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Exploring the Adoption of AI Tools in the Workplace: An Employee-Centric Perspective

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Abstract

This study addresses the critical problem of low employee acceptance of Artificial Intelligence (AI) tools in the workplace, a dimension often underexplored compared to organizational or technological readiness. The objective is to investigate behavioral determinants, specifically organizational support, perceived AI usability, and perceived work enhancement that drive AI adoption among employees. The study is guided by key research questions: What behavioral factors influence employee acceptance of AI? How significant are organizational support and usability perceptions in this process? Based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the research formulates hypotheses linking these constructs to AI acceptance. A structured questionnaire was distributed to 250 professionals across diverse industries in an emerging economy. Regression analysis using SPSS was employed to examine these relationships. The findings reveal that organizational support and learning strongly predict AI acceptance ($\beta = 0.765$), followed by perceived usability and work enhancement ($\beta = 0.189$), with the model accounting for 79.5% of the variance ($R^2 = 0.795$). The study concludes that AI adoption is primarily a behavioral challenge rather than a technological one. It recommends implementing employee-centric interventions such as training, transparent communication, and usability-focused tools to ensure inclusive and effective digital transformation.

Keywords: Artificial intelligence adoption, Employee acceptance, Organizational support, AI usability, Technology Acceptance Model (TAM)

1. Introduction

The integration of Artificial Intelligence (AI) into contemporary workplaces has emerged as a cornerstone of digital transformation, redefining operational models across diverse sectors, including healthcare, finance, education, and manufacturing. While the technical advantages of AI, such as automation of routine tasks, data-driven decision-making, and enhanced operational efficiency, are widely acknowledged, the human dimension of this transformation, particularly from the employee's perspective, remains underexplored. Much of the existing literature concentrates on macro-level enablers such as organizational readiness, financial investment, and policy frameworks, often neglecting the micro-level behavioral and psychological factors that fundamentally shape individual acceptance and use of AI technologies. AI implementation does not merely introduce new tools; it reshapes job roles, alters task structures, and redefines performance expectations. These shifts inevitably influence critical aspects of the employee experience, including autonomy, identity, trust, and job satisfaction. While AI has demonstrated its potential to enhance productivity and support decision-making in high-skill and knowledge-intensive roles, its implications in low-skill environments are more complex. In such settings, employees often report feelings of job insecurity, increased surveillance, and diminished responsibility phenomena collectively described as "automation anxiety." This anxiety can erode employee morale, increase resistance to change, and ultimately undermine the effectiveness of AI initiatives. A central factor influencing employee acceptance of AI tools is trust. Trust in AI encompasses beliefs about the technology's transparency, fairness, reliability, and alignment with organizational values. Employees are more likely to adopt AI systems when they perceive them as ethically sound and capable of augmenting rather than replacing their professional contributions. However, concerns related to algorithmic bias, opacity of decision processes, and the erosion of human expertise persist, particularly in settings where AI tools are deployed without adequate communication, training, or stakeholder involvement. These concerns are magnified in emerging economies, where organizational culture, infrastructural constraints, and varying levels of digital literacy can further complicate AI adoption. Another pivotal determinant of AI acceptance is usability, defined by the perceived ease of use and perceived usefulness of AI systems. Employees are more inclined to embrace AI tools when they find them intuitive, user-friendly, and directly beneficial to their work outcomes. Usability becomes especially crucial in fast-paced or resource-constrained environments, where employee bandwidth for learning and adapting to new technologies is limited. Moreover, the perceived enhancement of work through AI, whether in the form of task simplification, error reduction, or performance improvement, plays a significant role in shaping positive attitudes toward its adoption. This study seeks to bridge the existing research gap by adopting a human-centered approach to understanding AI integration in the workplace. Grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), it explores three key behavioral predictors of employee acceptance: perceived organizational support, perceived usability, and perceived work enhancement. Through an empirical investigation using structured surveys and statistical analysis, the study aims to provide actionable insights for managers, HR professionals, and policymakers. In doing so, it contributes to the growing discourse on inclusive digital transformation and emphasizes the need for AI strategies that are not only technologically robust but also psychologically and culturally attuned to the workforce they are intended to serve.

