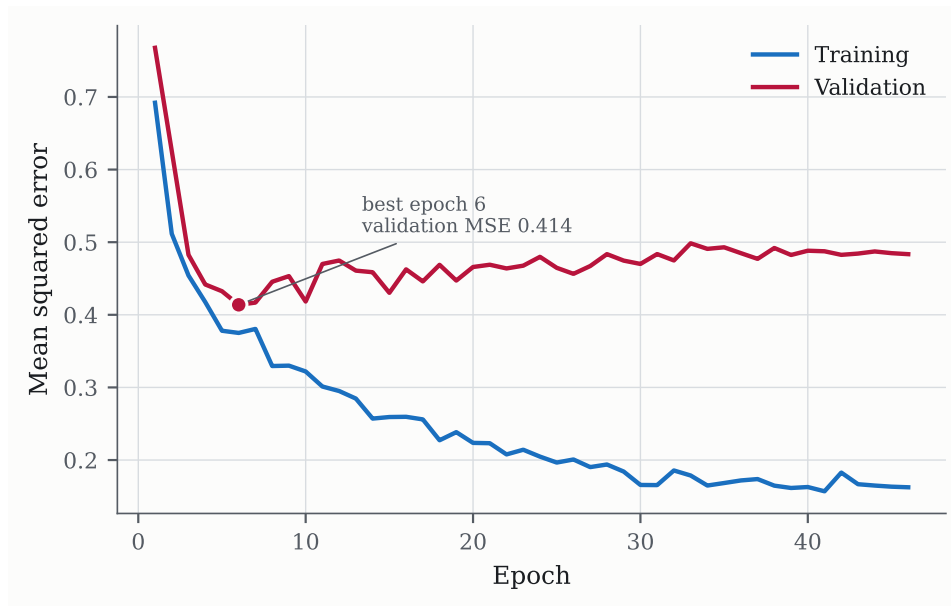


Figure 7. Training and validation error of the final convolutional network. Early stopping selected epoch 46 on validation loss. The separation between the two curves indicates moderate overfitting, controlled but not eliminated by dropout, weight decay and early stopping, and consistent with a sample size that is large for survey research but small for deep learning.

Table 9. Out-of-sample prediction of AI adoption intention: repeated cross-validation.

Model	RMSE (SD)	MAE (SD)	R^2 (SD)	Gain (%)	p
Random forest	0.6525 (0.0500)	0.5106 (0.0378)	0.5681 (0.0621)	+2.88	0.010
ANN (MLP)	0.6541 (0.0488)	0.5164 (0.0389)	0.5670 (0.0513)	+2.64	0.001
CNN-item	0.6580 (0.0533)	0.5177 (0.0366)	0.5622 (0.0519)	+2.06	0.032
CNN-score	0.6631 (0.0501)	0.5225 (0.0361)	0.5550 (0.0538)	+1.30	0.146
PLS-SEM structural	0.6718 (0.0586)	0.5356 (0.0419)	0.5436 (0.0582)	—	—
OLS (all indicators)	0.6918 (0.0579)	0.5483 (0.0439)	0.5159 (0.0610)	-2.97	<0.001

10-fold cross-validation repeated twice (20 folds); means with standard deviations across folds. Gain is the percentage reduction in RMSE relative to the PLS-SEM structural benchmark, with a paired t -test over the same folds. Positive gain favours the model.

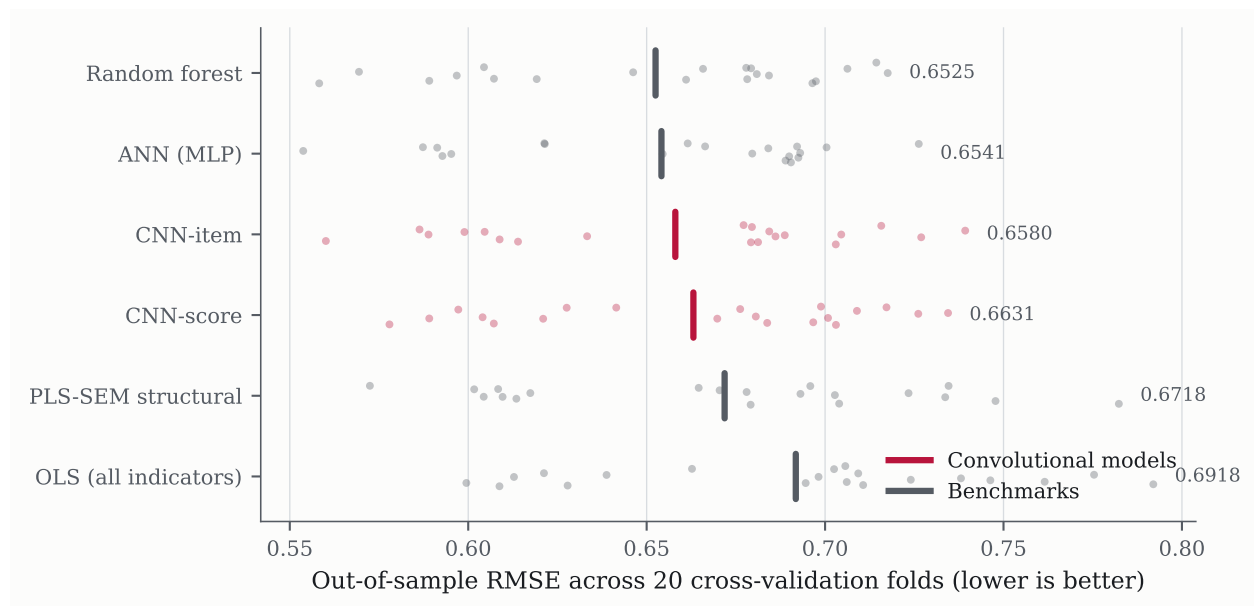


Figure 8. Out-of-sample error across twenty cross-validation folds. Each dot is one fold; the thick rule is the fold mean, printed at the right. All six models were evaluated on identical folds. The convolutional models improve on the PLS-SEM structural benchmark but not on the feed-forward network or the random forest, and ordinary least squares on all 68 raw indicators is the worst performer—worse than the two-predictor structural model.

