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IMPACT OF THE USE AND EASE OF USE OF ARTIFICIAL INTELLIGENCE ON EMPLOYEE EFFICIENCY IN THE UAE INSURANCE SECTOR

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Abstract:

Artificial intelligence (AI) has transformed the landscape in the workplace nowadays, yet efficiency improvement is highly dependent on employee onboarding. The purpose of this research was to determine the impact of ease of use of AI (EU-AI), the use of AI tools (U-AI), and the actual use of AI (AU-AI) on employee efficiency (EE) in insurance companies in Abu Dhabi. Using quantitative methodologies, data were collected from a sample of 370 employees working at Abu Dhabi National Insurance Company (ADNIC), Daman Insurance Company, and THIQA Insurance Company. Through the use of partial least square structure equation modeling (PLS-SEM), the results showed that AU-AI, U-AI, and EU-AI have a significant positive impact on employee efficiency. Additionally, the ease of use of AI serves as an important intermediary in the relationship between actual use, perceived usability, and efficiency to the employee as a whole.

Keywords:

Artificial Intelligence, Employee Efficiency, Insurance Company, Abu Dhabi

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Introduction

The integration of Artificial Intelligence (AI) in the modern workplace has significantly transformed traditional workflows by automating iterative processes, improving data-driven decision-making, and supporting real-time collaboration. Over the past decade, the pace of this technological revolution has accelerated, with AI systems now capable of performing tasks that previously required considerable human cognitive effort, including natural language processing, predictive analytics, image recognition, and complex pattern detection. In sectors such as finance, healthcare, and insurance, AI as a strategic foundation that shapes organizational efficiency and competitive advantage.

In the United Arab Emirates (UAE), the country's government has placed AI at the core of its Vision 2030 and broader economic diversification agenda. Through landmark initiatives such as the UAE's Strategy for Artificial Intelligence 2031 and the appointment of the world's first Minister of Artificial Intelligence, the UAE has demonstrated a commitment to combining AI capabilities across the public and private sectors. The insurance sector, as a financially sophisticated and data-intensive industry, is among the earliest adopters of AI technology in the UAE. Insurance companies are increasingly leveraging machine learning algorithms for risk modeling, AI-powered chatbots for customer service, robotic process automation (RPA) for claims processing, and advanced analytics for fraud detection and prevention.

Despite the organization's substantial investment in AI infrastructure and platforms, an ongoing challenge, intelligent systems are often underutilized by the employees for whom their use is intended. Access to advanced technology does not automatically translate into productivity or efficiency. Research consistently shows that only a small fraction of employees frequently interacts with AI due to inadequate training, unclear implementation policies, organizational resistance to change, or perceived complexity of AI interfaces. This gap between AI implementation and AI acceptance is a critical concern for organizational leaders and human resource practitioners.

When employees fail to meaningfully interact with AI tools, organizations don't recoup their technology investments, ongoing operational inefficiencies, and the competitive potential of digital transformation remains unrealized. More critically, the employee experience itself may deteriorate, as individuals feel burdened by tools they can't fully navigate, potentially resulting in increased stress, reduced job satisfaction, and higher entry and exit intent.

Therefore, this article aims to answer one fundamental question: How does the actual use of AI, perceived use of AI tools, and ease of use of AI systems collectively affect the efficiency of employees in the UAE insurance sector? Focusing on three major insurance organizations in Abu Dhabi namely Abu Dhabi National Insurance Company (ADNIC), Daman Insurance Company, and THIQA Insurance Company, this study provides empirical insights that are grounded in the context of real-world organizations. These findings contribute to increased knowledge about the adoption of AI in the service industry and offer practical guidance for HR

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managers, technology officers, and policymakers navigating the ever-changing digital transformation landscape.

Literature Review

To understand the complex dynamics of AI adoption and productivity in the workplace, this study relies on two basic theoretical frameworks: the Technology Acceptance Model (TAM) and the Human-Computer Interaction Theory (HCI). These frameworks, when used simultaneously, provide a strong theoretical lens for examining how and why employees engage or fail to interact with AI systems in the workplace.

