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Improving Digital Learning Experiences in TVET: A Computer-Aided Emotion Assessment Using LEIQ™

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Abstract

Emotional engagement plays a crucial role in shaping learning experiences, particularly in Technical and Vocational Education and Training (TVET), where practical and applied skills require high levels of user interaction. Integrating emotional responses into user experience (UX) evaluation in the digital era is essential for improving web-based learning environments. This research introduces a computer-aided assistive tool to enhance emotional UX assessment using Lokman's Emotions and Importance Quadrant (LEIQ™) model. By automating data collection and processing, the tool provides a systematic and scalable approach to understanding learners' emotional responses. Existing emotion measurement tools struggle to handle large datasets, often relying on manual processes that limit efficiency and accuracy. To address these limitations, this paper presents the design, development, and evaluation of an automated LEIQ™-based assistive tool, comparing its effectiveness with traditional manual methods through qualitative analysis and user testing. Findings indicate that the tool significantly enhances the accuracy and efficiency of emotion assessment, providing valuable insights for educators, instructional designers, and researchers in the education sector. This advancement has broader implications for UX practitioners, technology developers, and researchers, offering a scalable solution for integrating emotional intelligence into digital learning environments. By refining the LEIQ™ assessment process, this research contributes to the development of more engaging, responsive, and effective educational tools, ultimately enhancing learning outcomes in vocational and technical education.

1. Introduction

In the evolving landscape of Technical and Vocational Education and Training (TVET), digital learning environments play a crucial role in equipping learners with the skills needed for industry readiness. While traditional learning methodologies in TVET emphasize hands-on practice and technical competencies, the integration of digital tools has expanded opportunities for flexible, interactive, and personalized learning experiences (Razak et al., 2022). However, ensuring that these digital environments effectively engage learners goes beyond functionality, it requires an understanding of their emotional experiences during interaction with educational technologies. Emotional engagement is a key factor in motivation, learning retention, and overall success in digital education (Kordrostami & Seitz, 2021). User experience (UX) research has demonstrated that emotions significantly impact on how users interact with digital platforms (Hussain et al., 2018; D'Errico et al., 2016). Positive emotions can enhance engagement and cognitive processing, whereas negative emotions may hinder learning outcomes. Despite the growing importance of emotional UX in education, existing evaluation methods often rely on manual assessments that are time-consuming and inefficient, particularly in large-scale learning settings. The Lokman's Emotions and Importance Quadrant (LEIQ™) model has been recognized for its effectiveness in measuring emotional responses in various contexts, including education (Sheikh et al., 2022). However, its traditional paper-based implementation limits its applicability in digital learning systems.

To address this gap, this research introduces a computer-aided assistive tool that automates the evaluation of emotional UX using the LEIQ™ model. By streamlining data collection, processing, and analysis, the proposed tool enhances the accuracy and efficiency of emotional assessments in digital TVET learning environments. This study explores the design, development, and validation of the tool, comparing its effectiveness with traditional manual approaches through qualitative analysis and user testing. The findings of this research have significant implications for TVET educators, instructional designers, and policymakers, providing insights into how emotional engagement can be better integrated into digital learning systems. By bridging the gap between UX evaluation and digital education, this study contributes to the development of more adaptive, engaging, and learner-centred tools that support the evolving needs of TVET institutions.

2. Literature Review

In this section, the article explores key aspects of emotional assessment in digital learning environments within TVET. It examines the role of user emotions in shaping learning experiences, the significance of UX evaluation in educational technology, and the limitations of existing emotion assessment methods. Additionally, it discusses the LEIQ™ model and its potential for automation in enhancing digital learning experiences.

2.1 Emotion Assessment in Digital Learning

Emotions play a crucial role in shaping learning experiences and influencing engagement, motivation, and cognitive retention. In digital learning environments, emotional responses can determine the effectiveness of educational tools, as positive emotions enhance learning outcomes while negative emotions may hinder progress (Ahmad et al., 2024). Within Technical and Vocational Education and Training (TVET), where practical and applied skills are central, interactive and engaging digital platforms are essential. However, current digital learning solutions often overlook the role of emotions in UX, limiting their ability to support learners effectively. Understanding emotional UX in digital learning requires examining how emotions impact various aspects of user interaction, including motivation, satisfaction, and usability. Studies indicate that learners who experience positive emotions, such as curiosity and excitement, are more likely to engage actively with digital learning platforms (Wijekumar, 2021). Conversely, frustration and confusion can lead to disengagement, reducing the effectiveness of educational tools. Researchers emphasize that designing digital learning environments with emotional responsiveness in mind can significantly improve learner retention and performance (Mohamed et al., 2022).

Moreover, emotional UX plays a fundamental role in self-directed learning, which is often emphasized in TVET settings. Digital learning platforms that incorporate features such as adaptive feedback, gamification, and emotion-aware design can help mitigate negative emotions and foster a more engaging experience (Ennouamani & Mahani, 2017). By integrating emotional UX principles, TVET institutions can create learning environments that not only deliver technical knowledge but also support students' psychological well-being. To effectively measure emotional engagement in digital learning, it is crucial to adopt methodologies that capture both explicit and implicit user responses. Traditional approaches, such as self-report surveys and direct observations, provide valuable insights but are limited in scalability. Emerging technologies, such as artificial intelligence (AI) and machine learning, offer new possibilities for real-time emotion assessment. These innovations pave the way for more personalized and adaptive learning experiences (Vistorte et al., 2024). In summary, integrating emotional UX into digital learning design can significantly enhance engagement and learning outcomes in TVET. This section provides a foundation for understanding how emotions influence digital learning and highlights the need for more effective emotion assessment tools.

2.2 Technical and Vocational Education and Training (TVET)

Technical and Vocational Education and Training (TVET) play a vital role in preparing individuals for the workforce by equipping them with industry-relevant skills and competencies. Unlike traditional academic education, TVET emphasizes hands-on training, practical knowledge, and skill development tailored to specific professions (Tsang, 1997). This focus on applied learning makes TVET a crucial component of economic growth, as it helps bridge the skills gap and meets labor market demands. TVET institutions incorporate a variety of learning approaches, including classroom instruction, workshops, apprenticeships, and online training. The integration of digital learning technologies has transformed TVET, making education more accessible and flexible (Chiang et al., 2021). Online simulations, virtual labs, and interactive modules allow learners to develop technical skills in a controlled environment before applying them in real-world settings. However, digital learning in TVET also presents challenges, such as the need for specialized instructional design, ensuring hands-on learning experiences, and maintaining student engagement.