Explanatory and predictive importance compared

Permutation importance estimates from the CNN and the absolute standardised path coefficients exhibit broad concordance but differ in specific details (Table 10, Fig. 9). Both methods rank awareness as the dominant predictor by a substantial margin and trust as the second most important predictor; together, these two constructs account for essentially all recoverable predictive signal. Specifically, awareness attains a normalised importance of 100, compared with 16.9 for trust, and no other construct exceeds a value of 6. Considering all fourteen predictors, the rank-order association is moderate and does not reach conventional levels of statistical significance (Spearman $\rho = 0.503$, $p = 0.067$).

Two discrepancies merit particular consideration. Complexity increases by nine positions in the predictive ranking (5th by permutation importance versus 14th by $|\beta|$), and financial readiness increases by seven positions. Conversely, relative advantage decreases in rank from 6th to 13th. This pattern is consistent with the intent of the comparison: divergences between the two orderings are more plausibly attributable to misspecification of the linear model than to error in the network-based ranking.

Interpretation should be constrained to what the data support. The permutation importances for the seven lowest-ranked constructs fall between -0.002 and 0.005 RMSE units, with standard deviations of comparable magnitude. These values are therefore statistically indistinguishable from zero and from one another, implying that their relative ordering is dominated by noise. Consequently, only the separation of awareness, trust, and—more marginally—perceived usefulness, digital literacy, and complexity from the remaining constructs is substantively interpretable.

Table 10. Predictive importance in the CNN compared with explanatory importance in PLS-SEM.

Construct	CNN rank	Normalised importance	$ \beta $	PLS-SEM rank
AI awareness (AIA)	1	100.0	0.651	1
Trust in AI (TR)	2	16.9	0.173	2
Perceived usefulness (PU)	3	5.9	0.122	5
Digital literacy (DL)	4	3.8	0.155	3
Complexity (CPLX)	5	3.5	0.051	14
Financial readiness (FR)	6	2.4	0.058	13
Top management support (TMS)	7	1.8	0.133	4
Competitive pressure (CP)	8	1.4	0.075	10
Vendor and infrastructure support (VIS)	9	0.7	0.086	8
Innovation culture (IC)	10	-0.0	0.093	7
Compatibility (COMP)	11	-0.0	0.063	12
Perceived ease of use (PEOU)	12	-0.1	0.082	9
Relative advantage (RA)	13	-0.4	0.102	6
Government support (GS)	14	-0.6	0.069	11

Permutation importance is the increase in test-set RMSE when a construct's indicator block is permuted (50 repetitions), normalised to the largest value. Spearman rank correlation between the two columns of importance: $\rho = 0.503$, $p = 0.067$.

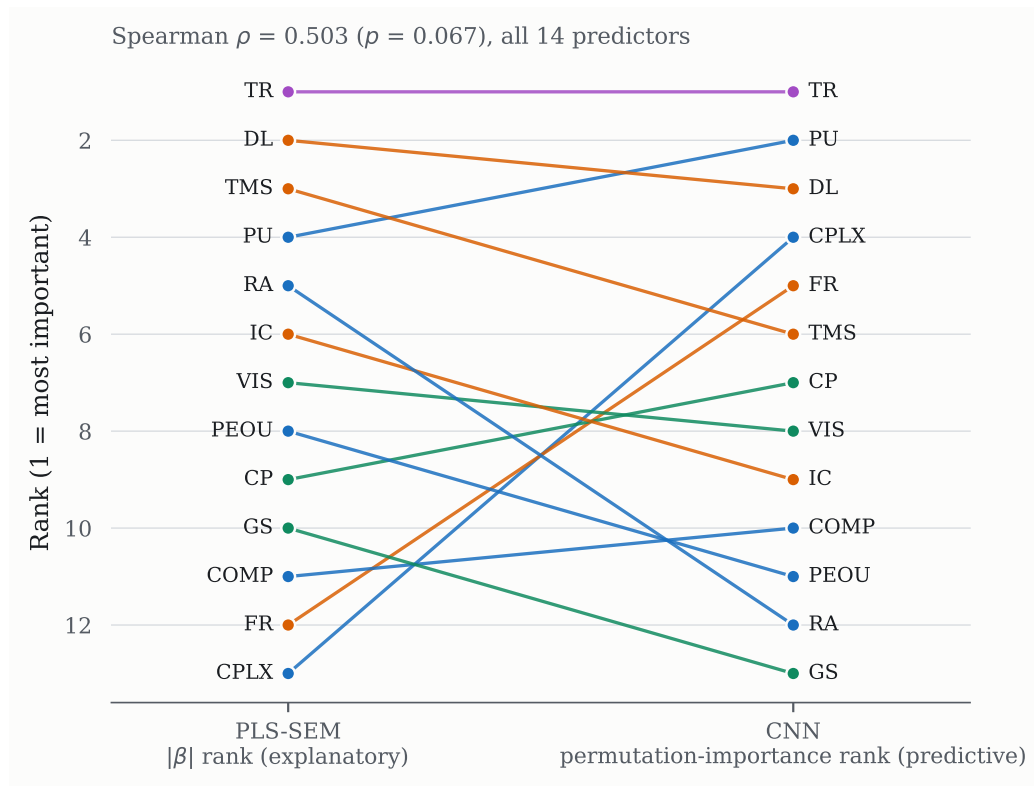


Figure 9. Explanatory and predictive importance orderings compared. Left, constructs ranked by absolute standardised path coefficient in PLS-SEM; right, ranked by permutation importance in the CNN. Lines connect the same construct in the two orderings and are coloured by theoretical block. The mediator is omitted because its importance dominates the scale. The orderings agree in outline but diverge at complexity and financial readiness, which rise in the predictive ordering, and at relative advantage, which falls.

Demographic covariates

Of six demographic and firm characteristics tested as covariates of awareness, only age band was significant ($F(5, 1204) = 3.56$, $p = 0.003$). Gender ($t(842) = -0.55$, $p = 0.583$), education ($F(4, 1205) = 0.44$, $p = 0.777$), years in operation ($F(4, 1205) = 0.55$, $p = 0.700$), sector ($F(5, 1204) = 1.36$, $p = 0.237$) and firm size ($F(2, 1207) = 0.02$, $p = 0.977$) were not.

