Indonesian Journal of Infomatics

E-ISSN: 3124-033X

Research Article

Integrating Multimodal Data Processing Techniques to Enhance User Experience Evaluation in Interactive Digital Platforms

Khoirudin; [1]*, Nurtriana Hidayati [2],

[1] Universitas Semarang e-mail : khoirudin@usm.ac.id
[2] Universitas Semarang e-mail : anna@usm.ac.id
* Corresponding Author: Khoirudin

Abstract: User experience (UX) evaluation plays a crucial role in understanding how users interact with digital platforms and in improving product design. Traditional UX evaluation methods, such as surveys and interaction logs, often rely on a single data source, which limits the depth of analysis. This study explores the integration of multimodal data processing techniques in UX research, aiming to enhance the accuracy and comprehensiveness of UX evaluations. By combining interaction logs, visual attention data, and physiological measurements, this approach provides a more holistic understanding of user behavior, emotional responses, and satisfaction. Interaction logs offer objective data on user actions, while eye-tracking and physiological data capture users' emotional states, providing richer insights into usability and user experience. This study highlights the effectiveness of multimodal integration in identifying patterns that traditional methods overlook, such as emotional responses to interface elements and real-time feedback from users. The findings reveal that multimodal data processing improves the precision of UX assessment by combining objective behaviors with subjective emotional responses, offering a more complete view of user interactions. The study also discusses the challenges of data synchronization and the potential ethical concerns related to the use of physiological data. The integration of these data sources shows great potential for enhancing the design process, allowing designers to make informed decisions based on comprehensive insights. Finally, this research underscores the future potential of multimodal analytics in UX research, suggesting further exploration of additional data modalities and real-time applications in various digital environments.

Keywords: Multimodal Data; UX Evaluation; User Behavior; Eye-Tracking Systems; Real-Time Feedback.

Received: 21, November 2025
Revised: 10, December 2025
Accepted: 29, December 2025
Published: 15, January 2026
Curr. Ver.: 20, January 2026

1. Introduction

User Experience (UX) evaluation is a critical aspect of interactive digital platforms, focusing on understanding how users interact with products and assessing their overall satisfaction. UX extends beyond traditional usability measures, encompassing emotional responses and user contentment with the product [1]. To capture a comprehensive picture of user interaction, various UX evaluation methods are employed, including surveys, emotion recognition, attention recognition, and physiological signals [2], [3]. These methods aim to provide a deeper understanding of how users engage with interactive platforms, which is crucial for improving design and enhancing user satisfaction [4].

Traditional UX evaluation methods, however, often rely on single-source data such as interaction logs or questionnaires. While these methods provide valuable insights, they present several challenges that can limit the effectiveness of the evaluation. One major limitation is the narrow scope of single-source data, which may fail to capture the full spectrum of user experiences, particularly emotional and contextual factors [5]. Moreover, traditional methods require significant human involvement for data collection and analysis, making ongoing UX monitoring labor-intensive and less scalable [6]. These methods also struggle to provide contextual insights, which are necessary to understand the underlying causes of UX challenges [7]. Additionally, some evaluation technologies, such as biometric systems, may cause discomfort for users, potentially skewing the authenticity of the data [8].

To address these challenges, researchers are focusing on developing more advanced and automated UX evaluation systems. These systems integrate multiple data sources and employ sophisticated technologies like artificial intelligence (AI) to enhance data analysis, providing deeper insights into user behavior [9]. For example, the Multimodal Interactive Dashboard (MIND) integrates facial emotion recognition, EEG-based attention recognition, and image generation to offer a more comprehensive UX evaluation [5]. Additionally, AI-driven techniques such as machine learning and natural language processing are being applied to handle both structured and unstructured data, thereby making the UX evaluation process more efficient and scalable [10].

User Experience (UX) evaluation plays a crucial role in enhancing the interaction between users and digital products. A comprehensive understanding of user behavior and interaction quality is essential for improving the design and functionality of digital services. Traditional UX evaluation methods, often reliant on subjective feedback, can be limited by biases and incompleteness, providing a partial view of user experience [11]. To overcome these limitations, integrating multimodal data processing techniques has become a promising approach for gaining deeper insights into user behavior. Multimodal UX evaluation uses a variety of data sources-such as facial expressions, physiological responses, and user interactions-to offer a more holistic assessment of user experience [12].

