© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10 I1-1719434

Artificial Intelligence Adoption and Employee Relations: A Conceptual Model of Trust as The Mediating Mechanism Linking AI-Assisted HR Decision-Making and Workforce Adaptability to Organizational Outcomes

COLLINS VINCENT TAMUNOSEIPRIYE[1], DR HELEN NNEKA OFOR[2]
[1,2] *Department of Employment Relations and Human Resource Management Ignatius Ajuru University of Education, Rumuolumeni, Port Harcourt, Rivers State, Nigeria*

Abstract-* *The accelerating diffusion of artificial intelligence (AI) into human resource management has outpaced scholarly understanding of how AI-related organizational change actually shapes the employment relationship. Existing research tends to treat AI-assisted decision-making, employee adaptability, and employee trust in AI as parallel, co-equal predictors of relational outcomes such as satisfaction, engagement, and workplace trust, despite accumulating evidence that trust performs a mediating rather than a merely additive function. This conceptual paper addresses that gap by synthesizing the technology acceptance, unified technology acceptance and use, psychological contract, and trust-in-automation literatures into an integrative model, termed the AI-HR Relational Trust Cascade, in which employee trust in AI systems is positioned as the conversion mechanism through which AI-assisted HR decision-making and employee adaptability translate into employee relations outcomes, rather than as one variable operating alongside them.The paper adopts a systematic narrative review methodology, critically analysing peer-reviewed literature published predominantly between 2019 and 2026 across human resource management, organizational psychology, and information systems journals. The review finds consistent evidence that the transparency, explainability, and perceived fairness of AI-driven decisions determine whether AI adoption strengthens or erodes the psychological contract, and that adaptability functions as a precondition for, rather than a substitute for, trust formation. Where these conditions are absent, AI adoption is associated with technostress, perceived breach of the psychological contract, and declining engagement, even where the underlying technology performs efficiently. The paper concludes that organizations pursuing AI-enabled HR transformation without deliberately building employee trust risk converting efficiency gains into relational deficits. Theoretical contributions, practical implications for HR governance, and an agenda for future empirical validation of the proposed model are discussed.

Keywords:* *Artificial Intelligence, Human Resource Management, AI-Assisted Decision-Making, Employee Trust; Psychological Contract, Employee Engagement, Workplace Trust, Technology Adoption, Employment Relations

I. INTRODUCTION

1.1 Background and Context

Artificial intelligence (AI) has moved from a peripheral experimental technology to a structural feature of human resource management (HRM) practice within little more than a decade. Organizations now deploy AI across the employee lifecycle, from algorithmic candidate screening to predictive attrition modelling, performance analytics, and AI-mediated learning and development.

Global investment in AI is projected to approach US$1.5 trillion in 2025, and survey evidence suggests that approximately ninety-five per cent of firms are now experimenting with or actively using generative AI tools in some part of their operations (Brynjolfsson et al., 2023; Moin et al., 2025).

Within HRM specifically, AI is credited with relieving practitioners of routine administrative work and freeing capacity for strategic decision-making (Nawaz et al., 2024), and has been associated with administrative workload reductions of as much as twenty-seven per cent alongside shortened onboarding cycles (Nawaz et al., 2024).

Yet the rapid organizational embrace of AI has not been matched by employee readiness or confidence. Survey evidence reveals a persistent gap between managerial enthusiasm and workforce trust, with industry research finding that fewer than half of employees trust AI to render unbiased human resource decisions (PwC, 2021).

Recent applied research on HR change management similarly identifies job displacement fears, distrust of AI systems, and perceived complexity as the primary drivers of employee resistance to AI adoption, even where organizational leadership is strongly supportive of the underlying technology (Priyanghaa, 2025). This asymmetry between adoption speed and relational readiness is the central problem this paper addresses.

1.2 Statement of the Research Problem

A common assumption in applied HR technology literature is that AI adoption produces relational benefits more or less automatically — that AI-assisted decision-making improves fairness and consistency, that employees adapt over time, and that trust accumulates as a by-product of exposure and competence. Empirical findings complicate this assumption considerably.

AI systems characterized by opacity reinforce employee distrust of the underlying decision logic (Park et al., 2021), small or unrepresentative training datasets introduce discriminatory outcomes that generate disputes between HR functions and affected employees (Tambe et al., 2019; Harper & Millard, 2023), and AI-driven restructuring has in some documented cases produced what employees experience as a breach of the psychological contract — a felt violation of the implicit mutual obligations underpinning the employment relationship (Shekhar & Saurombe, 2026).

At the same time, a separate stream of research finds that where AI systems are perceived as transparent, fair, and well communicated, they can enhance engagement, organizational commitment, and subjective well-being by relieving employees of monotonous tasks (Berretta et al., 2023; Prasad & De, 2024).

The research problem, therefore, is not whether AI adoption affects employee relations — the literature is unambiguous that it does — but how, and under what conditions, this effect is constructive rather than corrosive. Most existing studies examine AI-assisted decision-making, employee adaptability, and employee trust in AI as parallel independent variables predicting relational outcomes, implicitly treating trust as one input among several rather than as the mechanism connecting the others to outcomes.

This paper argues that such a parallel specification misrepresents the underlying causal structure, and that trust instead functions as a mediating variable: a necessary conversion point through which the other dimensions of AI adoption are translated into, or blocked from becoming, positive relational outcomes.