Discussion

The present study aimed to empirically evaluate—rather than presuppose—the two standard propositions underlying hybrid structural-plus-machine-learning architectures: (i) that the structural component yields predictive performance, and (ii) that the subsequent neural component provides incremental predictive value beyond the structural model. Both propositions were directly testable in this setting because all candidate models were assessed under an identical cross-validation fold structure.

Evidence for the first proposition was mixed. Cross-validated predictive relevance was positive for both endogenous constructs; however, relative to a naïve linear benchmark, the structural model outperformed the benchmark for the mediator but underperformed it slightly for the outcome. Accordingly, a model may satisfy the conventional $Q^2_{predict} > 0$ threshold while nonetheless failing to exceed a theory-free benchmark. Given that $Q^2_{predict}$ is often reported without explicit benchmark comparison, this finding indicates a reporting limitation rather than an idiosyncratic result and aligns with prior reviews documenting inconsistent implementation of out-of-sample evaluation in applied PLS-SEM^{28,29}.

The second claim is supported; however, the underlying mechanism appears to differ from the conventional interpretation. The CNN yielded a statistically significant improvement over the structural model, with a moderate effect size. In contrast, it did not outperform either a feed-forward neural network or a random forest. These comparisons indicate that no detectable incremental contribution can be attributed to the CNN architecture per se; rather, the observed improvement is consistent with the adoption of a nonlinear functional form. This distinction is consequential because the hybrid SEM-ANN literature commonly ascribes performance gains to the inclusion of a neural component as such^{32–35}. Moreover, prevailing evaluation practices, specifically the absence of non-neural nonlinear baselines and the lack of paired statistical testing, do not permit discrimination between architectural effects and functional-form effects. Our findings are consistent with broader evidence that, for tabular data at survey scale, tree-based ensemble methods often match or exceed neural networks, and that improvements over well-specified linear models are typically on the order of only a few percentage points^{30,72}.

The third finding was unanticipated. An ordinary least squares (OLS) specification fit to all 68 indicators performed significantly worse than a structural model estimated using two construct scores. This result indicates that the measurement model contributes substantively to predictive performance: for $N \approx 1,000$ observations with 68 correlated indicators, theory-guided dimensionality reduction outperforms reliance on a flexible estimator to infer an effective latent structure directly from the raw indicators. Accordingly, these results support the continued relevance of measurement theory in the context of highly flexible learning algorithms. Moreover, they provide the strongest justification for the coupled design adopted here: the CNN input tensor is usable precisely because it is organised by the measurement model.

Awareness as the gateway

The observed mediation pattern constitutes the most systematically structured result. Specifically, 12 of the 13 previous variables were associated with intention exclusively through awareness. In the technological, organisational, and environmental domains, contextual factors appear to influence intention primarily by increasing decision-makers' awareness of AI capabilities, rather than by exerting a direct effect on willingness. Trust was the only construct that showed both indirect and direct pathways, the magnitudes of these components being approximately equivalent. This pattern is consistent with the staged decision logic articulated in diffusion theory¹³ and with recent empirical findings that conceptualise awareness and trust as distinct constructs that are sequentially ordered^{39,40,63}.

The observed awareness profile exhibited a systematic asymmetry that would be obscured by aggregation into a single composite awareness metric. Awareness was consistently high for customer-facing, content-generating tools and consistently lower for back-office functions, with statistically meaningful pairwise differences concentrated at this interface rather than being uniformly distributed across categories. Consequently, modelling awareness as a unidimensional construct constitutes a nontrivial measurement choice, as it collapses heterogeneity that includes a separation exceeding 20 percentage points.

Methodological implications

We propose two recommendations for research that integrates structural models with machine learning. First, employ identical cross-validation folds across models. Comparisons between a structural model and a neural network are not methodologically valid when they are evaluated on different data partitions; harmonising the folds is essentially costless and is necessary to convert a hybrid approach from an expository demonstration into a falsifiable empirical test. Second, benchmark against non-neural alternatives. In the absence of baselines such as a tree-based ensemble and a linear model evaluated on the same folds, any observed advantage of a neural network cannot be causally attributed to architectural inductive biases or representational capacity; in our analysis, omitting such benchmarks would have incorrectly attributed a performance gain to the CNN that could be achieved more parsimoniously by a random forest.

Limitations

Given the cross-sectional nature of the data, the proposed mediation model should be interpreted as a statistical decomposition rather than as evidence of temporal precedence or causal ordering. Although the sample size ($N = 1,210$) is comparatively large for survey-based research, it is modest for training deep learning models, and the observed train–test performance gap suggests that the CNN may be operating near the limits imposed by the available data. Consequently, the relative performance of the evaluated architectures may differ under alternative data scales. In addition, only a single family of deep neural architectures was examined.

Future work

Longitudinal study designs would allow the proposed awareness–mediation framework to be tested as an explicit temporal process, rather than being inferred from cross-sectional covariation. Moreover, employing multi-source measurement would reduce biases associated with common-method variance. In contexts where model interpretability is required, Shapley-type attribution procedures implemented at the indicator (rather than construct) level would facilitate a more granular identification of non-linear effects compared with block permutation approaches^{73,74}.

Conclusion

Hybrid research designs that integrate structural equation modelling (SEM) with machine learning have become increasingly prevalent in technology-adoption research; however, their typical implementation does not adequately support the inferences often claimed. Specifically, the SEM and machine-learning components are frequently assessed on non-identical datasets, without an explicit benchmark, and without uncertainty quantification for the between-stage performance difference. Here, we specify a hybrid design in which the coupling is architectural rather than sequential: the validated measurement model parameterises the input tensor of a convolutional neural network, and we evaluate all candidate models, including the structural model, using the same cross-validation folds.