A comprehensive approach to UX evaluation, which integrates multiple data sources, allows for a richer understanding of user interactions. Traditional methods, such as surveys or interaction logs, may miss key emotional and contextual elements of the user experience [13]. By combining diverse data types, such as facial emotion recognition, EEG-based attention tracking, and physiological responses, UX researchers and designers can achieve more accurate and objective measurements of user behavior, enhancing the quality of evaluations and product designs [14], [15]. This integration provides a more reliable and user-centric approach to UX assessment, addressing the limitations of traditional single-modal methods.

The main objective of this article is to explore how integrating multimodal data processing techniques can enhance UX evaluation. The fusion of physiological measurements, behavioral data, and contextual feedback helps provide more comprehensive insights into users' cognitive states, emotional reactions, and interaction quality [5]. Moreover, advanced technologies such as automated facial expression analysis and machine learning algorithms can predict cognitive states, improving the efficiency of UX evaluation and ensuring that digital products meet user needs more effectively [16]. This article discusses the key benefits of multimodal data processing, such as enhanced predictive accuracy, a holistic understanding of user interactions, and improved product quality [11]. Additionally, the integration of these techniques enables the scalability and efficiency of UX evaluations, making them more suitable for large-scale and diverse user bases [12].

2. Literature Review

Review of Traditional UX Evaluation Methods and Their Limitations

Traditional User Experience (UX) evaluation methods, such as surveys and interaction logs, have been widely used to assess user satisfaction and behavior in digital systems. Surveys are commonly used to collect subjective user feedback on their experiences, perceptions, and satisfaction levels. However, these methods often fail to capture the full range of user emotions and can be influenced by biases such as self-reporting errors [2]. Similarly, interaction logs provide valuable objective data on user behavior by tracking system interactions, but these logs lack the contextual understanding needed to interpret why users behave in certain ways and do not capture emotional responses [17]. Task analysis and observations, which assess usability aspects like efficiency and effectiveness, also have limitations, as they often overlook users' emotional and cognitive states [18].

Despite their widespread use, traditional methods suffer from several key limitations. One major issue is their reliance on self-reported data, which can be biased and incomplete, limiting the reliability and validity of the insights gathered [18]. Additionally, these methods often fail to provide emotional and cognitive insights that are crucial for a comprehensive understanding of user experience [19]. Interviews and think-aloud protocols, while useful for in-depth analysis, are time-consuming and can be uncomfortable for certain users, making them less practical for large-scale studies [20]. Furthermore, methods like interaction logs and task analysis, while providing data on user actions, often lack the necessary context to fully understand the reasons behind those actions [17]. These limitations highlight the need for more comprehensive UX evaluation approaches.

Explanation of Multimodal Data Sources Used in UX Research

To overcome the limitations of traditional methods, researchers have turned to multimodal data sources that provide a more holistic and accurate understanding of user experiences. Interaction logs, while still valuable for tracking user behavior, are often complemented by other data types such as visual attention data, which is captured through technologies like eye-tracking. This type of data helps researchers understand where users focus their attention during interactions, providing valuable insights into usability and design effectiveness [5]. Additionally, user feedback, whether collected through surveys, interviews, or think-aloud protocols, continues to play a crucial role in providing subjective insights into user perceptions, experiences, and satisfaction [2]. However, when combined with more objective data, these subjective methods can provide a deeper and more reliable understanding of user behavior.

Another important source of multimodal data is physiological measurements, which provide objective insights into users' emotional and cognitive states. Data from sensors measuring heart rate, skin conductance, and electroencephalography (EEG) can offer real-time information about user engagement and stress levels during interactions, enhancing the depth of UX evaluations [16]. Facial emotion recognition is another powerful tool in multimodal UX research, as it analyzes users' facial expressions to infer their emotional states during interactions with digital systems. This allows for a more nuanced understanding of user experiences, offering real-time feedback and enabling designers to make immediate adjustments to improve user satisfaction [12]. By integrating these diverse data sources, UX researchers can gain a more comprehensive and accurate picture of user interactions, ultimately improving product design and user experience.

Previous Studies on the Integration of Multimodal Analytics in User Experience Research

Multimodal analytics in user experience (UX) research involves integrating data from various modalities such as text, audio, video, and physiological signals, offering a comprehensive understanding of user interactions and experiences. This approach has been applied across various fields, including healthcare, education, and interactive systems. One of the primary uses of multimodal analytics in interactive systems is to enhance user experience by integrating and synchronizing different data sources. For example, convolutional neural networks (CNNs) have been employed for image and video processing, while recurrent neural networks (RNNs) are used for text and audio processing, allowing for a holistic analysis of user behavior [21]. Similarly, in-vehicle interactions have been a focus of multimodal UX research, with studies identifying key aspects such as attention and duration that significantly impact user experience. A conceptual model for understanding users' expectations during in-vehicle multimodal experiences has also been proposed to aid designers in aligning systems with user needs [22].

