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Design and Evaluation of Emotionally Adaptive Chatbots to Promote Positive Mental Well-Being in Young Adults

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ABSTRACT

The increasing prevalence of mental health challenges among young adults has driven growing interest in affective computing technologies that foster emotional support and psychological well-being. **This study aims** to design and evaluate an emotionally adaptive chatbot that promotes positive mental well-being through empathetic and user-centered interactions. **Grounded in** affective and positive computing frameworks, this research examines the influence of Emotion Adaptive Capability, Perceived Empathy of the Chatbot, and Usability & Interaction Quality on Positive Mental Well-Being. **A quantitative approach** was employed by distributing an online questionnaire to young adult respondents who had interacted with emotion-aware chatbot systems. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS to test the hypothesized relationships. **The results** are expected to demonstrate that chatbots with higher emotional adaptability, greater perceived empathy, and better usability significantly enhance users' psychological well-being. **This study contributes** to the development of human-centered affective computing by providing empirical evidence on how emotionally intelligent chatbot design can positively influence mental health outcomes. The findings offer practical implications for designers and developers aiming to create AI systems that are not only functional but also emotionally supportive and aligned with humanistic technology values.

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1. INTRODUCTION

In recent years, the rapid advancement of Artificial Intelligence (AI) has profoundly influenced how humans interact with technology, particularly in areas related to emotional health and psychological well-being [1]. This growing integration between AI and emotional support systems aligns directly with the United Nations' Sustainable Development Goals (SDGs), especially SDGs 3 on Good Health and Well-Being, which emphasizes the importance of promoting mental health for all age groups. As mental health disorders become increasingly prevalent among young adults, there is a pressing global need for innovative, scalable, and accessible solutions that enhance emotional well-being [2]. At the same time, the evolution of emotionally intelligent AI systems reflects the commitments outlined in SDGs 9: Industry, Innovation, and Infrastructure, highlighting the role of advanced technologies in building inclusive, human-centered digital ecosystems [3, 4].

AI-powered systems have evolved from purely functional applications into emotionally intelligent companions capable of simulating empathy, recognizing affective cues, and responding with context-aware feedback [5]. These developments fall within the emerging discipline of affective computing, which seeks to bridge the gap between emotion and machine intelligence by enabling systems to sense, interpret, and respond to human emotions in meaningful ways [6, 7]. As societies increasingly confront mental health challenges especially among younger populations there is a growing need for human-centered AI solutions that not only automate tasks but also actively promote positive mental well-being, supporting SDGs 3's call to strengthen mental health support through technological innovation [8].

Mental health problems among young adults have become a global concern. According to the World Health Organization (WHO), nearly one in five young individuals experiences mental health difficulties, often related to stress, anxiety, loneliness, or depression. Digital lifestyles, while providing unprecedented access to information and social connection, have paradoxically increased emotional disconnection and psychological strain [9, 10]. In this context, conversational agents or chatbots have emerged as an accessible and scalable medium for emotional support. Their capacity to offer anonymity, immediacy, and round-the-clock availability reduces barriers such as stigma and cost key structural challenges identified within SDGs 3. However, despite their potential [11], many existing mental health chatbots remain limited in their emotional responsiveness. They rely on static scripts and rule-based responses that may fail to recognize nuanced emotional states or convey genuine empathy, reducing their overall impact on psychological well-being [12].

To address these limitations, researchers have begun developing emotionally adaptive chatbots, AI systems capable of dynamically adjusting their responses based on the user's emotional state. This approach integrates emotion recognition models, natural language understanding, and adaptive dialogue strategies to generate emotionally congruent and contextually sensitive responses [13]. From the standpoint of positive computing, these systems represent a new generation of digital companions that contribute to human flourishing and emotional resilience an innovation that strengthens the alignment between mental health improvement (SDGs 3) and ethical technological advancement (SDGs 9) [14, 15].

