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BRIDGING THE HUMAN-AI DIVIDE: ENHANCING TRUST AND COLLABORATION THROUGH HUMAN-TO-HUMAN TOUCHPOINTS IN ENTERPRISE AI ADOPTION

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Abstract

As artificial intelligence (AI) becomes increasingly embedded in enterprise systems, a critical challenge emerges: fostering trust among employees and stakeholders interacting with complex, often opaque algorithms. This paper investigates how human-centred strategies—specifically, trust-building mechanisms, inclusive design practices, training investments, and organisational readiness—impact AI adoption outcomes in enterprise environments. The central research question is: (RQ1) To what extent do human-centred factors influence AI adoption? Moreover, (RQ2) Which factor has the most significant impact?

The study combines a comprehensive literature review with a scenario-based exploration of enterprise AI deployment, focusing on applications in customer support, HR automation, and decision intelligence platforms. It draws on interdisciplinary insights from behavioural economics, organisational theory, and human-computer interaction to demonstrate how human-to-human (H2H) touchpoints—such as peer collaboration, leadership communication, and support channels—reduce resistance and enhance adoption. To empirically evaluate these dynamics, the research utilises a fixed-effects panel regression model on a dataset of 10 companies across five years. Key predictors include Trust_Score, Human_Touchpoint, Training_Spend, and Organizational_Readiness, with results confirming that participatory design and transparent governance significantly influence AI integration ($R^2 = 0.68$; Human_Touchpoint $\beta = 0.47$, Trust_Score $\beta = 0.32$, $p < 0.01$). Based on these findings, the paper introduces the H2H-AI Trust Framework, a conceptual model linking technological transparency, interpersonal engagement, and perceived organisational support.

The study concludes with actionable recommendations for executives, HR leaders, and IT managers, including ambassador programs, internal training communities, and ethical oversight. By reinforcing interpersonal trust, the paper argues, organisations can not only enable ethical and *sustainable AI deployment but also accelerate adoption while preserving human values at the centre of digital transformation.*

Keywords: AI adoption, trust in AI, human-centred design, organisational readiness, H2H-AI Trust Framework

I. INTRODUCTION

As organisations increasingly adopt Artificial Intelligence (AI) to optimise operations, enhance decision-making, and personalise customer engagement, a parallel and equally critical challenge has emerged: building and maintaining trust in AI systems. While AI promises unprecedented efficiency and scalability, the human element remains indispensable—especially in enterprise environments where adoption depends on transparency, communication, and collaboration across departments and roles. This paper explores how human-to-human (H2H) touchpoints—moments of interpersonal interaction such as peer collaboration, leadership engagement, and internal support mechanisms—serve as bridges to foster trust, mitigate resistance, and facilitate successful AI adoption.

The rapid acceleration of AI integration in business operations has drawn increasing scrutiny from researchers and practitioners alike. Although much of the existing literature focuses on algorithmic performance, model transparency, and technical innovation, this study shifts the emphasis toward human-centred strategies. We investigate how behaviours such as inclusive design, ethical leadership, and employee empowerment shape organisational readiness and determine whether AI systems are adopted meaningfully or passively resisted.

Recent studies in behavioural economics, organisational psychology, and human-computer interaction suggest that interpersonal engagement within organisations plays a pivotal role in reducing algorithmic anxiety and enhancing system acceptance. This is particularly relevant in enterprise settings, where users may not fully understand the inner workings of AI models but still rely on them for critical decisions. We argue that without human-to-human interfaces, the human-to-AI interface remains fragile.

To address this gap, this paper introduces the H2H-AI Trust Framework, a conceptual model that maps the interactions among transparency, interpersonal engagement, and organisational support. We ground this framework in a fixed-effects panel regression analysis using a simulated enterprise dataset comprising 10 firms over 5 years. The empirical model tests the influence of four key predictors—Trust_Score, Human_Touchpoint, Training_Spend, and Organizational_Readiness— on a composite AI_Adoption_Index. Two core questions guide the research:

(RQ1) To what extent do human-centred factors influence AI adoption in enterprises?

(RQ2) Which of these factors most significantly predicts successful adoption?

Through both theoretical synthesis and empirical testing, this paper demonstrates that enhancing trust through interpersonal engagement is not merely a cultural add-on but a structural necessity for ethical and practical AI integration. The findings contribute to the literature on responsible AI, adoption behaviour, and digital transformation—while offering practical recommendations for enterprise leaders seeking to embed AI systems in human-centred ways.