In the context of education, systems like M2LADS and MIND have been developed to integrate and visualize multimodal data, capturing biometric and behavioral signals to improve learning experiences. These systems also provide real-time feedback, enhancing the learning process by offering personalized insights [23]. Furthermore, big data techniques have been used to aggregate, cluster, and visualize UX data, revealing key research hotspots and trends in the field of UX research [24]. The integration of multimodal data sources in these studies underscores the importance of a more holistic approach to understanding user experiences, enabling more effective and user-centered design improvements across diverse fields.

Theoretical Background on Pattern Recognition and Analytics in Multimodal Data Processing

Pattern recognition in multimodal data processing plays a vital role in analyzing and interpreting complex, multidimensional data. This approach often involves two primary components: exploratory data analysis and classification methods. Exploratory data analysis is used to detect anomalies and extract important variables, while classification methods group samples into predetermined categories, providing a structured way to understand data from different modalities. Common pattern recognition algorithms, such as Principal Component Analysis (PCA), Support Vector Machine (SVM), and Artificial Neural Networks (ANNs), are widely applied to analyze and classify data from various sources, including spectroscopic methods [25]. These algorithms allow for the effective processing of multimodal data, enabling more accurate insights into user behavior and experiences.

The integration of multimodal frameworks with computational models, such as big data analytics, cloud computing, and natural language processing, enhances the analysis of multimodal data. This integration allows for empirical testing and validation of multimodal theories, supporting the development of more robust models for UX evaluation [26]. In educational settings, multimodal learning analytics (MMLA) has been used to analyze and predict student behavior, offering insights into cognitive states and engagement levels. This approach facilitates personalized learning experiences and provides real-time feedback, which is increasingly crucial in modern educational environments [27]. These advancements in multimodal data processing are enabling more comprehensive UX evaluations, highlighting the potential of these methods to improve user-centered design and enhance the overall user experience.

3. Proposed Method

The research integrates multiple data sources-interaction logs, visual attention data, and user feedback-to enhance UX evaluation. Interaction logs provide objective data on user behavior, while eye-tracking systems capture users' visual attention, revealing usability insights. User feedback, gathered through surveys and interviews, offers subjective perspectives on user satisfaction and emotional responses. These diverse data sources are analyzed using machine learning algorithms, pattern recognition, and data fusion techniques to identify patterns and correlations in user behavior, emotional states, and satisfaction levels. The methodology includes data collection, preprocessing, integration, and analysis, using tools such as eye-tracking systems, surveys, and machine learning algorithms to provide a comprehensive, accurate, and scalable understanding of the user experience.

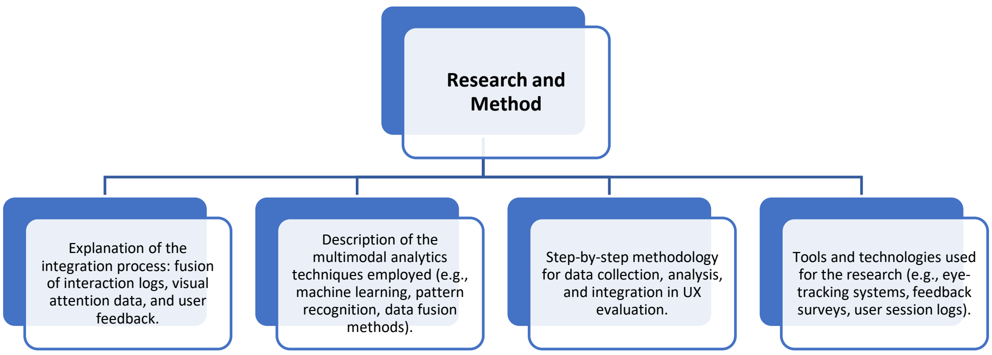

Figure 1. Research Methodology Flowchart Structure.

