

## IMPROVING USER EXPERIENCE OF MOBILE APPLICATIONS BASED ON USER FEEDBACK

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The quality of the user experience is an important factor affecting the lifespan of the software. Therefore, improving the user experience of the software has become the focus of the major software companies. Improving software user experience includes accurately assessing user experience and acquiring factors that affect user experience. Accurately evaluating user experience can obtain real user experience and provide reliability for obtaining factors that affect user experience [1].

This objective is to develop recommendations for improving the user experience of mobile applications based on user feedback based on AI and ML techniques.

User experience (UX) analysis is integral to understanding how users interact with software, influencing design, satisfaction, and engagement levels. UX analysis includes both the evaluation of user experience and the study of factors that affect it. Current methodologies for UX evaluation can be divided into subjective, objective, and combined approaches. Subjective evaluations are typically based on user feedback, such as surveys or interviews. In contrast, objective evaluations rely on physiological data and performance metrics to provide a more unbiased insight into the user experience. Hybrid methods merge these approaches, enabling a more comprehensive UX assessment by comparing subjective reports with objective data, as seen in studies analyzing user feedback alongside physiological signals like heart rate variability [3, 4].

This study aims to develop a comprehensive UX analysis framework using subjective-objective evaluation and small-sample analysis methods. The objective is to establish a highly accurate, interpretable model that links UX with user traits and software factors. This framework seeks to provide a richer, more reliable evaluation of UX through enhanced data acquisition methods, such as integrating subjective surveys with physiological measurements. Additionally, the study aims to apply and refine TrAdaBoost and TrCart algorithms to optimize small-sample analysis, ensuring that UX models remain accurate and interpretable across varied user scenarios [6, 4].

Subjective evaluation primarily captures self-reported experiences. Questionnaire-based methods, widely adopted in research, assess user traits and UX, helping researchers understand both individual and contextual influences on user experience. Scholars like Martin Schrepp and Katy Tcha-Tokey have advanced UX evaluation tools by creating generalizable questionnaires particularly suited for VR applications [2]. In contrast, objective methods collect physiological data, such as heart rate or electrodermal activity, which correlate with emotional states or task difficulties. For instance, M. S. Perez used multi-signal analysis to accurately identify emotional states, while L. Yao's research demonstrated that physiological metrics varied notably between successful and failed tasks, providing deeper insights into user frustration or engagement [8].

The combined subjective-objective approach is increasingly popular for its balanced evaluation capabilities. For example, Carrillo's study compared self-reported emotions with brainwave data during user interaction with various images, revealing valuable discrepancies that single-method approaches might overlook. Similarly, R. L. Mandryk's research

highlighted how game stage difficulty affects players' heart rates differently for beginners and experienced players, enhancing UX assessment by correlating self-reported and physiological responses [3].

Traditional statistical methods and machine learning (ML) techniques are extensively used to identify factors impacting UX. Statistical approaches often rely on surveys or flow questionnaires to establish general relationships between UX and influencing factors, as shown in Arttu Perttula's study on educational games [4]. However, these methods can be limited in depth, especially when it comes to uncovering detailed, real-time interactions or responses. More advanced studies have employed ML methods to detect patterns across various data sources, enabling dynamic interaction insights and real-time analytics. G. Goncalves' work, for instance, used brainwave data to compare UX with different game controllers, revealing notable UX distinctions between control types [5].

Due to data scarcity and the high costs of data collection in UX research, small-sample analysis is often necessary, utilizing machine learning-based and transfer learning approaches. Small-sample ML methods, such as Liu Yingdong's modified KNN algorithm, employ clustering to classify unlabeled data accurately, improving model performance even with limited data [6]. Transfer learning techniques, such as instance-based TrAdaBoost and model-based approaches like TransferinCart, allow models trained on auxiliary data to be adapted for UX, enhancing prediction accuracy for smaller datasets [7].

This research confirms the value of combining subjective and objective methods for UX analysis, as they provide complementary perspectives on user interactions. By incorporating instance-based and model-based transfer learning algorithms, the study presents an advanced approach to small-sample UX analysis, achieving higher accuracy and interpretability.

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