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

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## 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 themselves[1–5]. 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 firms[8–10].

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 theory[13], the technology acceptance model[14] 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 outcomes[16–19]. The same apparatus is applied across settings as varied as enterprise workforces, professional users and student populations[20–25], 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 innovation[13], while the technology acceptance model (TAM)[14] and UTAUT2[15] 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 adoption[36], and evidence from TAM meta-analyses in AI contexts indicates that the perceived usefulness and perceived ease-of-use pathways remain robust across settings[38].

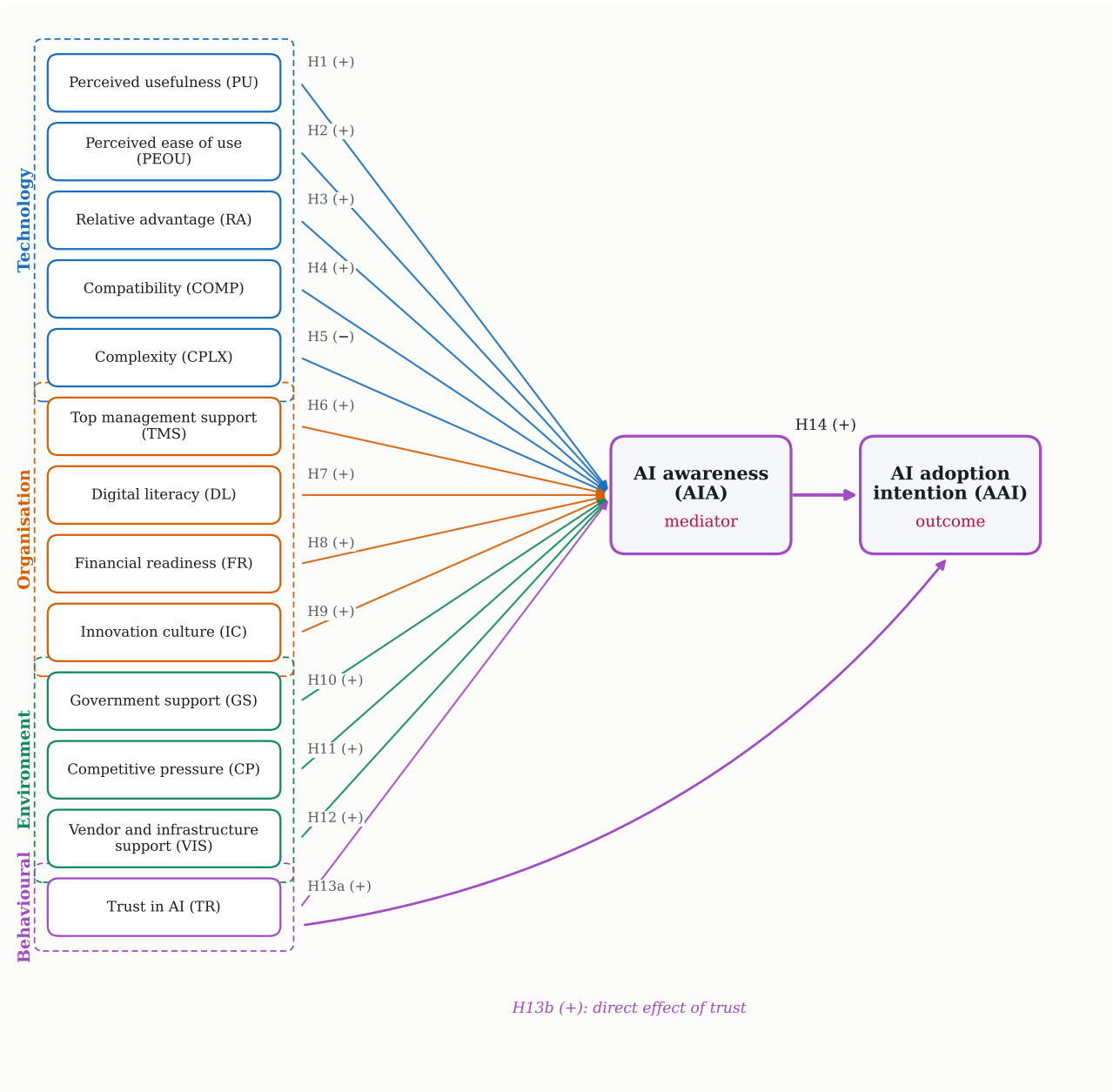


**Figure 1. Conceptual model and hypotheses.** Thirteen antecedent constructs, organised into the technological, organisational, environmental, and behavioural domains of the integrated TOE–DOI–behavioural framework, are hypothesised to influence AI awareness, which is posited to mediate their effects 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 decisions[13]—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 population[46]. 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 acceptance[51], a finding corroborated by a decade of AI-literacy research in educational contexts[52]. 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 models[30]. The hybrid SEM–ANN paradigm is now well established, with applications reported across e-learning continuance[33], whistleblowing-application adoption[34], adaptive supply-chain contexts[35], and AI adoption among SMEs[32]. 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 settings[71].

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 sector[80], as well as AI adoption among SMEs in Saudi Arabia[81], Pakistan[32], 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 from[82] and[83].

#### *Sample size determination*

The minimum required sample size was determined using Yamane's[84] formula:

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

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's[85] proportionate allocation method was subsequently applied to apportion the sample across zones:

$$n_h = \frac{n \cdot N_h}{N} \tag{2}$$

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 benchmark[86] 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 relationships[87].

### 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 on[14] and[46]. The DOI constructs (RA, COMP, CPLX) drew on[13], and the operationalisations of[32] and[81]. Organisational constructs (TMS, DL, FR, IC) drew

on[32,88] and[16]. Environmental constructs (GS, CP, VIS) followed[59]. Trust was operationalised from[65] and[16]. AI adoption intention used the UTAUT2 behavioural-intention items of[15].

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.

