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Research Article

From Readiness to Performance: Modelling AI-Enabled HR Analytics Adoption Capability as a Second-Order Formative Construct in Nigerian SMEs

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Abstract

Objective: This study examines how AI-enabled HR Analytics Adoption Capability (AIHRA), a second-order formative construct, is associated with operational performance among Nigerian SMEs.

Design: Drawing on UTAUT2, the Resource-Based View, and Socio-Technical Systems Theory, a survey was administered to 296 respondents across SMEs in Lagos, Abuja, Port Harcourt, and Kano. PLS-SEM via SmartPLS 4.0.9.9 was used for analysis.

Findings: Technological Readiness (weight = 0.584, $p<0.001$) and Organisational Support (weight = 0.532, $p<0.001$) significantly form AIHRA. Perceived Value and Use is non-significant (0.119, $p = 0.219$) but shows absolute importance. AIHRA is positively associated with operational performance ($\beta = 0.626$, $R2 = 0.392$).

Policy Implications: Managers and policymakers should prioritise digital infrastructure and organisational support before AI procurement.

Originality: This study contributes an empirically tested higher-order formative model linking AI-HR analytics adoption capability to operational performance in Nigerian SMEs, extending prior technology-organisation-environment evidence by showing structural determinants dominate perceptual constructs within a multi-theory, capability-based specification.

Introduction

The integration of artificial intelligence and data analytics into human resource management has catalysed a shift from intuition-based HR administration toward data-driven decision-making, enabling organisations to forecast attrition, detect skills gaps, and improve hiring efficiency (Faruk, 2025; Bonilla-Chaves et al., 2024; Wang et al., 2023). Marler and Boudreau (2016, p.15) describe HR analytics as a practice "enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, and organisational performance to establish business impact and enable data-driven decision-making." Evidence from developed economies associates AI-enhanced HR practices with improvements in productivity, talent acquisition, and organisational agility (Bonilla-Chaves et al., 2024; Wang et al., 2023). However, a systematic review by Alvarez-Gutierrez et al. (2022) of 79 HR analytics articles found the literature largely promotional and geographically concentrated in high-income economies. Sub-Saharan Africa receives negligible attention; a theoretical concern, since adoption theories validated in resource-rich settings may not capture dynamics where infrastructure is unreliable, institutional voids are pervasive, and digital skills are scarce (Hussain et al., 2024; Raza et al., 2025).

Nigeria provides the empirical stage. As Africa's largest economy, its SME sector accounts for approximately 48% of GDP and over 80% of formal employment (National Bureau of Statistics, 2023), yet operates amid persistent electricity failures, fragmented broadband, volatile macroeconomic conditions, and systemic institutional voids (Sadiq et al., 2022; Shadrach & Umemezia, 2025). Ebuka et al. (2023), studying 379 Nigerian SMEs, found only 11% actively used AI tools, confirming a significant gap between awareness and organisational capacity. Additionally, adoption challenges in Nigeria: infrastructure deficits, limited capacity, and scarce digital talent, mirror conditions across EU accession states (Arroyabe et al., 2024) and developing economies in Southeast Asia (Shahadat et al., 2023), reinforcing the broader international theoretical relevance of this study. Within this context, AI-enabled HR Analytics Adoption Capability (AIHRA) occupies a paradoxical position: structural vulnerabilities create compelling demand for AI-driven HR tools (Alvarez-Gutierrez et al., 2022; Bonilla-Chaves et al., 2024), yet prerequisites for effective implementation remain severely constrained (Sadiq et al., 2022).

Three interrelated gaps motivate this study. First, a geographic gap: the near-complete absence of quantitative HR analytics adoption research in Sub-Saharan African SME contexts (Alvarez-Gutierrez et al., 2022). Second, a methodological gap: the dominant treatment of AI adoption as a unidimensional construct collapsing technological, organisational, and perceptual dimensions into a single measure (Ekka & Singh, 2022; Tanantong & Wongras, 2024). Third, an outcome gap: the focus on financial performance metrics that are theoretically distant from HR quality and frequently unavailable from SME respondents (Samson & Bhanugopan, 2022).

This study addresses all three gaps by investigating the formation and performance implications of AIHRA, defined as a second-order formative organisational adoption capability composed of Technological Readiness, Organisational Support, and Perceived Value and Use among Nigerian SMEs. Three formative contribution hypotheses and one structural hypothesis are tested using PLS-SEM via SmartPLS 4.0.9.9, applied to personal survey data from 296 owner-managers and senior HR practitioners across Lagos, Abuja (FCT), Port Harcourt, and Kano. The theoretical framework synthesises UTAUT2 (Venkatesh et al., 2012; Venkatesh, 2021), the Resource-Based View (Barney, 1991; Teece et al., 1997), and Socio-Technical Systems Theory (Trist & Bamforth, 1951). Contributions are theoretical through an integrated multi-theory framework; methodological through higher-order formative modelling; empirical through quantitative adoption-performance evidence from Nigerian SMEs; and practical through dimensionally disaggregated guidance for managers and policymakers.

Literature Review

Theoretical Foundations and Integration

This study synthesises three complementary theoretical pillars that together address the limitations of any single-theory approach to AI adoption in resource-constrained environments. UTAUT2 (Venkatesh et al., 2003; 2012; Venkatesh, 2021) provides the demand-side explanatory architecture, identifying Performance Expectancy, Facilitating Conditions, Price Value, and Social Influence as the primary mechanisms through which individual and organisational adoption intentions are formed. Validated across multiple HR analytics adoption studies (Ekka & Singh, 2022; Bonilla-Chaves et al., 2024; Tanantong & Wongras, 2024), UTAUT2 has demonstrated substantial explanatory power for adoption intentions in high-resource settings. However, it provides limited guidance on firm-level capability accumulation or the organisational process conditions under which adoption intentions translate into embedded use and performance improvement gaps that the other two theoretical pillars address.

The Resource-Based View (RBV) (Barney, 1991; Wernerfelt, 1984; Teece et al., 1997) bridges this gap by framing AIHRA as a multidimensional organisational adoption capability whose value is determined by the configuration of its constituent dimensions. The RBV suggests that when firms develop the organisational capacity to deploy, sustain, and derive intelligence from AI-HR tools, supported by adequate infrastructure, committed leadership, and positive usage beliefs, they may accumulate a capability that supports operational advantage. Samson and Bhanugopan (2022) provide direct empirical support, showing that strategic human capital analytics capability is positively associated with both organisational and market performance. Wang et al. (2023) similarly identify effective HR analytics as a capability that enhances HR operations and positions the HR function as a strategic partner. These findings are consistent with RBV logic, though the VRIN characteristics of AIHRA were not directly measured in this study and are treated as theoretical propositions rather than empirically confirmed attributes.