Three principal results emerge. First, the convolutional neural network reduced out-of-sample error relative to the structural model by 2.06% ($p = 0.032$, $d = 0.52$); however, its performance was statistically indistinguishable from that of a feed-forward neural network and a random forest. This pattern indicates that the observed improvement is attributable primarily to relaxing linear functional-form assumptions rather than to convolutional structure or network depth per se. Second, although the structural model met the conventional predictive-relevance criterion, it did not outperform a naïve linear benchmark on the outcome construct, a limitation that would not have been detected from the criterion alone. Third, a validated two-construct measurement model yielded significantly better predictive performance than ordinary least squares across all 68 raw indicators, suggesting that theory-guided dimensionality reduction preserves predictive information at typical survey sample sizes.

Within the proposed model, AI awareness operated as a near-universal mediating gateway: adoption intention was influenced indirectly through AI awareness for twelve of the thirteen antecedent constructs, whereas trust was the only construct exhibiting both direct and AI-awareness-mediated pathways.

Data availability

The datasets generated and/or analysed during the present study are available from the corresponding author upon reasonable request. Public access to these data is restricted due to confidentiality agreements with the participating small and medium-sized enterprises (SMEs).

Acknowledgements

The authors thank the reviewers and editors whose comments improved this manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

Author contributions

A.I. conceptualised the study, designed the hybrid modelling strategy, implemented the data collection and analysis pipelines, produced the figures and tables, and drafted the manuscript. O.R.O. advised on the statistical design, specified and verified the calibration and robustness procedures, and carried out the independent replication. Y.H. and Y.T.B. supervised the project, contributed to the theoretical framing and hypothesis development, and critically revised the manuscript. All authors reviewed and approved the submitted version.

Competing interests

The authors declare no competing interests.

Ethics declarations

This study was conducted in accordance with the principles of the Declaration of Helsinki and received ethical approval from the Babcock University Health Research Ethics Committee (protocol code: BUHREC 292/25; approval date: 11 April 2025).

Informed Consent

Written informed consent was obtained from all study participants. Prior to enrolment, participants were informed of the intended uses of the collected data (e.g., dissemination in scientific publications) and of their rights regarding control over the processing and subsequent disposition of any (potentially identifiable) personal data obtained.

Additional information

Supplementary information accompanies this paper. It comprises the construct and indicator inventory (Table S1), the full McNemar post-hoc matrix (Table S2), the complete outer-loading table (Table S3), the hyperparameter search grid (Table S4), the HTMT and Fornell–Larcker matrices (Tables S5–S6), the measurement-quality figure (Figure S1). **Correspondence** and requests for materials should be addressed to A.I.

References

1. Arroyabe, M. F., Arranz, C. F. A., Fernandez De Arroyabe, I. & Fernandez de Arroyabe, J. C. Analyzing AI adoption in European SMEs: a study of digital capabilities, innovation, and external environment. *Technol. Soc.* **79**, 102733, DOI: [10.1016/j.techsoc.2024.102733](https://doi.org/10.1016/j.techsoc.2024.102733) (2024).
2. Oldemeyer, L., Jede, A. & Teuteberg, F. Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. *Manag. Rev. Q.* **75**, 1185–1227, DOI: [10.1007/s11301-024-00405-4](https://doi.org/10.1007/s11301-024-00405-4) (2025).
3. Muhammad, S. S., Dey, B. L., Kamal, M. M., Samuel, L. & Alzeiby, E. A. Digital transformation or digital divide? SMEs' use of AI during global crisis. *Technol. Forecast. Soc. Chang.* **217**, 124184, DOI: [10.1016/j.techfore.2025.124184](https://doi.org/10.1016/j.techfore.2025.124184) (2025).
4. Belete, A. K. & Murthy, K. V. R. A scoping review on the nexus between artificial intelligence and business sustainability in Africa. *Discov. Sustain.* **7**, 771, DOI: [10.1007/s43621-026-03097-w](https://doi.org/10.1007/s43621-026-03097-w) (2026).
5. Mienye, I. D., Sun, Y. & Ileberi, E. Artificial intelligence and sustainable development in Africa: a comprehensive review. *Mach. Learn. with Appl.* **18**, 100591, DOI: [10.1016/j.mlwa.2024.100591](https://doi.org/10.1016/j.mlwa.2024.100591) (2024).
6. Cooper, R. G. SMEs' use of AI for new product development: adoption rates by application and readiness-to-adopt. *Ind. Mark. Manag.* **126**, 159–167, DOI: [10.1016/j.indmarman.2025.01.016](https://doi.org/10.1016/j.indmarman.2025.01.016) (2025).
7. Sánchez, M. A., Calderón, J. & Herrera, L. Artificial intelligence adoption in SMEs: survey based on TOE–DOI framework, primary methodology and challenges. *Appl. Sci.* **15**, 6465, DOI: [10.3390/app15126465](https://doi.org/10.3390/app15126465) (2025).
8. Sharma, A. *et al.* AI and sustainable business model innovation: a systematic literature review. *Sustain. Futur.* **10**, 101204, DOI: [10.1016/j.sfr.2025.101204](https://doi.org/10.1016/j.sfr.2025.101204) (2025).
9. Islam, A. *et al.* Configuring AI-guided sustainable competitive advantage for SMEs through business model innovation: a systematic literature review approach. *J. Eng. Technol. Manag.* **78**, 101921, DOI: [10.1016/j.jengtecman.2025.101921](https://doi.org/10.1016/j.jengtecman.2025.101921) (2025).
10. Wang, S., Ma, L., Hao, F. & Zhang, H. Artificial intelligence innovation to sustainable knowledge: the dual role of enterprise resilience. *J. Innov. & Knowl.* **10**, 100832, DOI: [10.1016/j.jik.2025.100832](https://doi.org/10.1016/j.jik.2025.100832) (2025).
11. Tornatzky, L. G. & Fleischer, M. *The Processes of Technological Innovation* (Lexington Books, Lexington, MA, 1990).
12. Baker, J. The technology–organization–environment framework. In Dwivedi, Y., Wade, M. & Schneberger, S. (eds.) *Information Systems Theory: Explaining and Predicting Our Digital Society*, vol. 1, 231–245 (Springer, New York, 2012).
13. Rogers, E. M. *Diffusion of Innovations* (Free Press, New York, 2003), 5 edn.
14. Davis, F. D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* **13**, 319–340, DOI: [10.2307/249008](https://doi.org/10.2307/249008) (1989).