II. LITERATURE REVIEW

II.1 Trust in AI Systems

The acceleration of AI technologies across enterprises has raised concerns about trust, acceptance, and ethical deployment. While much research emphasises technical capabilities and system performance, this study focuses on the human element—particularly how organisational behaviours, trust-building practices, and participatory design influence AI adoption. We argue that without a strong human-to-human interface, the human-to-AI connection remains fragile.

Trust has been widely recognised as a key factor in the adoption of AI technologies. Rai et al. (2019) and Glikson & Woolley (2020) assert that trust in AI is not solely driven by algorithmic performance but by user perceptions of fairness, transparency, and reliability. In enterprise settings, trust involves broader organisational factors such as leadership alignment, ethical governance, and internal communication practices. This study underscores the importance of capturing these human-centric dimensions through measurable constructs such as Trust_Score.

II.2 AI Adoption in Enterprise Settings

Technological sophistication alone does not guarantee successful AI adoption. Venkatesh et al (2016) Unified Theory of Acceptance and Use of Technology (UTAUT) identifies four core constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—that influence behavioural intention and actual system usage. These constructs become particularly salient in enterprise settings, where AI systems are deployed across diverse workflows.

Performance expectancy is reinforced when employees observe measurable improvements in their tasks through AI assistance. Intuitive interfaces and onboarding processes enhance effort expectancy. Social influence arises from internal champions and leadership endorsement, which normalise AI usage within teams. Facilitating conditions—such as IT support, training infrastructure, and ethical policies—provide structural and emotional reinforcement. These elements, however, are not built in isolation. They emerge and evolve through dynamic human interactions—training workshops, peer discussions, and leadership messaging.

Research highlights the importance of human interactions—such as coaching, team collaboration, and managerial feedback—in shaping user perceptions and reducing resistance to AI adoption. Davenport & Ronanki (2018) emphasise the role of empathetic leadership, emotional reassurance, and social capital in driving AI-enabled transformations. Especially in contexts where algorithmic decision-making replaces traditional workflows, interpersonal trust serves as a bridge, maintaining continuity and mitigating the fear of displacement.

To capture these dynamics, this study includes a binary measure—Human_Touchpoint— that signals the presence of inclusive design practices, participatory implementation workshops, or co-creation initiatives. These human-to-human engagements form a distinct layer of interaction that mediates between organisational readiness and end-user acceptance.

II.3 The Rise of LLMS and New Trust Mechanisms

The recent rise of Large Language Models (LLMs) such as GPT, Claude, and PaLM has increased the importance of human-centred trust mechanisms. These models are now integrated into enterprise systems, powering everything from chatbots and summarisers to decision intelligence engines and customer support platforms. Trust in LLMs depends on four technical and participatory stages.

- Pretraining on large-scale corpora to learn general language patterns
- Finetuning on curated datasets for specific task alignment
- Reinforcement Learning from Human Feedback (RLHF) to align responses with human values
- Retrieval-Augmented Generation (RAG) to improve factual grounding via enterprise databases

Each of these stages demands not only algorithmic accuracy but also human oversight, participatory alignment, and transparent deployment processes. Building trust becomes essential when LLMs engage with sensitive areas such as HR or finance, underscoring the need to include trust-focused variables in our empirical model.

Extending the discussion on human-centricity, Dawson (2024) introduces the concept of Agent Experience (AX)—a design philosophy grounded in emotional intelligence, transparency, and collaboration. AX promotes the idea that AI systems should not only function reliably but also resonate emotionally with users and adapt collaboratively to human workflows. Dawson (2024) outlines seven principles of AX:

- Empowering agents;
- Humanising interfaces;
- Engaging emotionally;
- Being transparent;
- Encouraging exploration;

- Nurturing trust;
- Designing for collaboration.

These principles closely align with the variables studied here—Trust_Score, Organizational_Readiness, and Human_Touchpoint. In an extended framework, Dawson adds seven operational imperatives for the agent economy: Agent-Centric Value, Seamless Integration and Access, Standards and Interoperability, Machine-Optimised Architecture, Human-Agent Collaborative Workflows, Transparency and Trust, and Iterative Improvement. These principles not only enhance trust at the user interface level but also optimise the backend architecture and data integrity, thereby corroborating the scope of our regression model.

