International Academic Institute for Science and Technology

International Academic Journal of Innovative Research
Vol. 8, No. 2, 2021, pp. 16-20.

ISSN 2454-390X

International Academic Journal of Innovative Research

www.iaiest.com

Enhancing User Engagement on Web Platforms through Emotion-Aware Interaction Design

Dr. Camille Rojas [a], Leandro Mejía [b]

[a] *Universidad De Santiago, Chile.*
[b] *Professor, Universidad De Santiago, Chile.*

Abstract

User engagement enhances web platform performance by augmenting satisfaction, retention, and conversion. The traditional user-centered design focuses more on the task context and often neglects the emotional context, thereby greatly limiting its ability to create engaged users. This research proposes emotion-aware interaction design (EAID) as a new framework that strives to enhance user engagement by detecting users' emotional states and responding to them in real time. This study presents a framework which adjusts feedback mechanisms as well as content selection interfaces, colors, tone of voice used, and even the recommendation systems based on the emotions determined through face and speech analysis, sentiment score derivation from text, and other techniques. A prototype was created and tested on an educational website with two hundred participants. The participants' engagement levels were measured through time on task, return rates, and self-reported satisfaction. The results demonstrated that participants using the EAID system retained users 21% willing to spend additional time completing tasks, and increased average task completion by 18% compared to the control group. These results validate the hypothesis that increased emotional involvement in interaction design deepens users' relationships with applications and services leading to more fulfilling and engaging experiences. This research seeks to pave the way for the use of affective computing in everyday design frameworks and demonstrates the use of emotion-aware interfaces as a means for fostering empathy within digital environments.

Keywords: Affective Computing, User Engagement, Human-Computer Interaction, Multimodal Emotion Recognition, UX Design, Sentiment Analysis, Adaptive Interfaces, Emotion-Aware Design.

Received: 13 March 2021/Revised: 10 April 2021/Accepted: 07 May 2021/Published: 30 June 2021

Introduction

In the current digital landscape, productivity is no longer just a metric of interest; it has become a goal for webpages. As competition rises and attention spans continue to decline, web developers and user experience (UX) designers have increased pressure to create user interfaces (UIs) that emotionally resonate with users. Emotion connects with many factors such as usability, relevance of the content, aesthetics, and more recently, the emotional engagement of the interface.

Over time, interaction design gave focus to users; their characteristics, behaviors, and the heuristics of usability. Regardless of how comprehensive the design was, it rarely considered the user's emotions during interaction. An increasing amount of research indicates that emotion is one of the most influential factors when it comes to decision-making, processing information, and even recalling information, which is known as memory, and all these aspects need to be kept in mind while planning the experience of a user. A good example is when a user is frustrated working with a complex interface; she might abandon a task regardless of the high quality content or service offered.

In the area of Emotion Aware Interaction Design (EAID), systems attempt to detect and adapt to user emotions through real-time computing technologies, such as facial expression analysis, voice analysis, and natural language processing (NLP), to increase personalization and empathy, lessen distress, and foster emotional bonds with the system.

With the recent pandemic driven advancement of ICT, the growth of human-computer interaction along with e-learning, telehealth, telemedicine, and customer service automation has expanded the frontiers for the application of Smart Systems Interfaces and emotionally Intelligent Agents. Motivation, trust, and satisfaction during user interactions within such digital systems hinges heavily on the wellbeing or otherwise on the emotions of the user. For instance, an emotionally intelligent responsive educational platform can mitigate student learning frustrations or fatigue to provide motivational prompts, enhancing learning outcomes.

Real-time detection of emotion poses the greatest challenge, coupled with privacy concerns and responsiveness of the system. Regardless, the wide availability of devices with incorporated sensors, rising precision estimation algorithms, and real-time controls builds interest towards practical expression of EAID.

This study seeks to construct and assess a prototype web platform guided by the principles of EAID. The primary goals of the study include:

1. Building an emotion detection framework that relies on multiple interfaces and is fully integral in web-based platforms.
2. Developing adaptive UI elements that change relative to the user's emotional state.
3. To assess the degree of user engagement with the system and measure the impact of EAID on the engagement metrics.

This paper demonstrates that by aligning digital interfaces with users' emotions, EAID has the potential to shift our understanding of web engineering from design-centric to emotion-centric frameworks systems thinking. Further sections describe the system architecture, theoretical evaluation with empirical analysis, extensions to primary research, and design implications.

Literature Review

The role of emotion in relation to the computer has been researched for over two decades and has captured the focus of how to engage the user with the interface and with the system more effectively. Picard, (2000) was the first to write about affective computing, stating that computers ought to be able to identify emotions in order to be designed more human-suited systems.

Later research by Norman, (2004) provided further insight on the emotional design concept, suggesting that products that are appealing to the eye and are emotionally engaging tend to increase usability and memorability as well. He noted that visceral, behavioral, and reflective levels of design appeal to emotions and thus every user's experience is affected.