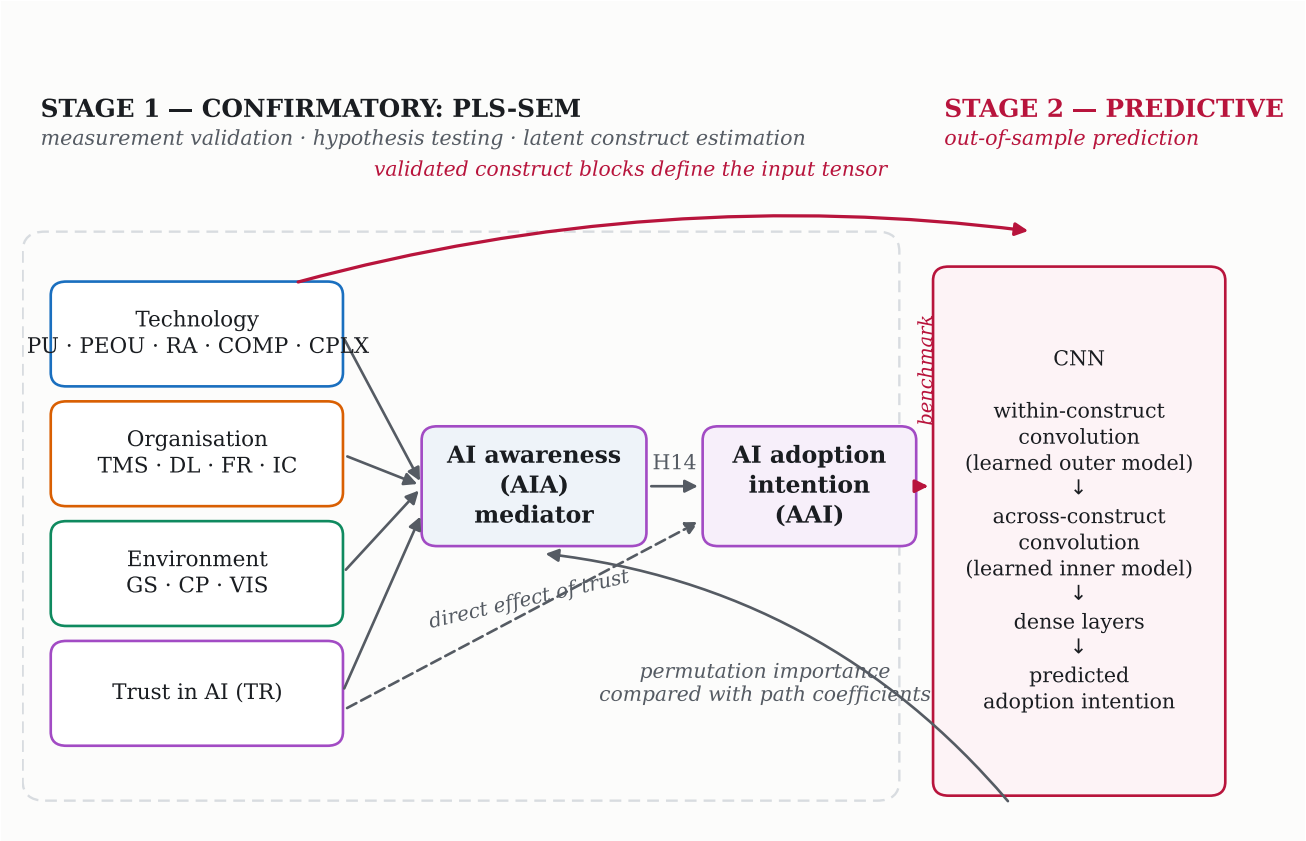


**Figure 2. The two-stage hybrid design.** Stage 1 (PLS-SEM) validates the measurement model, estimates the latent constructs and tests the hypotheses. Stage 2 (CNN) performs prediction. The coupling is architectural: the construct blocks validated in Stage 1 define the rows of the network's input tensor, 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 followed[89]:

### *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 scheme[89]. 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 $\alpha$, $\rho_A$ and composite reliability $\rho_c$), 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 PLSpredict[26].

### *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, $1 \times 3$ 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, $3 \times 1$ 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 x 6 x 1 tensor: rows are validated constructs, columns are their standardised indicators, zero-padded | 1 x 14 x 6 |
| Conv2D-1 (within-construct) | 32 filters, kernel 1x3, padding (0,1), BatchNorm, ReLU | 32 x 14 x 6 |
| Conv2D-2 (within-construct) | 32 filters, kernel 1x3, padding (0,1), BatchNorm, ReLU | 32 x 14 x 6 |
| Pool (indicator axis) | adaptive average pool over indicators only; the construct axis is preserved (learned outer model) | 32 x 14 x 1 |
| Conv2D-3 (across-construct) | 64 filters, kernel 3x1, padding (1,0), BatchNorm, ReLU | 64 x 14 x 1 |
| Conv2D-4 (across-construct) | 64 filters, kernel 3x1, padding (1,0), BatchNorm, ReLU (learned inner model) | 64 x 14 x 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 $3 \times 10^{-4}$, weight decay of $1 \times 10^{-4}$, 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 | $n$ | % |
|---|---|---|---|
| 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).

