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Enhancing User Experience in E-Learning: Real-Time Emotional Analysis and Assessment

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Abstract: This study addresses the limited research on the user experience of e-learning platforms, specifically focusing on cognitive and emotional outcomes. The study proposes a non-invasive method to assess the emotional effects associated with e-learning platforms. The experiment involved 23 university students and compared the effectiveness of a real-time face and eye detection methodology (MIORA) with a retrospective questionnaire (SAM) to understand the emotional responses during user-platform interaction. Usability issues were intentionally introduced in the system to observe students' emotional reactions and examine the consistency between the two tools. The results confirmed the hypothesis that real-time non-invasive tools for assessing emotional reactions are more comprehensive and reliable compared to the SAM questionnaire. These tools also allow for dynamic adaptations to the site's usability and interface based on the student's emotional reactions, potentially enhancing satisfaction, and learning outcomes. These findings provide valuable insights for future research on the impact of emotional responses to e-learning platforms on user experience and learning outcomes. Ultimately, this study lays a foundation for effectively assessing the emotional outcomes of e-learning to improve online and hybrid education.

Keywords: E-Learning User Experience; Real-Time Emotional Analysis; Non-Invasive Emotional Assessment; User-Platform Interaction; Learning Outcomes.

1. Introduction

In recent decades, online education and educational platforms have experienced significant growth due to technological advancements and the widespread availability of the Internet. The market value of these platforms has exceeded initial estimates, reaching $315 billion in. Additionally, there are currently around 600,000 to 470 million mobile education apps available on the App Store and Google Play [1]. The Covid-19 pandemic and subsequent lockdowns have further accelerated the transition from traditional to digital learning environments [2]-[4]. These platforms allow educators and trainers to upload course content that students can access or download from anywhere and on any device, enabling sustainable learning [4]-[6].

As these platforms become increasingly relevant, it is crucial to understand the impact of User Experience (UX) on engagement and the emotional and cognitive aspects of learning. A well-designed e-learning system should prioritize good usability and user experience for a wide range of users to prevent negative emotional and cognitive states during task performance. Research indicates that evaluating UX in education platforms is essential for learning success [6-8]. Within the realm of user-centered design, UX encompasses the entirety of a user's interaction process with a product, service, or website, from initial engagement to disengagement. This journey represents the user's active exploration and evaluation as they seek to acquire knowledge and form impressions [9].

Various aspects contribute to UX and designing interactive platforms, including content quality, technical aspects of the platform, attractiveness, clarity, efficiency, reliability, emotional stimulation, and novelty [10]. Since much of human interaction with software involves non-verbal communication, researchers have focused on the user's emotional state during their UX [9]-[12]. Exploring emotion detection techniques can enhance course content and the intuitiveness of the platform interface [11]. Conducting a thorough usability assessment can lead to platform customization, influencing user behavior and ultimately improving UX [12]. Usability testing, a popular method for evaluating and optimizing usability, involves having participants attempt typical tasks the software should perform. Various tools, both invasive and non-invasive, can be used for platform usability assessment.

Different instruments, such as retrospective or real-time approaches, can be utilized to assess platform usability. Questionnaires, like the SAM Questionnaire, ask participants to recall their feelings, but they may only capture high-dominance emotions and fail to capture intensity accurately [13]. Technological innovations have facilitated novel approaches to understanding the behavior and decision-making of online users, primarily through non-invasive methodologies. Non-invasive methodologies allow for real-time identification of users' unconscious emotions, avoiding retrospective bias and ensuring reliable results [14].

This paper investigates the emotional and cognitive states during the evaluation of usability and UX on an online course platform. It utilizes the MIORA monitoring software and involves 23 university students in an experiment. While previous studies have applied artificial intelligence methods for learner tracking in e-learning platforms to enhance educational content acquisition, this research pioneers the investigation of user experience in educational platforms. The study employs the MIORA framework and the Self-Assessment Manikin (SAM) retrospective evaluation tool [15]. Emphasizing emotional outcomes over cognitive outcomes, the paper presents a structured approach discussing the theoretical background, emotional aspects in UX, and UX assessment. The research aim, design, methodology, data collection, and outcomes are sequentially presented, followed by a comprehensive discussion of the implications for theory, education, and practice [16].