1.3 Significance of the Study

This paper makes three contributions. First, it offers a focused theoretical synthesis of literatures that have so far developed largely in parallel — technology acceptance research, psychological contract theory, and the trust-in-automation tradition — applying them specifically to the HRM employment relationship rather than to AI adoption in general terms.

Second, it proposes an original integrative model, the AI-HR Relational Trust Cascade, which repositions employee trust in AI systems as a mediating rather than additive variable, addressing a gap that several recent empirical studies gesture toward without formally modelling (see, for example, the mediating role of trust identified in generative AI and HRM research; Prasad & De, 2024), and the moderating role of AI acceptance identified in psychological-contract research linking AI to organizational commitment (Moin et al., 2025).

Third, the paper translates this theoretical contribution into a practical governance agenda for HR practitioners and policymakers operating in contexts, including Nigeria and other emerging-market economies, where AI-enabled HR systems are being adopted without commensurate investment in the conditions that sustain employee trust.

1.4 Research Objectives and Questions

The paper pursues three objectives:

1. To critically synthesize the existing literature on three dimensions of AI adoption in HRM — AI-assisted HR decision-making, employee adaptability to AI, and employee trust in AI systems — and their relationship to employee satisfaction, employee engagement, and workplace trust.
2. To identify the theoretical mechanisms through which these dimensions of AI adoption translate into, or undermine, positive employee relations outcomes.
3. To develop and justify an integrative conceptual model specifying the structural relationship between AI adoption dimensions and employee relations outcomes, suitable for future empirical testing.

Correspondingly, the paper is organized around three research questions:

1. RQ1: What does the existing literature establish about the relationship between AI-assisted HR decision-making, employee adaptability to AI, and employee trust in AI systems, on the one hand, and employee satisfaction, engagement, and workplace trust, on the other?
2. RQ2: Do these three dimensions of AI adoption operate as independent, parallel predictors of employee relations outcomes, or does one dimension function as a mediating mechanism for the others?
3. RQ3: What theoretical model best accounts for the documented variation in outcomes, ranging from enhanced engagement to psychological contract breach, across organizational contexts of AI adoption?

1.5 Thesis Statement

This paper argues that employee trust in AI systems is not merely one of several co-equal dimensions of AI adoption affecting employee relations, but the principal mediating mechanism through which AI-assisted HR decision-making and employee adaptability are converted into employee satisfaction, engagement, and workplace trust.

Where this mediating mechanism is absent or compromised, whether through opacity, perceived unfairness, or inadequate organizational communication, the relational benefits of AI adoption fail to materialize regardless of the technology's functional sophistication.

1.6 Scope of the Study

The paper is conceptual and theoretical in nature. It draws on peer-reviewed literature published predominantly between 2019 and 2026, spanning human resource management, organizational behaviour, information systems, and organizational psychology journals, with particular attention to studies addressing AI-assisted decision-making, algorithmic management, technology acceptance, and the psychological contract.

The scope is deliberately confined to the employment relationship within formal organizational settings; it does not extend to AI's labour-market effects on aggregate employment levels, wage structures, or occupational displacement, which fall outside the relational focus adopted here.

The proposed model is developed for subsequent empirical validation across organizational and national contexts, including, but not limited to, the Nigerian institutional environment from which the author's broader research interests are drawn.

II. LITERATURE REVIEW

This review is organized around four areas: the conceptual landscape of AI adoption in HRM; the three adoption dimensions specified in this paper's framework; the relevant theoretical lenses; and the resulting research gap. Throughout, the review privileges critical comparison over description, foregrounding points of disagreement and unresolved tension in the literature.

2.1 AI Adoption in Human Resource Management: The State of the Field

The literature on AI in HRM has expanded rapidly, with reviews documenting applications spanning recruitment and selection, performance management, learning and development, workforce planning, and employee relations functions (Ekuma, 2024; Nawaz et al., 2024).

A substantial body of this work is celebratory in orientation, emphasizing efficiency gains: automation of repetitive tasks, reduction of human bias in screening, and enhanced analytical capacity for workforce planning (Nawaz et al., 2024).

Brynjolfsson et al. (2023), in one of the more methodologically rigorous studies in this stream, report that generative AI assistance increased productivity among customer-service employees by approximately fourteen per cent on average, with substantially larger gains, around thirty-four per cent, among less experienced staff, suggesting AI's potential to compress skill-based performance gaps.

A second, more cautionary stream emphasizes the social and psychological costs of this transformation. Reviews note that AI adoption can simultaneously enhance efficiency and engagement while increasing job stress and perceived insecurity, and that job insecurity stemming from AI implementation can directly suppress employee engagement and performance (Morandini et al., 2023).

Bakir et al. (2025) similarly find that AI awareness, the employee's cognitive recognition that AI may substitute for their role, can have adverse effects on engagement, organizational commitment, and job satisfaction, an effect explainable through cognitive load theory: employees experiencing heightened uncertainty about AI's implications for their role face additional cognitive demands that degrade task performance and relational investment (Sweller, 1988).

These two streams are not strictly contradictory; rather, they describe a conditional relationship in which the valence of AI's relational effect depends on factors that the celebratory literature tends to under-specify.

The systematic review by Ekuma (2024) is useful in beginning to name these conditioning factors, identifying transparency and explainability as decisive: organizations that provide clear, justifiable explanations for AI-driven decisions are more likely to secure employee trust and acceptance, whereas opaque systems generate resistance regardless of their technical accuracy.

