

Analysis of Factors Affecting Ai-Powered Design Tool Adoption in Ux Design in Sri Lanka

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Abstract: The integration of Artificial Intelligence (AI) into User Experience (UX) design has introduced significant transformations by enhancing efficiency, creativity, and decision-making. This study examines the critical factors influencing the adoption of AI-powered design tools among UX professionals in Sri Lanka. Employing a quantitative research approach, data were collected via a structured survey and analyzed using Structural Equation Modeling (SEM) through SmartPLS 4. Results reveal that positive attitudes toward technology, effort expectancy, performance expectancy, and facilitating conditions significantly predict adoption intention, while perceived risks and social influence exhibit limited influence. This research advances theoretical understanding by validating the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) within the UX context. Practical implications are drawn for encouraging AI adoption by creating supportive environments and enhancing perceptions of ease and usefulness. Limitations and directions for future cross-cultural and longitudinal research are discussed.

Keywords: UX Design, AI-Powered Tools, Technology Adoption, Sri Lanka, Structural Equation Modeling

I. Introduction

The integration of AI into UX design is reshaping traditional design processes by enhancing creative ideation, user personalization, and decision support (Gmeiner et al., 2023; Yang et al., 2024). Globally, AI-powered design tools have seen increasing adoption, driven by the need for efficiency and innovation (Verganti et al., 2020). However, the Sri Lankan UX industry faces unique challenges, such as limited AI literacy, infrastructural inadequacies, and organizational inertia (Khanolkar et al., 2023; Fonseka et al., 2021).

Despite the global momentum, local adoption remains limited due to concerns over technological complexity, data privacy, and fears of professional displacement (Kalantari & Lethbridge, 2022; Vall & Araya, 2023). Therefore, understanding the underlying factors affecting the adoption of AI-powered tools in the Sri Lankan UX sector is crucial. The research objective of this research are to identify the factors influencing the adoption of AI-powered design tools in UX design in Sri Lanka and to examine the strength and significance of relationships between these factors and adoption behavior. This study enriches the discourse on digital transformation in emerging markets and offers strategies to overcome adoption barriers.

II. Literature Review

The integration of artificial intelligence (AI) into user experience (UX) design has created transformative opportunities across industries, enabling designers to enhance creativity, streamline processes, and better understand user behaviors. AI-powered design tools are increasingly recognized for their ability to automate repetitive tasks, provide predictive insights, and facilitate human-AI collaboration in UX evaluation. For example, recent work by Fan et al. (2022) demonstrates how explanation and synchronization features in AI tools can significantly enhance human evaluators' ability to identify usability issues more efficiently. Similarly, Gu and Sung (2023) emphasize that AI's role in analyzing interaction trends is reshaping the way designers approach user behavior assessment.

In emerging economies like Sri Lanka, the adoption of AI-powered design tools offers an important pathway for addressing local constraints, such as limited resources and skilled labor shortages. Amarasinghe and Wickramasinghe (2020) highlighted how AI applications in healthcare design have improved diagnostic tools for diseases like leishmaniasis, a trend that could be paralleled in UX to create more user-centered health applications. Fonseka et al. (2022) further argue that AI adoption within Sri Lankan businesses can drive significant improvements in operational performance and customer experience. Despite these promising potentials, practical adoption remains limited, hindered by infrastructural challenges, limited awareness, and concerns over complexity and trust in AI systems (Khanolkar et al., 2023; Vall & Araya, 2023).

To better understand technology adoption in professional domains, established theoretical models provide valuable frameworks. The Technology Acceptance Model (TAM) introduced by Davis (1989) posits that perceived usefulness and perceived ease of use are key determinants influencing users' attitudes and intentions toward adopting new technologies. Later frameworks, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), expanded this understanding by introducing performance expectancy, effort expectancy, social influence, and facilitating conditions as critical drivers of adoption. These models have proven robust across a wide range of technological contexts, including the adoption of AI-driven solutions (Na et al., 2022; Chen et al., 2021).

Adding a behavioral dimension, the Theory of Planned Behavior (Ajzen, 1991) and the earlier Theory of Reasoned Action (Fishbein & Ajzen, 1975) highlight how attitudes, subjective norms, and perceived behavioral control collectively shape individuals' intentions to engage with new technologies. Recent studies continue to build on these theories, suggesting that while technical factors remain important, personal agency, prior experiences with technology, and contextual cultural factors are increasingly influential in emerging economies (Yang et al., 2024; Kapoor et al., 2022).

Empirical investigations into AI-powered tool adoption reveal a consistent set of critical factors. Performance expectancy – the belief that AI tools will enhance work efficiency – strongly predicts adoption intentions (Dwivedi et al., 2019; Dora et al., 2021). Effort expectancy, or the perceived ease of learning and using AI tools, also plays a pivotal role (Wang et al., 2020). Facilitating conditions, including access to training, technical support, and organizational encouragement, further strengthen adoption behaviors (Oliveira et al., 2014; Kapoor et al., 2022). Interestingly, while social influence traditionally impacts adoption in collaborative or hierarchical settings (Baptista & Oliveira, 2015), its significance appears diminished among creative professionals like UX designers who often prioritize autonomy and personal tool fit (Hong Chuyen & Vinh, 2023).