To gain insights into the role of emotions in User Experience (UX), a comprehensive review of influential literature in the field was conducted. Previous research has established a correlation between emotions and user response behavior [13][14][17].Emotions are considered a crucial factor in determining the UX when interacting with interactive technologies. Forlizzi and Battarbee (23) emphasize that emotions influence users' interactions with products and their perceptions and outcomes. The FACS construct, which identifies six primary emotions (happiness, surprise, sadness, anger, fear, and disgust), is commonly referenced [18][19].These emotions are used to describe how learners feel while using a website, with happiness representing satisfaction and excitement, anxiety reflecting insecurity, sadness indicating discouragement, and anger expressing frustration or irritation towards a prolonged website. However, the relationship between these emotions is complex, and the presence of one does not necessarily exclude the presence of another [20]. To optimize UX, it is essential to dynamically modify the design based on users' emotional reactions during website interaction. Identifying users' emotions, experiences, and skills and determining areas that require changes are critical for this purpose [21].

Previous research has explored student reactions on online platforms using Artificial Intelligence techniques. These studies have analyzed signals from facial expressions, head posture, and gaze [19][20]. D'Mello, Chipman, and Grasser utilized student posture to differentiate between low and high involvement, specifically boredom. Buono *et al.* (2022) aimed to detect student involvement by comparing invasive self-assessment questionnaires at the end of the test with non-invasive facial expression coding. They considered involvement as comprising perceived task difficulty and emotional responses elicited during the learning process. While Buono *et al.* (2022) acknowledged the emotional dimension of involvement, their focus was primarily on cognitive involvement, with limited exploration of the emotional component. Only a few studies have employed deep learning and AI to recognize students' real-time emotions and adapt the platform accordingly [22][23]. Therefore, this paper proposes a non-invasive tool for evaluating emotions during an e-learning course, aiming to enhance the satisfaction of learning and the platform.

With advancements in machine learning, assessing emotions in digital services has made significant progress in recent years (32). There are subjective and objective measurements, as well as retrospective and real-time measurements. Self-reported methods involve participants reporting their feelings and thoughts through questionnaires, which are cost-effective for gathering information on user recognition in the experience (UX) section. Standardized usability questionnaires, such as QUIS, SUMI, and SUS, have been developed to assess UX in the literature [23].Subjective evaluations, where users fill out questionnaires like SAM, are the most common method for assessing emotional states . SAM allows participants to rate their emotional states using rating scales and has advantages in terms of reproducibility, comparability, and ease of application [24]. However, subjective ratings of emotions have limitations, as emotions are fleeting and may be challenging to remember later. Self-reported evaluations, such as thinking aloud during a website usability test, can lead to lack of concentration and unnatural behavior.

Retrospective or self-report instruments are easy and cost-effective for measuring emotions. However, these evaluations are influenced by the subject's consciousness and cognitive bias, making them less reliable [2][6][7]. Recent advances in psychology and neuroscience have explored the use of biometric sensors to provide objective evaluations of emotional states. These sensors, like Galvanic Skin Response, measure physiological signals such as skin sweating to assess arousal. Other sensors include electromyography (EMG), heart rate (HR), and electroencephalography (EEG). However, these sensors are intrusive and require the presence of experts, making them expensive and limited to controlled environments.

To address these limitations, non-invasive user assessment instruments have been developed as an alternative. These monitoring systems utilize video-based facial expression analysis, emotion recognition from the human voice, and eye-tracking technology. Eye-tracking, which captures eye movements and determines focus positions, has been used in interface design studies and can measure engagement, arousal, stress, and fatigue during user interaction [26]. Mapping facial expressions and tracking emotional responses have shown promise in understanding user experience and improving interaction with platforms and content. Eye tracking has also been applied in various contexts, including video games and digital entertainment.