2.2 AI-Assisted HR Decision-Making

AI-assisted decision-making refers to the use of algorithmic systems, machine learning models, and predictive analytics to inform or automate HR judgements, including recruitment screening, performance evaluation, promotion and compensation decisions, and attrition forecasting.

The promise of this dimension rests substantially on a fairness argument: that algorithmic decision-making can neutralize the cognitive biases that distort human judgement in personnel decisions (Nawaz et al., 2024).

This promise is contested on both empirical and conceptual grounds. Algorithmic systems trained on historical organizational data risk encoding and amplifying the very biases they are intended to eliminate, particularly where training datasets are small, unrepresentative, or reflect prior discriminatory patterns (Tambe et al., 2019).

Where this occurs, the resulting decisions can generate legal disputes and create friction between HR functions and diversity and inclusion stakeholders (Harper & Millard, 2023).

A separate but related concern is opacity: many AI decision systems function as functional black boxes whose internal logic is not interpretable even to the HR professionals deploying them, let alone to the employees affected by their outputs.

Park et al. (2021) find that this opacity directly reinforces employee distrust of HRM decision processes, since employees cannot verify the basis on which decisions affecting their livelihoods were reached.

A further complication concerns the redistribution of decision-making authority itself. Research on human-AI collaborative decision-making finds that employees vary considerably in the cognitive ‘weight' they are willing to assign to AI recommendations, a willingness shaped by the AI system's perceived transparency, interpretability, and reliability (Glikson & Woolley, 2020), as well as by the individual employee's prior experience, selfefficacy, and disposition toward technology (Wen et al., 2025).

This suggests that AI-assisted decision-making is not a uniform organizational input with a fixed relational effect; its consequences are filtered through individual and contextual variation that the dominant efficiency-focused literature frequently abstracts away.

2.3 Employee Adaptability to AI

Employee adaptability denotes the capacity of the workforce to adjust skills, work routines, and professional identity in response to AI-driven organizational change.

The literature situates adaptability as both an individual psychological resource and an organizational outcome shaped by deliberate investment.

The World Economic Forum and LinkedIn Workforce Report data, as synthesized in recent dual-paradox analyses of AI and labour dynamics (Obi & Frempong, 2025), identify AI literacy, critical thinking, and complex problem-solving as the principal competencies organizations must cultivate to sustain adaptive capacity, alongside structural interventions such as redesigning business processes around human-AI collaboration rather than treating AI purely as a replacement mechanism.

A persistent theme is that adaptability is asymmetrically distributed within the workforce. Less experienced employees appear to benefit disproportionately from AI assistance in performing complex tasks (Brynjolfsson et al., 2023), suggesting that AI may, under favourable conditions, function as a levelling mechanism for skill gaps.

Conversely, employees whose professional identity is closely bound to tasks now subject to automation report more acute psychological strain, including what qualitative research has characterized as ‘eroded identities and heightened technostress (Shekhar & Saurombe, 2026).

Critically, adaptability in this literature is frequently treated as a precondition for positive relational outcomes rather than a sufficient cause of them. An employee may successfully acquire the technical competence to work alongside an AI system while remaining distrustful of its fairness or threatened by its implications for job security; adaptability in this sense addresses the capability dimension of AI adoption without resolving the relational dimension. This distinction, underdeveloped in much of the applied literature, is central to the model proposed later in this paper.

2.4 Employee Trust in AI Systems

Trust in AI systems has emerged as the most theoretically developed of the three dimensions, owing substantially to the trust-in-automation tradition in human factors research.

Lee and See (2004) define trust in this context as the attitude that an automated agent will help an individual achieve a goal under conditions of uncertainty and vulnerability, a definition that foregrounds the relational and risk-laden character of trust rather than treating it merely as a confidence judgement about technical accuracy.

Empirical findings consistently identify transparency, perceived fairness, and managerial communication as the principal antecedents of trust in AI systems within HRM contexts (Ekuma, 2024; Moin et al., 2025).

Industry survey data illustrate the scale of the resulting deficit: in one widely cited cross-sector survey, only forty-seven per cent of employees reported trusting AI to make unbiased HR-related decisions (PwC, 2021).

Importantly, research on generative AI adoption finds that trust does not function merely as an outcome of AI use but as a determinant of continued, voluntary engagement with AI tools: employees who perceive generative AI systems as reliable and useful are more likely to sustain positive usage patterns and favourable perceptions over time (Prasad & De, 2024), while a documented absence of trust produces negative adaptive intentions that, in turn, depress engagement, commitment, and increase turnover intentions (Prasad & De, 2024).

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DOI: https://doi.org/10.64388/IREV10 I1-1719434

This dimension intersects directly with psychological contract theory, discussed below, which provides a more institutionally embedded account of why trust violations associated with AI carry relational consequences beyond simple dissatisfaction with a tool.

2.5 Theoretical Frameworks

2.5.1 Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT)

The Technology Acceptance Model (Davis, 1989) explains technology adoption through two core constructs: perceived usefulness and perceived ease of use.

While foundational, TAM's exclusively cognitive orientation has been criticized as insufficient for AI-specific contexts, where adoption decisions are shaped not only by utility judgements but by emotional and psychological responses to systems that simulate agency and exercise discretionary judgement over consequential outcomes (Malin et al., 2025).

The Unified Theory of Acceptance and Use of Technology (UTAUT) extend TAM by incorporating social influence and facilitating conditions, and has been explicitly adapted in recent scholarship to model employee AI adoption and usage patterns in organizational settings, while still requiring contextual extension to capture trust and well-being considerations specific to AI (Moin et al., 2025).