Socio-Technical Systems (STS) Theory (Trist & Bamforth, 1951; Pasmore, 1988; Zhang et al., 2025) addresses the organisational process conditions under which adoption succeeds or fails. STS theory holds that every organisation comprises two interdependent subsystems; a technical subsystem (technology, tasks, and processes) and a social subsystem (people, norms, competencies, and governance structures), and that optimal performance requires joint optimisation of both. Applied to AI-HR analytics adoption, STS theory explains why technically advanced AI systems frequently fail to deliver anticipated benefits when the social subsystem: staff training, change management, and governance is neglected (Wang et al., 2023; Zhang et al., 2025). Together, UTAUT2 explains adoption intentions at the individual-perceptual level, STS theory explains organisational alignment conditions, and the RBV explains the capability-to-performance logic, yielding a theoretically complete, multi-level framework.

Operational Performance as the Dependent Variable

This study adopts operational performance rather than financial performance as its primary outcome variable. Operational performance is conceptualised as a four-dimensional construct encompassing workforce productivity, HR process efficiency, service delivery quality, and organisational responsiveness: dimensions directly and proximally influenced by HR management quality and data-analytic capability (Samson & Bhanugopan, 2022; Wang et al., 2023). Three arguments justify this choice. First, operational performance is more proximate to HR practices than financial outcomes, which are substantially mediated by macroeconomic and regulatory factors. Second, financial metrics are frequently unreliable or unavailable in Nigerian SME contexts. Third, operational performance represents the immediate first-order consequence of improved HR decision-making, the mechanism through which downstream financial effects are eventually realised (Samson & Bhanugopan, 2022).

AIHRA as a Second-Order Formative Adoption Capability

A central methodological contribution of this study is the operationalisation of AIHRA, defined as a second-order formative organisational adoption capability composed of Technological Readiness, Organisational Support, and Perceived Value and Use as a higher-order formative construct. A second-order structure is warranted because AIHRA is genuinely multidimensional; its three constituent dimensions represent theoretically distinct yet systematically related facets of a broader adoption state that cannot be captured by any single dimension alone (Hair et al., 2017; Sarstedt et al., 2019). A formative specification is appropriate because the three dimensions collectively form AIHRA rather than being interchangeable reflections of a common underlying factor (Coltman et al., 2008; Diamantopoulos & Winklhofer, 2001). A firm with high Technological Readiness but deficient Organisational Support occupies a qualitatively different adoption state than a firm with the reverse profile; these are distinct configurations that jointly define the firm's AIHRA level.

Technological Readiness (TR)

Technological Readiness constitutes the foundational infrastructural and data-capability baseline determining whether a firm's technical environment can support AI applications (Wang et al., 2023). Three components form this dimension: digital infrastructure adequacy (power reliability, internet connectivity, and hardware capacity); data quality and governance (structured, accessible, and governable HR data); and digital human capital (staff capacity to deploy and interpret AI outputs). In the Nigerian context, Sadiq et al. (2022) identified infrastructure deficiencies as the strongest ICT adoption failure predictor among 322 Nigerian SMEs, while Shahadat et al. (2023) confirmed infrastructure's dominant role across developing economy SMEs. These findings are consistent with UTAUT2's Facilitating Conditions construct and the RBV's proposition that infrastructure constitutes the foundational resource stock upon which digital capability is built (Venkatesh et al., 2012; Barney, 1991).

Organisational Support (OS)

Organisational Support, grounded in the social subsystem of STS theory and UTAUT2's Social Influence construct, refers to the internal institutional climate, resource allocation, training provision, and governance structures that facilitate or impede the embedding of AI analytics practices (Faiz et al., 2024; Shahadat et al., 2023). Arroyabe et al. (2024), drawing on Eurobarometer data from 12,108 European SMEs, found that management support and digital maturity were more influential adoption determinants than environmental pressures, a finding that resonates in the Nigerian SME context, where adoption authority is typically concentrated in a single owner-manager. Organisational support also manifests through structured digital literacy training and AI governance frameworks addressing algorithmic bias, data privacy, and decision transparency; a prerequisites for sustained and ethically responsible AI deployment (Wang et al., 2023; Giermindl et al., 2021).

Perceived Value and Use (PVU)

The Perceived Value and Use dimension captures the cognitive and evaluative architecture of adoption, the extent to which SME managers hold positive beliefs about the relative advantage of AI analytics over manual processes, and demonstrate actual utilisation behaviour consistent with those beliefs (Bonilla-Chaves et al., 2024). Integrating UTAUT2's Performance Expectancy and Price Value constructs with the Relative Advantage construct of the TOE framework (Tornatzky & Fleischer, 1990), this dimension is particularly relevant in Nigeria's high-inflation, high-opportunity-cost environment. Ekka and Singh (2022) demonstrated that organisational culture can create a significant gap between adoption intention and actual usage, confirming that usage behaviour must be measured as a component of adoption rather than merely as its consequence. A critical intersecting phenomenon is AI anxiety, the discomfort arising from algorithmic surveillance and displacement concerns, which Giermindl et al. (2021) document produces a "panopticon effect" undermining authentic adoption engagement, particularly in collectivist, high-power-distance cultures typical of Nigerian SMEs (Xue et al., 2024).

Theoretical Justification and Research Hypotheses

The three dimensions of AIHRA are not ordinary causal predictors; they are formative components that collectively constitute the higher-order adoption capability. Each dimension contributes a distinct, theoretically irreplaceable component to AIHRA. Removing any one dimension would meaningfully alter the construct's conceptual domain, confirming the appropriateness of the formative specification (Coltman et al., 2008; Diamantopoulos & Winklhofer, 2001). The following hypotheses reflect formative contribution relationships rather than standard causal hypotheses.

H1: Technological Readiness contributes positively to the formation of AI-enabled HR analytics adoption (AIHRA) among SMEs in Nigeria.

From a UTAUT2 perspective, Facilitating Conditions determine whether users can act on their adoption intentions (Venkatesh et al., 2012). From an RBV perspective, infrastructure constitutes the foundational resource stock for AI capability (Samson & Bhanugopan, 2022). From an STS perspective, the technical subsystem must reach a minimum operational threshold before joint optimisation with the social subsystem can generate meaningful adoption outcomes. Sadiq et al. (2022) and Shahadat et al. (2023) provide empirical corroboration in comparable contexts.

H2: Organisational Support contributes positively to the formation of AI-enabled HR analytics adoption (AIHRA) among SMEs in Nigeria.

