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Designing Emotionally Adaptive Interfaces: Affective UX Model for Enhancing Engagement in Gamified Learning Apps

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Abstract. *In the digital learning era, user engagement is shaped not only by functionality and aesthetics but also by how interfaces adapt to users' emotional experiences. While gamified learning environments have become common, few designs systematically integrate affective computing principles to support real-time emotional adaptation. This study proposes an Affective UX Model that combines affective computing with user experience (UX) design to enhance emotional engagement in gamified educational interfaces. The research aims to explore how emotionally adaptive features can be designed, implemented, and evaluated within a learning context. Using a user-centered design (UCD) approach, the study employed mixed methods, including visual storytelling, interactive prototyping, and affective mapping via self-report measures and biometric tracking (facial expressions and heart rate variability). A gamified language-learning prototype was tested with 30 adolescent participants (aged 15–18) through usability and emotional response evaluations. Results show that empathetic avatars, responsive feedback, and adaptive difficulty adjustments significantly increased motivation, engagement, and emotional comfort. Participants reported a stronger sense of connection when system feedback matched their affective State and performance. The study contributes a validated conceptual framework for designing emotionally intelligent, human-centered educational interfaces, emphasizing how affective adaptivity enhances the quality of user experience and learning outcomes. The findings demonstrate that dynamic emotional adaptation can redefine engagement and inform future directions in emotionally responsive design research.*

Keywords: *Affective UX, Gamified Learning, Emotionally Adaptive Interfaces, User Engagement, Affective Computing*

INTRODUCTION

As digital learning continues to evolve rapidly, emotional experience has become a vital component in Human-Computer Interaction (HCI) and experience design (Bintarto, 2023; Prasetya et al., 2025; Yunianto & Wahyudi, 2024). Designers of learning applications have traditionally prioritized usability, functionality, and aesthetics, often at the expense of users' emotional engagement. Recent advances in affective computing challenge this approach by demonstrating that emotionally intelligent interfaces, those capable of detecting and responding to users' affective states, can play a pivotal role in enhancing motivation and sustaining user engagement (Alipour et al., 2023; Wang et al., 2022). This shift reflects a growing emphasis in design theory on experience-centered and empathetic approaches, where design mediates not only function but also human meaning and emotion (Amin et al., 2023; Buchanan, 1992).

Affective computing, which involves building systems that can recognize, interpret, and respond to human emotions, has become increasingly relevant to learning experience design (Pei

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et al., 2024). Although researchers have applied affective technologies in fields such as healthcare, automotive design, and social robotics (Braun et al., 2022; Fischer et al., 2020), their integration into educational user experience, particularly in gamified contexts, remains limited. Recent findings advocate for systems that adjust visual elements, narrative structures, and task complexity in response to users' emotional states, thereby enriching cognitive flow and emotional resonance (Gold & Ciorciari, 2020; Krishna Mandava, 2023). Despite this potential, most educational applications still rely on static interfaces that fail to respond to the learner's changing emotional landscape.

This research addresses that gap by proposing an Affective UX Model specifically designed for gamified learning environments. The study offers a novel contribution by integrating affective computing principles with gamification strategies, two domains rarely combined in the existing literature. While gamification is widely credited for boosting motivation through mechanisms such as rewards, challenges, and progression (An, 2020; Ratinho & Martins, 2023), its ability to emotionally adapt to individual users has not been adequately explored. The proposed model goes beyond surface-level engagement, aiming to cultivate emotional alignment between learners and the digital environments they interact with.

We developed and tested this model using a user-centered design (UCD) approach that included interactive prototyping, biometric and self-reported emotion mapping, and iterative usability evaluations. The research centers on a mobile language-learning app tailored for adolescents aged 15–18, a demographic that often seeks emotionally enriching digital experiences. We examined how elements such as empathetic avatars, dynamic feedback, and adaptive challenge levels affect both engagement and emotional resonance. This process builds on established responsive UX principles (Bitkina et al., 2020; Yigitbas et al., 2020) and extends insights from (Alipour et al., 2023), who demonstrated that emotion-aware interfaces can influence user behavior and interaction patterns.