15. Venkatesh, V., Thong, J. Y. L. & Xu, X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Q.* **36**, 157–178, DOI: [10.2307/41410412](https://doi.org/10.2307/41410412) (2012).
16. Popa, R.-G. C., Popa, I.-C., Ciocodeiță, D.-F. & Mihălcescu, H. Modeling AI adoption in SMEs for sustainable innovation: a PLS-SEM approach integrating TAM, UTAUT2, and contextual drivers. *Sustainability* **17**, 6901, DOI: [10.3390/su17156901](https://doi.org/10.3390/su17156901) (2025).
17. ul Haq, F., Suki, N. M., Zaigham, H., Masood, A. & Rajput, A. Exploring AI adoption and SME performance in resource-constrained environments: a TOE–RBV perspective with mediation and moderation effects. *J. Digit. Econ.* **5**, 160–181, DOI: [10.1016/j.jdec.2025.07.002](https://doi.org/10.1016/j.jdec.2025.07.002) (2026).
18. Khanfar, A. A., Mavi, R. K. & Iranmanesh, M. Employee adoption of artificial intelligence systems in the electrical and electronics industry: a hybrid PLS–fsQCA analysis. *Cogn. Technol. & Work.* **28**, 533–552, DOI: [10.1007/s10111-025-00852-3](https://doi.org/10.1007/s10111-025-00852-3) (2026).
19. Susanty, A., Puspitasari, N. B., Siahaan, G. S., Setiawan, S. & Syafrudin, M. Factors influencing the intention of textile and garment SMEs to adopt digital technologies and its impact on performance. *Sci. Reports* **15**, 20807, DOI: [10.1038/s41598-025-94625-7](https://doi.org/10.1038/s41598-025-94625-7) (2025).
20. Alshammari, S. H., Alrashidi, M. E., Alshammari, M. H., Alshammari, A. E. A. & Alkhwalidi, A. F. Determinants of student adoption of artificial intelligence applications in higher education. *Sci. Reports* **15**, 35921, DOI: [10.1038/s41598-025-19851-5](https://doi.org/10.1038/s41598-025-19851-5) (2025).
21. Cao, K., Wang, P. & Jiang, X. AI anxiety and adoption intention in higher education based on an extended TAM-UTAUT and PLS-SEM analysis. *Sci. Reports* **16**, 3672, DOI: [10.1038/s41598-026-35823-9](https://doi.org/10.1038/s41598-026-35823-9) (2026).
22. Uludağ, F., Kılıç, E. & Çelik, H. E. Artificial intelligence, social influence, and AI anxiety: analyzing the intentions of science doctoral students to use ChatGPT with PLS-SEM. *Humanit. Soc. Sci. Commun.* **12**, 1308, DOI: [10.1057/s41599-025-05641-x](https://doi.org/10.1057/s41599-025-05641-x) (2025).
23. Jiang, X., Cao, K. & Wang, P. Adoption intention of generative artificial intelligence among Chinese college students: an extended TAM-UTAUT2 model from the four-helix perspective. *Front. Educ.* **10**, 1686408, DOI: [10.3389/feduc.2025.1686408](https://doi.org/10.3389/feduc.2025.1686408) (2025).
24. BinJwair, A. Predicting STEM students’ adoption of generative AI in academic contexts: an application of the UTAUT model. *Front. Educ.* **10**, 1669750, DOI: [10.3389/feduc.2025.1669750](https://doi.org/10.3389/feduc.2025.1669750) (2025).
25. Zhang, R. & Wang, J. Perceptions, adoption intentions, and impacts of generative AI among Chinese university students. *Curr. Psychol.* **44**, 11276–11295, DOI: [10.1007/s12144-025-07928-3](https://doi.org/10.1007/s12144-025-07928-3) (2025).
26. Shmueli, G. *et al.* Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *Eur. J. Mark.* **53**, 2322–2347, DOI: [10.1108/EJM-02-2019-0189](https://doi.org/10.1108/EJM-02-2019-0189) (2019).
27. Hair, J. F., Risher, J. J., Sarstedt, M. & Ringle, C. M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **31**, 2–24, DOI: [10.1108/EBR-11-2018-0203](https://doi.org/10.1108/EBR-11-2018-0203) (2019).
28. Kante, M. & Michel, B. Use of partial least squares structural equation modelling (PLS-SEM) in privacy and disclosure research on social network sites: a systematic review. *Comput. Hum. Behav. Reports* **10**, 100291, DOI: [10.1016/j.chbr.2023.100291](https://doi.org/10.1016/j.chbr.2023.100291) (2023).
29. Demir, S. & Uşak, M. Analyzing the implementation of PLS-SEM in educational technology research: a review of the past 10 years. *SAGE Open* DOI: [10.1177/21582440251345950](https://doi.org/10.1177/21582440251345950) (2025).
30. Kyriazos, T. & Poga, M. Application of machine learning models in social sciences: managing nonlinear relationships. *Encyclopedia* **4**, 1790–1805, DOI: [10.3390/encyclopedia4040118](https://doi.org/10.3390/encyclopedia4040118) (2024).
31. Hassija, V. *et al.* Interpreting black-box models: a review on explainable artificial intelligence. *Cogn. Comput.* **16**, 45–74, DOI: [10.1007/s12559-023-10179-8](https://doi.org/10.1007/s12559-023-10179-8) (2024).
32. Soomro, R. B. *et al.* A SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs. *Sci. Reports* **15**, 5438, DOI: [10.1038/s41598-025-86464-3](https://doi.org/10.1038/s41598-025-86464-3) (2025).
33. Xu, S., Wang, Y. & Luo, W. Hybrid SEM-ANN model for predicting undergraduates’ e-learning continuance intention based on perceived educational and emotional support. *PLOS ONE* **19**, e0308630, DOI: [10.1371/journal.pone.0308630](https://doi.org/10.1371/journal.pone.0308630) (2024).
34. Walle, Y. M. Deep learning-based hybrid SEM–neural network approach for predicting mobile application adoption in whistleblowing services. *Int. J. Discl. Gov.* **22**, 896–909, DOI: [10.1057/s41310-025-00295-2](https://doi.org/10.1057/s41310-025-00295-2) (2025).