Management support constitutes the primary social subsystem investment required for joint optimisation with the technical AI subsystem (Wang et al., 2023). Without leadership commitment, resource allocation, and cultural change management, technically superior AI systems are likely to be bypassed or used superficially. UTAUT2's social influence is particularly powerful in SME contexts where the owner-manager commands singular adoption authority. Arroyabe et al. (2024) and Ekka and Singh (2022) provide empirical support across multiple contexts.

H3: Perceived Value and Use contribute positively to the formation of AI-enabled HR analytics adoption (AIHRA) among SMEs in Nigeria.

Performance Expectancy consistently demonstrates the strongest effect on adoption intention across UTAUT2 applications (Xue et al., 2024; Bonilla-Chaves et al., 2024). In Nigeria's high-constraint environment, value beliefs about cost reduction through AI-enabled attrition prediction and automated screening are salient motivational factors (Sadiq et al., 2022). However, the translation from value perception to actual embedded use is neither automatic nor guaranteed (Bonilla-Chaves et al., 2024), reinforcing the need to capture usage behaviour as a component of AIHRA formation. Following the formative contribution hypotheses for AIHRA, one structural hypothesis examines the relationship between adoption capability and firm performance:

H4: AI-enabled HR analytics adoption (AIHRA) is positively associated with operational performance among SMEs in Nigeria.

The theoretical mechanism linking AIHRA to operational performance operates through three stages consistent with the integrated framework: AIHRA generates data-analytic capability (RBV mechanism); this capability produces predictive HR intelligence, including attrition risk assessments and optimised staffing (STS jointoptimization mechanism); this intelligence supports superior management action that reduces waste, improves decision speed, and enhances workforce productivity (UTAUT2 performance fulfilment mechanism). Samson and Bhanugopan (2022) and Wang et al. (2023) provide empirical support for this chain, while Ebuka et al. (2023) specifically corroborate the performance association in the Nigerian context.

Conceptual Model

Figure 1 presents the conceptual model. Three first-order formative dimensions, TR, OS, and PVU, jointly form the second-order AIHRA construct (H1-H3). AIHRA is associated with SME Operational Performance (H4). The formative arrows signify that TR, OS, and PVU causally define the firm's adoption capability state rather than reflect it, consistent with the RBV's conceptualisation of strategic capabilities as multidimensional organisational configuration

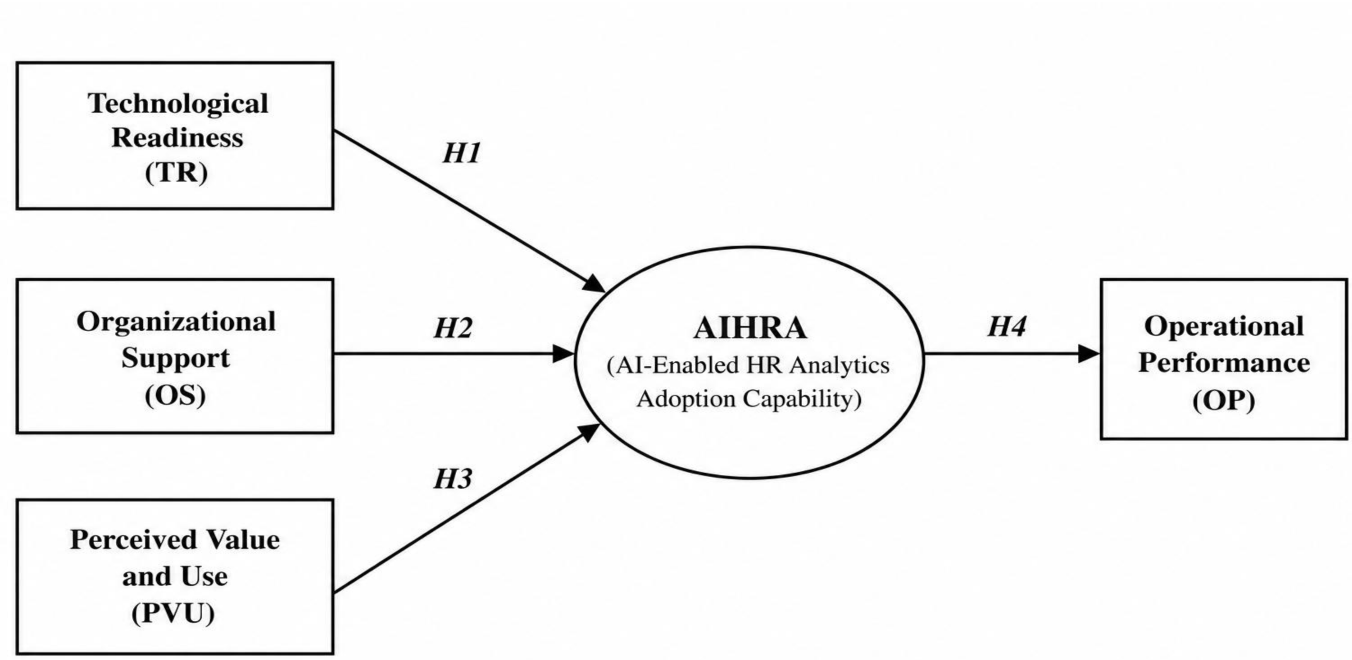

Figure 1. Conceptual Model of the Study

Note: AIHRA is a second-order formative construct; TR, OS, and PVU are first-order formative dimensions. Theoretical grounding: UTAUT2 (Venkatesh et al., 2012; 2021), RBV (Barney, 1991; Teece et al., 1997), STS Theory (Trist & Bamforth, 1951).

Methodology

Research Design and Sampling

This study adopts a post-positivist epistemological stance and employs a cross-sectional quantitative survey design (Creswell & Creswell, 2018; Sekaran & Bougie, 2016). Data were collected through personal face-to-face questionnaire administration, preferred over online methods to maximise response quality and accommodate the digital literacy variability characteristic of Nigerian SME contexts. Analysis employed PLS-SEM via SmartPLS 4.0.9.9 (Ringle et al., 2022), selected for its native suitability for formative and higher-order construct specifications, tolerance of non-normal Likert data, superior power at small-to-medium samples, and prediction-oriented philosophy (Hair et al., 2017; 2022; Rigdon, 2016).