2. Research Method

Previous literature has explored the relationship between engagement and performance in e-learning [12][19][22]. This study introduces two assessment methods that investigate the emotional aspects of e-learning platform usage and the influence of graphical/layout settings on satisfaction and overall user experience (UX). Additionally, it aims to detect the level of emotional and cognitive student engagement during online lessons to adapt the course content accordingly. The research proposes a web-based tool called MIORA for remote usability testing of an online teaching website. MIORA assesses usability by analyzing users' emotional reactions in real-time using facial recognition and eye tracking without the need for sensors, only utilizing a built-in webcam. The tool records the user's face and screen, and it includes modules for facial expression analysis based on the FACS manual, recognizing primary emotions, and assessing satisfaction based on valence and arousal.

The evaluation process generates a UX report accessible to the user, and researchers can manually evaluate specific moments in the experience using screen recordings. The study monitors student behavior throughout the course, including self-assessment questionnaires. However, it deliberately introduces platform usability problems to examine students' emotional reactions. The objectives of the study are:

1) Propose and test the MIORA tool for UX analysis of educational platforms.
2) Compare the simultaneous evaluation method (MIORA) with a retrospective evaluation tool (SAM).
3) Present empirical analysis results based on emotion detection and analysis to dynamically improve platform usability and UX evaluation.

The investigation formulates two hypotheses derived from the research objectives:

1) H1: Non-invasive methods, such as MIORA, provide more comprehensive and reliable results compared to retrospective subjective self-assessment systems (SAM), which can be influenced by external conditioning.
2) H2: Non-invasive methods enable real-time customization of the graphical user interface (GUI) and lead to better UX evaluation, ultimately improving the user experience.

2.1 Criteria

Participants for the experiment were recruited through email invitations sent to all students enrolled in a degree course. The participation was voluntary, and there were no rewards involved. Informed consent was obtained from all respondents, and the study followed relevant guidelines and regulations. The tests were conducted at the Polytechnic University of Marche (Ancona), and participants gave their consent for the publication of their pictures.

The initial sample consisted of N=50 students, and inclusion and exclusion criteria were applied to ensure a cohesive and suitable sample for the experiment. The criteria were as follows:

1) *Exclusion criteria*
   a) Students over the age of 45 were excluded to maintain consistency within the sample, as the average age was around 24.
   b) Students located far from the test venue (more than 50km radius) were excluded due to mobility limitations.
   c) Students who expressed a need for more familiarity with computers and the Internet were excluded.
   d) Students who showed no interest in participating in the test were excluded to prevent unwilling and unreliable responses.
   e) Participants with no basic knowledge or understanding of user experience were excluded to ensure comprehension of the test questions.
   f) Students with visual, auditory, or cognitive disabilities that could hinder their participation and distort the results were excluded.
2) *Inclusion criteria*
   a) Participants were required to have proficiency in the English language since the test was conducted exclusively in New Zealand.
   b) Students who had previously participated in a similar experiment within the past five years were included.

2.2 Participants

The study included a final sample of 23 participants with an average age of 24 years. Many participants identified as male (70%) while the remaining participants identified as female (30%). All participants were enrolled in universities located in New Zealand, with diverse backgrounds in engineering disciplines. Specifically, 39% were from the Computer Engineering department, 39% were from the Electronic Engineering department, and 22% were from the Biomedical Engineering department. The participants consisted of 74% bachelor's degree students and 26% Master's degree students. These participant characteristics provide an overview of the demographics and academic backgrounds of the individuals involved in the study.