35. Chowdhury, T. M. & Anzum, K. M. T. From resilience to flexibility: a hybrid SEM-ANN model of AI-enabled adaptive supply chains. *Glob. J. Flex. Syst. Manag.* **27**, 123–153, DOI: [10.1007/s40171-025-00478-4](https://doi.org/10.1007/s40171-025-00478-4) (2026).
36. Pinto, A. S., Abreu, A., Cota, M. P. & Paiva, J. A meta analysis of TOE factors driving organizational adoption of artificial intelligence across industries. *Discov. Artif. Intell.* DOI: [10.1007/s44163-025-00747-2](https://doi.org/10.1007/s44163-025-00747-2) (2025).
37. Ali, W. & Khan, A. Z. Factors influencing readiness for artificial intelligence: a systematic literature review. *Data Sci. Manag.* **8**, DOI: [10.1016/j.dsm.2024.09.005](https://doi.org/10.1016/j.dsm.2024.09.005) (2025).
38. Xue, L., Mahat, J. & Ghazali, N. Technology acceptance model in artificial intelligence in education: a meta-analysis. *SAGE Open* DOI: [10.1177/21582440251409441](https://doi.org/10.1177/21582440251409441) (2026).
39. Chiu, M.-L. Exploring user awareness and perceived usefulness of generative AI in higher education: the moderating role of trust. *Educ. Inf. Technol.* **30**, 21317–21351, DOI: [10.1007/s10639-025-13612-7](https://doi.org/10.1007/s10639-025-13612-7) (2025).
40. Shahzad, M. F., Xu, S. & Javed, I. ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone. *Int. J. Educ. Technol. High. Educ.* **21**, 46, DOI: [10.1186/s41239-024-00478-x](https://doi.org/10.1186/s41239-024-00478-x) (2024).
41. Fel, S., Kozak, J. & Horodyski, P. Responsibility and AI: exploring technology acceptance models. *J. Innov. & Knowl.* **10**, 100852, DOI: [10.1016/j.jik.2025.100852](https://doi.org/10.1016/j.jik.2025.100852) (2025).
42. Reyes, G., Tolozano-Benites, R., George-Reyes, C., Rumbaut, D. & Barzola-Monteses, J. Adoption of artificial intelligence applications in higher education. *Front. Educ.* **10**, 1680401, DOI: [10.3389/educ.2025.1680401](https://doi.org/10.3389/educ.2025.1680401) (2025).
43. Mustofa, R. H., Kuncoro, T. G., Atmono, D., Hermawan, H. D. & Sukirman. Extending the technology acceptance model: the role of subjective norms, ethics, and trust in AI tool adoption among students. *Comput. Educ. Artif. Intell.* **8**, 100379, DOI: [10.1016/j.caeai.2025.100379](https://doi.org/10.1016/j.caeai.2025.100379) (2025).
44. Ali, F., Ahmed, A., Alipour, M. A. & Terashima-Marin, H. Adoption of AI-coding assistants in programming education: exploring trust and learning motivation through an extended technology acceptance model. *J. Comput. Educ.* **13**, 821–859, DOI: [10.1007/s40692-025-00375-w](https://doi.org/10.1007/s40692-025-00375-w) (2026).
45. Faiz, F., Le, V. & Masli, E. K. Determinants of digital technology adoption in innovative SMEs. *J. Innov. & Knowl.* **9**, 100610, DOI: [10.1016/j.jik.2024.100610](https://doi.org/10.1016/j.jik.2024.100610) (2024).
46. Ibrahim, F., Münscher, J.-C., Daseking, M. & Telle, N.-T. The technology acceptance model and adopter type analysis in the context of artificial intelligence. *Front. Artif. Intell.* **7**, 1496518, DOI: [10.3389/frai.2024.1496518](https://doi.org/10.3389/frai.2024.1496518) (2025).
47. Chatzinikolaou, D. & Abidi, D. K. Environmental saturation and uneven digital adoption among service SMEs in Qatar: a PLS-SEM study. *Societies* **16**, 294, DOI: [10.3390/soc16090294](https://doi.org/10.3390/soc16090294) (2026).
48. Himanshu, U., Jha, J. K., Kumar, R. S., Gupta, S. & Pattanaik, P. K. How internal organizational enablers influence AI-enabled HRM adoption: a dynamic capabilities perspective. *Inf. Syst. Front.* DOI: [10.1007/s10796-026-10778-4](https://doi.org/10.1007/s10796-026-10778-4) (2026).
49. Nguyen, K. M. *et al.* Fostering employees' AI adoption in strategic marketing planning and decision making: a mixed-method study in Vietnam. *Cogn. Technol. & Work.* **28**, 169–202, DOI: [10.1007/s10111-025-00838-1](https://doi.org/10.1007/s10111-025-00838-1) (2026).
50. Abdelrahman, M. *et al.* Organisational culture and knowledge management systems adoption: examining employee usage in multinational corporations. *Glob. J. Flex. Syst. Manag.* **26**, 439–467, DOI: [10.1007/s40171-025-00448-w](https://doi.org/10.1007/s40171-025-00448-w) (2025).
51. Piotrowski, B. & Revtiuk, Y. Digital skills and experience as drivers of AI acceptance: evidence from the Eurobarometer 2024. *Cent. Eur. J. Oper. Res.* DOI: [10.1007/s10100-026-01030-0](https://doi.org/10.1007/s10100-026-01030-0) (2026).
52. Yang, Y., Zhang, Y., Sun, D., He, W. & Wei, Y. Navigating the landscape of AI literacy education: insights from a decade of research (2014–2024). *Humanit. Soc. Sci. Commun.* **12**, 374, DOI: [10.1057/s41599-025-04583-8](https://doi.org/10.1057/s41599-025-04583-8) (2025).
53. Enshassi, M., Nathan, R. J., Soekmawati & Ismail, H. Unveiling barriers and drivers of AI adoption for digital marketing in Malaysian SMEs. *J. Open Innov. Technol. Mark. Complex.* **11**, 100519, DOI: [10.1016/j.joitmc.2025.100519](https://doi.org/10.1016/j.joitmc.2025.100519) (2025).
54. Kuhbanani, A. Z., Dana, L.-P., Bolandian, M. H., Kalyani, Z. N. & Parsanejad, M. When does AI adoption enhance SME innovation performance? the roles of absorptive capacity, entrepreneurial agility, and digital maturity. *J. Glob. Entrepreneurship Res.* **16**, 82, DOI: [10.1007/s40497-026-00560-w](https://doi.org/10.1007/s40497-026-00560-w) (2026).
55. Chen, C.-h. Influence of employees' intention to adopt AI applications and big data analytical capability on operational performance in the high-tech firms. *J. Knowl. Econ.* **15**, 3946–3974, DOI: [10.1007/s13132-023-01293-x](https://doi.org/10.1007/s13132-023-01293-x) (2024).
56. Chen, J. & Tajdini, S. A moderated model of artificial intelligence adoption in firms and its effects on their performance. *Inf. Technol. Manag.* **26**, 407–419, DOI: [10.1007/s10799-024-00422-5](https://doi.org/10.1007/s10799-024-00422-5) (2025).
57. Liu, Q., Tian, Q., Li, X. & Tan, H. How does organizational AI adoption affect employees' job crafting behaviors? an approach-avoidance perspective. *Front. Psychol.* **16**, 1690238, DOI: [10.3389/fpsyg.2025.1690238](https://doi.org/10.3389/fpsyg.2025.1690238) (2026).