One of the key challenges in TVET digital learning is replicating the experiential aspect of hands-on training (Mutebi et al., 2023). While digital tools provide theoretical knowledge and practice exercises, they may lack the depth of physical, real-world engagement. Augmented Reality (AR) and Virtual Reality (VR) have been increasingly explored as solutions to this issue, enabling immersive learning experiences that simulate real-world scenarios (Kuhail et al., 2022). These technologies allow learners to practice technical skills in a risk-free environment, enhancing their confidence and preparedness for actual work settings. Another significant aspect of TVET is competency-based learning, where students progress based on skill mastery rather than time-based assessments. This approach aligns well with adaptive learning technologies that personalize educational content based on learners' progress and emotional engagement. AI-driven platforms can track student performance and provide customized feedback, ensuring that learners acquire the necessary competencies before advancing to the next level (Ennouamani & Mahani, 2017). In summary, TVET is a crucial pillar in workforce development, providing learners with practical skills needed for various industries. The integration of digital learning technologies presents both opportunities and challenges, necessitating the development of emotion-aware and adaptive learning systems. Future advancements in TVET digital education should focus on leveraging AI, AR/VR, and emotional UX assessment tools to enhance student engagement and ensure effective skill acquisition.

2.3 Emotion Measurement Tools in Education

Assessing emotions in digital learning environments remains challenging due to limitations in existing measurement tools. Traditional methods, such as self-report surveys and structured interviews, often rely on subjective interpretations, making it difficult to obtain consistent and reliable data. While these approaches provide insights into learners' emotional experiences, they are time-consuming and may not capture real-time fluctuations in emotional states. Furthermore, the accuracy of self-reported data is often influenced by social desirability bias, in which participants may alter their responses to conform to perceived expectations. Another common emotion assessment approach uses facial recognition software and physiological sensors to track users' expressions, heart rates, and other biometrics. While these tools offer objective data collection, their implementation in educational settings faces several barriers. High costs, ethical concerns about data privacy, and the need for specialised hardware limit their widespread adoption (Dhirani et al., 2023). Additionally, cultural differences in emotional expression pose challenges for facial recognition-based assessments, as not all users exhibit emotions in the same way.

Sentiment analysis, which evaluates textual data such as student feedback and discussion forums, has gained popularity as an alternative method for assessing emotions in learning environments (Mite-Baidal et al., 2018). However, this approach also has limitations, as it relies heavily on natural language processing (NLP) algorithms that may struggle with context, sarcasm, and linguistic variation. Furthermore, sentiment analysis does not account for nonverbal emotional cues, limiting its ability to capture learners' true experiences (Zukerman & Litman, 2001). A major limitation of current emotion measurement tools is their lack of scalability. Traditional assessments require manual data collection and analysis, which can be impractical in large-scale educational settings. The lack of automated systems capable of efficiently processing large volumes of emotional data hinders educators' and researchers' ability to make data-driven decisions in real time. This highlights the need for more robust, scalable, and adaptable tools that seamlessly integrate with digital learning platforms. Accurately measuring emotions remains a complex assessment, especially in digital learning environments where understanding user emotions is crucial. Various tools have been developed to assess emotional responses, each with its strengths and limitations.

The challenges in emotional assessment tools include self-report surveys, facial recognition, sentiment analysis, and manual data collection, underscoring the need for innovative solutions. Each of the reviewed emotion measurement tools has distinct limitations that affect their usability in digital learning environments. Tools like Product Emotion Measurement (PrEmo) measure emotional responses by allowing users to select from predefined emotions and offer intuitive self-reporting, but they lack depth and may not capture complex or mixed emotions experienced by learners in digital environments (Desmet, 2018). Meanwhile, Kansei Engineering (KE) captures deep emotional responses by analysing users' affective impressions of products or digital experiences. It provides detailed assessments but requires extensive analysis (López et al., 2021). Thus, Lokman's Emotions and Importance Quadrant (LEIQ™) present a structured model to assess emotional UX, but it needs automation to improve scalability. Getting around these problems by collecting real-time data and automating tasks with AI can improve emotion assessment in digital learning, making TVET experiences more flexible and engaging. These problems can be addressed by developing a computer-assisted tool to help gather emotional UX data in digital learning environments. This procedure would provide educators with useful information they can use to improve the learning experience.

2.4 Lokman's Emotions and Importance Quadrant (LEIQ™) Model

The Lokman's Emotions and Importance Quadrant (LEIQ™) model provides a structured approach to understanding emotional experiences in digital learning environments. This model categorizes emotions based on their intensity and perceived importance, offering a systematic method for evaluating how users interact with digital platforms (Lokman et al., 2019). In the context of TVET, where learner engagement is critical, applying the LEIQ™ model enables educators and designers to assess emotional responses effectively and refine digital learning tools accordingly. The LEIQ™ model classifies emotions into four quadrants: high importance-high emotion, high importance-low emotion, low importance-high emotion, and low importance-low emotion (Lokman et al., 2022). This classification helps educators and developers determine which emotional states significantly impact learning experiences and which can be deprioritized. For instance, emotions such as frustration and confusion in the high importance-high emotion quadrant indicate critical barriers to learning that require immediate intervention.

Applying the LEIQ™ model in digital learning platforms allows for real-time monitoring and adaptation. By integrating emotion-aware features, such as adaptive feedback and dynamic content adjustments, learning systems can respond more effectively to users' emotional states (Caballe, 2015). This approach aligns with personalized learning strategies, ensuring that learners remain engaged and motivated throughout their educational journey. Despite its benefits, manual implementation of the LEIQ™ model in educational settings poses challenges, particularly regarding data collection and analysis. Traditional methods rely on self-reports and observational techniques, which are time-consuming and subject to bias. Automating the model through a computer-aided tool can enhance its scalability and accuracy, making emotion assessment more efficient in large-scale TVET programs. In summary, the LEIQ™ model presents a valuable tool for assessing emotional UX in digital learning. By automating its application, educators and researchers can gain deeper insights into learners' emotional states, ultimately leading to the development of more effective and emotionally intelligent digital education solutions.