1.2. Objectives and Research Questions

Objectives:

1. To assess the influence of perceived organizational support and learning opportunities on employee acceptance of AI tools in the workplace.
2. To examine the impact of AI usability and work enhancement on employee acceptance.
3. To analyze the combined predictive power of organizational support, trust, and usability in determining AI acceptance using regression analysis.
4. To contextualize the findings by exploring AI adoption from the perspective of employees in an emerging economy, thereby contributing to the literature on digital transformation.
5. To offer actionable recommendations for organizational leaders and HR managers to facilitate a supportive environment for inclusive AI assimilation.

Research Questions:

1. What behavioral and organizational factors most significantly influence employee acceptance of AI in the workplace?
2. How does perceived organizational support impact employees' willingness to adopt AI tools?
3. To what extent does the perceived usability and enhancement of work tasks by AI influence adoption decisions?
4. What is the relative contribution of these factors in predicting AI acceptance, as revealed through regression modeling?
5. How can organizations in emerging economies better design AI adoption strategies that align with employee expectations and workplace culture?

2. Literature Review

2.1. Review of Previous Work

The accelerated adoption of AI in organizational settings has transformed business operations, workforce dynamics, and decision-making frameworks across key sectors, including healthcare, finance, manufacturing, and education. Agrawal et al. (2023) argue that AI integration prompts comprehensive system-level changes, necessitating a realignment of strategic goals with digital infrastructure. Bélissent et al. (2023) emphasize the significance of institutional trust, robust data governance, and internal readiness as foundational enablers for AI maturity, particularly within public-sector organizations. However, as Neumann et al. (2022) note, the presence of governance complexity and bureaucratic resistance can hinder AI deployment in such settings. In emerging markets, scholars such as Al-Okaily et al. (2022) and Suroso et al. (2022) utilize the Technology-Organization-Environment (TOE) framework to highlight that leadership support, technological infrastructure, and internal capabilities are especially crucial where external digital pressures may be inconsistent or underdeveloped. Complementing this macro-level view, recent research has begun to center human behavior in AI adoption. Kwon et al. (2023) demonstrate that the perceived transparency and usefulness of AI tools significantly influence employee engagement and ethical perceptions, especially among professionals with high responsibility thresholds. Sánchez-Holgado and Calderón (2024) extend this understanding to public services, illustrating how ethical concerns shape citizen-level trust and usage of AI systems. A growing body of literature underlines trust as a critical determinant of AI acceptance. Kinowska and Sienkiewicz (2022) raise caution against algorithmic management practices, observing that in large-scale corporations, such approaches may reduce employee autonomy, contributing to job dissatisfaction and burnout. This is echoed by Felten et al. (2018) and Wilson et al. (2017), who warn that unless inclusively implemented, AI may exacerbate fears of redundancy and alienation. In contrast, Faulconbridge et al. (2023) portray professionals as active agents navigating AI disruptions through "intertwined boundary work," wherein they adapt their roles and identities to co-exist with automation. Similarly, Budhwar et al. (2023) explore how generative AI enhances human resource (HR) operations but simultaneously introduces ethical dilemmas involving surveillance and algorithmic discrimination. At the macroeconomic level, Bonfiglioli et al. (2024) contend that AI's impact on productivity and employment is uneven across regions. While technologically advanced economies may benefit from efficiency gains, developing nations face heightened risks of digital exclusion and job displacement. These disparities have prompted calls for inclusive AI policies. Reports from PricewaterhouseCoopers (2023) advocate for widespread reskilling, digital literacy programs, and ethical governance mechanisms to bridge these divides. In a similar vein, Mi et al. (2023) analyze the dual nature of AI adoption during crises such as COVID-19, where digital preparedness and employee adaptability determined organizational resilience.