Explanation of the Integration Process: Fusion of Interaction Logs, Visual Attention Data, and User Feedback

The integration process in this study involves combining three key data sources: interaction logs, visual attention data, and user feedback. Interaction logs provide objective data on user behavior by tracking system interactions, such as clicks, page visits, and time spent on specific tasks. However, these logs do not offer insights into the emotional or cognitive states of the users. To address this limitation, visual attention data, captured using eye-tracking technologies, is incorporated. Eye-tracking provides detailed information about where users focus their attention during interactions, allowing for a better understanding of usability and design effectiveness. Lastly, user feedback is collected through surveys and interviews, offering subjective insights into user experiences, perceptions, and satisfaction levels. By merging these diverse data sources, the research aims to provide a comprehensive understanding of user experience, integrating both objective and subjective data.

Description of the Multimodal Analytics Techniques Employed

The multimodal data collected is analyzed using advanced techniques such as machine learning, pattern recognition, and data fusion methods. Machine learning algorithms, including clustering and classification methods, are employed to process and analyze the complex data sets generated by the integration of interaction logs, visual attention, and user feedback. Pattern recognition is used to identify meaningful patterns and correlations between different types of data, enabling the detection of trends in user behavior, emotional responses, and interaction quality. Furthermore, data fusion methods are applied to combine the data from these diverse sources into a unified analysis framework, ensuring that the insights generated from each modality complement and enhance each other. The fusion of data enables more accurate predictions of user behavior and deeper insights into user experiences than would be possible using any single data source alone.

Step-by-Step Methodology for Data Collection, Analysis, and Integration in UX Evaluation

The methodology for UX evaluation follows a systematic approach, starting with data collection from three key sources: interaction logs, visual attention data, and user feedback. Interaction logs track user actions such as clicks, page views, and task completion times, providing objective behavior data. Visual attention data is captured through eye-tracking systems, which monitor where users focus their gaze during interactions, revealing areas of interest and usability aspects. User feedback, collected via surveys and interviews, offers subjective insights into users' experiences, emotions, and satisfaction levels. After data collection, preprocessing is performed to clean interaction logs, organize visual attention data by identifying key focus areas, and categorize user feedback into themes or sentiments.

Once the data is preprocessed, it is integrated using data fusion techniques, aligning the modalities temporally and spatially to ensure consistency across the different sources. This integration allows for a holistic view of the user experience, where visual attention data correlates with user actions and feedback is contextualized within specific tasks. Machine learning algorithms and pattern recognition techniques are then applied to classify and cluster the integrated data, identifying patterns and correlations in user behavior, emotional responses, and satisfaction levels. The analysis results are interpreted to generate actionable insights that inform improvements in design, usability, and functionality.

Tools and Technologies Used for the Research

Several tools and technologies are utilized to facilitate the data collection and analysis process in UX evaluation. Eye-tracking systems are employed to collect visual attention data, allowing for precise tracking of where users focus their attention during interactions. Feedback surveys and interviews provide subjective user insights into emotions, perceptions, and satisfaction levels, while user session logs track objective behavioral data, such as clicks and time spent on tasks. These data sources offer a well-rounded view of user experience, capturing both emotional responses and behavioral actions.

To analyze and integrate the collected multimodal data, machine learning algorithms and pattern recognition tools are employed. Machine learning algorithms classify and detect patterns in user behavior and experiences, enabling more accurate predictions. Pattern recognition tools further enhance the analysis by identifying correlations and trends within the data, providing deeper insights into the factors influencing UX. By combining these tools and techniques, the research aims to offer a comprehensive, accurate, and scalable UX evaluation that integrates both objective and subjective data, improving the overall understanding of user interactions and experiences.

4. Results and Discussion

The integration of multimodal data sources, such as interaction logs, visual attention data, and user feedback, significantly enhances UX evaluation by providing a more comprehensive and accurate understanding of user behavior. While traditional methods rely on single data sources like self-reported feedback or interaction logs, multimodal analytics captures both objective actions and subjective emotional responses, revealing patterns and insights that would otherwise be missed. This approach not only improves the precision of UX assessments but also uncovers new interaction patterns, such as emotional responses detected through physiological measurements. Despite challenges related to data synchronization and user discomfort with some technologies, multimodal analytics offers a holistic and real-time view of user experience, enabling more effective design improvements and deeper insights into user needs.