2.3 Instrument

The MIORA tool used two modules to analyze the participants' emotional states and attention during the experiment. The first module employed machine and deep learning algorithms to recognize facial expressions and categorize them according to Ekman's Facial Coding System, including emotions such as happiness, sadness, boredom, anger, fear, surprise, and neutrality. It also measured the valence and arousal levels of the emotions. The second module utilized eye-tracking technology to detect eye movement and head rotation, providing insights into the participants' attention or inattention. To ensure accurate analysis, the researchers excluded video frames with poor lighting conditions, low resolution, and paused sections. They also recorded the participants' screen activities. The experimental protocol received approval from the Ethics Committee of the University Research of the University of Macerata. Open-source software, such as Open-Face and Open-Pose, was used to extract features related to facial behavior and body posture. The dataset was annotated based on engagement rather than emotions, and a convolutional neural network was employed to analyze the temporal dynamics of the participants' reactions. The experiment took place in a laboratory within a single day, involving all 23 participants simultaneously. The participants were given four consecutive tasks to complete within a maximum time of one hour, involving searching and starting a lesson, stopping the video lesson after 30 minutes, taking a test, and changing an answer during the test. Unbeknownst to the participants, the developers deliberately introduced usability problems on the website to observe their reactions. These problems included automatic page reloads, delayed buttons, hidden toolbar menus, and error messages when attempting to change survey responses. The platform used for the experiment was an Open Access e-learning platform offering various courses, and an introductory engineering video course was selected for the participants. After each activity, the participants completed the SAM questionnaire, recalling their emotions, valence, dominance, and arousal. The results from the questionnaire were compared with real-time facial expression analyses by MIORA to assess response consistency. The SAM questionnaire utilized a 1- to 9-point Likert scale to measure pleasure, arousal, and dominance, represented by manikins indicating smiling or frowning, energetic or relaxed state, and controlled or in-control state, respectively.

A convolutional neural network (CCN) was employed in both cases to analyze the student's reactions and changes progressively by capturing the temporal dynamics of video sequences. The experiment took place in a laboratory over a single day, with all 23 participants simultaneously participating in a time trial lasting a maximum of one hour. Participants were recorded on video and timed as they performed a series of tasks instructed by the researchers.

The tasks included: 1) searching and starting the lesson by typing "Engineering Courses" in the course search bar and accessing the first Engineering Fundamentals lesson, 2) stopping the video lesson after 30 minutes, 3) completing a relevant test after ending the video course, and 4) changing an answer during the test. Participants were not aware of the deliberate usability problems intentionally introduced by the developers to observe their reactions to a poorly responsive website. These problems included automatic page reloads during the course, delayed buttons for starting, stopping, and ending the video lesson, accessing a toolbar menu that is not visible by default for the examination, and encountering an incomprehensible message error when attempting to change a response in the survey.

The participants were directed to an Open Access e-learning platform offering various courses, and for this experiment, an introductory engineering video course was chosen considering the sample's degree type. The participants were instructed to complete each task within the shortest possible time. After each task, the participants were administered the SAM questionnaire, which asked them to recall the negative or positive emotions they experienced, along with their valence, dominance, and arousal. These self-reported results were then compared with real-time facial expression analyses monitored by MIORA to assess the consistency of responses. The SAM test employed a 1- to 9-point Likert scale, also known as the PAD test, measuring emotions along three axes: 1) Pleasure (or Valence), 2) Arousal, and 3) Dominance. The emotional states were represented by different manikins, where a smiling, happy manikin denoted pleasure, an unhappy, frowning manikin represented the opposite pole, an animated manikin depicted high arousal, and a relaxed, eyes-closed manikin indicated low arousal. The dimensions of dominance were represented by a small manikin for controlled states and a large manikin for in-control states.

3. Result and Discussion

3.1 Results

The results of the study showed discrepancies between the scores generated by the SAM questionnaire and MIORA for each task. In the first task, which involved searching and starting the Fundamental lesson, participants faced difficulties due to the confusing graphic layout, inappropriate color, and font size. It took an average of two minutes for participants to start the course, as indicated by the heatmap in Figure 5, which showed confusion. During the initial ten minutes, when usability problems such as automatic page loading occurred, MIORA detected negative emotions and a decrease in attention levels among students. MIORA's analysis captured emotional changes related to usability issues and different modes of content delivery (slides vs. videos). Figure 6(a) provides an example of the student's emotional-cognitive reactions measured by MIORA at key points in the course. At the beginning, the student appeared perplexed and frustrated with the continuous loading of the page, as indicated by intense peaks of anger. However, as the usability problems disappeared, the student's engagement and emotional curve gradually improved. An experiment conducted by the professor excited the students, resulting in joy. The SAM questionnaire completed at the end of the 30 minutes indicated that students found the first task satisfactory, as shown in Figure 7. Moving on to the second task, which involved stopping the video lesson, MIORA identified a small percentage of frustration and an even smaller percentage of despondency.