The target population comprised owner-managers, operations managers, and HR officers of formally registered SMEs in Lagos, Abuja (FCT), Port Harcourt, and Kano: selected for their documented status as Nigeria's four largest SME hubs (SMEDAN, 2013), geographic and sectoral diversity, and accessibility. SMEs were defined as enterprises with 10-199 employees and annual turnover between NGN 5 million and NGN 1 billion (SMEDAN, 2013). Purposive sampling targeted respondents with direct HR and technology management responsibility, identified through the SMEDAN database, Corporate Affairs Commission records, and Chamber of Commerce directories. Responses were proportionally allocated: Lagos (140 = 40%), Abuja (88 = 25%), Port Harcourt (70 = 20%), and Kano (52 = 15%), yielding a target of 350; well above the PLS-SEM 10-times rule minimum of 40 (Hair et al., 2022). Of 350 questionnaires distributed, 327 were returned (93.43% response rate); after removing incomplete responses and outliers (12 cases identified via z-scores >3.29 and Mahalanobis distance at p=0.001), the final usable sample was 296. Non-response bias was assessed by comparing early and late respondents on construct means; no significant differences were found (p>0.05).

Measures, Pilot Testing, and Validity for Non-Fully-Adopting Firms

All constructs were measured through validated five-point Likert scales as shown in Table 1 (1=Strongly Disagree; 5=Strongly Agree) adapted from established instruments and refined via expert panel review and a 30-respondent pilot test. Technological Readiness (9 items: TR1-TR9) drew on Ekka and Singh (2022) and Wang et al. (2023); Organisational Support (9 items: OS1-OS9) on Faiz et al. (2024) and Shahadat et al. (2023); Perceived Value and Use (10 items: PVU1-PVU10) on Bonilla-Chaves et al. (2024) and Giermindl et al. (2021); and Operational Performance (12 items: OP1-OP12) on Samson and Bhanugopan (2022) and Wang et al. (2023). AIHRA was measured as an organisational adoption capability, capturing technological infrastructure, organisational readiness, and cognitive orientation toward AI-HR analytics, rather than as current usage intensity alone. Firms at various adoption stages can meaningfully evaluate these dimensions, and the sample profile (15.4% full implementation, 17.6% partial adoption, remainder reflecting varying readiness and planning stages) provides meaningful variance across the AIHRA continuum necessary for structural estimation.

Common Method Bias Assessment and Analytical Approach

Common method bias was addressed procedurally through anonymity assurance and questionnaire block separation, and statistically through Harman's single-factor test (29.1% variance; well below the 50% threshold) and full collinearity VIF assessment following Kock (2015); all VIF values below 3.3 (TR=1.486; OS=1.262; PVU=1.563; OP=1.311) confirming CMB is not a dominant concern (Podsakoff et al., 2003). The second-order AIHRA construct was operationalised using the two-stage approach (Becker et al., 2012; Hair et al., 2022): latent variable scores from Stage 1 reflective measurement served as formative indicators in Stage 2. Measurement model evaluation applied CR > 0.70, AVE > 0.50, and HTMT < 0.85 for reflective dimensions and VIF < 3.3 with outer weight significance for formative specifications (Hair et al., 2022). A Gaussian copula endogeneity test was conducted on the AIHRA→OP path (Hult et al., 2018). A bootstrapping permutation-based Multi-Group Analysis (MGA) was conducted across the four locations as a supplementary exploratory analysis (Hair et al., 2022; Henseler et al., 2009). An ethics statement: The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. No institutional ethics committee or institutional review board reviewed this study, and no formal approval reference number was issued or applies, and did not fall under a sponsoring institution's mandatory review requirement. All participation was voluntary; respondents were informed of the academic purpose, their right to withdraw, and their anonymity.

Table 1. Construct Sub-dimensions, Sample Items, and Key Sources (as originally administered)

Construct	Sub-dimension	Sample Item	Key Sources
Technological Readiness	Infrastructure	"Reliable electricity or backup power supports continuous digital operations."	Ekka & Singh (2022)
	Data governance	"HR data are stored in a structured, digitally accessible format."	Wang et al. (2023)
	Digital human capital	"Personnel can interpret AI outputs and translate them into HR decisions."	Ekka & Singh (2022)
Organisational Support	Management commitment	"Senior management actively supports AI-based HR tool adoption."	Faiz et al. (2024)
	Resource allocation	"A dedicated budget exists for acquiring and maintaining HR technology."	Shahadat et al. (2023)
	Training provision	"The organisation provides training to improve staff digital and HR analytics skills."	Faiz et al. (2024)
	AI governance	"Clear policies exist on fairness, transparency, and privacy in AI-based HR decisions."	Shahadat et al. (2023)
Perceived Value and Use	Performance expectancy	"AI-enabled HR analytics would improve recruitment and selection quality."	Bonilla-Chaves et al. (2024)
	Price value	"Long-term benefits would outweigh implementation costs."	Bonilla-Chaves et al. (2024)
	Usage behaviour	"Data or analytics are currently used to inform HR decisions such as hiring."	Bonilla-Chaves et al. (2024)
	AI confidence	"AI tools would be implemented fairly and transparently."	Giermindl et al. (2021)
Operational Performance	Workforce productivity	"Overall employee productivity has been satisfactory."	Samson & Bhanugopan (2022)
	Process efficiency	"HR processes are completed efficiently with minimal delays."	Wang et al. (2023)
	Service quality	"HR services provided to employees are consistently high quality."	Wang et al. (2023)
	Responsiveness	"The organisation quickly identifies and responds to workforce challenges."	Samson & Bhanugopan (2022)

Results and Discussion

Sample Characteristics

The final sample comprised 296 usable responses from SMEs across Lagos (39.2%), Abuja (26.4%), Port Harcourt (19.3%), and Kano (15.2%). Respondents were predominantly male (60.1%), with most in the 36-55 age range. Educational attainment was high, with 95.3% holding at least a tertiary qualification. HR managers/officers (33.4%) and owner-managers/CEOs (28.7%) formed the majority, with over 85% having more than seven years of experience. Most firms had operated for over 10 years (83.4%), reflecting organisational maturity (see Table 2). Regarding AI-HR tool usage, 15.4% reported full implementation and 17.6% partial adoption. The remaining respondents reflected varying stages of readiness, planning, or initial use, all constituting meaningful positions on the AIHRA capability continuum. The sample is skewed toward formally registered, organisationally mature SMEs, which limits generalisability to micro-enterprises and informal businesses.