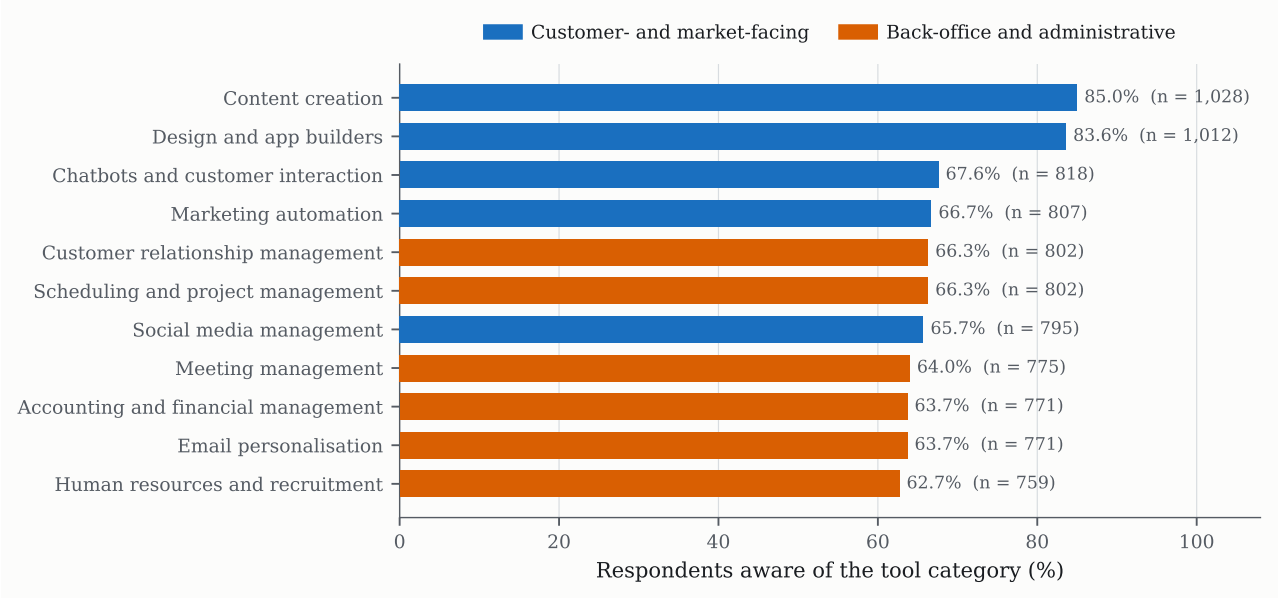


**Figure 3. Awareness of AI tools by functional category** ($N = 1{,}210$). The bars report the proportion of respondents indicating awareness of each category, with the corresponding counts displayed. Awareness is predominantly concentrated in customer- and market-facing categories and is consistently 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 $\alpha$ ranging from 0.793 to 0.943, $\rho_A$ 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 | $\alpha$ | $\rho_A$ | $\rho_c$ | 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 | $\beta$ | SE | 95% CI | $t$ | $p$ | $f^2$ | VIF | Decision |
|---|---|---|---|---|---|---|---|---|---|
| H1 | PU → AIA | 0.122 | 0.027 | [0.071, 0.177] | 4.54 | <0.001 | 0.018 | 2.15 | Supported |
| H2 | PEOU → AIA | 0.082 | 0.023 | [0.037, 0.125] | 3.61 | <0.001 | 0.012 | 1.46 | Supported |
| H3 | RA → AIA | 0.102 | 0.027 | [0.047, 0.154] | 3.75 | <0.001 | 0.012 | 2.20 | Supported |
| H4 | COMP → AIA | 0.063 | 0.023 | [0.019, 0.109] | 2.72 | 0.007 | 0.007 | 1.52 | Supported |
| H5 | CPLX → AIA | -0.051 | 0.020 | [-0.092, -0.012] | -2.55 | 0.011 | 0.005 | 1.29 | Supported |
| H6 | TMS → AIA | 0.133 | 0.023 | [0.087, 0.178] | 5.67 | <0.001 | 0.030 | 1.52 | Supported |
| H7 | DL → AIA | 0.155 | 0.023 | [0.109, 0.201] | 6.67 | <0.001 | 0.040 | 1.54 | Supported |
| H8 | FR → AIA | 0.058 | 0.022 | [0.017, 0.103] | 2.69 | 0.007 | 0.006 | 1.43 | Supported |
| H9 | IC → AIA | 0.093 | 0.023 | [0.048, 0.139] | 4.03 | <0.001 | 0.015 | 1.51 | Supported |
| H10 | GS → AIA | 0.069 | 0.022 | [0.026, 0.112] | 3.15 | 0.002 | 0.009 | 1.38 | Supported |
| H11 | CP → AIA | 0.075 | 0.022 | [0.032, 0.118] | 3.37 | <0.001 | 0.010 | 1.46 | Supported |
| H12 | VIS → AIA | 0.086 | 0.021 | [0.043, 0.127] | 4.01 | <0.001 | 0.013 | 1.47 | Supported |
| H13a | TR → AIA | 0.173 | 0.024 | [0.126, 0.220] | 7.09 | <0.001 | 0.046 | 1.66 | Supported |
| H14 | AIA → AAI | 0.651 | 0.021 | [0.609, 0.692] | 30.61 | <0.001 | 0.618 | 1.52 | Supported |
| H13b | TR → 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).