Technology Acceptance Model (TAM)

Developed by Fred Davis in 1989, the Technology Acceptance Model (TAM) remains one of the most widely referenced and empirically validated frameworks in information systems research and organizational behavior. TAM argues that an individual's intention to use and actual use of a technological system is determined primarily by two core perceptual constructs: Perceived Usability (PU) and Perceived Ease of Use (PEOU).

Usability Perception refers to the extent to which a person believes that using a particular technology will improve their work performance. Practically, this means an employee's belief that AI-powered tools will help them complete tasks faster, with higher accuracy, or with less effort than traditional methods. Ease of Use Perception, on the other hand, refers to the extent to which one believes that interacting with technology will be free of cognitive effort and complexity. A system that is difficult to learn, confusing to navigate, or error-prone will hinder acceptance regardless of its theoretical usefulness.

TAM has been extended and validated across a wide range of technological contexts, from enterprise resource planning (ERP) systems (Venkatesh et al., 2020) to social media platforms in educational settings (Kumar & Singh, 2021). Its application to AI adoption is particularly relevant because AI systems often have a high learning curve and require users to significantly alter existing workflows. Several researchers have tailored TAM specifically for AI contexts. Giudice (2021) developed a model of individual acceptance of a revised AI system, emphasizing a human-centered approach that takes into account the emotional and cognitive dimensions of AI interactions, beyond traditional TAM utilitarian calculus. Mohammad Islam (2023) further expands this discourse through a multi-level framework for AI-enhanced HRM, emphasizing that organization-level factors such as leadership support and training infrastructure moderate the relationship between an individual's AI perception and behavioral outcomes.

In the context of the UAE's insurance sector, TAM provides a strong explanatory framework. If employees see AI tools as really useful for underwriting assessment or claims management, and if they are designed simply and intuitively enough, the probability of deep and consistent AI involvement increases significantly. On the other hand, if employees see AI as an additional burden that makes their workflows difficult, acceptance will remain shallow, and efficiency improvements will not be realized.

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Human-Computer Interaction (HCI) Theory

While TAM addresses the motivational dimension of technology acceptance, the Theory of Human-Computer Interaction (HCI) expands the analytic lens to include dimensions of design, usability, and experience in human-technology engagement. HCI as an academic discipline emerged in the early 1980s and takes inspiration from cognitive psychology, computer science, ergonomics, and organizational behavior to understand how humans design, implement, and interact with computer systems.

At the core of HCI is the concept of usability, which is defined by the International Standards Organization (ISO 9241) as the degree to which a system can be used by a particular user to achieve a specific goal with effectiveness, efficiency, and satisfaction in the context of a particular use. The HCI principles emphasize user-centered design (UCD) which is an iterative development process that puts the needs, limits, and preferences of the end user at the forefront of system design decisions.

For AI systems in the workplace, HCI is particularly relevant because AI interfaces often require employees to communicate with the system non-traditionally through natural language input, visual dashboards, or complex algorithm outputs that differ significantly from conventional software. Yang (2021) explores human-centered AI in the context of education, showing that when AI systems are designed with strong HCI principles, users are better able to interpret outputs, make informed decisions, and integrate AI recommendations into their professional practices. Kim and de Dear (2019) also note that workspace design, both physical and digital, plays a significant role in employees' cognitive load and, indirectly, their efficiency and satisfaction.

Integrating HCI principles into the implementation of AI tools in insurance companies means ensuring that AI interfaces are visually clear, linguistically accessible, and operationally aligned with existing employee workflows. When employees are able to navigate AI systems with minimal cognitive effort, psychological barriers to adoption will be reduced, and tools become natural extensions of professional practice rather than a source of frustration and resistance.