2.5.2 Trust in Automation Framework

As developed above, the trust-in-automation framework (Lee & See, 2004) provides the most direct theoretical account of why employees extend or withhold confidence in algorithmic systems operating under uncertainty.

Its principal contribution to this paper's argument is its explicit framing of trust as a precondition for willingness to accept vulnerability and risk, rather than as a passive sentiment that accumulates automatically with exposure.

2.5.3 Psychological Contract Theory

Psychological contract theory (Rousseau, 1995) holds that, beyond the formal employment contract, employees and employers maintain implicit mutual expectations: employees expect fair treatment, a reasonable degree of job security, and opportunities for development in exchange for loyalty and effort.

This framework has proven especially generative for explaining the relational stakes of AI adoption, since it reframes employee reactions to AI not merely as technology-acceptance judgements but as appraisals of whether the organization is honouring or violating its implicit obligations.

Qualitative research applying this lens has identified recurring thematic patterns, including a sense of corporate betrayal, eroded professional identity, and cynicism about the prospect of adapting, particularly where AI implementation is associated with layoffs or significant unilateral role changes (Shekhar & Saurombe, 2026).

Complementary quantitative work demonstrates that psychological contract fulfilment positively predicts both employee trust and organizational commitment, while AI acceptance moderates the strength of this relationship, indicating that the psychological contract and AI-specific trust are conceptually distinct but empirically interdependent (Moin et al., 2025).

2.5.4 Social Exchange Theory

Social exchange theory complements the psychological contract framework by explaining the reciprocal logic underlying employee responses to organizational treatment: employees calibrate their discretionary engagement and commitment in proportion to the fairness and value of treatment received from the organization.

Within AI-adoption research, this lens has been used to explain why perceived organizational support during AI implementation, such as participatory consultation and skills investment, generates reciprocal increases in trust and commitment, whereas unilateral imposition generates reciprocal withdrawal (Moin et al., 2025).

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DOI: https://doi.org/10.64388/IREV10 I1-1719434

2.6 Limitations in Prior Studies and the Research Gap

Three limitations recur across the reviewed literature and together justify the present paper's contribution. First, a substantial proportion of empirical studies in this domain are sector-specific or geographically concentrated, frequently drawing on samples from information technology or single-country contexts (see, for example, the service-industry sampling in Diaz & Romero, 2024, and Türkiye-based sampling in related psychological-contract and emotional-labour research), limiting generalizability across the diverse organizational and institutional contexts, including those of emerging-market economies such as Nigeria, in which AI-enabled HR systems are increasingly deployed.

Authors of conceptual work in this space explicitly flag this as an unresolved limitation, noting that the applicability of integrative frameworks linking AI, trust, and the psychological contract across different sectors and organizational contexts remains untested (Malin et al., 2025).

Second, and most consequential for the present paper, the majority of empirical and conceptual studies specify AI-assisted decision-making, adaptability, and trust as parallel predictors of relational outcomes rather than testing or theorizing a sequential or mediating relationship among them.

Where mediation is examined, it tends to be modelled narrowly: for instance, trust mediating the relationship between user perception and organizational commitment in a single-sector generative-AI study (Prasad & De, 2024), or AI acceptance moderating, rather than mediating, the relationship between psychological contract fulfilment and its outcomes (Moin et al., 2025).

No identified study integrates all three adoption dimensions, AI-assisted decision-making, adaptability, and trust, into a single sequential model explicitly applied to the HRM employment relationship.

Third, the literature lacks a comprehensive and reliable integrative model capable of explaining the dimensions that jointly influence AI adoption outcomes for engagement, commitment, and performance, a gap explicitly acknowledged within the generative-AI and HRM literature itself (Prasad & De, 2024).

This paper's proposed model directly addresses that acknowledged gap by formalizing trust as the mediating mechanism connecting AI-assisted decision-making and adaptability to employee relations outcomes, a structural specification implied but not yet formally modelled across the reviewed literature.

III. METHODOLOGY

3.1 Research Design and Approach

This paper adopts a qualitative, conceptual research design, employing a systematic narrative review approach to literature synthesis. This approach is appropriate where the objective is theory development and integration rather than hypothesis testing against primary data (Brynjolfsson et al., 2023).

Unlike a purely descriptive literature summary, a systematic narrative review applies explicit, documented procedures for source identification and selection while retaining the interpretive latitude necessary to synthesize across heterogeneous theoretical traditions, in this case, technology acceptance research, psychological contract theory, and trust-in-automation scholarship, that a strictly systematic or meta-analytic review would not readily accommodate given the conceptual rather than statistical nature of the integration sought.

3.2 Data Collection: Source Identification Strategy

Sources were identified through structured searches of Scopus-indexed databases and major academic publishers, including SAGE, Elsevier (ScienceDirect), Springer, Frontiers, Nature Portfolio (Humanities and Social Sciences Communications), and MDPI, supplemented by targeted searches of working-paper repositories for emerging empirical work not yet indexed in final journal form. Search terms combined the core constructs of interest, including ‘artificial intelligence', ‘AI adoption', ‘algorithmic management', ‘HR decision-making', ‘employee trust', ‘psychological contract', ‘employee

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DOI: https://doi.org/10.64388/IREV10 I1-1719434

engagement', and ‘workplace trust', in varying Boolean combinations.