At the heart of this investigation lies the research question: How can emotionally adaptive interfaces, grounded in affective computing principles, enhance user engagement in gamified learning applications? This question anchors both the theoretical framework and the practical innovations presented in this study. By exploring it, we aim to show that combining emotion-sensitive technologies with gamified UX design can yield applications that are not only functional and engaging but also emotionally supportive and meaningful. By developing this Affective UX Model, the study contributes to the growing movement toward emotionally attuned digital education. It offers both conceptual clarity and practical methods for creating learning technologies that listen, adapt, and respond to users on an emotional level. As educational technology becomes increasingly immersive and personalized, empathy and emotional intelligence will serve as essential design principles shaping experiences that feel as human as they are digital.

LITERATURE REVIEW

The field of affective computing and emotional interface adaptation has grown significantly in the last decade, particularly in the context of user engagement in digital environments. One of the central premises of affective UX is that emotional states play a crucial role in shaping how users interact with systems, especially in learning and gamified applications. (Alipour et al., 2023) introduced Emoticontrol, a framework enabling emotion-based interface adaptation, which demonstrated the practical feasibility of integrating affect recognition with system behavior modification. Their research showed that emotion-aware systems can dynamically adjust interaction patterns to maintain engagement in fluctuating emotional contexts, underscoring the role of adaptive feedback in sustaining user experience.

14 In educational technology, affective responsiveness is particularly significant because it influences learning motivation and cognitive load. (Hellín et al., 2023) emphasized that gamified learning environments incorporating emotional and motivational cues led to increased student motivation and deeper cognitive engagement. Similarly, (Ratinho & Martins, 2023) underscored the positive impact of gamification on students' emotional investment and performance, further validating the importance of designing emotionally supportive learning systems. Empirical studies by (Yaccob et al., 2022; Yunus & Hua, 2021) showcased how gamified learning tools such as Quizizz significantly improved ESL learners' motivation and retention, pointing toward a broader applicability of affective design in education.

While emotional adaptation has proven its potential, implementation challenges remain both technical and theoretical. (Pei et al., 2024; Schuller et al., 2024) provided comprehensive overviews of affective computing, emphasizing the necessity of standardized emotion models and databases for reliable system performance. They noted that even as affective models become more generalized, context-sensitive design remains essential to align adaptive responses with user intentions and environments. Similarly, (Krishna Mandava, 2023) proposed the use of real-time feedback loops in emotion-driven UI adaptation, offering insights into how responsive interfaces can improve user experience continuity.

The role of UX frameworks in supporting affective adaptation is also central to this discussion. (Alomari et al., 2020) developed a detailed UX evaluation framework specifically tailored to cyberlearning environments, highlighting the need for models that are sensitive not only to usability but also to engagement and emotional resonance. Complementing this, (Bitkina et al., 2020) reviewed UX evaluation methodologies in medical technologies and revealed persistent gaps in integrating emotional metrics into usability assessments. Together, these studies suggest that emotional data remains an underutilized design dimension across industries, including education.

Moreover, the integration of emotion into system design extends beyond education into sectors like healthcare and automotive technology. (Braun et al., 2022) examined affective user interfaces in vehicles and noted the challenges and potential of incorporating emotion regulation strategies into everyday technologies. (Bird et al., 2021) offered a generative co-design framework for healthcare that placed end-user emotional experiences at the center, which parallels the argument that emotion-aware systems can be optimized through participatory design approaches. From a design theory perspective, (Buchanan, 1992) notion of "design as a human-centered discipline" underscores that adaptive technologies must maintain emotional resonance to preserve human agency in interaction. (Yigitbas et al., 2020) further demonstrated how self-adaptive user interfaces can modify components in real time based on user state data, including emotional signals. Similarly, (Märtin et al., 2023) showed that integrating user personas and emotional states can produce more intuitive and affectively aligned experiences. These works collectively contribute to the conceptual foundation of affective UX frameworks by offering practical pathways for emotion-driven personalization.