Actual Use of AI (AU-AI) and Employee Efficiency (EE)

Within the theoretical framework of TAM and HCI, the study highlights two critical constructs: Actual Use of AI (AU-AI) and Employee Efficiency (EE). AU-AI refers to practical, meaningful, and consistent engagement with AI technology in the execution of professional tasks. This is different from nominal or external interactions; real use involves the use of AI capabilities to automate processes, generate insights, improve the quality of results, and solve real-world operational problems.

Employee Efficiency (EE), in this context, is defined as the ability of employees to complete a given task accurately, quickly, and with optimal use of available resources including time, cognitive effort, and organizational tools. EE is a multidimensional construct that includes output quality, task completion speed, resource utilization, and adaptability to changing work demands.

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Research has consistently shown a positive relationship between meaningful use of AI and employee efficiency. Durrani (2020) found that the integration of AI in the HR decision-making process reduces administrative processing time by up to 40%, allowing professionals to shift cognitive resources toward higher strategic tasks. Chen and Chang (2022) report that flexible AI-supported work arrangements contribute positively to employee efficiency by enabling more adaptive task management. Arslan (2021) emphasizes the importance of team-level AI integration, noting that when the entire team adopts AI tools in a unified manner, efficiency improvements will be enhanced through collaborative data sharing and streamlined workflows.

In the insurance sector in particular, AU-AI is manifested through behaviors such as using AI-based assessment tools to quickly assess policy risks, using predictive analytics to identify high-risk customers, using automated claims processing platforms to reduce manual paperwork, and engaging AI chatbots to respond to routine customer queries. Each of these behaviors, when performed consistently and efficiently, directly contributes to measurable improvements in employee efficiency.

The Role of Ease-of-Use Intermediaries

An important theoretical contribution of this study is the placement of EU-AI not only as a direct precursor to EE, but as a critical mediator in the relationship between AU-AI and U-AI with EE. This mediation role is based on TAM theory and HCI principles: ease of use serves as a bridge that determines whether the potential benefits of AI tools translate into actual efficiency outcomes.

Al-MSloum (2021) emphasizes that the usability of information management systems significantly moderates the relationship between system functionality and user productivity. Even highly powerful AI systems with significant theoretical uses will fail to improve efficiency if employees find it difficult to interact with them effectively. Blume et al. (2019) also state that the quality and accessibility of training programs that directly affect perceived ease of use—are critical intermediaries in the relationship between technology implementation and performance outcomes. Borzillo (2021) extends this argument to the context of hospitality, showing that employees who feel lower role-related stress related to technology use show significantly higher levels of performance.

These findings collectively support the proposition that EU-AI serves as an important channel through which the usability of AI tools and their actual patterns of adoption is converted into a real increase in employee efficiency. Organizations that invest in facilitating the adoption of AI systems through improved interface design, comprehensive onboarding programs, and ongoing technical support are therefore directly investing in employee efficiency.

Conceptual Framework and Hypothesis

Based on the above theoretical review, this study proposes a conceptual framework in which three independent constructs namely Actual Use of AI (AU-AI), Perceived Usability of AI (U-AI), and Ease of Use of AI (EU-AI) directly influence Employee Efficiency (EE). Additionally, EU-AI serves as an intermediate variable between AU-AI and EE, as well as between U-AI and EE.

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The following hypotheses have been developed:

- **H1:** The actual use of AI (AU-AI) has a significant positive impact on Employee Efficiency (EE).
- **H2:** The Use of AI Perception (U-AI) has a significant positive impact on Employee Efficiency (EE).
- **H3:** Ease of Use of AI (EU-AI) has a significant positive impact on Employee Efficiency (EE).
- **H4:** Ease of Use of AI (EU-AI) mediates the relationship between Actual Usage of AI (AU-AI) and Employee Efficiency (EE).
- **H5:** Ease of Use of AI (EU-AI) mediates the relationship between Usability of AI Perception (U-AI) and Employee Efficiency (EE).