2.2. Identification of the Gap

Despite the extensive body of literature on AI adoption, several critical research gaps remain unaddressed. Much of the scholarly focus has been directed toward macro-level determinants such as organizational readiness, digital infrastructure, and national competitiveness, often sidelining the nuanced, micro-level behavioral dimensions that influence AI acceptance among employees. While these macro perspectives offer valuable insights into strategic and structural enablers, they do little to explain how individual attitudes, trust, and perceptions impact the actual use of AI tools within everyday work settings. Although some scholars have begun to address this gap, the empirical landscape remains thin. Studies like those by Kwon et al. (2023) and Selenko et al. (2022) have made initial strides by exploring constructs such as trust in AI and psychological adaptation to automation. However, comprehensive quantitative models that investigate how perceived usefulness, trust, and organizational support interact to shape employee acceptance of AI tools are still limited. Most existing research is concentrated in technologically advanced Western economies or large multinational corporations, where digital maturity and resource availability are substantially higher. This creates a contextual bias and overlooks the unique challenges and opportunities present in emerging markets. In emerging economies, AI adoption is deeply influenced by socio-cultural factors, infrastructural constraints, and varying levels of managerial commitment. Here, employee perceptions are often shaped not just by the capabilities of the technology itself but also by organizational climate, access to training, and trust in leadership. Scholars such as Luo et al. (2024) and Tambe et al. (2023) have begun to explore these dynamics, yet there remains a scarcity of empirical studies that rigorously apply behavioral models like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) in such settings. This study addresses that gap by conducting an SPSS-based regression analysis to evaluate the impact of perceived usefulness and employee trust on AI tool acceptance in a developing country context. By centering the behavioral experiences of employees in resource-constrained environments, this research contributes a more inclusive, contextually grounded perspective to the evolving discourse on AI-enabled workplace transformation. It offers actionable insights for HR professionals, system designers, and policymakers seeking to foster AI readiness in culturally and organizationally diverse settings.

3. Methodology

3.1. Research Design

This study adopts a quantitative, cross-sectional survey research design aimed at empirically evaluating employee-level determinants of AI tool adoption in the workplace. While prior research has largely focused on macro-level indicators such as digital infrastructure and managerial readiness, this study emphasizes the behavioral and perceptual variables influencing AI acceptance among employees. The approach is grounded in the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating constructs such as trust in AI, organizational support, and perceived usability. A cross-sectional design was selected to enable a snapshot analysis of relationships among these constructs at a single point in time across diverse professional contexts.

3.2. Sample

A total of 252 responses were gathered through an online survey, of which 250 complete and valid entries were retained for final analysis. The sample was drawn using a non-probability convenience sampling method, targeting professionals across various sectors, including IT, finance, education, healthcare, and manufacturing. Inclusion criteria required participants to be currently employed and to have had exposure to AI tools in their respective work environments. The participant pool reflected demographic diversity across age groups, genders, educational qualifications, industries, and years of professional experience, allowing for broader generalizability within emerging economy contexts.

3.3. Procedures

Data collection was conducted via a structured questionnaire developed using Google Forms and disseminated through email, professional associations, LinkedIn, and other relevant social media platforms. The instrument consisted of 25 closed-ended items mapped to three latent constructs: (1) Trust and Positive Intention Toward AI, (2) Organizational Support and Learning, and (3) AI Usability and Work Enhancement. Each construct was measured using five items on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument was adapted from validated scales in existing literature and modified for contextual relevance. Prior to data collection, participants were provided with informed consent details, ensuring voluntary participation and data confidentiality. No personal identifiers were collected, and respondents were informed of their right to withdraw at any point.

3.4. Data Analysis

Data were analyzed using IBM SPSS Statistics (Version 26). Initial data screening included checks for completeness, normality, and missing values. Descriptive statistics were employed to summarize demographic information and item responses. Scale reliability was evaluated using Cronbach's alpha, with an overall reliability score of 0.927 indicating high internal consistency. Construct validity was further tested using Exploratory Factor Analysis (EFA), applying Principal Component Analysis with Varimax rotation to identify factor structures and ensure discriminant validity. Subsequently, multiple linear regression analysis was conducted to examine the predictive relationships between independent variables (Trust and Intention Toward AI, Organizational Support and Learning, and AI Usability and Work Enhancement) and the dependent variable, Employee Acceptance of AI Tools. An additional variable, AI-related anxiety, was tested for its potential influence on adoption behavior. Regression diagnostics confirmed that key assumptions of normality, multicollinearity, linearity, and homoscedasticity were met. The final model achieved an R^2 of 0.795, indicating a strong explanatory power for the combined predictors. This empirical strategy contributes methodologically by integrating underexplored constructs such as anxiety into a robust analytical framework and by focusing on employee perspectives from emerging economies, an area underrepresented in current AI adoption literature.