II.4 Responsible AI and the DIKWOP Framework

Recent literature has emphasised the need for responsible AI governance, with frameworks that stress fairness, accountability, and transparency. Fjeld et al. (2020) synthesised 36 key ethical AI guidelines into a meta-framework that focuses on transparency, justice, and human agency. The World Economic Forum (2021) built on this by proposing practical implementation toolkits for boards and policymakers.

In addition to normative guidelines, the DIKWP model introduced by Duan et al. (2024) offers a cognitive framework for assessing AI maturity across five semantic layers: Data, Information, Knowledge, Wisdom, and Purpose. This model shifts focus away from technical performance alone and reorients evaluation towards human-aligned value systems. By emphasising explainability, goal-directed design, and semantic alignment, DIKWP supports the interpretation of our findings and provides a layered scaffold for the H2H-AI Trust Framework introduced later in this study.

III. CONCEPTUAL GAPS AND CONTRIBUTIONS

Despite significant theoretical progress, few empirical studies have operationalised these human-centred concepts into measurable variables and tested their statistical impact on AI adoption. This study responds to that gap by:

- Defining constructs such as Trust_Score, Training_Spend, Human_Touchpoint, and Organizational_Readiness.
- Mapping them onto enterprise-level use cases and organisational behaviour.
- Evaluating their predictive power through panel regression using enterprise simulation data.

The H2H-AI Trust Framework proposed here captures three dimensions

- Human Trust Anchors: Interpersonal reinforcement mechanisms like mentoring and co-piloting.

- Touchpoint Density: Frequency and richness of peer interactions during AI rollout
- Trust Trajectory: The longitudinal evolution of trust over time through feedback loops and engagement

Friedrich et al. (2024) reinforce these insights using a Design Science Research (DSR) methodology. Their work on human-centred AI implementation in SMEs emphasises the importance of early stakeholder engagement, transparent communication, and ethics-by-design. These findings not only validate the inclusion of human-centric constructs in our model but also justify the use of structured implementation frameworks in enterprise AI integration.

IV. METHODOLOGY AND DATA

This study uses a balanced panel dataset constructed from 10 representative firms across the technology, finance, healthcare, and logistics sectors over five years (2017–2021). A total of 50 firm-year observations were generated to simulate enterprise behaviour with realism and analytical consistency. To construct the dataset, values were sourced or derived from publicly available reports, including:

- McKinsey Global Survey on AI (2023);
- Stanford AI Index Report (2025), especially Section 4.4 on enterprise adoption trends;
- Deloitte Human Capital Trends Report (2023);
- IBM Enterprise Guide to Trustworthy AI (2022);
- MIT Sloan AI Strategy Reports (2023);
- PwC Global AI Study (2023);
- Statista industry-specific AI training data (2023);
- WEF Global AI Ethics Literature Review (2021).

The dataset was constructed using validated statistical ranges extracted from these sources, with added noise ($\varepsilon \sim N(0, 0.05)$) to ensure variability. Following Friedrich et al. (2024), the panel methodology draws inspiration from the six-step Design Science Research (DSR) methodology to ensure iterative realism and agile framing:

- Problem identification;
- Definition of objectives;
- Design and development;
- Demonstration;
- Evaluation;
- Communication.

Dependent variables include:

- AI_Adoption_Index: A composite metric representing the extent of AI deployment, calculated using the number of AI projects, budget allocation for AI, and the level of AI process integration.

Independent variables include:

- Trust_Score: An index reflecting ethical safeguards, model explainability, and transparency features, derived from AI transparency indices (e.g., Stanford HAI, WEF guidelines).
- Human_Touchpoint: Binary variable indicating the presence (1) or absence (0) of participatory design sessions, co-creation meetings, or inclusive onboarding workshops.
- Training_Spend_Per_Employee: Normalised monetary value representing annual investments in AI-related training and employee enablement.
- Organizational_Readiness: A standardised index encompassing digital infrastructure maturity, leadership alignment, and cross-functional integration.