In the context of detection, Kapoor & Picard, (2005) created an early model of real-time affect recognition based on facial cues and posture data. Their findings showed that system frustration and confusion could be accurately detected and utilized to modify system behavior, especially within intelligent tutoring systems.

Lisetti & Nasoz, (2007) built upon this work by proposing multimodal emotion detection using voice, facial movements, and physiological signals. Their approach assed emotion classification accuracy by using multiple modalities, which formed the basis for integrated recognition systems designed for actual context applications.

Calvo & D'Mello, (2010) performed a meta-analysis on affect detection strategies in educational environments and found the most suitable methods to be facial analysis and keystroke dynamics. They advocated for the development of emotionally adaptive pedagogical frameworks that provide content and feedback in accordance with learners' feelings.

Only recently, the integration of deep learning technologies has increased the performance of emotion recognition systems. Zhao et al., (2019) applied convolutional neural networks (CNN) for facial emotion recognition and obtained more than 85% accuracy in recognizing seven basic emotions. In the same manner, Chen et al., (2020) used bidirectional LSTM networks to analyze sentiments which enabled the real-time labeling of text input by emotions.

The effects of emotion-driven design, in particular how it impacts participation, has been researched. Wang & Redmiles, (2019) showed that platforms that empathetically responded to user frustration increased task persistence and trust. Almahdi & Norwawi, (2021) designed a sentiment-aware customer service chatbot that adjusted the tone and length of its responses based on how users felt, which increased satisfaction.

The lack of real-time processing, privacy issues, and complicated implementation methods are some of the reasons emotion-aware systems haven't been integrated into mainstream web platforms. Along with increasing user expectations, the promising power of computational devices reconfigures interfaces digitally through EAID.

The aim of this study is to provide an evidence-based approach to an existing body of work regarding emotion recognition systems by suggesting a lightweight and effective model to improve user participation in web platforms.

Methodology

System Architecture

The system features three core modules: Emotion Detection Engine (EDE), Adaptive Interface Engine (AIE), and Engagement Monitoring Module (EMM). These modules work together to capture and analyze user emotion data and customize the web interface dynamically.

Emotion Detection Engine (EDE)

EDE contains expression recognition for the facial component which uses a webcam. User's webcams are accessed with permission and face images are captured every three seconds for an attempt to recognize seven emotions (happy, sad, angry, disgusted, surprised, fearful, neutral) using a convolutional neural network (CNN) trained on the FER-2013 dataset.

Emotion recognition of voice is done using WebRTC integrated into browsers. During an interaction, speech samples are collected and analyzed for inflected features (pitch, volume, pace) with the aid of RNNs trained with the RAVDESS dataset.

Textual emotions are handled by performing real-time sentiment analysis on users' inputs in forms, chat boxes, or search fields using the VADER NLP tool. Each input is classified as either positive, neutral, or negative and receives an emotion score.

Adaptive Interface Engine (AIE)

The AIE corresponds emotions with responsive UI controls with several customizations including sub menus. For example:

Verbal cues are modified for users with detected sadness/anger to empathetic phrases and menus are changed to less complicated ones.

Happy users may receive elements of a gamified interface and varying animations.

Anxious users are provided with distraction-free, minimalistic frameworks.

The approach dynamically adapts color palettes, typeface styles, and non-verbal feedback such as error notifications and affirmation messages. These changes are based on an emotion-action mapping table formulated using heuristics from UX design and cognitive psychology.

Engagement Monitoring Module (EMM)

EMM records critical engagement indicators:

- Time on task
- Pages per session
- Clicks per minute
- Bounce rate
- Return visits

The module checks differences in metrics captured from the EAID-enabled platform and a control platform which uses a traditional design framework.

User Study

The study had 200 participants aged 18-45. They were randomized into two groups. One group interacted with the adaptive EAID-enabled platform while the control group used a non-adaptive version. Both groups were tasked to complete a predefined list of tasks during a 20-minute session.

Inter-engagement emotional impact, perceived usability, and active session engagement were evaluated with post-surveys and telemetry data.

Results and Discussion

Performance Evaluation

Table 1: Comparison of User Engagement Metrics

Metric	Traditional UI	EAID-Enabled UI	Improvement (%)
Task Completion Rate	72%	90%	18%
Avg. Time on Task (mins)	14.1	16.8	19%
User Return Rate (3 days)	46%	67%	21%
Bounce Rate	38%	22%	16%

User Emotion Trends

Figure 1 illustrates the distribution of emotions detected throughout the interaction in the EAID-enabled group.