Table 2. Respondent and Firm Profile

Category	Variable	Distribution
Sample	Returned / Valid / Usable	327 / 308 / 296
Gender	Male / Female	60.1% / 39.9%
Age	Dominant groups	36-45 (26.4%), 46-55 (28.7%)
Education	Tertiary (HND/BSc and above)	95.3%
Role	HR / CEO / Admin / Ops	33.4% / 28.7% / 27.0% / 10.8%
Experience	7 years or more	85.5%
Sector	Manufacturing / Trade	28.4% / 24.0%
Firm Size	10-49 employees	74.6%
Turnover	NGN 51M-200M	50.0%
Location	Lagos / Abuja / PH / Kano	39.2% / 26.4% / 19.3% / 15.2%
Years Active	11 years or more	83.4%
AI HR Usage	Full / Partial	15.4% / 17.6%

Common Method Bias

Harman's single-factor test extracted one component accounting for 29.1% of total variance, well below the 50% threshold (Podsakoff et al., 2003). Full collinearity VIF values (TR=1.486; OS=1.262; PVU=1.563; OP = 1.311) were all below 3.3 (Kock, 2015). Combined with the procedural remedies described in Common Method Bias Assessment and Analytical Approach section, these results provide reasonable assurance that CMB does not represent a significant methodological threat.

Reflective Measurement Model Assessment

Item Purification and Deletion Justification

An iterative purification procedure was applied: items were deleted only when their removal improved AVE toward 0.50 without dropping CR below 0.70, and only when deletion was theoretically defensible. Three items were removed from Organisational Support (OS7, loading=0.577; OS8=0.516; OS9=0.538), which improved AVE from 0.403 to 0.534. The training provision and AI governance sub-dimensions are consequently no longer represented in the final OS model; retained items OS1-OS6 cover management commitment and resource allocation. Two items were removed from Perceived Value and Use (PVU7=0.450; PVU8=0.451), improving AVE from 0.452 to 0.535; the actual usage behaviour sub-dimension is no longer represented, and the retained PVU items capture performance expectancy, price value, and AI-HR confidence orientation. Four items were removed from Operational Performance (OP5=0.586; OP4=0.606; OP6=0.615; OP1=0.622 after earlier deletions) in iterative sequence, improving AVE from 0.416 to 0.500; the process efficiency sub-dimension is consequently unrepresented. Retained OP items cover workforce productivity, service delivery quality, and organisational responsiveness. These sub-dimension losses represent genuine construct-coverage limitations acknowledged in this study. Among the retained items from OP2 and OP3 (loadings=0.558 each), OS1 (loadings=0.699), PVU5 and PVU6 (loadings=0.594; 0.605) remain below the 0.70 threshold; their removal did not improve AVE and they contribute to their respective sub-dimension coverage, so they are retained as a flagged sensitivity concern (Sarstedt et al., 2022; Hair et al., 2022).

Internal Consistency and Convergent Validity

All constructs exceeded the 0.70 threshold for Cronbach's alpha and composite reliability, confirming internal consistency. AVE values ranged from 0.500 to 0.574 as shown in Table 3, meeting the minimum threshold of 0.50 (Hair et al., 2022). Table 3 presents the final loadings and reliability statistics.

Table 3. Reflective Measurement Model Results

Construct	Items (retained)	Loading range	CA	rho_A	CR	AVE
Technological Readiness (TR)	TR1 – TR9	0.710 – 0.799	0.907	0.909	0.924	0.574
Organisational Support (OS)	OS1 – OS6	0.699 – 0.757	0.827	0.829	0.874	0.535
Perceived Value and Use (PVU)	PVU1 – PVU6, PVU9, PVU10	0.594 – 0.859	0.870	0.875	0.900	0.537
Operational Performance (OP)	OP2,OP3,OP7 – OP12	0.558 – 0.792	0.854	0.860	0.887	0.500

Note: CA=Cronbach's Alpha; rho_A=Dijkstra-Henseler; CR=Composite Reliability; AVE=Average Variance Extracted. PVU9 and PVU10 are positively worded confidence items, consistent in direction with remaining PVU indicators.

Within Perceived Value and Use, two items (PVU5=0.594; PVU6=0.605) fall below the 0.70 loading threshold; as with OS1=0.699, and also OP2 and OP3 (0.558 each), these items were retained because their removal did not meaningfully improve AVE or Composite Reliability and each contributes to the theoretical coverage of its respective sub-dimension (performance-value belief content for PVU; management commitment for OS; workforce-productivity content for OP), consistent with the retention criteria of Hair et al. (2022) and Sarstedt et al. (2022).

Discriminant Validity

Discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT), which is considered a robust criterion for evaluating construct distinctiveness in PLS-SEM (Henseler et al. 2015). As presented in Table 4, all HTMT values were below the conservative threshold of 0.85, indicating that the constructs are empirically distinct and that discriminant validity is established.

Table 4. Discriminant Validity - Heterotrait-monotrait ratio (HTMT) – Matrix

Variable	OP	OS	PVU	TR
Operational Performance (OP)				
Organisational Support (OS)	0.593			
Perceived Value and Use (PVU)	0.488	0.501		
Technological Readiness (TR)	0.600	0.425	0.624	

Overall, the results provide strong evidence that the reflective measurement model meets the required criteria for reliability and validity, thereby supporting its adequacy for further structural model analysis.

Formative Measurement Model Assessment – AIHRA Higher-Order Construct

The higher-order AIHRA construct was operationalised using the two-stage approach. In Stage 1, latent variable scores were generated from the confirmed first-order reflective measurement model. In Stage 2, these scores served as formative indicators of AIHRA, with outer weights estimated via bootstrapping (5,000 subsamples). The formative evaluation addressed three criteria: collinearity, relative importance (outer weights), and absolute importance (outer loadings). Outer weights indicate the relative importance of each dimension's unique contribution to AIHRA; their significance identifies which dimensions contribute most distinctively relative to one another. Outer loadings indicate absolute importance, showing whether each dimension maintains a meaningful relationship with the higher-order construct regardless of the other dimensions. Both are necessary for a complete formative evaluation (Hair et al., 2022).

Table 5A. Formative Measurement of AIHRA — Outer Weights (Relative Importance)

Dimension	Outer Weight	t-value	p-value	VIF	95% BCa CI	Relative Importance
Technological Readiness (TR)	0.584	7.233	< 0.001	1.486	(0.418, 0.738)	Significant - highest contributor
Organisational Support (OS)	0.532	7.088	< 0.001	1.262	(0.382, 0.676)	Significant - strong contributor
Perceived Value & Use (PVU)	0.119	1.229	0.219	1.563	(-0.071, 0.309)	Non-significant - see *Table 5B*

Note. Bootstrapping: 5,000 subsamples, two-tailed, BCa confidence intervals. VIF < 3.3 confirms no multicollinearity as shown in Table 5A (Diamantopoulos & Winklhofer, 2001; Hair et al., 2022).