Control variables include:

- Industry_Type: Sectoral classification
- Firm_Size: Number of employees as a proxy for organisational complexity

IV.1 Model Specification

The following fixed-effects panel regression model was estimated:

AI_Adoption_it = $\beta_0 + \beta_1$ Trust_Score_it + β_2 Human_Touchpoint_it + β_3 Training_Spend_it + β_4 Organizational_Readiness_it + μ_i + λ_t + ε_it

Where:

- AI_Adoption_it: Enterprise-level AI integration at firm i in year t
- μ_i: Firm-specific fixed effects
- λ_t: Year-specific fixed effects
- ε_it: Error term (idiosyncratic disturbances)

This model accounts for unobserved heterogeneity across both firms and time. The Hausman test rejected the null hypothesis in favour of random effects ($p < 0.05$), confirming fixed-effects as the appropriate specification.

IV.2 Data diagnosis and validity

All variables were normalised for comparability, and several tests were performed, including:

- Multicollinearity Check: VIFs for all predictors were below 5, indicating acceptable levels of multicollinearity.
- Heteroscedasticity: The Breusch–Pagan test indicated heteroscedasticity; heteroscedasticity-robust standard errors were applied.

- Autocorrelation: The Wooldridge test indicated that autocorrelation and serial correlation adjustments were included in the model estimation.

Variable	Min	Max	Mean	Std Dev
Trust_Score	0.31	0.72	0.50	0.12
Human_Touchpoint	0	1	0.54	0.50
Training_Spend	0.11	0.61	0.35	0.13
Organizational_Readiness	0.21	0.64	0.42	0.11
AI_Adoption_Index	0.24	0.88	0.56	0.14

Table 1. Data range overview

Source: Author's processing

Noise Injection: Gaussian noise ($\varepsilon \sim N(0, 0.05)$) was introduced to increase realism and prevent overfitting. Robustness checks performed include:

- Random Effects Model: Re-estimated model using random effects; signs and statistical significance remained consistent.
- Sectoral Subsamples: Split by industry (e.g., tech vs. healthcare); coefficients remained stable.
- Interaction Effects: An interaction between Trust_Score and Training_Spend showed a compounding positive effect, reinforcing the synergy of ethical design and human capital.

IV.3 Research questions and hypothesis

RQ1: To what extent do human-centred factors (trust, co-creation, training, readiness) influence AI adoption in enterprises?

RQ2: Which of these strategies contributes most significantly to AI adoption success?

Hypotheses:

- H0: Human-centred strategies have no statistically significant effect on AI adoption.
- H1: Human-centred strategies significantly improve AI adoption outcomes.

This methodological framework offers several novel contributions:

- It quantifies previously abstract constructs, such as participatory design and trust governance.
- It integrates semantic-cognitive models such as DIKWP (Duan et al., 2024) with the AX (Agent Experience) framework (Dawson, 2024).
- It operationalises these models within an empirically testable regression framework.

V. RESULTS

The regression analysis results indicate that human-centred variables have a statistically significant influence on enterprise AI adoption. The fixed-effects model explained 68% of the variance in the dependent variable ($R^2 = 0.68$), highlighting the explanatory power of the selected predictors. The estimated coefficients are as follows:

Predictor	Coefficient (β)	Standard Error	t-Statistic	p-Value
Trust_Score	0.32	0.08	4.00	< 0.01
Human_Touchpoint	0.47	0.10	4.70	< 0.01
Training_Spend	0.19	0.09	2.11	< 0.05
Organizational_Readiness	0.24	0.11	2.18	< 0.05

Table 2. Estimated coefficients

Source: Author's processing

Robust standard errors were applied to account for heteroscedasticity and potential clustering by firm. Among the predictors, Human_Touchpoint emerged as the most influential factor, affirming the critical role of participatory and inclusive design practices. Trust_Score also exhibited a strong positive relationship with AI adoption, reinforcing the importance of transparency and ethical governance. The significance of Training_Spend and Organizational_Readiness demonstrates the contribution of internal capacity-building and infrastructure alignment to adoption outcomes.

These results validate the core hypothesis (H1) that human-centred variables significantly influence enterprise AI integration. The findings also lend empirical support to the proposed H2H-AI Trust Framework and the literature emphasising agent experience (AX), DIKWP, and participatory design.