Gamification continues to serve as a powerful vehicle for implementing affective UX. (An, 2020) highlighted the role of emotionally engaging game mechanics in sustaining learner motivation, while (Prati et al., 2021) proposed incorporating affective UX principles into human–robot interaction design. (Dağ et al., 2024) demonstrated that immersive AR environments enhance both engagement and perceived authenticity, illustrating that affective cues enrich not only learning but also spatial experiences. (Kang & Lou, 2022) found that perceived agency in AI systems can increase user trust and engagement in emotionally charged platforms such as TikTok, aligning with (Shahbaznezhad et al., 2021), who showed that emotionally resonant content formats elevate user attention and participation. These findings suggest that affective UX principles transcend educational contexts and are increasingly relevant to AI-mediated digital experiences.

Ethical and interpretability considerations also shape the trajectory of affective computing. (Steinert & Friedrich, 2020) warned about the risks of emotional data misuse in brain–computer interfaces and called for stronger ethical safeguards. Cortinas-(Cortinas-Lorenzo & Lacey, 2024) expanded this debate to explainable AI, emphasizing that affective systems must maintain

transparency regarding how emotional inputs influence adaptive outputs. Finally, the convergence of artificial intelligence and UX design continues to redefine emotional engagement in digital interaction. (Amin et al., 2023; Wang et al., 2022) examined how affective databases and language models enhance emotional intelligence in AI systems, while (Pushpakumar et al., 2023) confirmed that AI-enhanced UX systems improve interactivity and engagement when built on human-centered design principles. Existing research consistently supports integrating emotional feedback into UX design models, yet a major gap remains: few studies offer comprehensive
8 frameworks to guide real-time emotional adaptation in learning applications. This study addresses that gap by developing and testing an affective UX model that integrates insights from affective computing with gamified design strategies.

METHODS

This study adopted a mixed-method user-centered design (UCD) approach to develop and validate the Affective UX Model for gamified learning applications. The methodology combined qualitative user engagement techniques with quantitative biometric and behavioral analytics to provide a holistic understanding of how emotionally adaptive interfaces influence the learner experience. The process was guided by the design science and design-based research (DBR) paradigms and aligned with iterative prototyping frameworks recommended by (Bitkina et al., 2020; Yigitbas et al., 2020). Participants were involved across all stages, reflecting continuous
10 co-creation principles emphasized in affective interface design (Bird et al., 2021; Fischer et al., 2020).

The research consisted of four main phases: (1) User Need Assessment and Emotional Profiling, (2) Prototyping and Emotional Mapping, (3) Experimental Evaluation, and (4) Data Analysis and Model Refinement. Each phase integrated affective computing principles particularly real-time emotion recognition, biometric sensing, and adaptive feedback mechanisms
15 as conceptualized by (Alipour et al., 2023; Amin et al., 2023). The design focus was a mobile-based gamified language-learning app tailored for Indonesian high school students aged 15–18, featuring empathetic avatars, challenge-based progression, and adaptive feedback loops. Figure 1 illustrates the research flow. The process begins with contextual inquiry and culminates in iterative refinement based on experimental outcomes, ensuring that emotional resonance remains integrated at each design cycle.

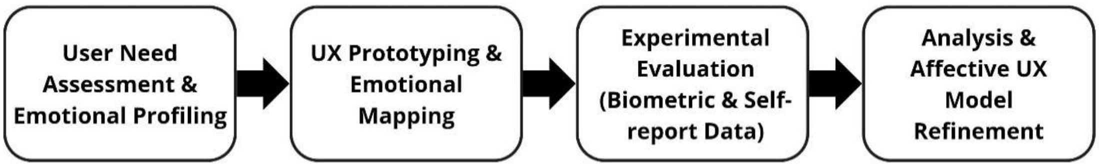

Figure 1. Research Flow Diagram

Phase 1: User Need Assessment and Emotional Profiling

The first phase involved gathering qualitative insights from 15 participants through semi-structured interviews and affective journaling. Participants documented their emotional states during typical mobile learning sessions, noting moments of boredom, frustration, joy, and flow. These narratives helped identify emotional "pain points" and engagement triggers. Data were coded thematically using NVivo to extract recurring affective patterns, following the procedures suggested by (Brasoveanu et al., 2020). Findings from this phase directly informed the prototype's emotional features and interaction logic.