Further analysis revealed that these negative emotions peaked when the student repeatedly clicked the 'stop' button without receiving any feedback from the platform. These negative emotions had low levels of arousal and dominance and dissipated once the platform responded correctly to the stop request.

Task 2: Stop the video-lesson
During the second task of stopping the video lesson after 30 minutes, MIORA analysis revealed a small percentage of frustration (anger) and an even smaller percentage of despondency (sadness) among the participants (Figure 8). To investigate further, the authors examined data from face detection, gaze detection, and screen recording to identify critical moments where negative emotional trends emerged. It was found that the peak of negative emotions occurred when students repeatedly clicked the 'stop' button without receiving any feedback from the platform. However, these negative emotions had low levels of arousal and dominance, and they disappeared once the platform responded appropriately to the request to stop the video. The SAM questionnaire did not reveal any specific factors that influenced the participants' emotions during this task (Figure 9).

Task 3: Take the test
In the third task, which involved going to the examination section and taking the test, participants did not all take the same course, resulting in varying durations for completing the task. The SAM questionnaire indicated a constant state of tension throughout the task, as time constraints and being timed generated competition anxiety among the participants (Figure 10). Those participants who were familiar with similar platforms and knew efficient ways to access the examination section took less time and reported less intense negative emotions. On the other hand, participants who took longer and more time-consuming routes experienced more intense negative emotions. MIORA's real-time analysis helped identify this difference more intensely among participants who took the longer route (Figure 11a, b).

Task 4: Change an answer
In the final task, participants experienced increased pressure due to time constraints as they were required to modify an answer in the quiz. This pressure triggered negative emotions, which further heightened when encountering an error message during the quiz. MIORA identified the fear of running out of time or being outperformed by other students as factors contributing to these emotions (Figure 12). The SAM questionnaire confirmed that this fear was closely linked to feelings of nervousness (Figure 13).

Overall, the results of the SAM questionnaire indicated that participants tended to report the most dominant emotions they experienced, while less intense emotions were not consistently reported. Some emotions confused the participants, as seen in the last task where MIORA detected fear while the SAM questionnaire indicated nervousness. The implications of these results will be discussed further in the following section.

3.2 Discussion

Usability is an important criterion for assessing the quality of user experience (UX), and emotions play a crucial role in shaping users' overall evaluation of the learning experience and their perceptions of usability. Previous research has shown that emotional responses can influence how users perceive the usability of e-learning platforms. This study aimed to measure usability metrics by assessing engagement and emotional responses of participants when faced with specific platform issues.

To assess emotions during a usability test, various instruments have been used in the literature, including invasive or non-invasive, real-time, or retrospective methods. This study compared emotional responses captured in real-time using the non-invasive MIORA tool, which records the user's face, gaze, and screen, with retrospective responses obtained through the SAM questionnaire. The findings supported the hypothesis that non-invasive methods, like MIORA, provide.

greater adherence to subjects' complex emotional reactions with reduced susceptibility to cognitive biases. The results revealed a gap between real-time emotional responses detected by MIORA and emotions reported in the retrospective SAM questionnaires. MIORA detected emotional alterations when usability problems occurred, which were perceived less intensively or not reported in the SAM questionnaires. The authors attributed this gap to the phenomenon described by Scherer's thesis, where emotions experienced over a brief period are unconsciously omitted during retrospective self-assessment.

Proper usability evaluation through real-time analysis of users' emotional reactions can enable responsive and immediate platform customization, leading to improved learning and satisfaction. MIORA can help identify the impact of usability problems on students' emotional and cognitive experience, which may not be directly perceivable through the SAM questionnaire. The findings confirmed the hypothesis that adapting the GUI and platform to the user's needs results in positive emotional changes.