2.5 Advantages of a Computer-Aided Assistive Tool in TVET

The integration of automation in UX and emotional assessment has revolutionized how emotions are analyzed in digital learning environments. Traditional UX evaluation methods, such as surveys and interviews, require significant time and resources (Lokman et al., 2019). Automated systems, leveraging artificial intelligence (AI) and machine learning, offer real-time emotion assessment, enhancing the scalability and precision of UX research. In the context of TVET, automation enables efficient analysis of learners' emotional engagement, ensuring that digital learning platforms cater to their needs effectively (Ahmad et al., 2024). Automated emotion assessment tools employ techniques such as facial expression recognition, sentiment analysis, and physiological monitoring to dynamically capture user emotions. These technologies help educators and instructional designers understand how learners respond to different digital learning materials, enabling real-time content adaptation. This capability is particularly beneficial for TVET, where practical engagement is key to skill acquisition.

One significant advantage of automation in emotional UX assessment is its ability to efficiently process large datasets. Unlike manual evaluation, which is constrained by human limitations, AI-driven systems can analyze vast amounts of learner feedback, detecting patterns and trends in emotional responses (Bolton & Bass, 2010). This data-driven approach supports continuous improvements in digital learning design, making platforms more responsive and user-centric. However, implementing automated emotion assessment tools also presents challenges. Despite the increasing recognition of emotional engagement in digital learning, TVET institutions lack effective tools for evaluating learners' emotional UX (Mebane et al., 2008). Current assessment methods rely on either subjective self-reports or complex biometric analysis, both of which present scalability challenges. A computer-aided assistive tool can bridge this gap by providing an automated and user-friendly approach to emotion assessment in digital learning environments. A well-designed assistive tool should integrate the LEIQ™ model to systematically assess and categorize learner emotions. By automating data collection and analysis, the tool can offer real-time insights into students' emotional states, enabling educators to tailor their instructional strategies accordingly (Kim et al., 2018). This approach aligns with personalized learning methodologies, which emphasize adapting content based on individual learner needs.

Incorporating technology-assisted emotion recognition into TVET digital platforms can enhance learning experiences by identifying and mitigating negative emotions such as frustration or confusion (Van Der Haar, 2019). This proactive approach ensures learners receive immediate support, whether through adaptive feedback, interactive problem-solving exercises, or peer collaboration. Such interventions can significantly improve engagement and retention rates in TVET education. Developing and implementing a computer-aided assistive tool requires careful consideration of technological, ethical, and educational factors. Ensuring data privacy, minimizing bias in emotion detection algorithms, and integrating seamlessly with existing TVET digital infrastructure are critical for successful adoption (Abu Bakar et al., 2024). Collaborative efforts between UX researchers, educators, and developers are essential in creating a tool that is both effective and practical for widespread use. In summary, a computer-aided assistive tool presents a promising solution for enhancing emotional UX assessment in TVET digital learning environments. By leveraging automation and the LEIQ™ model, such a tool can provide valuable insights into learner engagement, ultimately leading to more effective and adaptive vocational education programs.

3. Methodology

This section outlines the research methodology used to develop and evaluate the proposed computer-aided emotion assessment tool in digital learning. The study employs a mixed-methods approach, combining qualitative and quantitative techniques to ensure comprehensive analysis. Data collection includes user testing, surveys, and expert interviews, while statistical and thematic analysis methods are applied to interpret the findings. By integrating both subjective and objective measures, this methodology provides a robust model for assessing the tool's effectiveness in enhancing emotional UX in TVET environments.

3.1 Research Design

The study adopts a mixed-methods research design, integrating qualitative and quantitative approaches to provide an understanding of emotional UX in digital learning. Qualitative methods, such as semi-structured interviews and focus group discussions, are employed to gather in-depth insights from experts and users. Meanwhile, quantitative data is collected through surveys and system logs to measure the tool's impact on emotion assessment, accuracy, and efficiency.

3.2 Sampling Technique and Sample Size

The study utilises purposive sampling to select participants with relevant expertise and experience in UX, emotion assessment, and digital learning. The sample includes UX researchers, educators, and students unfamiliar with the LEIQ™ model to ensure a diverse perspective. A total of 20 participants were recruited to ensure a balance between expert insights and user experience.

3.3 Data Collection Methods

Data collection is conducted in three phases:

- Phase 1: Expert Interviews – Semi-structured interviews with UX specialists and LEIQ™ practitioners were conducted to refine the tool's design requirements.
- Phase 2: Prototype Development and Usability Testing – A web-based LEIQ™ prototype was developed and tested by participants through interactive sessions.
- Phase 3: Comparative Analysis – The results of manual LEIQ™ assessments were compared with those obtained using the automated tool to evaluate efficiency and accuracy.

3.4 Data Analysis Methods

The study applies both qualitative and quantitative analysis techniques; Thematic Analysis – Qualitative data from interviews and focus groups were transcribed and analyzed to identify recurring themes and patterns. A comparative analysis was conducted to measure the speed and scalability of manual and automated assessments and determine the benefits of automation in the LEIQ™ application.

In summary, the methodology employed in this study ensures a systematic evaluation of the proposed computer-aided emotion assessment tool. By leveraging a combination of qualitative and quantitative approaches, this research provides valuable insights into improving digital learning experiences in TVET later through emotion-aware UX design. This section outlines the research methodology used to develop and evaluate the proposed computer-aided emotion assessment tool in digital learning. The study employs a mixed-methods approach, combining qualitative and quantitative techniques to ensure comprehensive analysis. Data collection includes user testing, surveys, and expert interviews, while statistical and thematic analysis methods are applied to interpret the findings.