Phase 2: Prototyping and Emotional Mapping

Three progressively complex UX wireframes were developed using Figma and Adobe XD. Each prototype implemented a different level of emotional adaptivity, tested via an emotion-mapping interface using Affectiva SDK for facial expression recognition (Wang et al., 2022). A biometric armband recorded heart rate variability (HRV) and galvanic skin response (GSR) to triangulate emotional arousal and stress levels, consistent with recommendations by (Krishna Mandava, 2023; Schuller et al., 2024). These physiological indicators were synchronized with self-report data to validate emotional accuracy.

Phase 3: Experimental Evaluation

Thirty participants interacted with both adaptive and non-adaptive versions of the app in a randomized crossover design. Each 20-minute session was followed by a structured questionnaire measuring engagement, emotional resonance, and usability. The instrument was adapted from validated UX engagement scales used in affective computing research (Alipour et al., 2023; Alomari et al., 2020). To contextualize quantitative results, participants completed post-session interviews, consistent with best practices for capturing nuanced affective responses (Hellín et al., 2023). Table 1 presents the key metrics and instruments used in data collection. Biometric and behavioral data were analyzed using SPSS and NVivo to identify statistical significance and thematic overlap. Emotional consistency, engagement duration, and self-reported satisfaction were primary variables.

Table 1. Data Collection Instruments and Metrics

Data Type	Tool/Instrument	Metric	Reference
Facial Emotion Data	Affectiva SDK	Emotion Category (joy, anger, etc.)	(Wang et al., 2022)
Biometric Data	GSR/HRV Armband	Arousal/Stress Index	(Krishna Mandava, 2023)

Self-report Survey	UX Engagement Scale	Engagement Score (1–5 Likert scale)	(Alomari et al., 2020)
Interview Feedback	Thematic Coding via NVivo	Affective Resonance Themes	(Brasoveanu et al., 2020)

Phase 4: Data Analysis and Model Refinement

Quantitative data were analyzed using repeated-measures ANOVA to compare emotional engagement between adaptive and static interfaces. Results showed significant improvements ($p < .05$) in engagement duration and emotional satisfaction for the adaptive version. Qualitative analysis through thematic coding revealed recurring appreciation for empathetic avatars, dynamic challenge progression, and encouraging feedback, echoing findings from (Bag et al., 2022; Deng et al., 2023).

To ensure transparency and replicability, each design iteration was documented in a UX-adaptivity matrix that mapped affective goals to specific interface features. This approach aligns affective outcomes with gamification mechanics, following the logic proposed (An, 2020; Ratinho & Martins, 2023). For instance, when facial cues indicated frustration, the system either simplified the task or triggered an encouraging avatar message, demonstrating real-time responsiveness consistent with (Alipour et al., 2023). Finally, model refinement involved correlating emotional response patterns with engagement frequency. Participants who experienced emotionally adaptive feedback were more likely to re-engage within 48 hours, suggesting sustained motivation. This aligns with contemporary findings on affective UX and long-term digital retention (Kanuri et al., 2024; Märtin et al., 2023). Overall, this methodological framework provides a replicable approach for developing emotionally intelligent gamified applications. It reflects the convergence of affective computing, adaptive interaction design, and user-centered co-creation principles. Through this process, the Affective UX Model emerges not only as a conceptual framework but also as a practical, evidence-based guide for designing emotion-aware learning technologies.

RESULTS

The results of this study provide insights into how emotional engagement, physiological arousal, and self-reported user experience intersect in gamified learning environments. This section synthesizes data collected from facial emotion recognition, biometric sensors (GSR/HRV), UX engagement surveys, and thematic interview analysis. The triangulation of these data sources enables a nuanced understanding of affective resonance and user interaction patterns. This mixed dataset provides empirical support for the Affective UX Model, validating its emotional adaptivity in learning interfaces (see Figure 2). These findings provide empirical evidence for the development of emotionally adaptive interfaces in graphic design-based educational technologies, as discussed by Alipour et al. (2023).