All VIF values (TR=1.486, OS=1.262, PVU=1.563) are well below 3.3, confirming the absence of multicollinearity. TR (weight=0.584, p < 0.001) and OS (weight=0.532, p < 0.001) (see Table 5A) contribute significantly to AIHRA formation, supporting H1 and H2. PVU's outer weight is non-significant (p=0.219); however, its outer loading of 0.667 exceeds 0.50, and its BCa confidence interval (0.511, 0.789; see Table 5B) excludes zero, providing evidence of meaningful absolute contribution. PVU is therefore retained, consistent with Hair et al. (2022) and Coltman et al. (2008). This outcome is theoretically consistent with the structural constraint argument: in resource-constrained environments, perceptual dimensions exert weaker relative influence than capability-based dimensions, yet they remain part of the construct's conceptual domain and cannot be excluded without compromising content validity.

Table 5B. Formative Measurement of AIHRA — Outer Loadings (Absolute Importance)

Dimension	Outer Loading	95% BCa CI	Absolute Importance
Technological Readiness (TR)	0.848	(0.761, 0.919)	High – CI excludes zero
Organisational Support (OS)	0.800	(0.694, 0.889)	High – CI excludes zero
Perceived Value & Use (PVU)	0.667	(0.511, 0.789)	Moderate – CI excludes zero – retained

Note: PVU outer weight is non-significant; however, it's outer loading (0.667 > 0.50) and BCa CI exclude zero (see Table 5B) support retention based on absolute importance criteria (Hair et al., 2022; Coltman et al., 2008).

Structural Model Assessment

Collinearity, Normality, and Endogeneity

Before assessing endogeneity, collinearity was examined. As shown in Table 6A, the variance inflation factor (VIF) for the AIHRA → Operational Performance path was 1.00, indicating no collinearity concerns.

Table 6A. Collinearity Statistics (VIF)

Paths	VIF
AIHRA → Operational Performance	1.00

Because the Gaussian copula approach is applicable only when the endogenous regressor is non-normally distributed (Hult et al., 2018), the normality of the AIHRA latent variable scores was formally assessed. The Shapiro-Wilk test was employed because it generally provides greater statistical power than the Kolmogorov-Smirnov test for detecting departures from normality in small to moderate samples and is widely recommended for normality assessment (Razali & Wah, 2011). The test was statistically significant (W=0.984, n=296, p=0.002; see Table 6B), indicating that the AIHRA latent variable scores departed significantly from a normal distribution. Accordingly, the non-normality assumption required for the Gaussian copula procedure was satisfied.

Table 6B. Shapiro–Wilk Normality Test for AIHRA Latent Variable Scores

Test	Statistic	df / N	p-value	Conclusion
Shapiro-Wilk	W=0.984	296	0.002	Significant - non-normality confirmed

Following Hult et al. (2018), a Gaussian copula term was incorporated into the structural model to examine potential endogeneity. As presented in Table 6C, the copula term was not statistically significant (β=-0.396, SD=0.368, t=1.075, p=0.282), indicating no evidence of endogeneity in the relationship between AIHRA and Operational Performance. Methodologically, although the copula-augmented structural coefficient (β=1.012) exceeded the conventional upper bound of 1.0, this reflects the expected collinearity between the endogenous regressor and its copula term, rather than a model specification error (Hult et al., 2018). Consequently, only the coefficient from the original structural model (β=0.626 see Table 7) is interpreted substantively, while the copula term serves solely as a diagnostic test for endogeneity. The sole function of the copula-augmented model is to test the significance of the copula term itself as a diagnostic for endogeneity, which it does not detect.

Table 6C. Gaussian Copula Endogeneity Test

Path	Coefficient	STD	t-value	p-value	Interpretation
AIHRA → OP (copula-augmented model)	1.012	0.361	2.803	< 0.01	Significant
GC(AIHRA) → OP (copula term)	-0.396	0.368	1.075	0.282	Not significant

Path Coefficients and Hypothesis Testing

Bootstrapping with 5,000 resamples assessed the significance of structural relationships. AIHRA is positively and significantly associated with operational performance (β=0.626, t=18.339, p<0.001), supporting H4. Table 7 presents the full results.

Table 7. Structural Model Results — Formative Contributions and Hypothesis Testing

Hypotheses	Path	Weight/β	STD	T-Stat	p-value	Decision
H1	TR contributes to AIHRA formation	0.584	0.081	7.233	< 0.001	Supported
H2	OS contributes to AIHRA formation	0.532	0.075	7.088	< 0.001	Supported
H3	PVU contributes to AIHRA formation	0.119	0.097	1.229	0.219	Not Supported*
H4	AIHRA → Operational Performance	0.626	0.034	18.339	< 0.001	Supported

*Note: *PVU (H3) outer weight is non-significant, but PVU is retained based on outer loading (0.667 > 0.50) and BCa CI excluding zero (see Table 5B) (Hair et al., 2022). All values from bootstrapping with 5,000 subsamples.*

Explanatory Power, Predictive Relevance, and PLSpredict

Coefficient of determination (R^2) and Stone-Geisser Q^2 values for operational performance is shown in Table 8A. AIHRA explains 39.2% of operational performance variance (R^2=0.392). In-sample predictive relevance (Q^2=0.370) exceeds zero, confirming the model predicts better than the mean value baseline (Hair et al., 2022). It is noted that in a single-predictor model, f^2 is a mathematical function of R^2($f^2=R^2/[1-R^2]=0.645$) and does not constitute independent evidence of effect magnitude; explanatory power is therefore interpreted solely through R^2=0.392.

Table 8A. Explanatory and Predictive Power

Endogenous Construct	R^2	Q^2
Operational Performance	0.392	0.370

Out-of-sample predictive accuracy via PLSpredict (10-fold, 10 repetitions; Shmueli et al., 2019) is presented in Table 8B. All eight retained OP indicators yield positive Q^2predict values (range: 0.135−0.242), confirming meaningful out-of-sample predictive relevance. Following Shmueli et al. (2019), all values fall within the low predictive power range (0-0.25), indicating limited but consistent out-of-sample precision. The PLS-SEM model outperforms the naive linear model (LM) on RMSE for all eight indicators; however, OP2 and OP3: the two borderline-loading items show marginally higher MAE relative to the LM, consistent with their borderline psychometric quality. The strongest out-of-sample accuracy is observed for organisational responsiveness items (OP10: Q^2predict=0.226; OP12: Q^2predict=0.242).