Results

The integration of multimodal data sources significantly improved the precision of UX assessment. By combining interaction logs, visual attention data, and user feedback, the study was able to provide a comprehensive view of user experience, addressing the limitations of traditional single-source methods. Interaction logs offered objective data on user actions, such as clicks and time spent on tasks, while eye-tracking data revealed where users focused their attention during interactions, shedding light on usability issues that were not apparent from the logs alone. Additionally, user feedback provided subjective insights into users' emotional responses and satisfaction levels. The fusion of these three data sources allowed for a more accurate and holistic understanding of user experience, enhancing the reliability of UX evaluations.

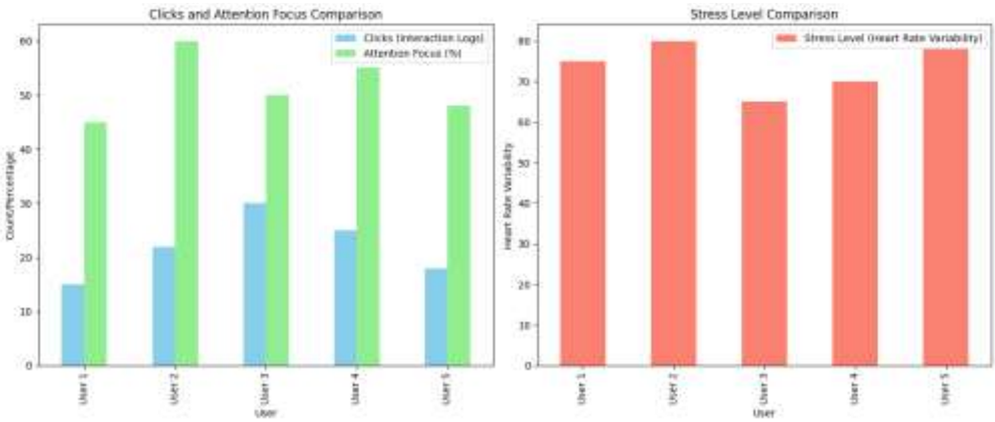

Figure 2.3. Stress Level Comparison.

The graphs presented above visually represent key insights from the results and discussion. The Clicks and Attention Focus Comparison graph contrasts the number of clicks recorded in the interaction logs with the attention focus percentage for each user, shedding light on how users engage with the interface and highlighting areas of interest and potential usability issues. Meanwhile, the Stress Level Comparison graph illustrates the heart rate variability (HRV) data, which measures user stress levels during interactions, offering a quantitative view of users' emotional responses and helping to identify individuals who experienced higher levels of stress during their interactions. These visualizations emphasize the added value of multimodal data in providing a more comprehensive understanding of user behavior.

Furthermore, multimodal integration revealed new interaction patterns that traditional methods failed to capture. Visual attention data, when combined with interaction logs, highlighted areas of the interface that caused confusion or were ignored by users, which was not evident from logs alone. Additionally, physiological measurements, such as heart rate and skin conductance, indicated stress levels in users, providing valuable insights into emotional reactions to different aspects of the interface. These patterns were further corroborated by user feedback, which often reflected or validated the emotional responses detected through physiological measurements, offering a more nuanced understanding of user behavior.

Discussion

The integration of multimodal data sources-such as interaction logs, visual attention data, and user feedback-provides several advantages in UX evaluation. The fusion of these different modalities allowed for a comprehensive assessment of both objective user actions and subjective emotional responses. Interaction logs provided insights into what users did, while visual attention data and physiological measurements offered a deeper understanding of why users behaved in a certain way. This integration led to more precise UX assessments, revealing inconsistencies between what users did and how they felt during interactions, which traditional methods often miss. By integrating these insights, the research was able to highlight areas of the interface that caused confusion or discomfort, leading to actionable recommendations for design improvements.

However, the integration of multimodal data also presented challenges. One of the main difficulties was the synchronization of data from different modalities, as each data source operates on its own timeline. For example, physiological data may be recorded continuously, while interaction logs are event-based, and eye-tracking data depends on user movements that are not always predictable. Aligning these data sources required sophisticated data processing techniques and careful attention to ensure accurate integration. Despite these challenges, the benefits of multimodal analysis outweighed the difficulties, providing a more complete and accurate picture of user experience.

Furthermore, while multimodal data analysis proved effective in revealing new insights into user behavior, it also highlighted the need for continuous user comfort and privacy considerations. Some methods, such as physiological measurement and facial emotion recognition, can be intrusive and may alter user behavior. Users' discomfort with wearing sensors or having their facial expressions analyzed could lead to unnatural responses, which may affect the authenticity of the data. Additionally, the use of sensitive data, such as emotional responses and biometric measurements, raises ethical concerns related to privacy and data security. Addressing these concerns will be essential for the widespread adoption of multimodal analytics in UX evaluation. Overall, multimodal analysis provides significant advantages in understanding user experience, but it must be implemented thoughtfully and responsibly to ensure that the insights gained are both accurate and ethically sound.