The search was restricted, with limited exceptions for foundational theoretical sources predating this window (notably Davis, 1989, on the Technology Acceptance Model; Rousseau, 1995, on psychological contract theory; and Lee & See, 2004, on trust in automation), to literature published between 2019 and 2026, reflecting the period of accelerated organizational AI adoption following advances in machine learning and, subsequently, generative AI.

3.3 Sampling Technique: Source Selection and Inclusion Criteria

Source selection followed a purposive sampling logic appropriate to narrative synthesis, prioritizing relevance and theoretical contribution over exhaustive coverage.

Sources were included where they: (a) addressed AI adoption within HRM or organizational management contexts specifically, rather than AI adoption in general consumer or industrial settings; (b) examined at least one of the three adoption dimensions specified in this paper's framework, or at least one of the three relational outcomes; (c) were published in peer-reviewed journals or, in a small number of cases involving very recent empirical contributions, in rigorously peer-reviewable working-paper form with transparent methodology; and (d) offered either primary empirical findings or a substantive theoretical contribution rather than purely promotional or practitioner-oriented commentary.

Sources were excluded where they addressed AI's labour-market or macroeconomic employment effects without reference to the relational dynamics of the employment relationship, as this falls outside the scope defined in Section 1.6.

3.4 Analytical Framework

Selected sources were analysed using a thematic synthesis procedure adapted from qualitative evidence synthesis methods (Ekuma, 2024, applies a comparable thematic analytic logic in a related systematic review).

Sources were first coded according to which of the three adoption dimensions and three relational outcomes they addressed; second, according to the theoretical framework(s) they invoked; and third, according to whether they specified a parallel, mediating, or moderating relationship among constructs.

This coding structure enabled systematic identification of the pattern, noted in Section 2.6, whereby trust is repeatedly implicated as a mediating mechanism without being formally modelled as such across the three adoption dimensions jointly.

The resulting conceptual model presented in Section 5 was developed iteratively, through comparison of convergent and divergent findings across sources, and refined against the theoretical logic of psychological contract theory and the trust-in-automation framework.

3.5 Ethical Considerations

As a conceptual paper relying exclusively on previously published, publicly available secondary literature, this study did not involve human participants, primary data collection, or any procedure requiring institutional ethics board review.

Nonetheless, the paper adheres to established ethical standards for academic literature synthesis: all sources are attributed using APA 7th edition referencing conventions to avoid plagiarism; claims attributed to specific authors are represented in a manner consistent with the original source's reported findings and scope, avoiding overstatement of certainty or generalizability; and the author declares no financial or professional conflict of interest that could bias the selection or interpretation of sources.

3.6 Reliability and Validity Considerations

In qualitative and conceptual research, reliability and validity are appropriately reframed in terms of trustworthiness criteria: credibility, transferability, dependability, and confirmability (Malin et al., 2025). Credibility is supported in this paper through triangulation across multiple independent theoretical traditions (technology acceptance, psychological contract, trust-in-automation, and social exchange

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theory) converging on a consistent structural inference regarding trust's mediating role.

Dependability is supported through the explicit, documented source-selection criteria specified in Section 3.3, which would allow another researcher to substantially replicate the literature base.

Confirmability is addressed through the paper's explicit acknowledgement, in Section 6.4 below, of contradictory findings and alternative interpretations rather than selectively presenting only confirmatory evidence.

Transferability, the extent to which the proposed model applies beyond the specific studies reviewed, is treated as an open empirical question and is the explicit subject of the future research agenda set out in Section 7.6.

IV. FINDINGS: SYNTHESIS OF THE REVIEWED LITERATURE

This section presents the systematic patterns identified through the thematic synthesis described in Section 3.4. As a conceptual paper, the 'findings' reported here are patterns and relationships drawn from the body of reviewed secondary literature, not primary data collected by the author; each pattern is traceable to the specific sources cited. Findings are organized according to the three research questions specified in Section 1.4.

4.1 Finding One: Documented Relationships Between Adoption Dimensions and Relational Outcomes (RQ1)

Table 1 summarizes the directionality and conditions of the relationships identified across the reviewed literature between each AI adoption dimension and each employee relations outcome.

The synthesis indicates that no adoption dimension exhibits a uniformly positive or uniformly negative relationship with relational outcomes; rather, each relationship is conditional on factors, principally transparency, fairness, and communication, that the literature treats inconsistently across studies.

Table 1. Synthesized relationships between AI adoption dimensions and employee relations outcomes, as reported across the reviewed literature.

Adoption Dimension	Relationship to Satisfaction	Relationship to Engagement	Relationship to Workplace Trust
AI-assisted HR decision-making	Conditional positive; contingent on perceived fairness (Ekuma, 2024)	Conditional positive; undermined by opacity (Tambe et al., 2019; Harper & Millard, 2023)	Negative where decisions are unexplained (Park et al., 2021)
Employee adaptability to AI	Positive, especially for less-experienced staff (Brynjolfsson et al., 2023)	Positive where organizational support is present (Obi & Frempong, 2025)	Indirect; adaptability alone does not resolve trust deficits (Shekhar & Saurombe, 2026)
Employee trust in AI systems	Strong positive; central mediating antecedent (Ekuma, 2024)	Strong positive; sustains continued use (Prasad & De, 2024)	Definitional overlap; trust in AI is a component of broader workplace trust (Wen et al., 2025)

4.2 Finding Two: Trust Functions as a Mediating Rather Than Parallel Mechanism (RQ2)

The second and most theoretically significant finding concerns the structural relationship among the three adoption dimensions.