Table 8B. PLSpredict Results (10-fold, 10 repetitions)

Item	Q2predict	PLS RMSE	PLS MAE	LM RMSE	LM MAE
OP2	0.135	0.670	0.538	0.672	0.534
OP3	0.162	0.658	0.527	0.660	0.521
OP7	0.172	0.682	0.536	0.683	0.538
OP8	0.168	0.709	0.559	0.712	0.563
OP9	0.172	0.704	0.550	0.705	0.553
OP10	0.226	0.621	0.495	0.622	0.496
OP11	0.208	0.597	0.479	0.598	0.480
OP12	0.242	0.618	0.493	0.620	0.493

Note: RMSE=Root Mean Square Error; MAE=Mean Absolute Error; LM=naive linear model. Q^2predict 0 - 0.25=low predictive power (Shmueli et al., 2019). OP2 and OP3 PLS MAE exceeds LM MAE, consistent with borderline loadings (loadings=0.558).

Model Fit

The SRMR is 0.174 and the NFI is 0.384, both outside conventional thresholds (0.08 and 0.90 respectively) as shown in Table 9. These values are acknowledged as relatively weak global fit indicators and are not dismissed. The equivalence of saturated model SRMR (0.174) and estimated model SRMR (0.174) indicates that misfit originates at the measurement level which is consistent with sub-dimension narrowing from item purification; rather than at the structural path level. Both indices require different calibration in PLS-SEM, where variance explanation rather than covariance reproduction is the estimation objective (Henseler et al., 2016); SRMR is also sensitive to indicator count in complex models (Hair et al., 2022). The model's primary evaluation criteria are satisfactorily demonstrated: Q^2=0.370, R^2=0.392, all AVE >= 0.500, all CR >=0.829, all HTMT <0.85 (Rigdon, 2016; Hair et al., 2022).

Table 9. Model Fit Statistics

	Saturated Model	Estimated Model
SRMR	0.174	0.174
NFI	0.384	0.384

Bootstrapping Multi-Group Analysis — Supplementary Exploratory Analysis

A PLS-SEM bootstrapping permutation MGA procedure was conducted across Lagos (Group 1, n=116), Abuja (Group 2, n=78), Port Harcourt (Group 3, n=57), and Kano (Group 4, n=45). With four groups and three direct first-order paths (OS to OP, PVU to OP, TR to OP), a complete pairwise comparison comprises six group-pair comparisons per path, or eighteen comparisons in total. All eighteen comparisons were estimable in the permutation procedure and are reported in full in Table 10. Three qualifications must be stated: this MGA is exploratory and does not constitute a robustness check for the primary H4 path; MICOM was not conducted so formal invariance cannot be claimed; and there is no mediation in the model (AIHRA is a formative construct, not a mediator). The MGA examined direct first-order paths as theoretically implied exploratory relationships using the non-parametric permutation approach (Hair et al., 2022; Henseler et al., 2009). None of the eighteen pairwise path differences were statistically significant (all p>0.05) at the conventional two tailed threshold, suggesting the exploratory relationships do not vary meaningfully across the four locations, consistent with the argument that systemic conditions are common across Nigeria's major commercial zones.

Table 10. Bootstrapping-based Partial Least Squares Multi-Group Analysis Results

Path	Group Comparison	Difference	2-tailed p-value	Decision
OS → OP	Lagos vs. Abuja	0.111	0.524	Not Significant
OS → OP	Lagos vs. Port Harcourt	0.004	0.918	Not Significant
OS → OP	Lagos vs. Kano	0.306	0.111	Not Significant
OS → OP	Abuja vs. Port Harcourt	-0.107	0.553	Not Significant
OS → OP	Abuja vs. Kano	0.195	0.391	Not Significant
OS → OP	Port Harcourt vs. Kano	0.302	0.200	Not Significant
PVU → OP	Lagos vs. Abuja	0.038	0.813	Not Significant
PVU → OP	Lagos vs. Port Harcourt	0.000	0.999	Not Significant
PVU → OP	Lagos vs. Kano	-0.235	0.253	Not Significant
PVU → OP	Abuja vs. Port Harcourt	-0.038	0.849	Not Significant
PVU → OP	Abuja vs. Kano	-0.273	0.226	Not Significant
PVU → OP	Port Harcourt vs. Kano	-0.235	0.323	Not Significant
TR → OP	Lagos vs. Abuja	-0.121	0.408	Not Significant
TR → OP	Lagos vs. Port Harcourt	-0.047	0.742	Not Significant
TR → OP	Lagos vs. Kano	-0.046	0.783	Not Significant
TR → OP	Abuja vs. Port Harcourt	0.074	0.627	Not Significant
TR → OP	Abuja vs. Kano	0.075	0.731	Not Significant
TR → OP	Port Harcourt vs. Kano	0.001	0.972	Not Significant

Discussion

The structural results suggest a theoretically meaningful hierarchy among the dimensions forming AIHRA. TR (H1) contributes most strongly (weight=0.584, p<0.001), followed closely by OS (H2) (weight=0.532, p<0.001), while PVU (H3) yields a non-significant outer weight (0.119, p=0.219). These results suggest that in the Nigerian SME context, AIHRA adoption capability is formed more strongly by structural and organisational factors than perceptual ones, consistent with the argument that feasibility precedes desirability in resource-constrained environments.

The dominant contribution of TR (H1) is consistent with RBV logic that foundational resource stocks are necessary preconditions for higher-order capability (Barney, 1991; Samson & Bhanugopan, 2022) and with STS Theory's proposition that the technical subsystem must reach a minimum threshold before joint optimisation can occur (Trist & Bamforth, 1951; Wang et al., 2023). Comparing with Arroyabe et al. (2024), where management support dominated across 12,108 European SMEs with assumed infrastructure, the present findings suggest a contextually differentiated expression of the same adoption logic: where infrastructure must be individually provisioned, it becomes the binding constraint. The comparable magnitudes of TR (H1) and OS (H2) further indicate that neither technical capacity nor organisational will alone is sufficient; their joint presence is required, directly supporting the STS joint optimisation proposition.

The non-significant outer weight of PVU (H3) is interpreted through two parallel explanations. From a contextual perspective, structural barriers may prevent positive value perceptions from translating into adoption action, consistent with the intention-behaviour gap documented by Ekka and Singh (2022). From a measurement perspective, the deletion of PVU's actual usage behaviour items (PVU7 and PVU8) narrowed the construct's domain to beliefs and attitudes rather than actual usage, possibly attenuating its relationship with AIHRA formation. Both explanations are plausible and the cross-sectional design cannot adjudicate definitively between them. Nonetheless, PVU's (H3) absolute contribution is confirmed (outer loading =0.667; BCa CI: 0.511-0.789 excluding zero), indicating PVU (H3) remains a meaningful construct component even if its relative weight does not reach significance in the presence of stronger TR and OS dimensions.