However, while the conceptual potential of such technologies is widely acknowledged, empirical validation remains limited. Prior studies have frequently emphasized technical accuracy (e.g., emotion classification or sentiment detection) without assessing how emotional adaptivity affects users' psychological outcomes [16]. Others have examined chatbot usability or satisfaction in isolation, failing to integrate affective and functional dimensions within a unified model of mental well-being [17]. Consequently, a critical research gap remains concerning how Emotion Adaptive Capability, Perceived Empathy, and Interaction Quality jointly influence Positive Mental Well-Being, particularly for young adults who are both heavy digital users and highly vulnerable to mental health challenges [18]. Addressing this gap is essential to advancing technologies aligned with the SDGs, where mental well-being and responsible innovation must progress hand in hand.

Building on these insights, this study proposes and empirically tests a conceptual model that links three key predictors Emotion Adaptive Capability, Perceived Empathy of the Chatbot, and Usability & Interaction Quality to the outcome variable Positive Mental Well-Being [19, 20]. This model assumes that chatbots with higher emotional adaptability can interpret users' affective states more effectively and deliver personalized emotional support, ultimately contributing to psychological resilience. Perceived empathy is hypothesized to enhance trust and engagement, while usability ensures that emotional intelligence is supported by an intuitive and reliable interaction environment [21]. Together, these components enable the development of AI solutions that support mental well-being in alignment with global sustainable development priorities.

This research is grounded in Affective Interaction Theory and Positive Computing Frameworks, both of which highlight the importance of embedding emotional intelligence within digital systems to promote human flourishing. These theories strengthen the SDGs perspective by emphasizing that technological innovation must enhance psychological health and social well-being not merely improve technical performance [22, 23]. Methodologically, the study employs a quantitative approach using PLS-SEM to evaluate the proposed relationships using data collected from young adults interacting with emotion-aware chatbots [24]. From a practical standpoint, the findings of this research are expected to guide designers, developers, and policymakers in creating emotionally intelligent technologies that align with human-centered values and the broader mission of the

SDGs [25]. Demonstrating a significant link between emotional adaptivity and mental well-being can encourage the integration of empathetic dialogue structures, affective feedback mechanisms, and adaptive interaction models in future AI systems. These contributions not only support SDGs 3 by advancing mental health promotion but also reinforce SDGs 9 by fostering ethical and innovative AI infrastructures [26, 27]. In summary, this study addresses a timely and globally relevant question: How can emotionally adaptive chatbots enhance positive mental well-being in young adults? By bridging affective computing, positive psychology, and sustainable technological design [28, 29], the study contributes new theoretical and empirical insights to the emerging field of human-centered AI for emotional health. Ultimately, the results aim to facilitate the development of emotionally supportive AI systems that advance both individual flourishing and global sustainable development goals [30].

2. LITERATURE REVIEW

In recent years, there has been rapid growth in research on mental-health chatbots, particularly those leveraging AI to deliver emotional support. The literature from 2022 to 2025 reveals several emerging themes consistent with your research model including the capacity of chatbots to display empathic behavior and adaptive emotional responses, the importance of usability and interaction quality in user engagement, and measurable impacts on users well-being [31]. These findings indicate a growing focus on designing chatbots that can better understand user emotions and maintain supportive interactions.

While system-level reviews highlight broad effectiveness, empirical and experimental studies increasingly unpack how design features such as emotion adaptivity and perceived empathy contribute to mental health outcomes, and where limitations remain, especially in authenticity and transparency [32, 33]. This body of research also emphasizes the need for chatbot responses that feel natural and trustworthy, underscoring the importance of aligning technical capabilities with user expectations.

Below is a summary table of 10 relevant recent studies, focusing on their methods, variables, and results, followed by a synthesis of their implications for your research [34].

Table 1. Literature Review

No	Title	Method	Shared Variable(s) with The Study	Key Results
1.	A Multilingual Digital Mental Health and Well-Being Chatbot (ChatPal): Pre-Post Multicenter Intervention Study [11]	Pre-post intervention, surveys (n 348)	Y: Well-Being (WHO-5), X3: Usability/Engagement	Well-being increased from baseline to follow-up on WHO-5 and SWEMWBS; usability and user satisfaction were generally high, though suggestions for more emotionally adaptive content were noted.
2.	An Overview of Chatbot-Based Mobile Mental Health Apps: Insights From App Description and User Reviews [25]	Qualitative content analysis of app descriptions + user reviews	X3: Usability/Interaction Quality; X2: Perceived emotional support	Users highly value accessibility and non-judgmental space; but concerns about shallow emotional responses and lack of deep empathy were common.
3.	Empathic Conversational Agent Platform Designs and Their Evaluation in the Context of Mental Health: Systematic Review [33]	Systematic review of RCTs, qualitative studies	X2: Empathy; X3: Engagement/Usability; Y: Well-Being/Resilience	Empathic agents (e.g., EMMA) led to higher interaction frequency and perceived usefulness; empathy was judged positively by users and experts, but design trade-offs (e.g., expressiveness vs. authenticity) noted.