Across the reviewed sources, employee trust in AI systems does not behave as a variable whose effects are simply additive to those of AI-assisted decision-making and adaptability; instead, it consistently behaves as the variable through which the relational

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DOI: https://doi.org/10.64388/IREV10 I1-1719434

consequences of the other two dimensions are realized.

Three converging strands of evidence support this finding. First, studies examining AI-assisted decision-making directly link its relational consequences to trust-relevant properties, transparency, explainability, and perceived fairness, rather than to the decision-making function itself (Ekuma, 2024; Park et al., 2021).

Where these properties are present, AI-assisted decisions support engagement and satisfaction; where absent, the same decision-making function generates distrust and disputes. This indicates that AI-assisted decision-making's relational effect is not direct but is channelled through the trust it does or does not generate.

Second, studies of generative AI adoption explicitly model trust as a mediator between user perception and organizational commitment (Prasad & De, 2024), providing direct empirical precedent, albeit within a single adoption dimension and a single national and sectoral context, for the structural claim advanced in this paper.

Third, the psychological-contract literature demonstrates that contract fulfilment affects organizational commitment through trust as an explicit mediator, with AI acceptance further moderating this mediated pathway (Moin et al., 2025).

Although this finding is framed in terms of psychological contract fulfilment generally rather than the three adoption dimensions specified in this paper, it provides independent theoretical corroboration that trust occupies a mediating, rather than parallel, position in the causal chain linking organizational treatment to relational outcomes.

Considered jointly, these findings answer RQ2: the reviewed literature does not support a model in which AI-assisted decision-making, adaptability, and trust operate as independent, additive predictors.

It instead supports, even where individual studies do not explicitly frame it this way, a sequential model in which decision-making and adaptability shape relational outcomes principally by shaping trust, which then governs whether those outcomes are positive or negative.

4.3 Finding Three: Adaptability Operates as a Precondition, not a Substitute, for Trust (RQ2 and RQ3)

A related but distinct finding concerns the specific role of adaptability within this sequential structure.

The evidence indicates that adaptability and trust are not interchangeable: an organization can successfully build employee technical adaptability to AI tools, through training, upskilling, and process redesign (Obi & Frempong, 2025), without thereby securing employee trust in those tools' fairness or in management's intentions in deploying them.

Conversely, no reviewed source identifies a pathway by which trust in AI systems develops in the complete absence of adaptive capacity, since some baseline familiarity and competence appears necessary before employees can meaningfully evaluate an AI system's fairness or reliability. This asymmetry suggests that adaptability functions as a necessary but not sufficient precondition within the sequential model: it enables the conditions under which trust can form, but does not itself guarantee that trust will form.

4.4 Finding Four: Contradictions and Boundary Conditions (RQ3)

Two notable contradictions in the literature merit explicit acknowledgement, as they identify boundary conditions for the model developed in Section 5. First, while the majority of sources find that AI-assisted decision-making transparency improves trust and relational outcomes, Bakir et al.

(2025) find that AI awareness itself, independent of any specific decision-transparency property, can degrade engagement and commitment through cognitive load, implying that even fully transparent AI systems may impose a relational cost simply by increasing employees' cognitive burden of monitoring and interpreting AI involvement in their work.

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This suggests the proposed model may require a boundary condition limiting the trust-mediation pathway's explanatory power in high-cognitive-load organizational contexts.

Second, findings regarding adaptability's distributional effects are not fully consistent: while Brynjolfsson et al. (2023) find that less-experienced employees benefit disproportionately from AI assistance, other research emphasizes that employees whose professional identity is most closely bound to automatable tasks experience the most acute psychological strain (Shekhar & Saurombe, 2026).

These findings are reconcilable, since productivity benefit and identity threat are not mutually exclusive within the same individual, but their coexistence indicates that the relationship between adaptability and relational outcomes is unlikely to be linear, and may instead follow a more complex function in which moderate task automation, e.g. of routine sub-tasks, benefits engagement while higher degrees of role-level automation threaten it.

V. THE AI-HR RELATIONAL TRUST CASCADE: A PROPOSED CONCEPTUAL MODEL

Building on the findings presented in Section 4, this section formalizes the paper's principal theoretical contribution: an integrative model specifying the structural relationship between the three AI adoption dimensions and the three employee relations outcomes under examination.

5.1 Model Specification

The AI-HR Relational Trust Cascade proposes that AI-assisted HR decision-making and employee adaptability to AI do not exert direct, independent effects on employee satisfaction, engagement, and workplace trust. Instead, their relational effects are substantially mediated by employee trust in AI systems, which functions as the conversion mechanism translating the technical and behavioural dimensions of AI adoption into relational outcomes.

Adaptability additionally functions as a moderating precondition: it does not independently produce trust, but the relationship between AI-assisted decision-making and trust is strengthened when employee adaptability is high, since adaptable employees possess the contextual competence to accurately evaluate an AI system's fairness and reliability rather than reacting from a position of unfamiliarity or anxiety.

Formally, the model proposes the following structural pathways:

1. AI-assisted HR decision-making exerts its effect on employee satisfaction, engagement, and workplace trust primarily indirectly, through its influence on employee trust in AI systems, rather than directly.
2. Employee adaptability to AI moderates the strength of the pathway between AI-assisted decision-making and trust: the relationship is stronger where adaptability is high and weaker, or potentially negative, where adaptability is low.
3. Employee trust in AI systems exerts a direct, positive effect on all three relational outcomes, employee satisfaction, employee engagement, and workplace trust, and functions as the principal proximal determinant of these outcomes within the model.
4. The strength and even the direction of the cascade is conditioned by organizational transparency and communication practices, which function as an exogenous contextual factor shaping how AI-assisted decision-making is perceived and, consequently, how strongly it predicts trust.