5. Comparison

The multimodal integration approach for UX evaluation provides several advantages over traditional UX methods. Traditional methods, such as surveys, interaction logs, and interviews, typically rely on a single data source to assess user experience. For instance, surveys gather subjective feedback from users, but they are often limited by biases such as self-reporting errors and fail to capture users' emotional or cognitive states. Interaction logs, on the other hand, provide objective data on user behavior, but they lack the context needed to understand why users engage with a system in a particular way or what their emotional responses are during the interaction. In contrast, multimodal integration combines data from various sources, such as interaction logs, eye-tracking data, physiological measurements, and user feedback, to provide a more complete and nuanced view of user behavior and experience. This fusion of data allows for a more accurate and holistic understanding of how users interact with digital platforms, addressing the limitations inherent in traditional single-source methods.

One of the key advantages of multimodal integration is its ability to improve evaluation accuracy. Traditional methods often struggle with providing a full picture of user experience. For example, while interaction logs can tell us what actions users take, they cannot explain why users take those actions or capture their emotional reactions. Multimodal integration, by incorporating data such as eye-tracking and physiological measurements, can reveal these underlying reasons and emotional states, providing deeper insights into user behavior. This fusion of multiple data sources enhances the reliability and precision of the evaluation process, reducing the potential for bias or incomplete data that is often found in traditional methods. Moreover, the integration of multimodal data allows for real-time analysis, enabling researchers and designers to make immediate adjustments to improve the user experience, something that traditional methods cannot offer.

Multimodal analytics also addresses many of the limitations of single-modal methods. For instance, while questionnaires and surveys are useful for gathering subjective user feedback, they often fail to capture the full range of emotions and cognitive responses that users experience during interactions. Similarly, interaction logs provide objective insights into user actions but lack the emotional context that is critical for understanding user satisfaction or frustration. By combining multiple data sources, multimodal analytics captures both objective behaviors and subjective emotional responses, offering a richer and more comprehensive analysis of user experience. This allows for the identification of interaction patterns and usability issues that might go unnoticed using traditional methods. For example, by integrating eye-tracking data with user feedback, researchers can uncover usability problems that are linked to users' emotional responses, such as frustration or confusion, providing valuable insights for improving design.

The added value of using multimodal data lies in its ability to provide more nuanced and comprehensive insights into user experience. Traditional methods often offer limited perspectives, focusing only on user actions or self-reported experiences. In contrast, multimodal data allows researchers to gain a deeper understanding of the cognitive, emotional, and behavioral aspects of user interactions. For instance, physiological measurements like heart rate and skin conductance can reveal users' emotional engagement during interactions, while eye-tracking data helps identify which elements of the interface attract or distract users' attention. When combined with user feedback, these insights form a more complete picture of the user experience, enabling designers to make data-driven decisions that improve usability, satisfaction, and overall product quality. The integration of multimodal data, therefore, provides a more powerful tool for UX evaluation, one that is capable of uncovering complex patterns and improving the design of digital products.

6. Conclusions

In summary, the integration of multimodal data processing techniques significantly enhances UX evaluation by providing a more comprehensive and accurate understanding of user experience. The key findings from this study reveal that combining data from multiple sources, such as interaction logs, visual attention data, and physiological measurements, allows for a more nuanced analysis of user behavior and emotional responses. This integration improves the precision of UX assessments, revealing interaction patterns and emotional states that traditional single-source methods often fail to capture. By addressing the limitations of traditional methods, such as surveys and interaction logs, multimodal analytics offers a deeper insight into user experiences, allowing for more informed design decisions.

The benefits of integrating multimodal data processing techniques are clear. Multimodal integration improves the accuracy and reliability of UX evaluations by providing a holistic view that combines both objective behaviors and subjective emotional responses. This approach overcomes the limitations of traditional methods that may lack emotional context or fail to capture the full spectrum of user interactions. By using technologies such as eye-tracking and physiological measurements, researchers and designers can uncover deeper insights into user experiences, improving the overall user experience of digital platforms. Additionally, the ability to perform real-time analysis through multimodal data allows for immediate adjustments during the design process, making it a powerful tool for improving user satisfaction and usability.