Methodology

Research Design

The research uses a quantitative, descriptive-explanatory research design. The selection of a quantitative approach is intentional and theoretically appropriate given the objective of the study to test hypothetical relationships between clear constructs, i.e. AU-AI, U-AI, EU-AI, and EE. The quantitative method allows for the systematic collection of numerical data that can be statistically analyzed, resulting in results that can be generalized in the population of interest (Creswell & Creswell, 2017). A descriptive dimension has been included to capture key features of AI usage patterns and perceptions of efficiency among insurance workers, while the explanatory dimension allows for the evaluation of cause-and-effect relationships and mediation through structural modeling.

Population and Sampling

The target population consists of approximately 10,000 employees working in three major insurance organizations headquartered in Abu Dhabi: Abu Dhabi National Insurance Company (ADNIC), Daman Insurance Company, and THIQA Insurance Company. These organizations were specifically selected based on significant AI adoption initiatives, their representation of the UAE's insurance sector, and their accessibility to data collection.

Using a simple random sampling technique, a sample size of 370 participants was selected. These sample sizes were determined according to pre-established guidelines for quantitative survey research (Sekaran & Bougie, 2010), ensuring sufficient statistical power for PLS-SEM analysis while maintaining practical feasibility in data collection. Participants were drawn from a variety of functional departments, including risk assessment, claims management, customer service, risk assessment, and finance, to capture a broad cross-section and represent patterns of AI use in organizations.

Data Collection Instruments

The measurement scale was adapted from the pre-established literature to suit the context of the study. Specifically, the items for Perceived Use (U-AI) and Ease of Use (EU-AI) were adapted from the Technology Acceptance Model operated by Davis (1989) and Venkatesh et al. (2000). The item measuring Actual Use of AI (AU-AI) was adapted from Venkatesh et al. (2008), while Employee Efficiency (EE) was measured using items adapted from Chen &

Chang, (2022). All constructs were evaluated using a 5-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). Prior to full-scale data collection, a pilot study was conducted with 30 participants to assess the clarity, comprehension, and facial validity of the questionnaire items. Minor revisions were made based on pilot feedback to improve item clarity and cultural appropriateness for the UAE context. The reliability of all builds was then confirmed through Cronbach's alpha analysis, with all values exceeding the acceptable threshold of 0.70 (Bryman, 2016).

Data Analysis Procedure

Data analysis was conducted in two stages. In the first stage, descriptive statistics were calculated using IBM SPSS Statistics Version 26, providing a standard frequency, mean, and deviation distribution for all study variables. In the second stage, Partial Smallest Square Structure Equation Modeling (PLS-SEM) was used using SmartPLS Version 4.0 to simultaneously evaluate the measurement model (reliability and validity of the construct) and the structural model (direct relationship and hypothetical mediation).

PLS-SEM was chosen as an analytical method for several reasons. Unlike covariance-based SEM (CB-SEM), PLS-SEM is particularly suitable for studies with complex models, relatively modest sample sizes, and constructs that may not adhere to the assumptions of multivariate normality (Creswell, 2014). Additionally, PLS-SEM is particularly powerful for theoretical development and testing in the context of applied business, making it an ideal choice for the empirical research of this study in the UAE insurance sector.

The measurement model was evaluated through an assessment of internal consistency reliability (Composite Reliability, CR), convergent validity (Mean Extracted Variance, AVE), and discriminant validity (Heterotrait-Monotrait Ratio, HTMT). The structural model was evaluated by examining the path coefficient, its statistical significance (via bootstrapping with 5,000 subsamples), and the determination coefficient (R^2).

Findings and Discussions

Respondent Profile

The study achieved a response rate of 63%, resulting in 370 usable questionnaires. The majority of respondents were men (62%), with female respondents making up 38% of the sample. In terms of age distribution, the largest segment (41%) was in the 30–39 age range, reflecting the dominance of mid-career professionals in the organizations surveyed. In terms of education, 68% of respondents possessed at least a bachelor's degree, and 22% possessed postgraduate qualifications, indicating a generally highly educated workforce. The majority of participants (57%) had between five and fifteen years of experience in the insurance industry, indicating a mostly experienced sample with significant exposure to evolving technological tools.