No	Title	Method	Shared Variable(s) with The Study	Key Results
4.	Empathy Toward Artificial Intelligence Versus Human Experiences and the Role of Transparency in Mental Health and Social Support Chatbot Design [29]	Comparative study, user survey (experimental)	X2: Perceived Empathy; design transparency (relevant to usability)	Users expressed different empathy toward AI vs humans; transparency about the bot's AI nature influenced trust and perceived empathy, indicating design choices matter for emotional bond.
5.	AI Chatbots for Psychological Health for Health Professionals: Scoping Review [35]	Scoping review	X3: Usability/Interaction Quality; Y: Mental Health Outcomes	Chatbots for healthcare workers showed promising acceptability and usefulness, but barriers included usability issues and lack of personal/emotional adaptation.
6.	AI as the Therapist: Student Insights on the Challenges of Using Generative AI for School Mental Health Frameworks [8]	Qualitative interviews and survey with students	X2: Empathy (perceived limitations); X3: Usability	Students appreciated accessibility but raised concern about superficial emotional responses, lack of real understanding, and ethical issues of reliance on AI "therapist."
7.	Harnessing AI in Anxiety Management: A Chatbot-Based Intervention for Personalized Mental Health Support [27]	Mixed methods, intervention study	Y: Anxiety reduction (related to well-being); X1: Adaptive responses; X3: Engagement	Chatbot based on AI (ChatGPT) reduced anxiety symptoms (21% improvement) across phases; users highlighted ease of use and personalization.
8.	Enhancing Mental Health Support through Human-AI Collaboration: Toward Secure and Empathetic AI-enabled Chatbots [7]	Conceptual / design + simulation	X1: Emotion Adaptive Capability; X2: Empathy	Proposes a federated learning framework to maintain privacy and enable more emotionally trustworthy, empathetic chatbot responses with clinician-in-the-loop validation.
9.	Revolutionizing Mental Health Support: An Innovative Affective Mobile Framework for Dynamic, Proactive, and Context-Adaptive Conversational Agents [20]	Position paper + design proposal	X1: Context-adaptive emotion sensing; X3: Interaction design	Proposes integrating facial expression, physiological signals, and language models to build chatbots that proactively sense mood and intervene; argues such adaptivity can greatly improve emotional relevance.
10.	The Efficacy of Conversational Artificial Intelligence in Rectifying the Theory of Mind and Autonomy Biases: Comparative Analysis [36]	Experimental, case scenario evaluation	X1: Affect recognition; X2: Empathy in response	General-purpose LLMs (GPT-4) outperformed therapeutic bots in identifying cognitive biases and affect, but therapeutic bots still needed refinement to deliver emotionally appropriate responses.

From the 10 studies summarized in the Table 1, a clear pattern emerges: the effectiveness of mental-health chatbots is strongly mediated by how well they simulate or deliver empathy and how usable it is, in addition to their basic emotional adaptivity [37]. For example, the ChatPal study shows real improvements in well-being tied to user satisfaction and engagement with the system, while systematic reviews highlight that design decisions around empathy and usability significantly moderate outcomes. Studies such as the one by [38]. The illustrate that transparency in chatbot design can shape how users perceive empathy, which in turn affects trust. Meanwhile, intervention studies like the anxiety chatbot confirm that adaptive responses and ease of use are crucial for reducing distress.