4. Results and Discussion

This section outlines the research methodology used to develop and evaluate the proposed computer-aided emotion assessment tool in digital learning. The study employs a mixed-methods approach, combining qualitative and quantitative techniques to ensure comprehensive analysis. Data collection includes user testing, surveys, and expert interviews, while statistical and thematic analysis methods are applied to interpret the findings. By integrating both subjective and objective measures, this methodology provides a robust model for assessing the tool's effectiveness in enhancing emotional UX in TVET environments.

The study began with semi-structured interviews conducted with two LEIQ™ practitioners to determine the essential design requirements for the assistive tool. The practitioners provided insights into the challenges of the manual emotion assessment process, including time-consuming data collection, difficulties in managing large datasets, and inconsistencies in self-reported emotions. They also emphasized the need for an automated approach to enhance data accuracy and streamline the assessment process.

Table 1 *Key findings from the interview highlighted*

Requirement	Discussion
Customization and Adaptability	The tool must offer configuration options to accommodate various TVET disciplines, enabling instructors and learners to tailor assessments to specific educational needs. This ensures flexibility and broader applicability across different learning scenarios.
Real-Time Feedback and Interaction	The tool should support real-time updates, instantly reflecting changes in emotional assessments as learners engage with digital content. This feature enhances responsiveness and allows educators to make timely interventions.
User Guidance and Support	To ensure ease of adoption, the tool should include comprehensive training resources such as tooltips, tutorials, and guided walkthroughs. These resources will reduce the learning curve and improve usability for both learners and educators.
Scalability and Performance Optimization	The system must be designed to support a growing number of users and increasing data inputs. Efficient backend processing and optimized performance should be implemented to maintain fast response times, even with extensive datasets.
Multi-platform and Cross-Browser Compatibility	The tool should be accessible across multiple devices and compatible with various web browsers. This ensures seamless usage in different learning environments, promoting accessibility and inclusivity.
Continuous Improvement via Feedback Mechanism	A structured feedback system should be integrated, allowing educators and learners to provide insights into usability and effectiveness. This mechanism will facilitate iterative updates to enhance functionality and align with evolving user needs in TVET digital learning.

After the requirement analysis phase, the design and development of a low-fidelity prototype for the web-based LEIQ™ assistive tool commenced using the Miro platform—an interactive digital workspace. The prototype was developed to incorporate the LEIQ™ model into a web-based platform, facilitating the systematic evaluation of users' emotional reactions in digital learning contexts.

5. Design for Improved Digital Learning

The prototype includes three practical features, each designed to help learners complete assessment tasks efficiently. These features enhance the user experience by providing clear, intuitive navigation while ensuring a seamless assessment process. The integration of Miro enabled remote collaboration and real-time updates, enabling iterative improvements based on expert feedback. Developed with flexibility in mind, the web-based tool supports a variety of assessment contexts beyond a single evaluation. This adaptability makes it particularly suitable for practical education, specifically in TVET, where learners are expected to apply knowledge independently and complete tasks without extensive guidance. By incorporating structured emotional UX assessment, the tool enables educators to monitor learners' emotional engagement across multiple subjects and learning conditions, enhancing overall learning outcomes. To assess the tool's usability and effectiveness, two focus group discussions were conducted, involving 20 participants from age 20 to 26 years old. The first group (12 participants) performed the LEIQ™ assessment manually using paper-based methods, while the second group (8 participants) utilized the developed web-based LEIQ™ prototype. The web-based tool eliminated the need for physical presence and assistance, allowing participants to engage in the assessment remotely and independently. Its three primary features played a crucial role in supporting learners by providing a structured and interactive platform, where students must independently transform information and ideas into practical applications beyond the guidance provided. Visual representations and detailed breakdowns of the prototype's interface and menu structures are provided in the following subsections, illustrating the transformation of gathered requirements into a functional design.

5.1 Computer-Aided Feature I

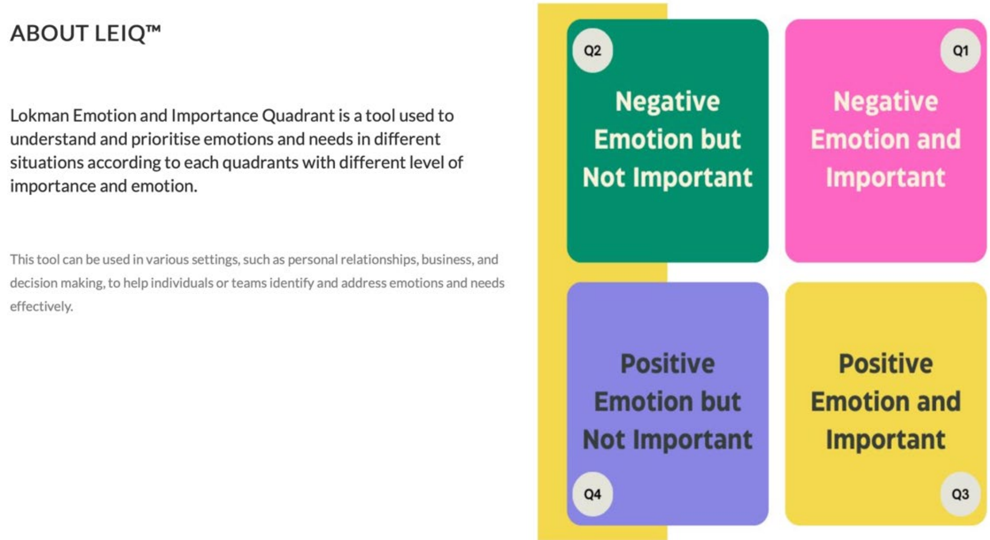

Fig. 1 *Computer-aided feature I: Introduction of LEIQTM model*

The introduction to the LEIQ™ model on the initial web page serves as an essential foundation for learners before they engage in the assessment. This introductory section is designed to ensure that participants fully understand the purpose and significance of emotional UX evaluation, particularly within the context of TVET education, where emotional engagement can directly impact skill acquisition and learning motivation. By providing a clear overview of the LEIQ™ model, the tool helps learners contextualize their upcoming assessment, reinforcing the importance of emotions in practical and applied learning environments. A visual representation of the LEIQ™ quadrants is strategically placed within this section, offering an immediate reference to the model's structure and key elements. This not only enhances comprehension but also supports self-directed learning, a critical aspect of TVET education, where students are expected to independently analyze, evaluate, and apply knowledge. By incorporating best practices in user-centered design, the tool ensures a seamless user experience, allowing learners to navigate the assessment with confidence and clarity.