For further research, there is potential to explore the integration of additional data modalities, such as voice recognition and contextual data from external sources, to further enrich UX evaluations. Future studies should also focus on refining data synchronization methods and improving the scalability of multimodal analytics for large-scale UX evaluations. Moreover, the application of multimodal analytics in diverse fields, such as education, healthcare, and virtual reality, can provide valuable insights into the specific challenges and opportunities of each domain.

In conclusion, the future of UX research lies in the continued development and application of multimodal analytics. As technology advances, the ability to integrate and analyze multiple data sources in real-time will revolutionize the way user experiences are evaluated. By enhancing the depth and accuracy of UX assessments, multimodal analytics will play a crucial role in creating more user-centered and intuitive digital products, ensuring that the needs and emotions of users are at the forefront of design and development.

References

[1] J. Liu, "AI in Automated and Remote UX Evaluation: A Systematic Review (2014–2024)," *Adv. Human-Computer Interact.*, vol. 2025, no. 1, 2025, doi: 10.1155/ahci/7442179.

[2] L. Rivero and T. Conte, "Using a study to assess user eXperience evaluation methods from the point of view of users," in *ICEIS 2015 - 17th International Conference on Enterprise Information Systems, Proceedings*, 2015, pp. 88 – 95. doi: 10.5220/0005377300880095.

[3] A. Aitim and M. Abdulla, "Data processing and analysing techniques in UX research," in *Procedia Computer Science*, 2024, pp. 591 – 596. doi: 10.1016/j.procs.2024.11.154.

[4] C. Rico-Olarte, D. M. López, and S. Kepplinger, "Towards a conceptual framework for the objective evaluation of user experience," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10918 LNCS, pp. 546 – 559, 2018, doi: 10.1007/978-3-319-91797-9_39.

[5] H. Jo, J. Lee, H. W. Park, M. Kim, Y. Kim, and W. H. Lee, "Developing an Integrated Dashboard to Analyze Multimodal Data for User Experience Evaluation," in *2023 IEEE International Conference on Consumer Electronics-Asia, ICCE-Asia 2023*, 2023. doi: 10.1109/ICCE-Asia59966.2023.10326366.

[6] L. Rivero and T. Conte, "A systematic mapping study on research contributions on UX evaluation technologies," in *ACM International Conference Proceeding Series*, 2017. doi: 10.1145/3160504.3160512.

[7] A. S. M. Tsui and A. Kuzminykh, "Detect and Interpret: Towards Operationalization of Automated User Experience Evaluation," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 14032 LNCS, pp. 82 – 100, 2023, doi: 10.1007/978-3-031-35702-2_6.

[8] I. Pettersson, A. Riener, A.-K. Frison, J. Nolhage, and F. Lachner, "Triangulation in UX studies: Learning from experience," in *DIS 2017 Companion - Proceedings of the 2017 ACM Conference on Designing Interactive Systems*, 2017, pp. 341 – 344. doi: 10.1145/3064857.3064858.

[9] H. M. Mustafa, O. Alsbaihi, S. Jahameh, A. Sayed, and M. Othman, "User interface, usability, and user experience: A bibliometric mapping for previous research and future research insight," *Inf. Des. J.*, vol. 29, no. 3, pp. 204 – 222, 2024, doi: 10.1075/idj.24006.mus.

[10] J. Qiu and S. Tokuhisa, "Dual-Track UX: A User Experience Evaluation Method for B2B SaaS Development," in *Conference on Human Factors in Computing Systems - Proceedings*, 2025. doi: 10.1145/3706599.3719968.

[11] M. Shamim, A. R. Faridi, and F. Masood, "Analysis of Emerging Trends and Challenges in Multimodal Data," in *Proceedings of the 2025 12th International Conference on Computing for Sustainable Global Development, INDIACom 2025*, 2025. doi: 10.23919/INDIACom66777.2025.11115680.

[12] A. Bosta and S. Vosinakis, "A Multimodal Approach to User Experience Evaluation: Integration of Physiological, Behavioral, Contextual and Self-Report data with UserSence," in *Proceedings of 3rd International Conference of the Greece ACM SIGCHI Chapter, CHIGreece 2025*, 2025, pp. 182 – 187. doi: 10.1145/3749012.3749047.