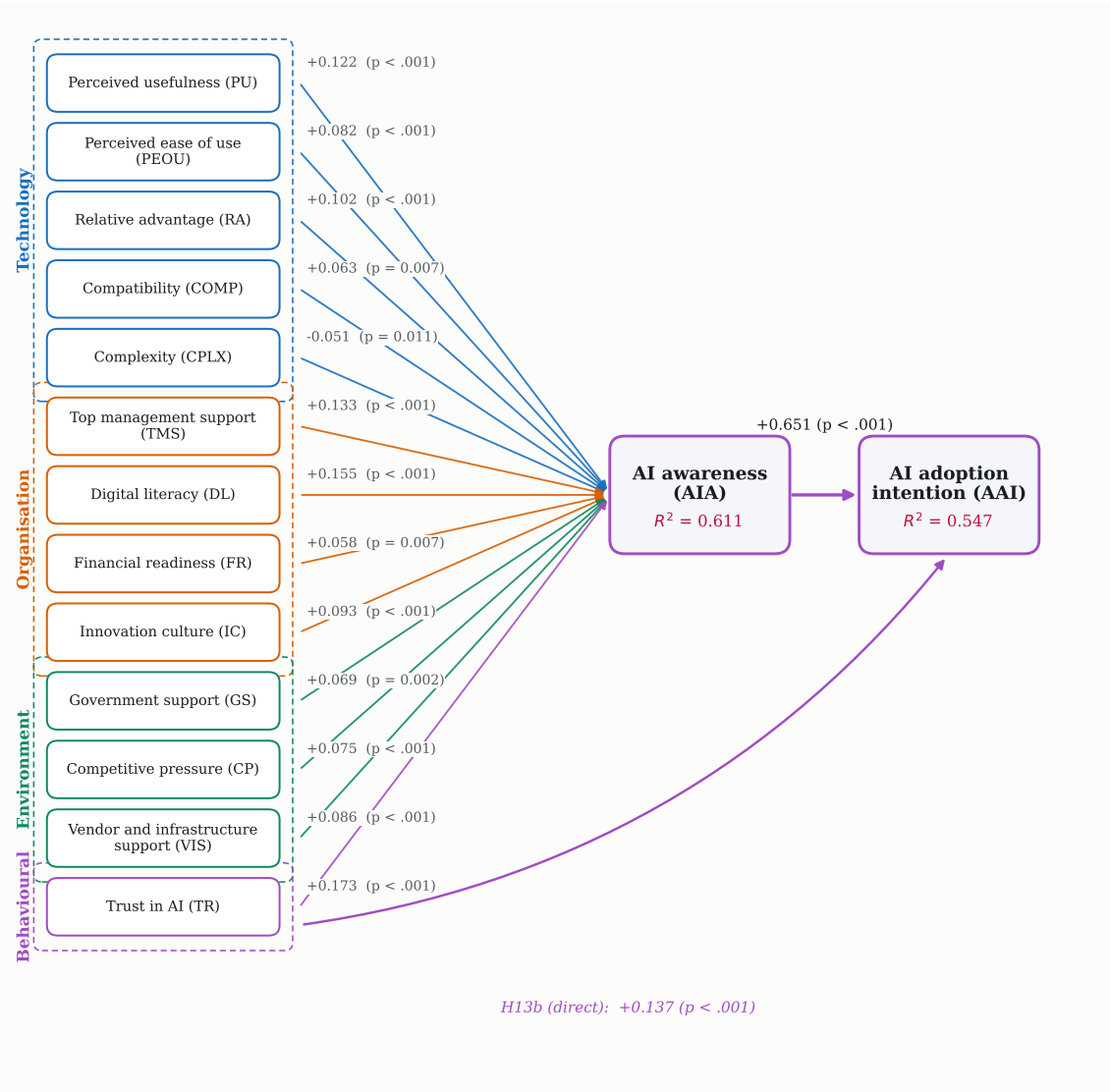


**Figure 4. Estimated structural model.** The model of Figure 1 reports the recovered parameter estimates, including standardised path coefficients with associated $p$-values obtained from 5,000 bootstrap resamples, as well as the coefficients of determination ($R^2$) for each endogenous construct. All 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.