5.2 Computer-Aided Feature II

Fig. 2 *Computer-aided feature II: Pre-recorded manual assessment example*

The start page features a section highlighting the manual assessment process conducted on December 16, 2023, at Universiti Teknologi MARA. This session, which preceded the web-based prototype testing, was strategically designed to provide the researcher with firsthand insights into the manual implementation of the LEIQ™ model. By facilitating direct observation and hands-on engagement in a focus group discussion, the session enabled the identification of key areas for improvement in developing the assistive tool for digital UX assessment. To document this transition from manual to web-based assessment, images from the session are prominently displayed on the start page via an interactive carousel (see Fig. 2). This feature provides users with a visual preview of the manual testing process, reinforcing the practical application of emotional UX assessment in an educational setting. Later, for TVET learners and educators, this visual representation serves as an educational resource, illustrating how manual emotion assessments were traditionally conducted and demonstrating the evolution toward digital methodologies. By integrating this historical perspective, the tool fosters a deeper understanding of UX evaluation, helping TVET students recognize the impact of emotions on learning experiences while equipping them with insights into digital transformation in educational assessment practices.

5.3 Computer-Aided Feature III

In computer-aided feature III, video-assisted support is provided to complete LEIQ tasks 1-4 in a sequential format, assisting participants in expressing their emotions and experiences regarding the pertinent topic or theme. Refer Fig. 3 and Fig.4 for tutorial Task 1 and Task 2.