Conversely, perceived risks surrounding AI – including concerns over data security, loss of creative autonomy, and ethical implications – can act as barriers to adoption (Pavlou, 2003; Rauschnabel et al., 2018). However, studies increasingly suggest that when professionals perceive tangible performance benefits, risk concerns may be outweighed, particularly if adequate transparency and user control mechanisms are embedded within the tools (Ferreira & Monteiro, 2020; Rai et al., 2021).

Despite the growing body of knowledge, there remains a notable gap in research focusing specifically on AI-powered tool adoption within UX design in developing countries like Sri Lanka. While studies such as Dwivedi et al. (2019) and Roy et al. (2021) have examined AI adoption from a business process improvement perspective, the cognitive, creative, and emotional dimensions unique to UX design professions have received limited scholarly attention. Furthermore, cultural factors, organizational readiness, and localized barriers are seldom explored in the context of creative industries, limiting the generalizability of existing models (Fonseka et al., 2022; Yang et al., 2024).

Understanding the adoption of AI-powered design tools in UX within Sri Lanka, therefore, requires not only applying established technology acceptance models but also critically adapting them to reflect the nuanced realities of local contexts. Addressing this gap could offer important insights for tailoring AI integration strategies in emerging economies, where balancing technological innovation with human-centered design values remains both a challenge and an opportunity.

Despite the growing interest in AI in UX, few studies explore adoption in emerging economies' creative industries (Yang et al., 2024; Fonseka et al., 2022). Sri Lanka's unique socio-technological context necessitates localized investigations into how professional attitudes, infrastructural support, and cultural factors interact to influence AI tool adoption.

III. Methodology

The conceptual framework for this study is designed to explore the factors influencing the adoption of AI-powered design tools in UX design in Sri Lanka. It is based on the integration of key constructs from established theoretical models, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). The framework incorporates factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risks, and attitude towards technology.

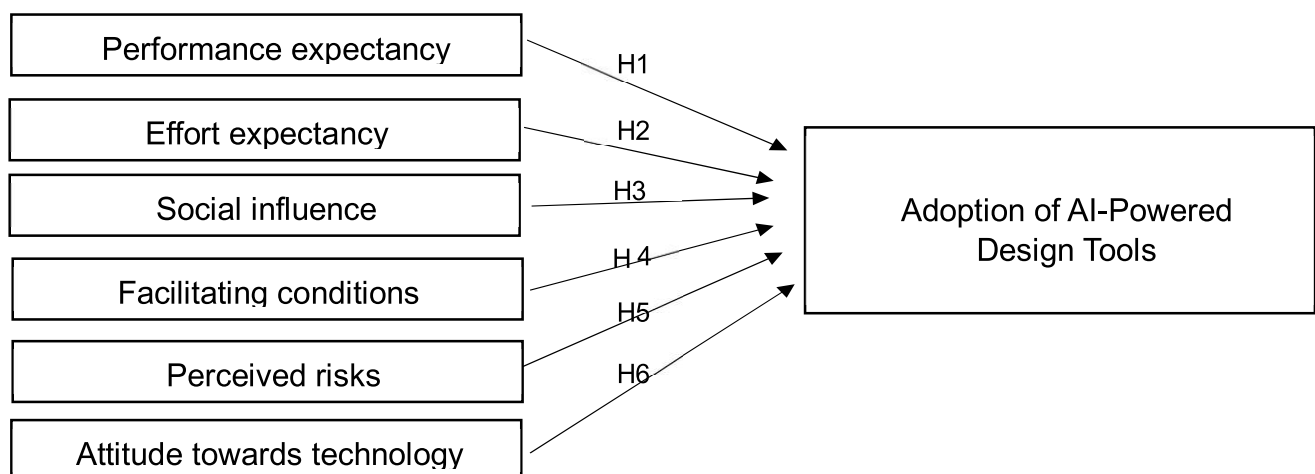


Figure *Error! No text of specified style in document.*1: Conceptual Framework

This study adopts a positivist paradigm and employs a quantitative approach to identify factors influencing the adoption of AI-powered design tools in UX design in Sri Lanka. Leveraging the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the research investigates key factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions.

An online questionnaire, validated through existing literature, was distributed to UX professionals in Sri Lanka's western province using convenience sampling. The questionnaire measured constructs such as perceived ease of use, perceived usefulness, and organizational support. Employing a cross-sectional design, data were collected at a single point in time. The unit of analysis was individual UX designers, while observations focused on design professionals with experience using AI.

A sample size of 98 participants was determined using Daniel Soper's "Sample Size Calculator," based on a statistical power level of 0.8 and a significance level of 0.05. The study was conducted in a non-contrived, natural setting to ensure authentic responses.