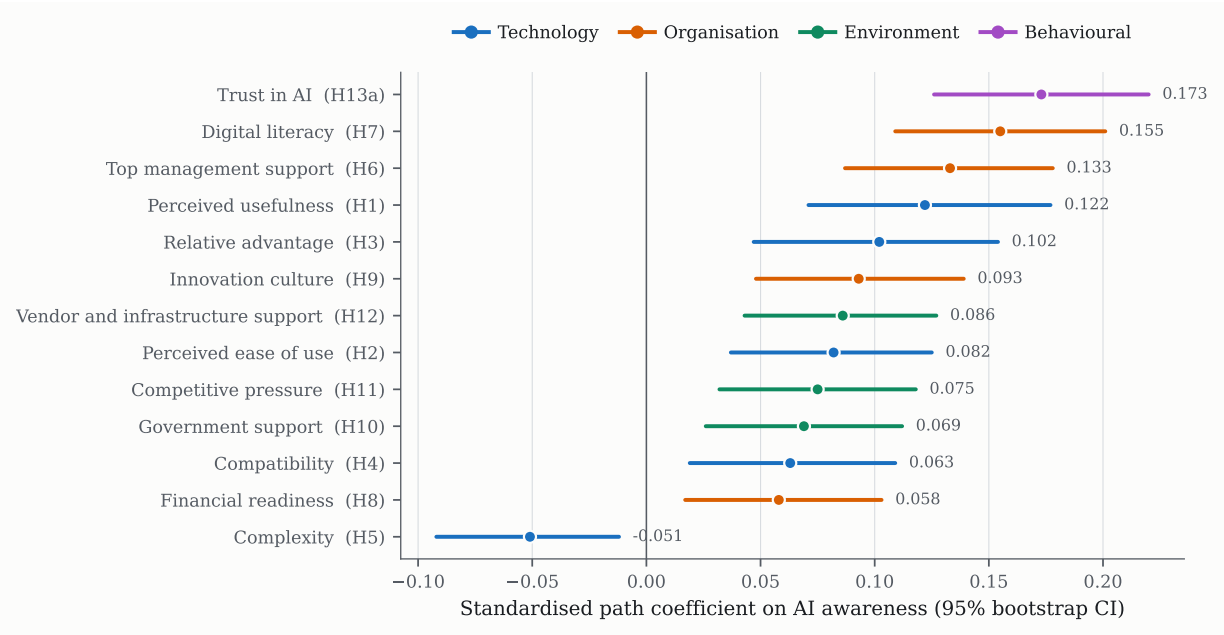


**Figure 5. Standardised path coefficients on AI awareness with 95% bootstrap confidence intervals.** Points are point estimates and horizontal bars are percentile intervals from 5,000 bootstrap subsamples, each re-estimating the complete measurement and structural model. Colour identifies the theoretical 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 | *p* | Direct | *p* | 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.

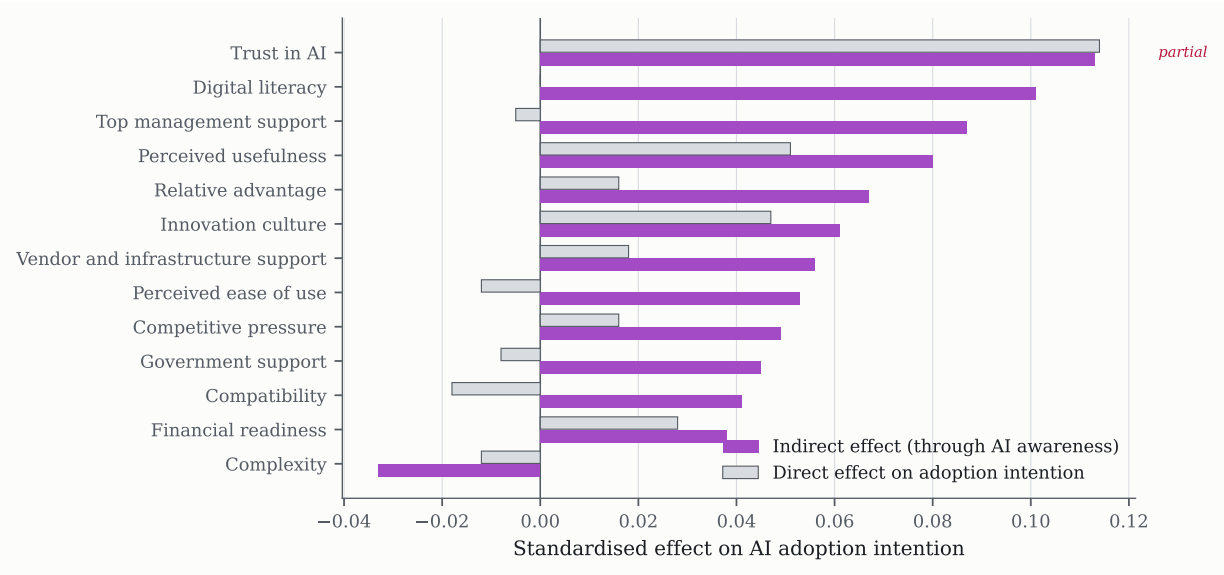


**Figure 6. Indirect and direct effects on AI adoption intention.** Indirect effects operate through AI awareness; direct effects are taken from the saturated outcome model. Twelve of thirteen antecedents show indirect-only (full) mediation, with direct effects indistinguishable from zero. Trust in AI 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 | $\text{RMSE}_{LM}$ | MAE | $\text{MAE}_{LM}$ |
|---|---|---|---|---|---|---|---|---|
| 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 $0.6525 \pm 0.0500$), feed-forward network ($0.6541 \pm 0.0488$), item-tensor CNN ($0.6580 \pm 0.0533$), construct-score CNN ($0.6631 \pm 0.0501$), the PLS-SEM structural model ($0.6718 \pm 0.0586$), and ordinary least squares using all indicators ($0.6918 \pm 0.0579$).