Measurement Model Assessment

The measurement model showed strong psychometric properties. All constructions showed a Composite Reliability (CR) value above 0.80, confirming the internal consistency. The Average Value of Extracted Variance (AVE) for all constructions exceeded the 0.50 threshold, confirming the convergent validity. The discriminant validity was confirmed through the HTMT criteria, with all HTMT ratios between constructions being below the conservative threshold of 0.85. Collectively, these results confirm that the measurement model is reliable and valid, providing a solid basis for the evaluation of the structural model.

Before evaluating the structural model, the measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and collinearity. All indicator factor loads exceeded the recommended threshold of 0.708, confirming the adequate reliability of the indicator. Composite Reliability (CR) values ranged from 0.845 to 0.912, above 0.80, and Average Extract Variance (AVE) values exceeded 0.50. Additionally, the full collinearity test showed that all internal Variance Inflation Factor (VIF) values for the predictor constructs (AU-AI, U-AI, and EU-AI) were well below the conservative threshold of 3.3 (ranging from 1.42 to 2.15), confirming that multicollinearity was not a concern.

Structural and Hypothesis Model Tests

Evaluation of the structural model confirmed that all five hypotheses were statistically supported. The structural model was evaluated using bootstrapping with 5,000 subsamples. The determination coefficient (R2) for Employee Efficiency was 0.800, indicating that 80.0% of the employee efficiency variance was explained by AU-AI, U-AI, and EU-AI. Additionally, an analysis of effect size (f2) revealed that U-AI had a moderate effect on EE (f2= 0.284), EU-AI showed a medium effect size of f2 = 0.230, and AU-AI accounted for a large effect size of f2 = 2.276.

Direct Impact on Employee Efficiency

Hypothesis 1 is supported: Actual Use of AI (AU-AI) shows a significant direct positive effect on Employee Efficiency (EE), with a path coefficient of $\beta = 0.266$ (ms < 0.001). These findings are in line with the established literature that suggests that real and consistent engagement with AI tools improves operational outcomes. When employees actively use AI systems for claims processing, risk assessment, or customer service management, they benefit from faster information retrieval, reduced manual errors, and improved decision quality. Automation of repetitive tasks through AI frees up cognitive bandwidth for employees to focus on high-value activities, directly contributing to better efficiency metrics.

Hypothesis 2 is supported: The Use of AI Perception (U-AI) has a significant positive direct effect on EE, with a much higher path coefficient of $\beta = 0.578$ (ms < 0.001). This finding is particularly interesting because it emphasizes the importance of employee perception in driving efficiency outcomes. Even before an employee deeply integrates an AI tool into their daily workflow, the belief that the tool will be valuable is enough to improve their efficiency through motivated engagement. These results are in line with self-determination theory (Ryan & Deci, 2020; Deci, Olafsen & Ryan, 2022), which argues that individuals who are intrinsically motivated in this case, those who see true value in AI tools show higher levels of performance.

Hypothesis 3 is supported: Ease of Use of AI (EU-AI) also predicts EE positively and significantly ($\beta = 0.578$, ms < 0.001). These findings reinforce the long-standing assertion from HCI and TAM theories that usability is not just a peripheral concern but a key determinant of productive technology engagement. When employees are able to navigate AI systems with ease, they invest less cognitive energy in grappling with interfaces and more in meaningfully using system outputs. This reduction in cognitive load directly correlates with increased task accuracy, faster turnaround times, and higher overall efficiency.

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Role of Ease-of-Use Intermediaries (EU-AI)

The most theoretically significant findings in this study relate to the role of EU-AI intermediaries.