5.2 Theoretical Justification

This specification synthesizes the four theoretical frameworks reviewed in Section 2.5. From the trust-in-automation framework (Lee & See, 2004), the model adopts the premise that trust governs willingness to accept the vulnerability inherent in delegating consequential decisions to an algorithmic system, providing the theoretical rationale for trust's proximal position in the model.

From psychological contract theory (Rousseau, 1995), the model adopts the premise that employees evaluate AI-driven organizational change against implicit expectations of fair treatment, such that AI-assisted decisions are processed not merely as technical events but as signals about whether the organization is honouring its relational obligations, providing the rationale for treating decision-making's effects as channelled through a trust-relevant appraisal process rather than acting directly on outcomes.

From the Technology Acceptance Model and UTAUT (Davis, 1989; Venkatesh et al., 2003), the model adopts the premise that perceived usefulness and facilitating conditions, including organizational support for skill development, shape adoption behaviour, providing the rationale for adaptability's moderating function.

From social exchange theory, the model adopts the premise that employees calibrate discretionary engagement reciprocally in response to perceived organizational fairness, providing the rationale for treating organizational transparency as an exogenous condition shaping the entire cascade.

5.3 Distinction from Prior Models

The proposed model differs from prior conceptualizations in the reviewed literature in two specific respects. First, where prior studies model trust as a mediator within a single adoption dimension, for instance, between generative AI user perception and organizational commitment (Prasad & De, 2024), the present model extends this mediating logic across both AI-assisted decision-making and adaptability jointly, treating trust as the common conversion mechanism for the cumulative behavioural and technical dimensions of AI adoption rather than for a single technology-use variable.

Second, where prior research treats AI acceptance as a moderator of the relationship between psychological contract fulfilment and its outcomes (Moin et al., 2025), the present model inverts this structural emphasis, positioning trust as the mediator and adaptability as the moderator, a specification that follows from treating trust, rather than general technology acceptance, as the most proximal determinant of relational outcomes specifically within the HRM decision-making context.

5.4 Schematic Representation

Figure 1 presents a simplified schematic of the proposed cascade. AI-assisted HR decision-making is positioned as the principal exogenous technical input; employee adaptability is positioned as a moderator of the pathway from decision-making to trust; employee trust in AI systems occupies the central mediating position; and the three relational outcomes are positioned as the model's joint dependent variables, all proximally determined by trust.

AI-Assisted HR Decision-Making	→ (moderated by Adaptability) →	Employee Trust in AI Systems	→ Satisfaction / Engagement / Workplace Trust

Figure 1. Schematic representation of the AI-HR Relational Trust Cascade, showing employee trust in AI systems as the mediating mechanism between AI-assisted decision-making (moderated by adaptability) and employee relations outcomes.

VI. DISCUSSION

6.1 Interpretation of Findings

The findings reported in Section 4 collectively suggest that the central question facing organizations adopting AI in HRM is not whether to adopt particular technical capabilities, but whether they can build and sustain the trust conditions under which those capabilities translate into relational benefit rather than relational harm.

This reframing carries an important implication: organizational investment decisions that focus narrowly on AI's technical sophistication or functional capability, without parallel investment in transparency, explainability, and communicative practice, are likely to be systematically misdirected relative to the actual determinants of relational outcomes identified in this review.

The finding that adaptability functions as a moderating precondition rather than a direct driver of relational outcomes (Section 4.3) further suggests that organizations that invest heavily in technical upskilling while neglecting the fairness and communication dimensions of AI governance may successfully build a workforce capable of using AI tools competently while leaving largely unaddressed the trust deficit that determines whether that

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DOI: https://doi.org/10.64388/IREV10 I1-1719434

competence translates into engagement or merely into compliant, disengaged tool use.

6.2 Comparison with Existing Literature

The proposed model is consistent with, and extends, several existing findings rather than contradicting the established literature wholesale. It is consistent with Ekuma's (2024) identification of transparency as decisive for trust and acceptance, with the trust-in-automation tradition's emphasis on trust as a precondition for accepting vulnerability (Lee & See, 2004), and with empirical demonstrations of trust's mediating role within single adoption dimensions (Prasad & De, 2024; Moin et al., 2025).

Its point of departure from this existing literature lies in scope and structural integration: rather than modelling trust's mediating role within one adoption dimension at a time, it proposes that this mediating logic generalizes across the technical (decision-making) and behavioural (adaptability) dimensions jointly, a more parsimonious and more readily falsifiable specification than treating each adoption dimension as a separate, unconnected research stream.

The model is also consistent with, while extending, the cautionary literature on AI-driven psychological contract breach (Shekhar & Saurombe, 2026). That literature documents the relational damage that follows when AI-driven organizational change violates implicit employee expectations, but tends to treat this as a discrete negative case rather than as the predictable downstream consequence of a breakdown at the trust-mediation stage of the cascade proposed here.

Read through the lens of the present model, the breach phenomena documented in that qualitative literature represent instances in which the moderating and mediating conditions specified in Section 5.1, adaptability support and trust formation, were absent or actively undermined, rather than instances of a qualitatively distinct phenomenon.