[13] C. J. Lin and L.-Y. Cheng, "Product attributes and user experience design: how to convey product information through user-centered service," *J. Intell. Manuf.*, vol. 28, no. 7, pp. 1743 – 1754, 2017, doi: 10.1007/s10845-015-1095-8.

[14] A. L. Damian *et al.*, "Evaluating UX Factors on Mobile Devices: A Feasibility Study," in *International Conference on Enterprise Information Systems, ICEIS - Proceedings*, 2024, pp. 265 – 272. doi: 10.5220/0012623600003690.

[15] P. Pannattee, Y. Fukuchi, and N. Nishiuchi, "MUXAS-VR: A Multi-Dimensional User Experience Assessment System for Virtual Reality," *IEEE Access*, vol. 13, pp. 93063 – 93083, 2025, doi: 10.1109/ACCESS.2025.3573382.

[16] M. Toribio-Candela, G. González-Serna, A. Magadan-Salazar, N. González-Franco, and M. López-Sánchez, "Automated Facial Expression Analysis for Cognitive State Prediction During an Interaction with a Digital Interface," *Lect. Notes Comput. Sci.*

(including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 14502 LNAI, pp. 41 – 49, 2024, doi: 10.1007/978-3-031-51940-6_5.

[17] M. Peruzzini, F. Grandi, M. Pellicciari, and C. E. Campanella, "User experience analysis based on physiological data monitoring and mixed prototyping to support human-centre product design," *Adv. Intell. Syst. Comput.*, vol. 777, pp. 401 – 412, 2019, doi: 10.1007/978-3-319-94706-8_44.

[18] E. Cavalcante, L. Rivero, and T. Conte, "MAX: A method for evaluating the post-use user eXperience through cards and a board," in *Proceedings of the International Conference on Software Engineering and Knowledge Engineering, SEKE*, 2015, pp. 495 – 500. doi: 10.18293/SEKE2015-136.

[19] E. B. Şahin and P. Onay Durdu, "Evaluating the potential of using EEG based BCI method in user experience research," *Univers. Access Inf. Soc.*, vol. 24, no. 3, pp. 2507 – 2530, 2025, doi: 10.1007/s10209-025-01207-5.

[20] L. Marques, W. Nakamura, N. Valentim, L. Rivero, and T. Conte, "Do scale type techniques identify problems that affect user experience? user experience evaluation of a mobile application," in *Proceedings of the International Conference on Software Engineering and Knowledge Engineering, SEKE*, 2018, pp. 451 – 455. doi: 10.18293/SEKE2018-161.

[21] X. Li, T. Anukul, and F. Ying, "Multimodal Content Analysis for Enhanced User Experience," *Int. J. Basic Appl. Sci.*, vol. 14, no. Special Issue 3, pp. 63 – 72, 2025, doi: 10.14419/txmrrk92.

[22] E. B. Ince, K. Cha, and J. Cho, "Towards a Conceptual Model of Users' Expectations of an Autonomous In-Vehicle Multimodal Experience," *Hum. Behav. Emerg. Technol.*, vol. 2024, 2024, doi: 10.1155/2024/7418597.

[23] A. Becerra, R. Cobos, and C. Lang, "Enhancing online learning by integrating biosensors and multimodal learning analytics for detecting and predicting student behaviour: a review," *Behav. Inf. Technol.*, 2025, doi: 10.1080/0144929X.2025.2562322.

[24] N. Song, X. He, and Y. Kuang, "Research hotspots and trends analysis of user experience: Knowledge maps visualization and theoretical framework construction," *Front. Psychol.*, vol. 13, 2022, doi: 10.3389/fpsyg.2022.990663.

[25] N. H. Hasbi, A. Bade, F. P. Chee, and M. I. Rumaling, "Pattern Recognition for Human Diseases Classification in Spectral Analysis," *Computation*, vol. 10, no. 6, 2022, doi: 10.3390/computation10060096.

[26] Á. Becerra, R. Daza, R. Cobos, A. Morales, and J. Fierrez, "User experience study using a system for generating multimodal learning analytics dashboards," in *ACM International Conference Proceeding Series*, 2023. doi: 10.1145/3612783.3612813.

[27] J. D. T. Guerrero-Sosa, F. P. Romero, V. H. Menéndez-Domínguez, J. Serrano-Guerrero, A. Montoro-Montarroso, and J. A. Olivas, "A Comprehensive Review of Multimodal Analysis in Education," *Appl. Sci.*, vol. 15, no. 11, 2025, doi: 10.3390/app15115896.