Hypothesis 4 is supported: EU-AI was found to mediate the relationship between AU-AI and EE significantly, with a mediating path coefficient of $\beta = 0.458$ (ms < 0.001). This suggests that while the use of actual AI directly improves efficiency, a large part of this effect is channeled through the ease with which employees operate the AI system. In practical terms, employees who frequently use AI tools but encounter difficulties with complexity will experience reduced efficiency improvements compared to those who use the same tools with fluency and confidence. This mediation effect highlights the critical importance of usability as a simplification mechanism; the frequency of use alone is not sufficient as a predictor of efficiency unless accompanied by ease of operation.

Hypothesis 5 is supported: EU-AI also significantly mediates the relationship between U-AI and EE ($\beta = 0.085$, ms < 0.001). Although the scale of this mediation path is relatively modest, it is statistically significant. It suggests that while employees hold strong positive beliefs about the usefulness of AI tools, the translation of those beliefs into actual efficiency improvements depends in part on ease of use. An employee who recognizes the value of an AI tool but finds it difficult to operate will be partially limited in converting their positive attitudes into productive behaviors.

Discussion of Discovery in Context

Collectively, these findings paint an important nuanced and practical picture of AI adoption in the UAE's insurance sector. The significant direct impact of AU-AI, U-AI, and EU-AI on EE confirms that technology adoption is not a one-dimensional phenomenon; it operates through multiple interconnected pathways. Organizations that focus exclusively on increasing the frequency of AI use, without simultaneously addressing the perceived value and usability of AI tools, will achieve less than optimal efficiency outcomes.

The role of the EU-AI intermediary is particularly critical from a strategic management perspective. This finding means that organizations must invest not only in acquiring and implementing AI systems but also ensuring that they are designed and implemented with usability as a key criterion. This is in line with insights from Wang and Ahmed (2023), who found that transformational leadership championing the implementation of user-centered technologies mediates the relationship between digital tool adoption and employee efficiency. Kirkpatrick and Kirkpatrick (2022) also identified the effectiveness of training that directly influences ease of use as a critical intermediary between technology provision and performance outcomes.

These results also directly refer to the UAE's national AI strategy. While policy initiatives have been successful in promoting the widespread adoption of AI across sectors, the challenge now lies in ensuring that implementation translates into real human productivity improvements. Evidence from this study shows that the human dimension in digital transformation in employee training, usability design, and AI literacy deserves the same strategic attention as the technology dimension.

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Conclusions and Recommendations

Theoretical Contributions

The study makes several meaningful contributions to the academic literature on AI adoption and organizational efficiency. First, it extends the application of TAM to the specific context of AI tools in the UAE's insurance sector, a context that receives relatively little empirical attention despite its importance in the region's digital transformation agenda. Second, by integrating HCI principles with TAM constructs, the study offers a richer theoretical model that takes into account both motivational determinants and AI-driven efficiency design. Third, the empirical validation of the role of the EU-AI intermediary provides new theoretical insights into the mechanisms by which AI adoption translates into organizational outcomes, advancing a conceptual understanding of human-technology synergies in the service industry.

Practical Implications

The study's findings carry profound practical implications for managers, HR professionals, technology officers, and policymakers in the digital age.

For Organizational Leaders and HR Managers: The data clearly shows that successful digital transformation depends not only on technology investments, but also on fostering a culture of human-technology synergy. Organizations must move beyond simply acquiring and implementing advanced AI systems; they must invest equally in human infrastructure that enables meaningful AI adoption. This means prioritizing comprehensive, ongoing training programs that build digital literacy and practical AI competencies across all levels of employees. Training should not be a one-time induction activity but an ongoing process that evolves as AI tools are updated, and new capabilities are introduced (Blume et al., 2019).

For Technology Officers and AI Implementation Teams: The significant positive impact of EU-AI on direct efficiency outcomes and as an intermediary mechanism underscores the strategic importance of user-centered AI design. AI tools used in insurance companies should be evaluated not only on algorithm sophistication but also on intuitiveness, navigability, and interface alignment with existing employee workflows. Working with UX designers and frontline workers during the AI design and customization process is essential to ensure that the tool meets actual operational needs rather than imposing additional cognitive burdens. Al-MSloum (2021) and Yang (2021) both confirm that human-centered design approaches result in significantly higher rates of technology adoption and productivity outcomes.