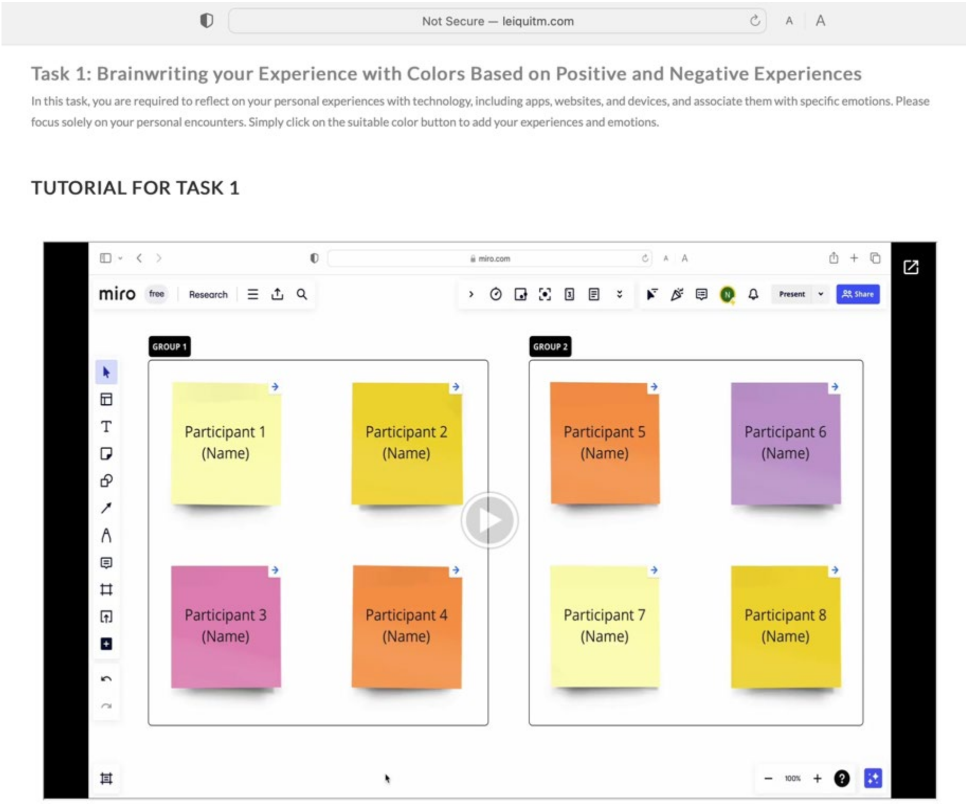

Fig. 3 *Computer-aided feature III: Tutorial for Task 1*

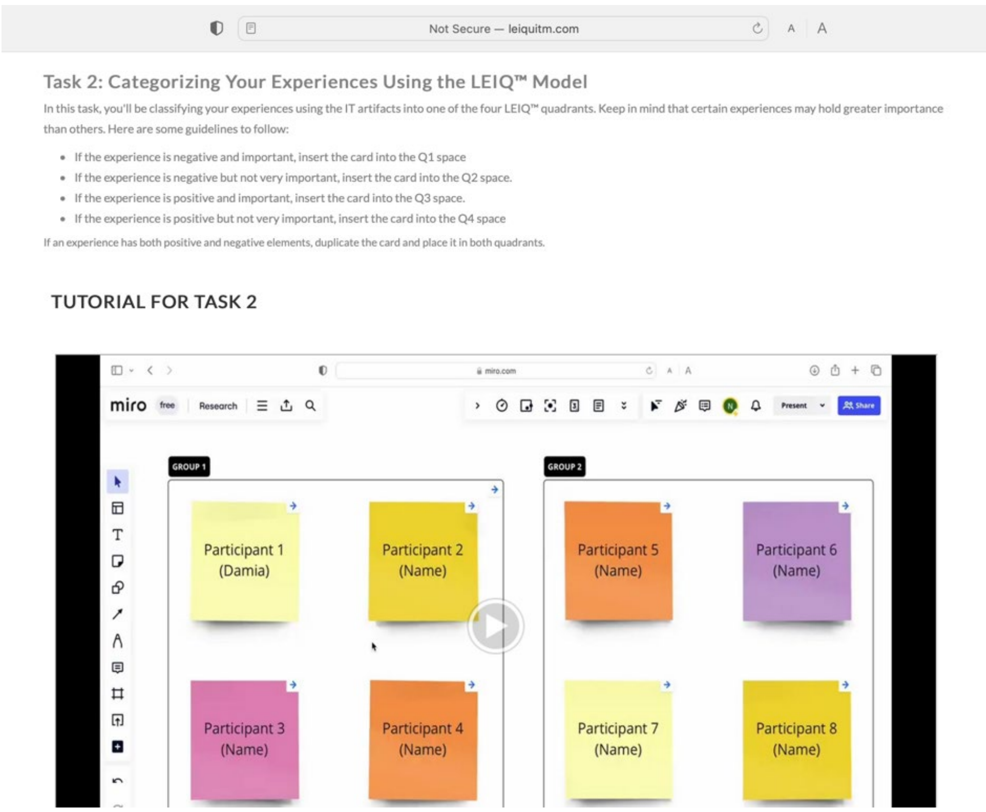

Fig. 4 *Computer-aided feature III: Tutorial for Task 2*

Task 1 board requires an introspective process of reflecting on one's own experiences relating to the given themes. We ask participants to connect their experiences with specific emotions. The procedure's completion is facilitated by the colour-coded sticky notes on the display board. The sticky note function allows simple board placement. We encourage participants to select a colour that accurately reflects their emotions and experiences, creating a visual depiction of their reflections. Sticky notes enable participants to effortlessly position them on the boards by allowing them to drag and drop them as required. This function offers a structured way for people to share their ideas and feelings. Blue sticky notes are for positive emotions, whereas pink sticky cards are for negative ones. In Task 2, participants categorise their experiences around desired themes in one of the four quadrants of the LEIQ™ model. The relevance of each encounter has a substantial impact on the participants, who assess its main value and positivity or negativity. The screen board has designated sections for each quadrant (Q1 through Q4), providing an ordered framework for participants to strategically put cards that represent their experiences. An example of LEIQ task execution which entails placing sticky notes according to personal relevance (non-verbal and intuitive) is shown in Fig. 5 below.