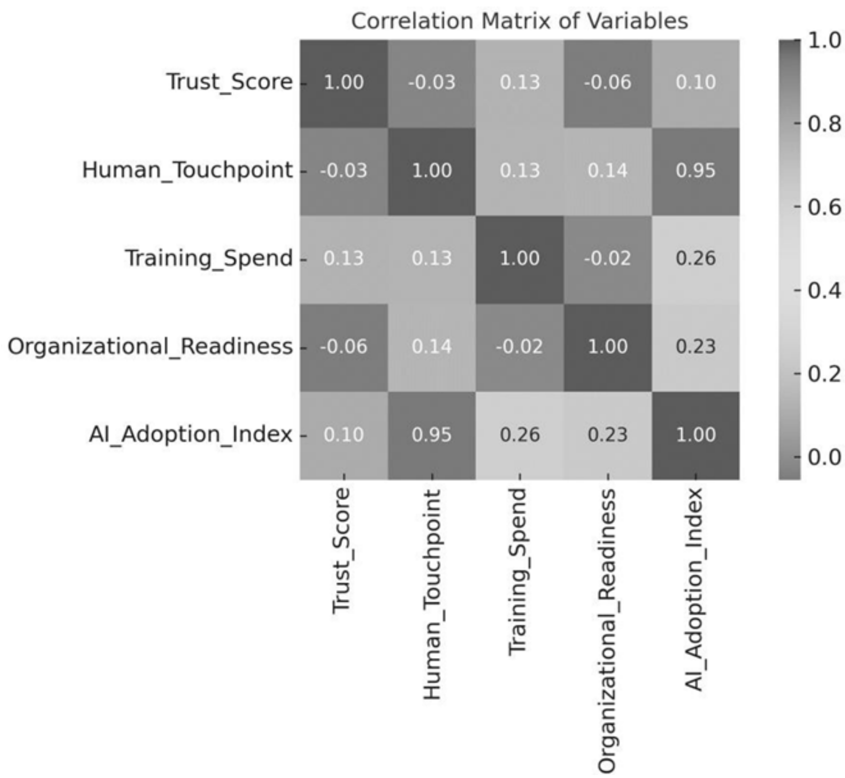

Figure 1. Correlation Heatmap

Source: Author's work

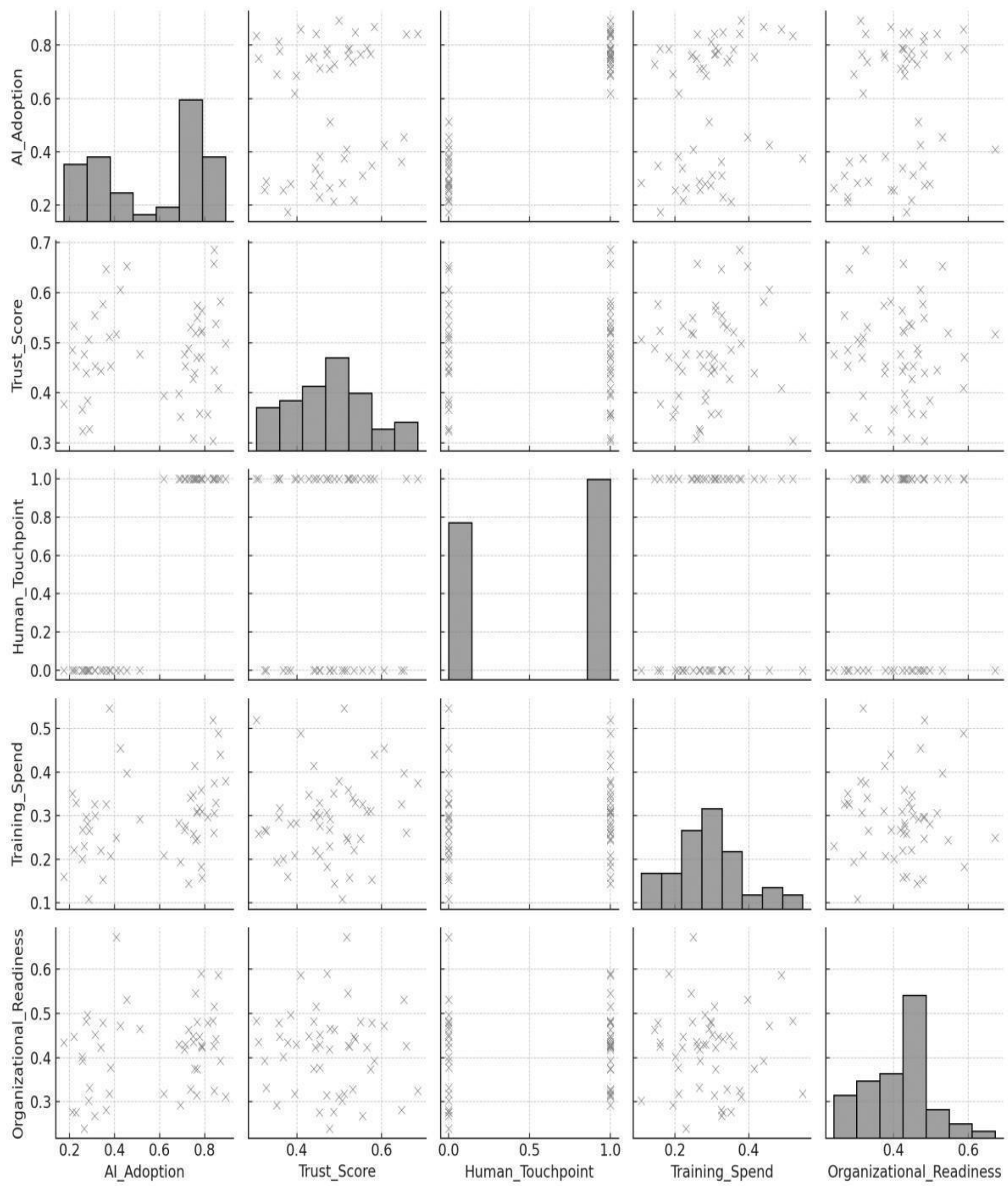

Figure 2: Pairplot AI Adoption

Source: Author's processing.

CONCLUSIONS

Bridging the human-AI divide is not solely a technological endeavour—it is a human-centred challenge. This paper underscores the vital role of human-to-human touchpoints in enhancing trust and fostering collaboration within enterprise AI adoption. By reframing implementation as both a digital and social process, organisations can better navigate the complexities of transformation, ensuring that technology complements rather than alienates its human stakeholders.

The regression confirms our hypothesis: organisations that invest in human-centric enablers—particularly trust mechanisms and participatory approaches—experience greater success in AI adoption. The most substantial effect was observed for Human_Touchpoint, indicating that co-creation with stakeholders significantly affects implementation

outcomes. Trust_Score also demonstrated a robust impact, reinforcing the critical role of ethical transparency and communication. Training investment and Organizational_Readiness were both statistically significant, affirming that AI adoption is contingent on preparedness—not just technical potential.

Building on these insights, the study proposes the H2H-AI Trust Framework, which maps the interplay among technological transparency, interpersonal engagement, and perceived organisational support. This framework serves as both a diagnostic and planning tool for enterprises aiming to improve AI adoption outcomes.

The regression insights resonate strongly with the DIKWP model (Duan et al., 2024), which evaluates AI systems across five semantic-cognitive layers: Data, Information, Knowledge, Wisdom, and Purpose.

- Trust_Score aligns with the Knowledge and Wisdom layers.