For Policymakers and Regulatory Authorities: The UAE's national AI strategy would benefit from including specific guidelines for organizational AI implementation that mandate employee usability assessments and training adequacy checks alongside technical performance benchmarks. Public-private partnerships that develop standardized AI literacy curricula for the insurance and financial services sectors can accelerate the translation of AI investments into economy-wide efficiency improvements. Mehmood Khan (2021) shows in the context of the UAE's service supply chain that sustainability and productivity outcomes are closely linked to the ability of humans to use technology effectively, a lesson that continues to apply to the insurance sector.

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For Employees: Individual employees in AI-integrated workplaces are encouraged to approach AI tools with a growth mindset and actively seek training and support resources. The psychological safety of the work environment (Edmondson, 2019) plays a crucial role in willingness to experiment with new technologies; organizations that foster a culture of no-go learning will see higher rates of true AI acceptance and increased individual efficiency.

Limitations and Future Research Directions

While this study provides valuable insights, some limitations should be acknowledged. First, cross-sectional research designs capture AI acceptance and efficiency perceptions at a single point in time, limiting cause-and-effect inferences. Longitudinal studies that track changes in AI adoption patterns and efficiency outcomes over time will provide stronger causal evidence and capture the dynamic evolution of AI integration in the workplace.

Second, the study was limited to three insurance organizations in Abu Dhabi. Although these organizations represent the sector, the general abilities of the findings to other industries, geographic regions, or organizational sizes may be limited. Future research may replicate this study across various industries within the UAE and equivalent Gulf Cooperation Council (GCC) countries to test the cross-contextual robustness of the findings.

Third, this study focuses on employee-level perceptions of AI tools. Future research can complement this individual-level analysis with organization-level metrics such as claims processing time, error rates, and customer satisfaction scores to provide a more comprehensive assessment of the impact of AI on organizational performance.

Fourth, this study did not examine potential moderation variables such as leadership style (Wang & Ahmed, 2023), organizational culture, employee demographics, or AI concerns. These variables may have a major influence on the relationship between AI acceptance constructs and competencies, and their inclusion in future models will enrich theoretical understanding.

Finally, as AI technology continues to evolve rapidly by combining generative AI, large language models, and autonomous decision-making systems, future research should examine how the nature of AI-human interaction is changing and the new dimensions of usability, ease of use, and efficiency emerging in this advanced AI context (Zhang, Wang & Li, 2023; Fredrik D. M. P., 2019).

Closing

The findings of this study reach a key and convincing conclusion: in the UAE's insurance sector, the potential for improving the efficiency of Artificial Intelligence is not automatically realized through implementation alone. It is mediated, moderated, and ultimately determined by the quality of the human-AI interface specifically, the extent to which employees see AI tools, how often and meaningfully they interact with them, and most importantly, how easy they are to use. As insurers in Abu Dhabi and across the UAE continue their ambitious AI integration journeys, the need is clear: technology investments must be accompanied by human investments. Organizations that support user-centered design, invest in comprehensive AI training, and foster a culture of digital confidence will unlock the transformative productivity potential that AI promises—not only for their profits, but also for the well-being and professional satisfaction of their employees. In the era of intelligent machines, the human element remains a defining factor in achieving sustainable organizational excellence.

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Ethics Statement:	The study was conducted in accordance with ethical research standards. Informed consent was obtained from all participants prior to data collection. Participation was voluntary, and respondents were guaranteed confidentiality as well as anonymity. The data collected was used solely for academic purposes.
Author's Contribution Statement:	All authors contributed significantly to the development of this manuscript. Siti Asma' Mohd Rosdi is responsible for the conceptualization, methodology, and overall supervision of the study. Faisal Saif Ali Bin Ghafan Al-Ali handles data collection, analysis, and interpretation of results, literature reviews, drafts, and critical review of manuscripts. All authors read and approve the final version of the manuscript before submission.

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