IV. Results and Discussion

To examine the relationships among the study variables, a Path Model was developed using the Structural Equation Modeling (SEM) approach, following best practices outlined by Hair et al. (2021). This approach allowed the research team to visually map out the proposed hypotheses and explore the connections between key factors influencing AI-powered tool adoption. The analysis incorporated both the measurement model and the structural model, utilizing Partial Least Squares SEM (PLS-SEM) through SmartPLS 4 software, which is particularly well-suited for exploratory research in emerging fields like UX and AI integration.

In the first phase of analysis, the measurement model was assessed to ensure the reliability and validity of the constructs. Outer loadings for all indicators exceeded the recommended threshold of 0.70, providing strong evidence of indicator reliability (Hair et al., 2019). Composite Reliability and Cronbach's Alpha values for each construct were also well above 0.70, confirming internal consistency. Furthermore, the Average Variance Extracted (AVE) values surpassed the 0.50 benchmark, indicating satisfactory convergent validity. These results suggest that the measurement model robustly captured the intended theoretical constructs.

Discriminant validity was evaluated using the Fornell-Larcker criterion, where the square root of each construct's AVE was compared to its correlations with other constructs. As recommended by Hair et al. (2021) and Nikolopoulou (2023), the results confirmed that each construct was sufficiently distinct from the others, reinforcing the model's validity and ensuring that overlapping concepts did not distort the findings.

Moving to hypothesis testing, the study revealed compelling insights into the factors driving AI adoption among UX professionals in Sri Lanka. Hypotheses H1 through H4 were supported, showing statistically significant relationships. Specifically, a positive attitude towards technology ($\beta = -0.335$, $T = 2.61$, $p = 0.005$), higher effort expectancy ($\beta = 0.377$, $T = 3.904$, $p = 0.000$), strong facilitating conditions ($\beta = 0.409$, $T = 3.541$, $p = 0.000$), and positive performance expectations ($\beta = 0.303$, $T = 2.885$, $p = 0.002$) all contributed significantly to the likelihood of AI tool adoption.

On the other hand, hypotheses H5 and H6, concerning perceived risks ($\beta = 0.115$, $T = 1.247$, $p = 0.106$) and social influence ($\beta = 0.047$, $T = 0.747$, $p = 0.228$), were not statistically supported. This finding suggests that fears around data privacy, job displacement, or peer opinions play a relatively minor role in influencing UX professionals' decisions to adopt AI-powered design tools, at least within this context.

Table 1. Hypothesis Testing Summary

Hypothesis	Relationship	Path Coefficient (β)	T-Statistic	P-Value	Decision
H1	Attitude Toward Technology $\rightarrow$ Adoption	-0.335	2.61	0.005	Supported
H2	Effort Expectancy $\rightarrow$ Adoption	0.377	3.904	0.000	Supported
H3	Facilitating Conditions $\rightarrow$ Adoption	0.409	3.541	0.000	Supported
H4	Performance Expectancy $\rightarrow$ Adoption	0.303	2.885	0.002	Supported
H5	Perceived Risk $\rightarrow$ Adoption	0.115	1.247	0.106	Not Supported
H6	Social Influence $\rightarrow$ Adoption	0.047	0.747	0.228	Not Supported

Together, these findings highlight the importance of fostering positive perceptions around AI tools, ensuring that they are easy to use, and providing an environment where users feel supported. They also suggest that, at least for UX professionals, external pressures and risk anxieties may not be as pivotal as personal and practical considerations. Organizations seeking to encourage AI adoption should therefore focus more on training, ease of use, and demonstrating clear performance benefits rather than simply addressing fears or relying on peer influence.

Future research could expand these insights by considering cultural differences, exploring the impact of organizational culture, and tracking how adoption behaviors evolve over time as AI technologies mature.

V. Conclusion

This study sheds new light on the factors that influence the adoption of AI-powered design tools within the UX design sector in Sri Lanka. The findings clearly show that performance expectancy, facilitating conditions, and positive attitudes toward technology are central drivers of successful AI integration. In particular, the perception that AI tools are useful, easy to adopt, and well-supported within the work environment significantly increases the likelihood of adoption.

Interestingly, concerns about risks such as data privacy or job security, as well as the influence of colleagues and peers, were found to have a limited impact on adoption decisions in this setting. This suggests that for UX professionals, practical factors like tool usability and organizational support outweigh more abstract fears or social pressures.

For organizations, the implications are clear: investing in training programs, ensuring technical support, and developing AI tools that are user-friendly can make a substantial difference in driving adoption. Emphasizing the tangible benefits of AI in terms of enhancing creativity, efficiency, and user-centered outcomes appears far more effective than merely addressing fears.

While this study provides valuable insights, it also has limitations. The sample was geographically limited to Sri Lanka's Western Province, and the cross-sectional design captured perceptions at a single point in time. Future research should explore these dynamics across different cultural settings, larger and more diverse samples, and over longer periods to examine how AI adoption evolves as users gain experience and as AI technologies themselves continue to develop.

Overall, this study contributes to a growing body of knowledge on technology adoption in creative industries and offers practical strategies for leveraging AI to enhance UX design practices in emerging economies.

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