3.5. Ethical Considerations

All ethical protocols for academic research were strictly followed. The questionnaire included a consent declaration outlining the purpose, voluntary nature, and confidentiality of the study. Respondents were not required to provide any identifying information. The study was conducted exclusively for academic purposes and ensured compliance with data privacy standards throughout the research process.

4. Results

TABLE 1: Demographic profile of respondents.

Variable	Category	Frequency	Percent (%)
Age	18–25	57	22.8
	26–35	70	28
	36–45	65	26
	46+	58	23.2
Gender	Female	125	50
	Male	125	50
Education Level	Diploma	3	1.2
	Doctorate	68	27.2
	Postgraduate	111	44.4
	Undergraduate	68	27.2
Top 10 Sectors of Employment	IT	21	8.4
	Education	18	7.2
	Healthcare	16	6.4
	Finance	15	6
	Research	13	5.2
	Manufacturing	12	4.8
	Government	11	4.4
	Retail	11	4.4
	Start-up	10	4
	BPO	8	3.2

Source: Primary Data

4.1. Model Summary and Goodness of Fit

A multiple linear regression analysis was conducted to determine the extent to which two independent variables, Organizational Support and Learning and AI Usability and Work Enhancement, predict the dependent variable, Employee Acceptance of AI Tools. The regression model yielded an R value of 0.892, indicating a strong positive correlation between the predictors and the outcome variable. The R Square value of 0.795 suggests that approximately 79.5% of the variance in employee acceptance of AI tools can be explained by the two predictors included in the model. The Adjusted R Square (0.793) confirms the model's robustness when accounting for the number of predictors. The standard error of estimate was 1.228, and the Durbin-Watson value of 1.638 indicates no significant autocorrelation in the residuals

TABLE 2: Model summary.

Model Summary							
					Change Statistics		Durbin-Watson
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Sig. F Change	
1	0.892	0.795	0.793	1.22835	0.795	0.000	1.638

Source: Primary Data

4.2. ANOVA and Model Significance

The ANOVA results show that the regression model is statistically significant, with F(2, 247) = 478.697, $p < 0.001$, indicating that the combination of the independent variables significantly predicts employee acceptance of AI tools. The total variance in the dependent variable is adequately captured by the model.

TABLE 3: ANOVA.

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1444.567	2	722.284	478.697	0.000
	Residual	372.687	247	1.509		
	Total	1817.254	249			

Source: Primary Data

4.3. Coefficients and Predictor Interpretation

As shown in Table 3, both independent variables made statistically significant contributions to the model:

- Organizational Support and Learning demonstrated a strong positive effect ($\beta = 0.765$, $p < 0.001$), with an unstandardized coefficient (B) of 0.779, indicating that a one-unit increase in perceived organizational support and learning corresponds to a 0.779 unit increase in employee acceptance of AI tools, holding other variables constant.
- AI Usability and Work Enhancement also significantly influenced acceptance ($\beta = 0.189$, $p < 0.001$), with an unstandardized coefficient (B) of 0.255, suggesting that increased perceived usability and enhancement lead to greater AI adoption.

The Variance Inflation Factor (VIF) values for both predictors were 1.558, well below the threshold of 10, confirming that multicollinearity is not a concern in the model. Tolerance values were 0.642 for both variables, indicating acceptable levels of predictor independence.

TABLE 4: Coefficients.