For practical implications, practitioners and platform developers should consider UX assessment methods that capture synchronous and interactive emotional reactions. These methods can provide insights into the quality of the platform's structure and content, as well as the impact of student involvement and emotional response. Real-time assessment methods can help evaluate navigability and effectiveness in educational terms, saving time and cost compared to in-depth analyses.

Despite the novelty of this work and its findings, there are several limitations that need to be addressed. The research sample size should be expanded and differentiated, and additional inclusion and exclusion criteria should be considered to strengthen the conclusions. The effectiveness of course evaluation tests submitted later should be examined, as well as the limitations of retrospective questionnaires. Future research could explore real-time verbal or oral self-assessment methods during experiments, combining them with continuous and real-time MIORA analyses to overcome these limitations.

4. Related Work

Previous research has extensively investigated the relationship between engagement and performance in the field of online learning platforms [12][19][20]. This study contributes to the existing literature by introducing and comparing two separate assessment methods that delve into the emotional aspects of e-learning platform use and the influence of graphical parameters layout to overall user experience (UX) and satisfaction. Furthermore, it aims to detect students' emotional and cognitive engagement in online classes to facilitate adaptive course content. This research is consistent with the growing recognition of the role of emotions in shaping users' perceptions of usability and the overall learning experience.

In the context of usability assessment, researchers have explored a variety of tools ranging from invasive to non-invasive and retrospective to real-time methods. Building on this background, the present study stands out by comparing real-time emotional responses recorded through the innovative non-invasive instrument MIORA with the retrospective responses obtained through questionnaires. SAM. By examining the dynamic interplay between emotion and friendliness, this work sheds light on specific emotional nuances that are often overlooked by traditional retrospective assessments, filling in the gaps emphasized. by Scherer's thesis that transient emotions tend to be overlooked during retrospective self-assessment.

Furthermore, the results highlight the importance of real-time sentiment analysis to improve understanding of user experience. The use of MIORA in this study offers an effective approach to identifying emotional changes associated with usability problems, providing insights far beyond what is commonly reported. reported in the retrospective questionnaire. These findings highlight the potential of real-time sentiment analysis to enable immediate and responsive platform customization, which can help improve the overall learning environment and student satisfaction. Building on this background, the research contributes to the ongoing dialogue about UX evaluation methods. This suggests that real-time assessment methods, such as MIORA, hold promise for capturing the complex interplay between emotion and friendliness. This is consistent with the broader trend toward effective assessment techniques that consider student emotional responses and engagement in educational contexts. By emphasizing practical implications for practitioners and developers, this study reinforces the value of integrating real-time sentiment analysis into usability assessments, potentially leading to learning experience in a more effective and personalized way.

However, it is important to recognize the limitations of this study. As with any study, a larger and more diverse sample size, as well as more refined inclusion and exclusion criteria, can strengthen a study's results. Exploring potential biases and constraints associated with retrospective questionnaires, and studying the combination of real-time emotion analysis with other assessment methods offer promising avenues for future research.

5. Conclusion

In conclusion, assessing user emotions during website interactions is essential for achieving a successful user experience (UX). This study compared the effectiveness of non-invasive real-time emotional analysis using MIORA software with the retrospective SAM questionnaire. The results revealed a significant gap between the retrospective and simultaneous evaluation of emotions, highlighting the advantages of non-invasive methods in capturing complex emotional reactions with reduced cognitive bias. Additionally, adapting the GUI and platform to the user's needs based on real-time emotional analysis resulted in positive emotional changes and improved engagement and educational outcomes. This research provides theoretical, pedagogical, and practical insights for the implementation of e-learning platform assessment methods, enabling educators, researchers, platform providers, and designers to understand the role of emotions in the learning experience and outcomes. Furthermore, this study contributes to the exploration of real-time customization and adaptation of graphical user interfaces based on users' emotional responses, suggesting avenues for future research.

The complete and filtered dataset generated by the questionnaire, including the inclusion/exclusion criteria, is currently not publicly available for security reasons. Please be aware that the data supporting the findings of this study, which were obtained under license from Emoj, are also subject to restrictions and are not publicly accessible. However, individuals who are interested in accessing the data may request it from the authors, with the understanding that permission from Emoj will be required.

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