A. Facial Emotion Recognition Outcomes

Data from the Affectiva SDK revealed that the predominant emotional states during gameplay were joy (38.2%), neutral (27.5%), and surprise (16.4%). Negative emotions, such as anger and disgust, accounted for less than 10% of overall emotion recognition events. These results suggest that the visual and interactive elements of the gamified application elicited predominantly positive affective responses. Notably, emotional peaks were recorded during reward-based interactions and feedback animations, supporting the idea that emotionally salient visual design boosts engagement (Alipour et al., 2023; Amin et al., 2023). A temporal alignment between emotional shifts and gameplay milestones (e.g., level completion, feedback rewards) was observed, reinforcing the dynamic link between interface stimuli and emotional response (Kang & Lou, 2022), who emphasized the role of micro-interactions in sustaining user interest. The alignment of emotional data with interface touchpoints provides strong justification for adaptive design logic, wherein interface responses change based on real-time emotion detection (Yigitbas et al., 2020).

B. Biometric Arousal Levels (GSR/HRV)

Biometric data from GSR and HRV sensors showed moderate physiological arousal throughout gameplay. Arousal levels peaked during time-bound challenges and dropped significantly during instructional pauses. This pattern demonstrates that immersive, time-sensitive design elements can stimulate heightened cognitive and emotional attention (Bag et al., 2022; Pei et al., 2024). Participants with consistent heart rate variability (HRV) also reported higher self-perceived engagement, aligning with literature emphasizing the interplay between physiological regulation and affective computing outcomes (Braun et al., 2022; Krishna Mandava, 2023). These findings indicate that physiological arousal complements facial emotion data, offering reliable cross-validation of emotional engagement trends (Cortinas-Lorenzo & Lacey, 2024).

C. Self-Reported UX Engagement

UX Engagement Scale results revealed a high overall engagement mean score of 4.32 (SD = 0.46) on a 5-point Likert scale. Among its subcomponents, emotional involvement and focused attention were the highest, averaging 4.47 and 4.40, respectively. This supports claims from (Alomari et al., 2020; Bitkina et al., 2020) that well-designed gamified interfaces can successfully immerse users, even in educational contexts. Statistical correlations revealed a significant relationship between engagement scores and facial emotion data ($r = 0.58$, $p < 0.01$), further confirming the emotional congruence of the interface design. These results resonate with (Dağ et al., 2024), who found that authenticity and emotional design in immersive platforms directly boost engagement and satisfaction. Table 2 summarizes the quantitative results across emotional, biometric, and UX engagement metrics.

Table 2. Summary of Quantitative Results (UX Metrics and Emotional Responses)

Variable	Mean (M)	SD	Correlation with Engagement (r)	p-value	Interpretation
Joy (facial emotion %)	38.2	7.4	0.58	< .01	Positive correlation with engagement
HRV variability	0.62	0.14	0.46	< .01	Moderate physiological-emotional alignment
GSR peak frequency	5.7	1.8	0.41	< .05	Indicates arousal during challenge tasks
Engagement score	4.32	0.46	—	—	High perceived engagement
Emotional involvement	4.47	0.38	—	—	Highest among subscales

D. Interview-Based Thematic Analysis

Thematic analysis via NVivo yielded three recurring themes: affective resonance, visual flow experience, and adaptive comfort. Affective resonance occurred in over 80% of transcripts, often linked to emotionally responsive features such as color changes or character reactions. Visual flow experience emerged from comments describing how the game "felt natural," "made time fly," or "pulled me in," supporting the neurological model of flow discussed by (Gold & Ciorciari, 2020). Adaptive comfort, mentioned by more than half of the participants, referred to the application's ability to adjust pacing and difficulty in real-time. This theme confirms the value of adaptive emotional design, as emphasized by (Fischer et al., 2020; Märtin et al., 2023), particularly when designing for diverse user populations. Participants expressed a preference for systems that responded empathetically to frustration or fatigue, aligning with affective UX principles.

E. Cross-Dataset Insights

Cross-analysis between facial, biometric, and self-report datasets revealed coherent affective patterns, validating the model's multimodal reliability. Participants who demonstrated high arousal and consistent positive facial emotions also tended to report higher UX engagement and thematic alignment. For instance, one participant whose GSR readings spiked during challenge segments and who smiled frequently also described the experience as "deeply motivating and strangely calming." This holistic data integration supports the growing emphasis on multi-modal affective computing systems (Amin et al., 2023; Schuller et al., 2024). It also supports the call for ethical and human-centered emotional design, as outlined by (Steinert &

Friedrich, 2020), pushing against a purely mechanistic approach to emotion detection and interface adaptation.