		Coefficients						
		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	0.194	0.451		0.431	0.667		
	Organizational Support and Learning	0.779	0.037	0.765	21.278	0.000	0.642	1.558
	AI usability and work enhancement	0.255	0.048	0.189	5.269	0.000	0.642	1.558

Source: Primary Data

4.4. Synthesis of Findings

These results collectively affirm the central hypothesis that employee acceptance of AI tools is significantly influenced by behavioral and organizational factors rather than by technological availability alone. The dominance of organizational support as a predictor underscores the pivotal role of institutional culture, managerial encouragement, and skills development in facilitating digital transformation. Meanwhile, the significance of usability factors suggests that employee experiences with AI tools must be seamless and functionally beneficial to drive adoption. The findings directly respond to the research gap identified in the literature review, which highlighted the limited empirical exploration of employee-level perceptions in AI adoption studies, especially in the context of emerging economies. By statistically validating these perceptual constructs, the study advances both theoretical and practical understanding of how to enable inclusive, behaviorally grounded AI integration strategies in the modern workplace.

5. Discussion

5.1. Comparison with Previous Studies

The findings of this study strongly align with and extend prior research in the domain of AI adoption and employee behavior. In particular, the significant influence of organizational support and learning on employee acceptance of AI tools ($\beta = 0.765$) corroborates earlier work by Al-Okaily et al. (2022) and Suroso et al. (2022), who emphasized the central role of organizational infrastructure and leadership in fostering technological adoption. Similarly, the positive effect of AI usability and work enhancement ($\beta = 0.189$) echoes findings by Kwon et al. (2023) and Budhwar et al. (2023), who found that perceived usefulness and intuitive design features significantly enhance employee willingness to interact with intelligent systems. However, this study adds further depth by offering quantitative evidence from an emerging economy, a context underrepresented in the dominant literature that often draws from Western or technologically advanced regions (e.g., Felten et al., 2018; Wilson et al., 2017). While prior models such as TAM and UTAUT have typically emphasized cognitive factors such as perceived ease of use and intention, this study enriches these frameworks by integrating the social and emotional aspects of workplace learning and trust-building, thereby offering a more holistic view of AI assimilation.

5.2. Theoretical and Practical Implications

From a theoretical perspective, the study advances the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) by reinforcing the importance of social-organizational variables, specifically support mechanisms and workplace learning cultures as determinants of technology acceptance. It also integrates employee behavioral psychology into traditional acceptance models, addressing calls by Neumann et al. (2022) and Sánchez-Holgado and Calderón (2024) for more inclusive models that incorporate trust, ethical considerations, and emotional engagement. Practically, the results offer actionable insights for human resource managers, organizational leaders, and technology developers. The strong predictive power of organizational support suggests that companies must invest in comprehensive training programs, mentorship structures, and feedback mechanisms to foster a positive climate for AI adoption. Moreover, developers should prioritize usability, customization, and role-specific functionality to ensure that AI tools genuinely support rather than disrupt workflows. These strategies are particularly relevant for organizations in emerging markets, where digital infrastructure may be less mature and employee resistance higher due to cultural and informational gaps.

5.3. Limitations

Despite its contributions, the study is not without limitations. Firstly, the use of non-probability convenience sampling limits the generalizability of findings across broader populations. While the sample included diverse industries, it may not fully capture sector-specific nuances or informal economy contexts. Secondly, the cross-sectional research design prevents assessment of causality or changes in employee perceptions over time. A longitudinal approach would offer deeper insight into how acceptance evolves as AI tools become more embedded in organizational routines. Self-reported data may be subject to bias, such as social desirability or inaccurate self-assessment of AI familiarity.

5.4. Future Recommendations

To enhance the robustness of future research, several directions are proposed:

1. **Longitudinal Studies**: Future work should examine how employee acceptance changes over time and whether initial support interventions produce lasting behavioral shifts.
2. **Experimental or Quasi-Experimental Designs**: These could test the causal impact of specific training programs or interface changes on AI adoption behavior.

3. **Cross-Cultural Comparisons**: Expanding the research to include multiple emerging economies or comparing results with data from developed countries could reveal how cultural and socio-economic contexts shape AI acceptance.
4. **Inclusion of Additional Variables**: Constructs such as algorithmic fairness, AI-related anxiety, job security perceptions, and ethical transparency could further enrich understanding of the multidimensional nature of AI acceptance.
5. **Mixed Methods Approach**: Incorporating qualitative interviews or case studies would provide deeper insights into the lived experiences behind the quantitative trends observed, particularly for specific industries such as education, healthcare, or public administration.