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.

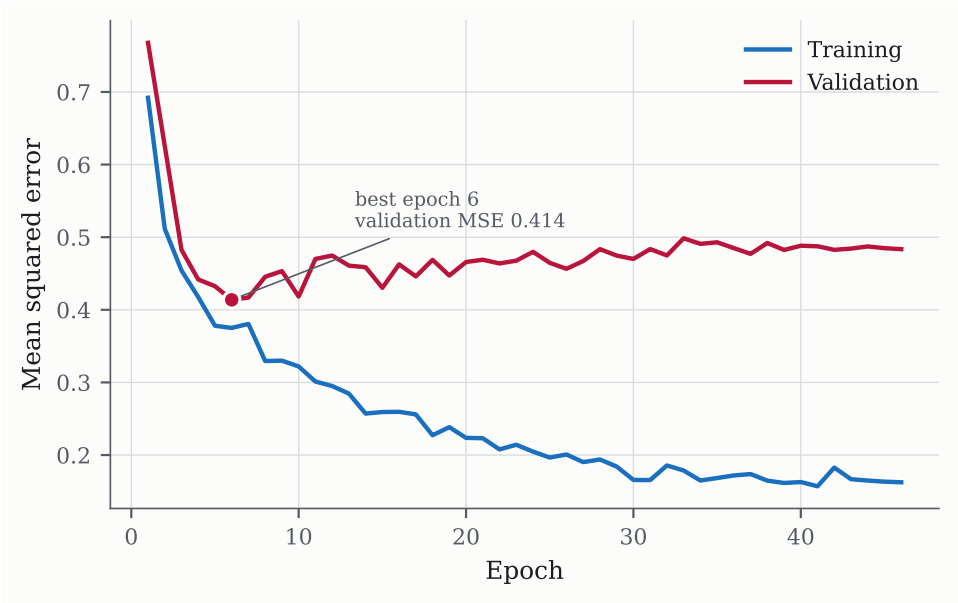


**Figure 7. Training and validation error of the final convolutional network.** Early stopping selected epoch 46 on validation loss. The separation between the two curves indicates moderate overfitting, controlled but not eliminated by dropout, weight decay and early stopping, and consistent with a sample 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.