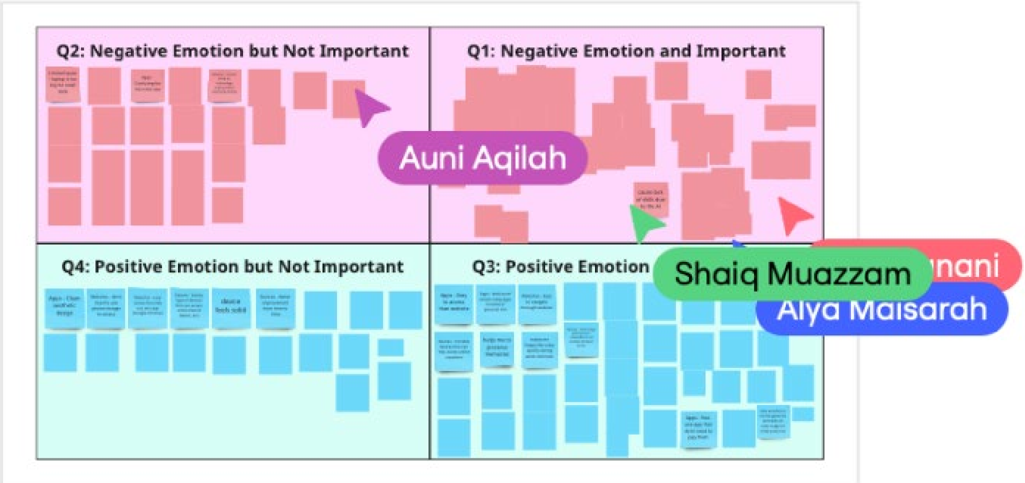

Fig. 5 *Computer-aided feature III: Implementation of Task 1 and Task 2*

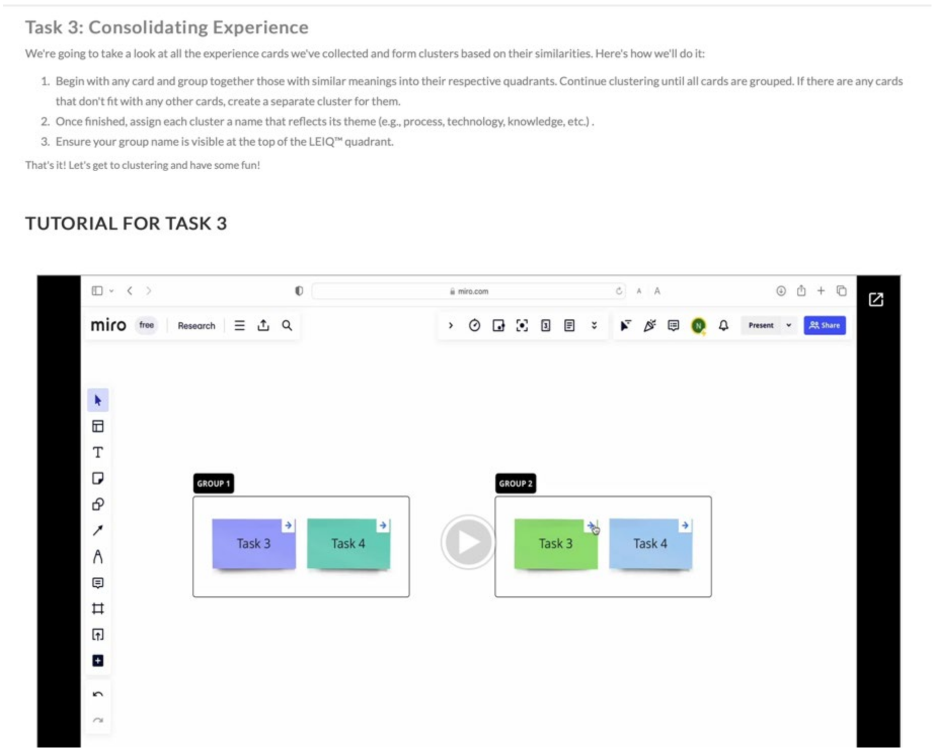

Fig. 6 *Computer-aided feature III: Tutorial for Task 3*

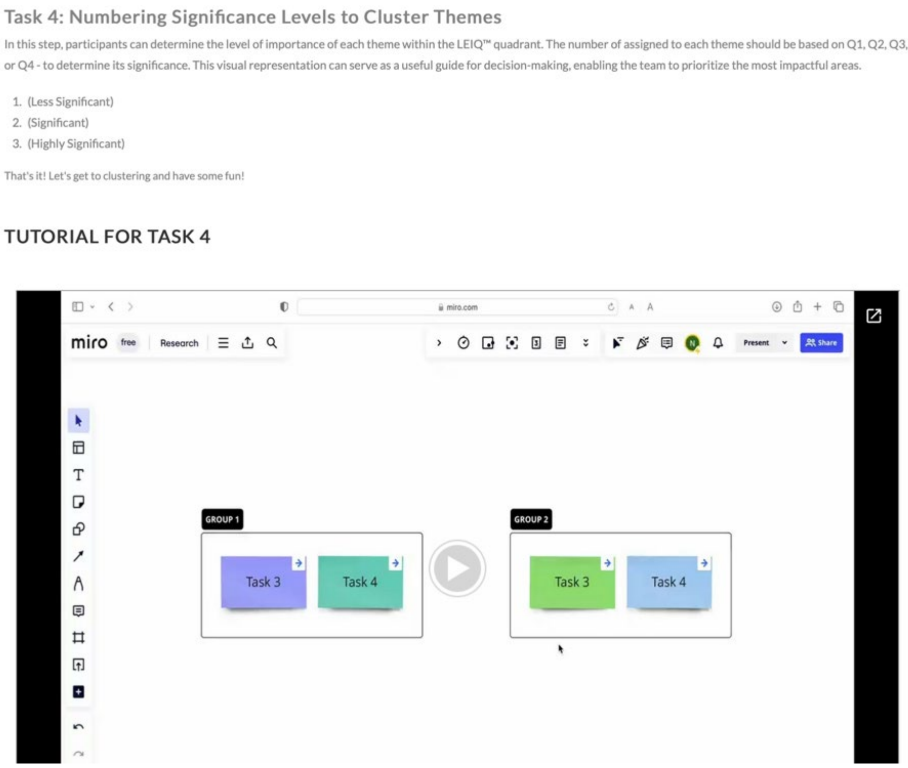

Fig. 7 *Computer-aided feature III: Tutorial for task 4*

On each page designed specific tasks within the web-based tools, participants are not only presented with detailed written instructions but also benefit from tutorial videos to facilitate their engagement during the assessment. This transition from the manual method is marked by a shift in roles, where the manual method role of an instructor providing verbal guidance is now meticulously replaced with comprehensive written instructions. Concurrently, the supportive role once undertaken by multiple facilitators in the manual method is transitioned into tutorial videos, which serve as effective tools to aid participants in navigating and comprehending the assessment process. Fig. 6 and Fig. 7 shows video on how to conduct for Task 3 - Task 4 respectively. This deliberate incorporation of written instructions and tutorial videos ensures a seamless and instructive user experience, mirroring the manual support structure while leveraging the advantages of digital mediums for enhanced participant guidance and comprehension.

Task 3 entails the synthesis of experiences, requiring participants to analyse the gathered notes and categorise them according to their shared characteristics. Participants are instructed to commence the clustering procedure by selecting a card and utilising the ‘Cluster Objects’ tool to group those with equivalent meanings inside their designated quadrants. This iterative clustering process persists until all cards are properly categorised. When certain cards do not correspond with others, participants are advised to form a separate cluster for them. After the clustering process, participants must provide a thematic term for each cluster that encapsulates its principal theme, such as "process", "technology", or "knowledge". This feature enables a systematic arrangement of experiences, improving the clarity and analysis of grouped data. Furthermore, participants are instructed to maintain the visibility of the group name at the apex of the LEIQ™ quadrant, thereby enhancing the clarity and coherence of the consolidated clusters.

In Task 4, participants evaluate significance levels for clustered themes in the LEIQ™ quadrant (Fig. 7). The numbering system, from 1 to 3, reflects the significance levels of each cluster according to their positions in Q1, Q2, Q3, and Q4. This step offers a visual depiction that facilitates decision-making by enabling the team to prioritise high-impact areas. The vibrant 'Tag' function categorises three levels—less significant (1), significant (2), and highly significant (3) as descriptors for the allocated numbers, thus improving the clarity of the visual guide. This feature enhances comprehension of the significance assigned to various theme clusters, aiding educated decision-making in the analysis process. Fig. 8 below illustrates the participants' implementation for the final task, wherein they assigned cluster names based on their consensus. Subsequently, all these inputs will be exported to an Excel file prior to completing the analysis.