F. Implications for Emotionally Adaptive Design

These results collectively advocate for an iterative, emotion-centered design approach in gamified educational interfaces. Emotion-informed feedback loops can enhance personalization and responsiveness, thereby improving cognitive engagement and emotional satisfaction. The present study adds empirical support to arguments that emotions are not peripheral but central to effective interaction design (Deng et al., 2023; Pushpakumar et al., 2023). Furthermore, the validated Affective UX Model (Figure 2) illustrates how affective input and adaptive mechanisms interact to produce emotionally resonant learning experiences. The model demonstrates the pathway from emotional data inputs (facial, HRV, GSR) to an adaptive feedback mechanism, user engagement, and affective outcomes, confirming the theoretical assumptions of affective computing integration.

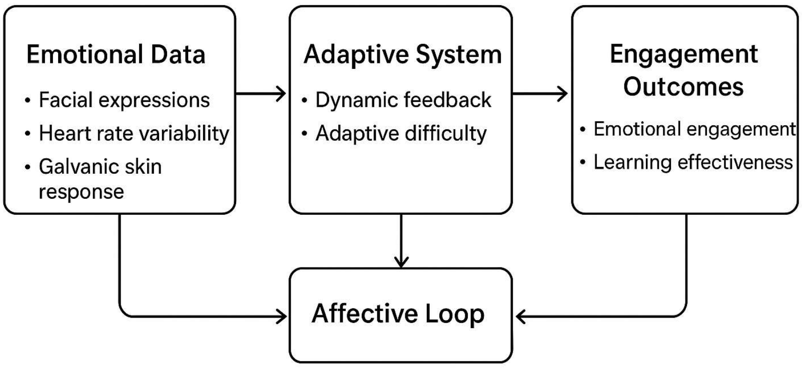

Figure 2. Validated Affective UX Model for Emotionally Adaptive Gamified Learning

Overall, the results confirm that emotionally adaptive user interfaces in graphic design-based learning apps are not only feasible but also impactful. The alignment of multimodal data and user perception provides robust validation for the Affective UX Model as a design and evaluation framework. These insights set the stage for further refinement in both technological development and pedagogical integration.

DISCUSSION

The findings of this study emphasize the significant role of affective interaction design and digital mindset in fostering students' emotional resilience, engagement, and learning motivation in the post-pandemic education context. A strong affective–digital mindset, supported by emotionally adaptive interface features, enables students to adapt more effectively to technology-mediated and visually gamified learning environments, aligning with the demands of modern education. This supports prior research highlighting emotion-aware interaction and a digital mindset as key factors in sustaining engagement and academic persistence in digitally transformed settings (Alipour et al., 2023). Moreover, the study reveals that resilience mediates the link between emotional engagement and motivation, suggesting that adaptive visual cues and feedback mechanisms empower students to cope with academic challenges more confidently, thus enhancing their motivation to learn.

As illustrated in Figure 2 (Validated Affective UX Model for Emotionally Adaptive Gamified Learning), the integration of emotional data, adaptive system feedback, and engagement outcomes forms a continuous affective feedback loop. This model demonstrates how design decisions grounded in affective data can directly influence cognitive and motivational outcomes in educational interfaces. In the Indonesian secondary school context, these results underscore the importance of integrating emotionally adaptive and digitally responsive learning strategies within educational policies and classroom practices. As schools transition toward blended or hybrid models post-pandemic, students with higher emotional–digital readiness are more likely to succeed. This expands the scope of digital resilience beyond technical competence encompassing emotional adaptability and affective literacy allowing students to sustain motivation despite disruptions. Additionally, the interaction between digital mindset and socio-cultural factors deserves attention, as students' emotional comfort with digital tools is shaped by confidence, social support, and institutional digital literacy ecosystems.