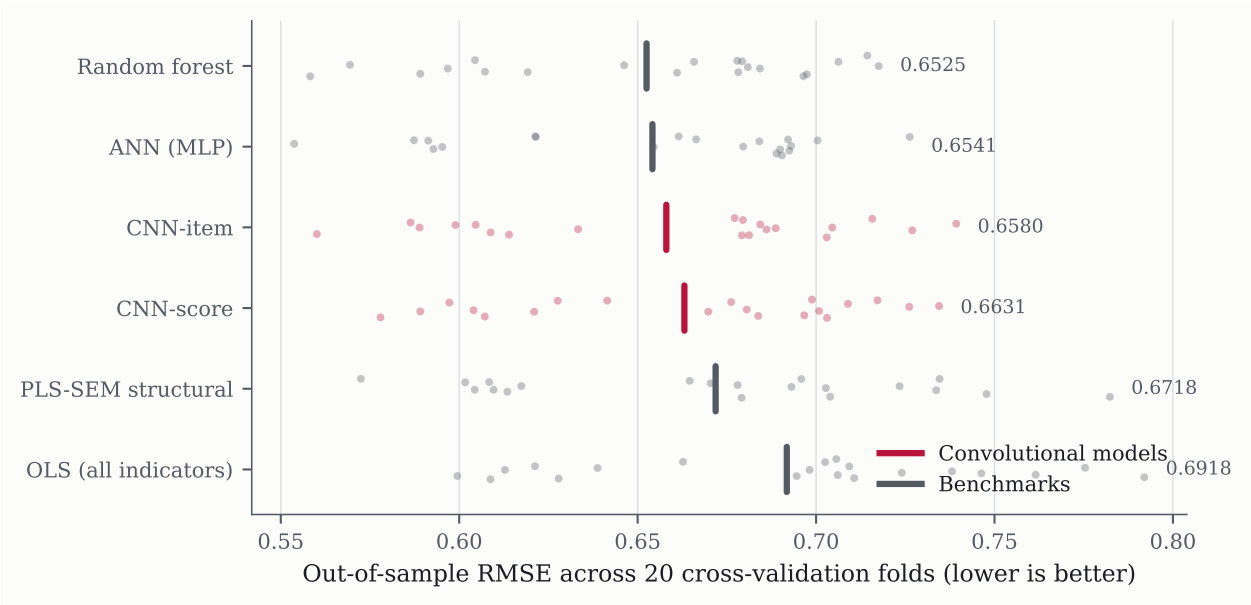


**Figure 8. Out-of-sample error across twenty cross-validation folds.** Each dot is one fold; the thick rule is the fold mean, printed at the right. All six models were evaluated on identical folds. The convolutional models improve on the PLS-SEM structural benchmark but not on the feed-forward network 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 | $\lvert\beta\rvert$ | 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: $\rho = 0.503$, $p = 0.067$.

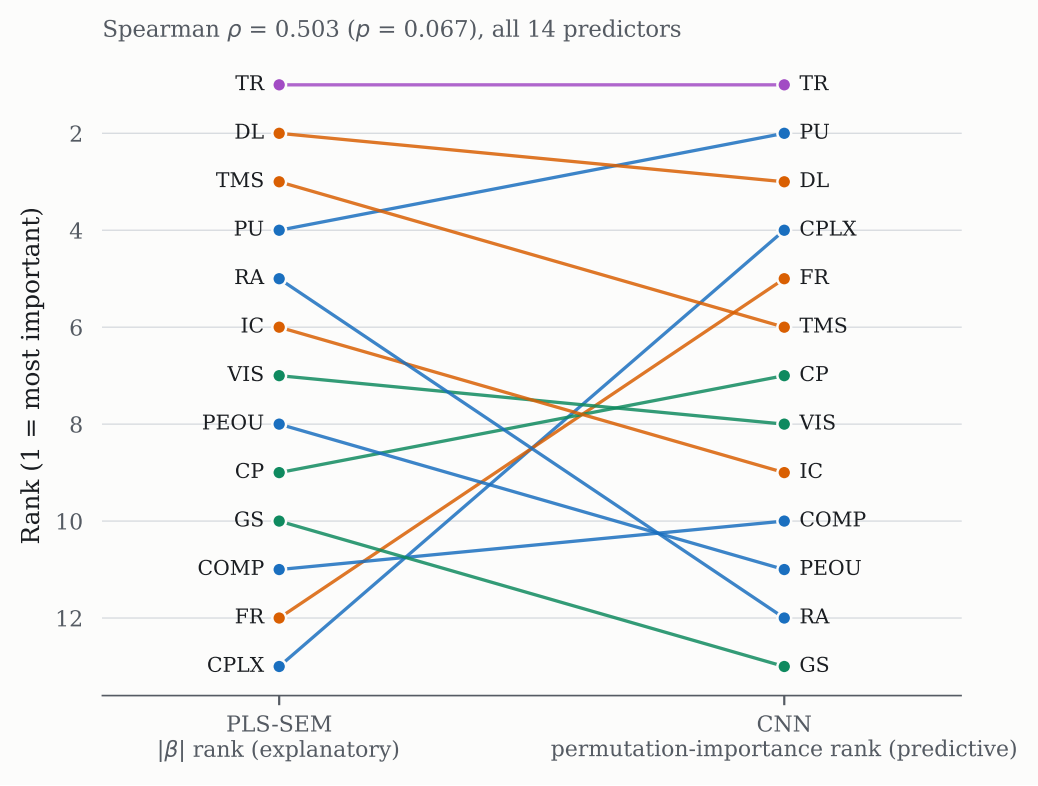


**Figure 9. Explanatory and predictive importance orderings compared.** Left, constructs ranked by absolute standardised path coefficient in PLS-SEM; right, ranked by permutation importance in the CNN. Lines connect the same construct in the two orderings and are coloured by theoretical block. The mediator 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 theory[13] 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).

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## 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.

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