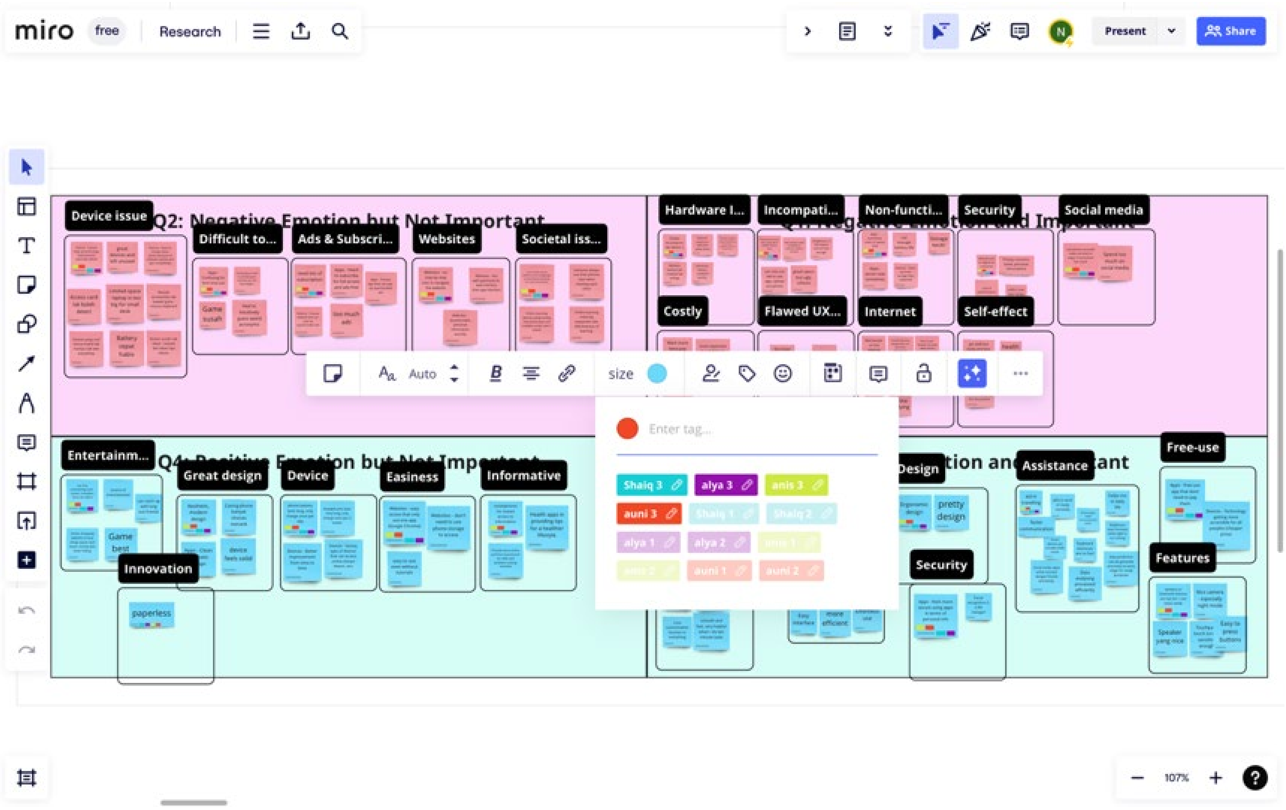

Fig. 8 *Computer-aided feature III: Implementation of task 3 and task 4*

6. Discussion

The findings of this study demonstrate a notable advancement in evaluating the LEIQ™ model using a web-based assistive tool, particularly compared to the traditional manual assessment method. The data indicate that participants produced a significantly greater volume of emotional data using the digital platform. The finding suggests that digital tools offer considerable advantages for more efficient, robust UX evaluations. The comparative analysis in Table 2 shows that both groups (G1 and G2) completed the tasks more quickly when using the assistive tool. For instance, Group 1 reduced task time from 159 minutes and 31 seconds (manual) to 126 minutes and 20 seconds (web-based), while Group 2 saw a similar reduction from 155 minutes and 16 seconds to 124 minutes and 10 seconds. This efficiency gain is complemented by a marked increase in the number of emotion data cards produced; G1 increased from 54 to 122, and G2 from 47 to 156. These results underscore the potential of digital environments to support both faster task completion and more comprehensive emotional input.

Table 2 *Comparative analysis task performance for emotion data extracted*

Group	Total Time Taken (M)	Total Time Taken (AT)	Total No. of Cards (M)	Total No. of Cards (AT)
G1	159:31	126:20	54	122
G2	155:16	124:10	47	156

(M) - Manual; (AT) – Assistive Tool Using Web-Based

These improvements are largely attributed to the intuitive interface and user-friendly features of the digital tool, including drag-and-drop functionality and rapid text entry, which minimises cognitive load and improves user satisfaction. The digital platform also significantly reduced errors associated with manual data entry, ensuring greater consistency in categorisation and formatting. These features facilitated the generation of richer datasets within the same time constraints and contributed to more accurate and reliable outcomes. These findings are particularly relevant. TVET emphasises practical, task-oriented training, where students are expected to perform efficiently and independently. The use of web-based tools that replicate real-world industry applications enhances the assessment process and prepares students for the digital competencies required in modern work environments. Nevertheless, it is important to acknowledge that some participants initially experienced difficulties navigating the digital platform, particularly those with limited exposure to technology-based assessments. These challenges diminished with continued use, indicating that supporting digital literacy within

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TVET programs is essential. Providing learners with early exposure to assistive technologies can enhance their adaptability and readiness for digital transformation in the workforce.

In conclusion, the integration of a web based UX assessment tool in the LEIQ™ model has proven to be a significant enhancement over manual methods. The improved efficiency, data accuracy, and user engagement observed in this study affirm the value of adopting digital solutions in TVET settings. Such innovations not only improve educational outcomes but also align with broader efforts to digitise vocational training to support national and global industry standards.

7. Conclusion

This research makes a significant contribution to the field of user experience (UX) assessment by identifying essential design requirements for a web-based assistive tool tailored to capture emotional responses. Prioritising usability, interactivity, and adaptability, the findings offer a foundational framework for developing tools that support emotion-driven assessments. The successful development and deployment of a functional prototype demonstrate the practical viability of the proposed approach, which serves as a reference point for future implementations in similar educational and user-centred contexts. The comparative evaluation of manual and web-based methods further underscores the advantages of integrating digital tools into UX assessments. Notable improvements—such as increased data volume, reduced task completion times, and lower error rates—highlight the efficiency and reliability of technology-enhanced methodologies. These benefits are particularly relevant to Technical and Vocational Education and Training (TVET), where real-time feedback and streamlined assessment processes are critical to learner engagement and instructional effectiveness.

The main goal of this study is to develop a scalable, computer-based assistive tool that improves emotional UX assessment by easily integrating the LEIQ™ model. By achieving this, the research not only deepens understanding of nuanced emotional interactions in digital environments but also enables more efficient transformation of raw emotional data into actionable insights. While the current work meets its objectives, it also lays the groundwork for further refinement and user-centric enhancements, ultimately moving toward full automation of the LEIQ™ assessment process. The implications of this research extend beyond theoretical contributions, offering actionable insights for researchers, practitioners, and developers aiming to advance emotion-aware systems. As the demand for adaptive, emotionally intelligent interfaces continues to grow, this study provides a valuable stepping stone for future innovations in the field of emotional user experience assessment.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

Saidatul Rahah Hamidi contributed the ***overall concept, the writing, and the editing*** *of the paper. Nur Batrisyia Damia Mustafa provided* ***resources, administered the data management, and writing the project report****. Anitawati Mohd Lokman assisted in* ***writing the method, analysis, and discussions****. Mitsuo Nagamachi assisted with the method and the* ***overall abstract****.*

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