AIHRA is positively associated with operational performance (β=0.626, $p<0.001$, R^2=0.392, Q^2=0.370). The Gaussian copula endogeneity test (copula coefficient beta =-0.396, t=1.075, p=0.282) provides no evidence of reverse causality bias. These results are consistent with RBV arguments that when Nigerian SMEs develop the adoption capability to deploy and derive intelligence from AI-HR tools, this may be associated with improvements in workforce productivity, service quality delivery, and organisational responsiveness. The cross-sectional design prevents causal inference, and retained OP items cover three of four originally specified sub-dimensions; these limitations temper the strength of performance-related conclusions.

Theoretical Contributions

This study makes three contributions. First, it advances technology adoption theory by demonstrating that TR (weight=0.584) and OS (weight=0.532) contribute significantly to AIHRA formation while PVU does not, suggesting that single-theory UTAUT2 models may underspecify AI adoption where structural constraints are binding. Whether this constitutes a formal UTAUT2 boundary condition requires multi-context comparative studies to establish; the present finding is consistent with, rather than a definitive test of this hypotheses, and extends established technology-organisation-environment adoption evidence (Sadiq et al., 2022; Shahadat et al., 2023) into the specific domain of AI-enabled HR analytics. Second, the study provides findings consistent with RBV arguments that AIHRA may function as a valuable organisational adoption capability, with a positive performance association (β=0.626, R^2=0.392) supporting the logic that the joint configuration of TR and OS produces an adoption capability with performance implications. VRIN attributes were not directly measured and are treated as theoretical formations. Third, by integrating UTAUT2, RBV, and STS Theory within a formally specified higher-order formative model, the study offers a methodologically explicit multi-theory capability-based framework for AI-HRM in Nigerian SMEs, addressing geographic and theoretical gaps documented by Alvarez-Gutierrez et al. (2022), while acknowledging that the underlying adoption logic, structural preconditions preceding perceptual drivers builds incrementally on, rather than departs sharply from, prior adoption research in comparable emerging market contexts.

Practical Implications

For SME managers, TR's dominant contribution indicates that digital infrastructure investment: power resilience, broadband, HR data digitalisation, and digitally capable staff should, precede AI software procurement. OS's comparable contribution confirms that management commitment, training, and AI governance frameworks are core capability investments. The non-significant PVU weight suggests awareness campaigns alone, without accompanying structural investments, may have limited effectiveness. For HR technology strategists, the comparable magnitudes of TR and OS suggest dual-track implementation; simultaneously addressing infrastructure and organisational change management is more likely to be effective than single-track vendor-led approaches. For policymakers; SMEDAN and NITDA, the findings support integrated interventions addressing both infrastructural and organisational preconditions, with priority toward broadband expansion, power subsidies, digital literacy curricula, and AI governance guidelines.

Limitations and Future Research

The cross-sectional design precludes causal inference and cannot capture the longitudinal process through which AIHRA capability accumulates and performance effects manifest over time. Longitudinal panel designs would provide stronger causal evidence. Measurement limitations from item purification represent a significant constraint: training/governance was removed from OS; actual usage behaviour from PVU; and process efficiency from OP. These sub-dimension losses reduce construct coverage and should be addressed through improved instrumentation in future research. Operational performance was self-reported by the same respondents who evaluated AIHRA, creating potential for common method and social desirability bias; future research should triangulate with objective HR metrics such as turnover rates, time-to-hire, or cost-per-hire records. PVU5 and PVU6 (loadings=0.594 and 0.605); OS1 (loadings=0.699); OP2 and OP3 (loadings = 0.558) represent a borderline reliability sensitivity concern. The sample is skewed toward formally registered, organisationally mature SMEs (83.4% operating over 11 years; 95.3% tertiary qualified) and findings are most directly generalisable to this segment rather than to micro-enterprises or informal businesses; future research should employ stratified sampling to include under-represented segments. Bootstrapping MGA should be extended to include formal MICOM and to test the AIHRA-OP path directly with larger sub-samples.

Two categories of future research are specifically recommended. First, moderation and mediation studies: it is theoretically appropriate and methodologically valuable to examine whether CEO digital literacy, institutional quality, or sectoral digital maturity moderates the relationship between AIHRA dimensions and AIHRA formation, or between AIHRA and operational performance. Similarly, mediating mechanisms: such as HR decision quality, employee engagement, or dynamic capability formation between AIHRA and performance warrant empirical investigation, as they would provide a more granular process theory of the adoption-to-performance causal chain. These analyses would benefit from longitudinal data and larger sample sizes. Second, contextual extension studies: future research should examine whether the capability-based adoption model replicates across other Sub-Saharan African economies and in comparable emerging market contexts, enabling the development of a more generalisable, Africa-specific theory of AI-HRM adoption that accounts for the heterogeneity of institutional environments across the continent.

Conclusion

This study developed and empirically examined a capability-based model of AI-enabled HR analytics adoption and its association with operational performance among Nigerian SMEs. AIHRA, conceptualised as a second-order formative adoption capability formed by Technological Readiness, Organisational Support, and Perceived Value and Use, was tested within an integrated UTAUT2-RBV-STS framework. TR (weight=0.584) and OS (weight=0.532) contribute significantly to AIHRA formation, while AIHRA is positively associated with operational performance (β=0.626, R^2=0.392). A non-significant Gaussian copula (p=0.282) supports robustness; PLSpredict confirms consistent but low out-of-sample predictive accuracy (Q^2predict range: 0.135-0.242). These findings suggest that feasibility precedes desirability as an adoption logic in structurally constrained environments, that dual-track infrastructure and organisational investment is required, and that awareness campaigns without structural accompaniment may be insufficient. Measurement limitations, including sub-dimension coverage losses and borderline item loadings, appropriately bound the conclusions and should temper the strength with which the findings are generalised. The study contributes a methodologically explicit multi-theory empirical adoption-performance framework for AI-HRM in a Sub-Saharan African context that remains under examined in the wider literature, with implications for SME managers, implementation strategists, and Nigeria's national digital transformation agenda that warrant further empirical corroboration in future longitudinal and comparative research.

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Ethics Approval and Informed Consent:
The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. No institutional ethics committee or institutional review board reviewed this study, and no formal approval reference number was issued or applies. All participation was voluntary; respondents were informed of the academic purpose, their right to withdraw, their anonymity and voluntarily provided consent prior to completing the survey.

Data Availability Statement:
An anonymized dataset supporting this study's findings is available from the corresponding author upon reasonable request.

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