58. Prasannath, V., Adhikari, R. P., Gronum, S. & Miles, M. P. Impact of government support policies on entrepreneurial orientation and SME performance. *Int. Entrepreneurship Manag. J.* **20**, 1533–1595, DOI: [10.1007/s11365-024-00993-3](https://doi.org/10.1007/s11365-024-00993-3) (2024).
59. Wang, S., Gao, M. & Zhang, H. Strengthening SMEs competitiveness and performance via industrial internet: technological, organizational, and environmental pathways. *Humanit. Soc. Sci. Commun.* **11**, 1366, DOI: [10.1057/s41599-024-03903-8](https://doi.org/10.1057/s41599-024-03903-8) (2024).
60. Shahzad, A. *et al.* Adoption of fourth industrial revolution 4.0 among Malaysian small and medium enterprises (SMEs). *Humanit. Soc. Sci. Commun.* **10**, 693, DOI: [10.1057/s41599-023-02076-0](https://doi.org/10.1057/s41599-023-02076-0) (2023).
61. Jamwal, A., Palit, N., Kumari, S., Agrawal, R. & Sharma, M. A decision framework for SMEs to address sustainability issues with Industry 4.0 technologies. *Annals Oper. Res.* **359**, 615–643, DOI: [10.1007/s10479-025-06560-5](https://doi.org/10.1007/s10479-025-06560-5) (2026).
62. Bandhana, A. & Vokřínek, J. AI-driven manufacturing: surveying for Industry 4.0 and beyond. *Oper. Res. Forum* **6**, 145, DOI: [10.1007/s43069-025-00554-6](https://doi.org/10.1007/s43069-025-00554-6) (2025).
63. Huynh, M.-T. & Aichner, T. In generative artificial intelligence we trust: unpacking determinants and outcomes for cognitive trust. *AI & SOCIETY* **40**, 5849–5869, DOI: [10.1007/s00146-025-02378-8](https://doi.org/10.1007/s00146-025-02378-8) (2025).
64. Dang, Q. & Li, G. Unveiling trust in AI: the interplay of antecedents, consequences, and cultural dynamics. *AI & SOCIETY* **41**, 669–692, DOI: [10.1007/s00146-025-02477-6](https://doi.org/10.1007/s00146-025-02477-6) (2026).
65. Song, L., Liu, J., Yasin, M. & Mokhtar, M. M. Perceived risk and trust towards health chatbots: extending TAM with self-efficacy. *Information* **17**, 439, DOI: [10.3390/info17050439](https://doi.org/10.3390/info17050439) (2026).
66. Yolcu, S., Şahin, A., Erdoğan, A. & Dirsehan, T. Can AI chatbots recover service failures? exploring user experience and continuance intentions. *Electron. Mark.* **36**, 62, DOI: [10.1007/s12525-026-00918-8](https://doi.org/10.1007/s12525-026-00918-8) (2026).
67. Ngo, T. T. A. *et al.* Understanding continuance intention toward the use of AI chatbots in customer service among generation Z in Vietnam. *Acta Psychol.* **259**, 105468, DOI: [10.1016/j.actpsy.2025.105468](https://doi.org/10.1016/j.actpsy.2025.105468) (2025).
68. Zhao, Y., Yang, X. & Fam, K.-S. AI chatbot service adoption among C2C second-hand sellers: an integrated UTAUT-TTAT framework. *Behav. Sci.* **16**, 1670, DOI: [10.3390/bs16091670](https://doi.org/10.3390/bs16091670) (2026).
69. Chivkula, A. & Pokhriyal, D. The role of AI-driven chatbots in enhancing sustainable customer service: a survey-based study on consumer perceptions. *J. Innov. Entrepreneurship* **15**, 40, DOI: [10.1186/s13731-026-00653-6](https://doi.org/10.1186/s13731-026-00653-6) (2026).
70. Liu, J. & Qu, J. Investigating lifelong learners' adoption of generative artificial intelligence using PLS-SEM and fsQCA within the UTAUT2 framework. *Sci. Reports* DOI: [10.1038/s41598-026-62247-2](https://doi.org/10.1038/s41598-026-62247-2) (2026).
71. Miralmasi, A. & Moradi, M. Predicting AI adoption in research: a hybrid SEM-systematic review through an ethical lens. *AI Ethics* **6**, 290, DOI: [10.1007/s43681-026-01114-2](https://doi.org/10.1007/s43681-026-01114-2) (2026).
72. Oparina, E. *et al.* Machine learning in the prediction of human wellbeing. *Sci. Reports* **15**, 1632, DOI: [10.1038/s41598-024-84137-1](https://doi.org/10.1038/s41598-024-84137-1) (2025).
73. Khan, F. S., Mazhar, S. S., Mazhar, K., AlSaleh, D. A. & Mazhar, A. Model-agnostic explainable artificial intelligence methods in finance: a systematic review, recent developments, limitations, challenges and future directions. *Artif. Intell. Rev.* **58**, 232, DOI: [10.1007/s10462-025-11215-9](https://doi.org/10.1007/s10462-025-11215-9) (2025).
74. Pfeifer, B., Krzyzinski, M., Baniecki, H., Holzinger, A. & Biecek, P. Explaining and visualizing black-box models through counterfactual paths. *Pattern Analysis Appl.* **28**, 154, DOI: [10.1007/s10044-025-01532-8](https://doi.org/10.1007/s10044-025-01532-8) (2025).
75. Gonzalez Tejada, Y. & Mayer, H. A. Deep learning with convolutional neural networks: a compact holistic tutorial with focus on supervised regression. *Mach. Learn. Knowl. Extr.* **6**, 2753–2782, DOI: [10.3390/make6040132](https://doi.org/10.3390/make6040132) (2024).
76. Reza, M. H. *et al.* A comprehensive review of convolutional neural networks: foundations, enhancements and applications. *Neural Comput. Appl.* **38**, 56, DOI: [10.1007/s00521-025-11827-w](https://doi.org/10.1007/s00521-025-11827-w) (2026).
77. Ersavas, T., Smith, M. A. & Mattick, J. S. Novel applications of convolutional neural networks in the age of transformers. *Sci. Reports* **14**, 10000, DOI: [10.1038/s41598-024-60709-z](https://doi.org/10.1038/s41598-024-60709-z) (2024).
78. Nardi, P. M. *Doing survey research: A guide to quantitative methods* (Routledge, 2018).
79. Creswell, J. W. & Creswell, J. D. *Research design: Qualitative, quantitative, and mixed methods approaches* (Sage publications, 2017).
80. Assaf, R. *et al.* Assessing the acceptance for implementing artificial intelligence technologies in the governmental sector: An empirical study. *Eng. Technol. & Appl. Sci. Res.* **14**, 18160–18170, DOI: [10.48084/etasr.8711](https://doi.org/10.48084/etasr.8711) (2024).