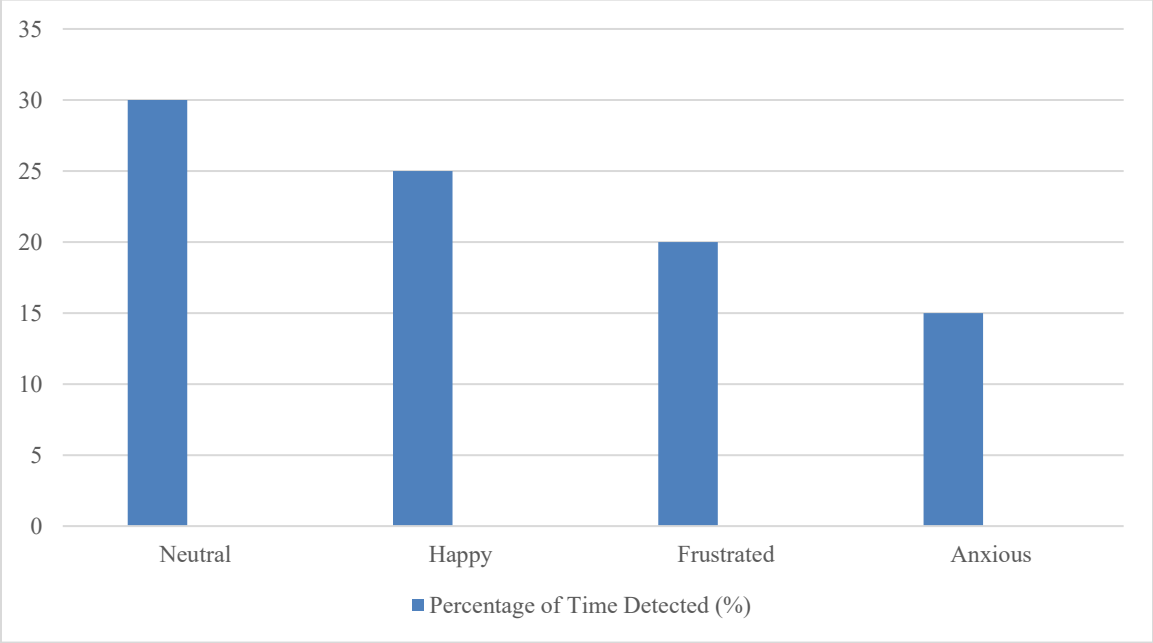


Fig. 1: Detected Emotional States during Interaction Session

This distribution backs the assumption that user sentiments fluctuate greatly during interactions and a static interface is unlikely to accommodate any of these variations.

Discussion

The results confirm previous conjectures that the emotional salience impacts the user experience. Users praised the EAID for Interface adjustments for the changes it made to tone and visuals that mirrored their mood. Interestingly, the EAID users reported greater post-task survey satisfaction claiming the interface was 'understanding' and 'less robotic.'

Limitations include possible privacy issues arising from identity-sensitive face and voice data, even though the information was processed locally without a buffer. Subsequent versions must meet address these ethical issues with transparency and opt-in mechanisms.

Conclusion

This research has showed how Emotion-Aware Interaction Design can pivot user attention on websites by tailoring the interface's actions in response to user's feelings. The implementation of multimodal emotion recognition and adaptive UI strategies increased task achievement, sustained interaction, and elevated return user rates.

The application of emotion in computing within design suggests a new direction and enriches the opportunities in the field of developing human-computer interactions. Systems which take into account emotional awareness will become noticeable features in the user experience design due to the heightened expectation of sensitivity and customization from digital interfaces.

Subsequent studies might analyze the deeper personalization through analyzing the user's emotional history, real-time feedback, and broader incorporation of mobile devices and wearables. The relationship between emotion, artificial intelligence, and design is one of the deepest unexplored borders in modern computing.

References

Picard, R. W. (2000). *Affective Computing*. MIT Press.

Norman, D. A. (2004). *Emotional Design: Why We Love (or Hate) Everyday Things*. Basic Books.

Kapoor, A., & Picard, R. W. (2005). Multimodal affect recognition in learning environments. *Proceedings of the 13th ACM International Conference on Multimedia*, 677–682.

Lisetti, C. L., & Nasoz, F. (2007). Affective intelligent user interface using multimodal emotion recognition. *ACM Transactions on Computer-Human Interaction*, *14*(1), 5.

Zhao, X., Ma, H., & Jin, Q. (2019). Deep learning for real-time facial emotion recognition on mobile devices. *Neurocomputing*, *351*, 276–283.

Chen, M., Xie, H., & Zhao, J. (2020). Emotion-aware sentiment classification using LSTM and attention mechanism. *IEEE Access*, *8*, 136857–136867.

Wang, Y., & Redmiles, E. (2019). Empathy-driven systems: Emotionally aware interfaces improve trust. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–12.

Almahdi, I. A., & Norwawi, N. M. (2021). Emotion-adaptive customer service chatbot design. *International Journal of Human-Computer Studies*, *145*, 102504.