6. Conclusion

6.1. Summary of Findings

This study sought to investigate the behavioral and perceptual determinants of employee acceptance of AI tools in the workplace. Specifically, it focused on two key independent variables, Organizational Support and Learning, and AI Usability and Work Enhancement, and examined their predictive influence on the dependent variable: Employee Acceptance of AI Tools. Utilizing a structured quantitative design grounded in the Technology Acceptance Model (TAM) and supported by insights from the Unified Theory of Acceptance and Use of Technology (UTAUT), the study applied regression analysis to data collected from 250 respondents across diverse industries. The findings demonstrated a statistically significant and robust relationship between the independent variables and employee acceptance, with an R^2 value of 0.795, indicating that nearly 80% of the variance in AI acceptance behavior could be explained by the model. Organizational support and learning emerged as the strongest predictors ($\beta = 0.765$), followed by AI usability and perceived work enhancement ($\beta = 0.189$). These results underscore the centrality of human and organizational enablers in driving AI adoption in professional settings.

6.2. Relevance and Contribution to the Field

The study contributes meaningfully to both theoretical and practical domains. From a theoretical standpoint, it enriches the extant literature on technology acceptance by shifting the lens from organizational and technological readiness to employee-centered behavioral factors. While traditional TAM/UTAUT frameworks have highlighted cognitive dimensions such as perceived usefulness and ease of use, this research extends their applicability by incorporating organizational support mechanisms and usability perceptions into the adoption model. Moreover, it validates the relevance of these constructs in the developing economy context, an area often underrepresented in global AI adoption discourse. In terms of practical relevance, the study offers actionable insights for managers, HR leaders, and policy-makers who aim to foster inclusive and successful AI integration. The results indicate that employee acceptance is not an automatic consequence of tool deployment; rather, it is contingent upon how well the organization communicates, supports, and empowers employees throughout the digital transformation process. Emphasis on intuitive interface design, workplace learning opportunities, and visible managerial commitment to digital skill-building are essential strategies to drive engagement. Organizations operating in resource-constrained or change-sensitive environments will particularly benefit from creating psychologically safe ecosystems that facilitate curiosity, trust, and learning. The study also identifies several limitations that provide directions for future research. The use of non-probability convenience sampling, while appropriate for exploratory inquiry, limits generalizability across broader or more segmented labor populations. Self-reported responses may be influenced by social desirability bias or incomplete knowledge of AI functionalities. The cross-sectional design restricts temporal understanding of how perceptions evolve, particularly as AI tools become more integrated and employees gain deeper experiential familiarity. Future studies should therefore consider longitudinal designs to track changes in employee behavior over time, and explore potential moderating or mediating variables such as digital literacy, job type, perceived algorithmic fairness, or organizational culture. Incorporating mixed methods approaches, combining survey data with qualitative interviews, could also deepen understanding of context-specific dynamics and lived employee experiences.

6.3. Concluding Remarks

In sum, this study addresses a critical but often overlooked dimension of digital transformation: the employee-level acceptance of AI tools. It bridges a key gap in the literature by moving beyond top-down assessments of readiness and infrastructure, and instead foregrounds behavioral, emotional, and organizational variables that shape AI adoption from the ground up. By integrating empirical data with established theoretical models, the research offers a nuanced and statistically grounded perspective on the drivers of AI acceptance in the workplace. Its findings advocate for a people-first approach to technological change, wherein trust-building, user-centric design, and organizational encouragement are as vital as technological sophistication. As AI continues to reshape industries, the future of work will depend not only on deploying intelligent systems, but on empowering intelligent human engagement with those systems.

Conflict of Interest Statement

The author(s) declare that there is no conflict of interest regarding the publication of this article, "Exploring the Adoption of AI Tools in the Workplace: An Employee-Centric Perspective". The research has been conducted independently, without any financial or personal relationships that could have influenced the interpretations or conclusions presented in this study.

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