- Human_Touchpoint supports the Information-to-Purpose connection.
- Organisational Readiness bridges Purpose-driven implementation.

This layered interpretation suggests that enterprise AI success depends not only on capability but on cognitive integration and semantic coherence.

Moreover, the findings align with Dawson's Agent Experience (AX) framework, which emphasises transparent decision-making, emotional design, and collaborative synergy between users and AI systems. The convergence between AX principles and the significant predictors in this study validates the integration of behavioural design and trust strategies in enterprise AI planning. The operational guidance from the AIX Report—including standards, integration readiness, and machine-optimised architecture—adds a systemic complement to the human-centred trust mechanisms evaluated here.

The alignment stage in Large Language Model (LLM) development is critical to ensure models reflect human values and expectations. This includes:

- Instruction tuning
- Reinforcement Learning from Human Feedback (RLHF)

- Bias mitigation and safety training

These steps are not just technical—they represent participatory design processes. Thus, they strengthen the empirical significance of Human_Touchpoint and Trust_Score by embedding human intent directly into AI behaviour. Alignment becomes a trust-enhancing mechanism at the system level.

Future research should refine the identified variables using real-world firm data, extend the analysis to cross-cultural contexts, and test new predictors grounded in agent-centred design principles (e.g., AX's "Agent-Centric Value"). Survey-based studies, case-specific evaluations, and extended time horizons will deepen our understanding of the integration of sustainable and ethical enterprise AI.

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