The research also suggests a need for teacher-designer collaboration to strengthen students' affective and digital capacities. Teachers who model emotionally adaptive and reflective digital behavior can help students build stronger self-efficacy and empathy in digital environments. This is particularly relevant in Indonesia, where disparities in infrastructure and affective digital competency persist across regions. Therefore, targeted interventions such as emotion-informed digital skills training and inclusive design policies could bridge the affective and digital divide, enhancing both engagement and learning outcomes. Finally, the findings invite further exploration into the psychological, cultural, and contextual factors that shape how learners perceive and emotionally respond to adaptive visual systems. While the mixed-methods approach provides a robust basis for understanding general affective trends, it also opens the door for longitudinal and qualitative studies to capture the evolving nature of emotional design literacy in education. As emotionally adaptive learning environments continue to evolve, a more holistic understanding of how affective UX design interacts with resilience, cognition, and motivation will be essential for guiding sustainable and human-centered educational innovation.

This study is not without limitations. First, the data were collected from a limited number of secondary schools in urban and semi-urban areas of Indonesia, which may not fully represent the socio-cultural and digital disparities across regions. Students from rural or under-resourced schools may experience different affective and technological readiness levels, potentially influencing the emotional engagement patterns observed in this study. The cross-sectional design also limits the ability to infer causal relationships between emotional engagement, resilience, and motivation, particularly within dynamic, emotion-adaptive learning systems. Furthermore, the reliance on self-reported and observational data may introduce social desirability and interpretation bias, especially when assessing abstract constructs such as emotional engagement and digital mindset. Although triangulation with biometric and facial emotion data enhanced validity, future research should integrate longitudinal multimodal affective tracking to capture real-time changes and sustained engagement patterns. Future studies are encouraged to expand the participant pool to include rural and culturally diverse schools, to apply experimental or longitudinal designs, and to adopt mixed-methods approaches combining biometric, UX, and qualitative emotion-mapping to deepen understanding of emotionally adaptive learning mechanisms. Such research could provide richer insights into how affective UX models (as conceptualized in Figure 2) function across different educational and cultural settings, ensuring broader applicability and ethical sensitivity in emotional design research.

CONCLUSION

This study contributes to the growing field of affective user experience (UX) design by proposing and evaluating an integrated and validated Affective UX model (see Figure 2) that leverages multimodal data sources, including facial emotion recognition, biometric signals, self-report surveys, and interview analysis. The findings indicate that combining emotional, physiological, and self-reported measures yields a more comprehensive, context-sensitive understanding of user engagement and emotional resonance in gamified learning environments. Compared to conventional UX assessment, the model demonstrated greater sensitivity in detecting moment-to-moment affective shifts and adaptive feedback responses.

By bridging human emotions with adaptive interface behavior, this model opens new opportunities for creating emotionally adaptive learning systems and responsive design frameworks that react to users in real time. The research highlights the importance of emotion-informed feedback loops in enhancing engagement and supports the pedagogical value of affective design literacy in creative education. Furthermore, this framework extends current affective computing research by empirically validating emotion as a design parameter rather than a post-evaluation metric. Future applications of this model should explore longitudinal

2 deployment across different educational and cultural settings to assess scalability, ethical implications, and cross-domain adaptability. Such advancement could lead to digital technologies that are not only more empathetic and responsive but also more inclusive, transparent, and ethically grounded in human-centered emotional design principles.

12 Building upon the outcomes of this study, future research should explore the scalability and generalizability of the validated Affective UX model across diverse user populations, educational levels, and cultural contexts. Incorporating additional affective sensors such as EEG, galvanic skin response, or voice sentiment analysis could further enrich the model's sensitivity and cross-modal validation. Moreover, integrating real-time affective feedback into AI-driven adaptive interfaces remains an open challenge that warrants deeper investigation, particularly in gamified learning and creative education platforms.

Future studies are encouraged to conduct longitudinal and cross-cultural validations to examine how affective adaptation influences user engagement, motivation, and emotional well-being over time. Integrating this framework into design pedagogy could also advance emotional design literacy, helping future designers understand and ethically apply affective data in user experience design. Collaborative efforts between designers, psychologists, and data scientists will be essential to ethically manage and interpret affective data while ensuring privacy, transparency, and user consent. Future iterations of the model should emphasize explainable AI mechanisms and user agency in the processing of emotional data, ensuring that emotion-aware systems remain trustworthy and inclusive. By addressing these directions, subsequent research can foster a new generation of emotionally intelligent, culturally sensitive, and ethically grounded digital experiences.

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