81. Badghish, S. & Soomro, Y. A. Artificial intelligence adoption by smes to achieve sustainable business performance: application of technology–organization–environment framework. *Sustainability* **16**, 1864 (2024).
82. National Bureau of Statistics. National survey of micro, small and medium enterprises (msmes) 2017. Tech. Rep., National Bureau of Statistics, Abuja (2017). Available online: <https://www.nigerianstat.gov.ng/elibrary/read/966> (accessed on 14 January 2025).
83. Small and Medium Enterprises Development Agency of Nigeria. 2021 msme survey report. Tech. Rep., SMEDAN, Abuja (2021). Available online: <https://smedan.gov.ng/downloads/> (accessed on 14 January 2025).
84. Yamane, T. *Statistics: An introductory analysis* (Harper and Row, New York, 1967), 2 edn.
85. Bowley, A. L. Measurement of the precision attained in sampling. *Bull. Int. Stat. Inst.* **22**, 6–62 (1926).
86. Ali, F. Sample size practices and guidelines in services marketing survey research. *The Serv. Ind. J.* **46**, 623–648 (2026).
87. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y. & Podsakoff, N. P. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* **88**, 879–903, DOI: [10.1037/0021-9010.88.5.879](https://doi.org/10.1037/0021-9010.88.5.879) (2003).
88. Yesuf, Y. & Fields, Z. Artificial intelligence adoption as a driver of innovation and competitiveness in smes: A bibliometric and systematic review. *F1000Research* **14**, 1187 (2025).
89. Hair, J. F., Hult, G. T. M., Ringle, C. M. & Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (Sage, Thousand Oaks, CA, 2022), 3 edn.
90. Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S. & Wang, L. C. Reporting reliability, convergent and discriminant validity with structural equation modeling: a review and best-practice recommendations. *Asia Pac. J. Manag.* **41**, 745–783, DOI: [10.1007/s10490-023-09871-y](https://doi.org/10.1007/s10490-023-09871-y) (2024).
91. Henseler, J., Ringle, C. M. & Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **43**, 115–135, DOI: [10.1007/s11747-014-0403-8](https://doi.org/10.1007/s11747-014-0403-8) (2015).
92. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y. & Podsakoff, N. P. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J. Appl. Psychol.* **88**, 879–903, DOI: [10.1037/0021-9010.88.5.879](https://doi.org/10.1037/0021-9010.88.5.879) (2003).
93. Chen, C.-F. & Ding, C. G. An improvement in the detection of common method biases. *Qual. & Quant.* **60**, 791–815, DOI: [10.1007/s11135-025-02167-x](https://doi.org/10.1007/s11135-025-02167-x) (2026).
94. Sturman, M. C., Richardson, H. A., Simmering, M. J. & Ukhov, A. Simplifying common method variance mitigation: the role of additional variables. *J. Bus. Psychol.* DOI: [10.1007/s10869-025-10074-z](https://doi.org/10.1007/s10869-025-10074-z) (2025).
95. Merkle, A. C. Item level correction: detecting, removing, and reporting common methods variance. *J. Mark. Anal.* **13**, 405–423, DOI: [10.1057/s41270-025-00399-2](https://doi.org/10.1057/s41270-025-00399-2) (2025).
96. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences* (Lawrence Erlbaum Associates, Hillsdale, NJ, 1988), 2 edn.
97. Chin, W. W. The partial least squares approach to structural equation modeling. In Marcoulides, G. A. (ed.) *Modern Methods for Business Research*, 295–336 (Lawrence Erlbaum Associates, Mahwah, NJ, 1998).
98. Zhao, X., Lynch, J. G. & Chen, Q. Reconsidering Baron and Kenny: myths and truths about mediation analysis. *J. Consumer Res.* **37**, 197–206, DOI: [10.1086/651257](https://doi.org/10.1086/651257) (2010).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [AladoptionSRsupplementary.pdf](#)