6.3 Theoretical and Practical Significance

Theoretically, the model contributes a more precise specification of causal structure to a literature that has, to date, been more successful at identifying relevant constructs than at specifying how those constructs relate to one another.

By formally distinguishing mediation from moderation within the AI-adoption-to-employee-relations pathway, the model offers a basis for sharper empirical hypothesis generation than the additive specifications common in prior survey-based research.

Practically, the model implies a specific sequencing logic for organizational AI implementation. Rather than treating technical deployment, employee training, and trust-building communication as parallel workstreams of equal priority, the model implies that communication and transparency practices function as upstream conditions that determine whether subsequent investment in technical capability and adaptability training will yield relational returns.

This has direct implications for HR governance structures, particularly in contexts such as Nigerian public and private sector organizations, where AI-enabled HR systems are frequently introduced through top-down technical deployment with comparatively limited parallel investment in explainability infrastructure or employee consultation mechanisms.

6.4 Addressing Contradictions and Unexpected Patterns

As noted in Section 4.4, the finding that AI awareness itself may impose a cognitive-load-related relational cost independent of transparency (Bakir et al., 2025) complicates a model that treats transparency as straightforwardly beneficial.

This suggests a refinement to the model's scope conditions: transparency and explainability efforts may need to be calibrated to avoid overwhelming employees with interpretive burden, an implication consistent with research on explainable AI more broadly, which distinguishes between technically complete explanations and explanations that are cognitively accessible to lay users (Langer & König, 2023).

The model as specified in Section 5.1 should therefore be understood as proposing a positive relationship between transparency and trust up to a point of cognitive accessibility, rather than a strictly monotonic relationship at all levels of informational complexity, an important nuance for future empirical specification.

VII. CONCLUSION

7.1 Summary of Key Findings

This paper set out to critically synthesize the literature on three dimensions of AI adoption in HRM, AI-assisted decision-making, employee adaptability, and employee trust in AI systems, and their relationship to employee satisfaction, engagement, and workplace trust.

The review found that these relationships are uniformly conditional rather than direct, that employee trust in AI systems functions as a mediating mechanism rather than as a co-equal parallel predictor, and that employee adaptability functions as a moderating precondition for trust formation rather than as an independent driver of relational outcomes.

7.2 Answers to the Research Questions

In response to RQ1, the literature establishes that AI-assisted decision-making and adaptability are associated with relational outcomes only conditionally, principally through their effect on perceived fairness and trust, while employee trust in AI systems is associated with relational outcomes directly and consistently across the reviewed sources.

In response to RQ2, the evidence does not support a parallel, additive specification; it supports a sequential specification in which trust mediates the effects of the other two dimensions.

In response to RQ3, the AI-HR Relational Trust Cascade, developed in Section 5, is proposed as the model that best accounts for the documented variation in outcomes, while explicitly incorporating the boundary condition, identified in Section 6.4, that excessive cognitive burden associated with AI transparency efforts may attenuate the model's otherwise positive trust-formation pathway.

7.3 Scholarly Contribution

The paper's principal scholarly contribution is the formal integration of trust-in-automation, psychological contract, technology acceptance, and social exchange perspectives into a single sequential model applied specifically to the HRM employment relationship, addressing a gap explicitly acknowledged but not resolved within the existing literature (Prasad & De, 2024; Malin et al., 2025).

7.4 Practical and Policy Implications

For HR practitioners, the model implies that investment in AI-driven decision-making capability should be sequenced alongside, rather than after, investment in transparency and communication infrastructure, since the latter substantially determines whether the former yields positive or negative relational returns.

For policymakers in jurisdictions such as Nigeria, where regulatory frameworks for algorithmic accountability in employment contexts remain at an early stage of development, the findings suggest that policy attention directed at mandating explainability and consultation requirements for AI-assisted HR decisions may yield greater protective value for the employment relationship than policy attention directed solely at the technical accuracy or non-discrimination properties of AI systems, important as those properties remain in their own right.

7.5 Recommendations

1. Organizations should establish explainability protocols for AI-assisted HR decisions that are calibrated to employee comprehension rather than to technical completeness alone, in light of the cognitive-load boundary condition identified in Section 6.4.
2. Organizations should sequence AI implementation programmes so that communication, consultation, and trust-building measures precede or accompany, rather than follow, technical deployment.
3. HR functions should treat employee adaptability training as a necessary but insufficient condition for successful AI adoption, pairing technical upskilling with explicit governance measures addressing fairness and algorithmic accountability.

4. Regulatory and professional bodies in employment relations should consider developing sector-specific guidance on AI explainability standards in HR decision-making, particularly in emerging-market contexts where such guidance is currently underdeveloped.

7.6 Suggestions for Future Research

The model developed in this paper is conceptual and requires empirical validation. Future research should prioritize cross-sectional and longitudinal survey-based testing of the proposed mediation and moderation pathways using validated multi-item scales for each construct, alongside structural equation modelling techniques capable of formally testing mediated and moderated-mediation specifications.

Given the geographic concentration of existing empirical work in information-technology-sector and higher-income-country samples, future research should prioritize replication and adaptation of the model across diverse organizational sectors and national contexts, including Nigerian and other African institutional settings in which AI-enabled HR systems are being adopted under markedly different regulatory, infrastructural, and cultural conditions than those reflected in the bulk of the reviewed literature.

Future research should also empirically investigate the cognitive-load boundary condition identified in Section 6.4, examining whether there exists an identifiable threshold beyond which additional AI transparency efforts cease to enhance, and may begin to undermine, employee trust.

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