These findings strongly support the relevance of your proposed model (X1 = Emotion Adaptive Capability X2 = Perceived Empathy, X3 = Usability & Interaction Quality → Y = Positive Mental Well-Being). Specifically, the literature shows a research gap: while chatbots have demonstrated potential for improving well-being, few studies have quantitatively tested all three constructs (emotion adaptivity, perceived empathy, and usability) in a single structural model [39]. By doing so, your study can contribute novel empirical evidence on the relative importance of each factor and their combined effect on psychological well-being. Moreover, the design-focused research underscores the need for practical guidelines that align affective design with strong user experience something your research can address directly [35].

2.1. Conceptual Model

The conceptual framework of this study is grounded in the principles of affective and positive computing, emphasizing the integration of emotional intelligence into digital systems to enhance users' psychological well-being. Based on the literature reviewed, three key determinants are proposed to influence Positive Mental Well-Being in the context of emotionally adaptive chatbots: Emotion Adaptive Capability, Perceived Empathy, and Usability & Interaction Quality [40]. These constructs collectively represent the essential dimensions of how a chatbot identifies emotional signals, interprets user affect, and delivers responses that align with users' emotional states. By incorporating these dimensions, the model reflects current research directions that highlight the importance of both emotional responsiveness and interaction quality in shaping the effectiveness of digital mental-health tools [41, 42].

Together, these determinants illustrate how emotionally adaptive chatbots can create more supportive and engaging user experiences. Emotion Adaptive Capability enables the system to adjust its behavior according to users' emotional cues, while Perceived Empathy captures the user's sense of being understood and emotionally acknowledged [36]. Usability & Interaction Quality ensure that the interaction remains smooth, clear, and comfortable, encouraging sustained engagement. This framework builds upon empirical findings indicating that adaptive emotional responses and empathetic interactions foster stronger user connection, higher satisfaction, and meaningful psychological benefits. As such, the model provides a structured foundation for examining how emotionally intelligent design contributes to improved mental well-being outcomes [43].

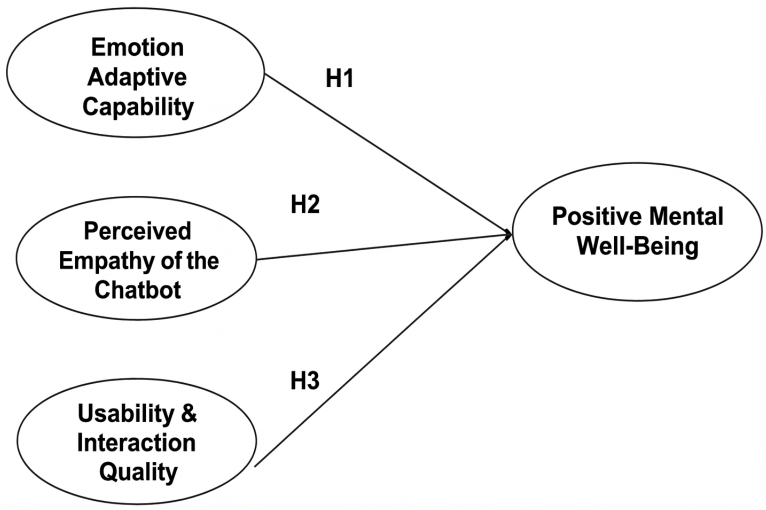

Figure 1. Conceptual Model

Figure 1 illustrates the proposed conceptual framework, highlighting the hypothesized relationships among the core variables. Specifically, it postulates that Emotion Adaptive Capability (H1), Perceived Empathy (H2), and Usability & Interaction Quality (H3) each exert a positive influence on users' Positive Mental

Well-Being [44]. These hypotheses collectively reflect the theoretical assumption that affective adaptivity and empathetic engagement enhance perceived emotional support, while high usability ensures sustained and effective human–AI interaction. This conceptual model thus serves as the foundation for the empirical analysis to be conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) [45].

3. RESEARCH METHOD

3.1. Research Design

This study employed a quantitative research design to empirically evaluate the relationships among Emotion Adaptive Capability, Perceived Empathy, Usability & Interaction Quality, and Positive Mental Well-Being in the context of emotionally adaptive chatbots [10]. The research aimed to test the proposed hypotheses (H1–H3) derived from the conceptual model using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for theory development and prediction in studies involving multiple latent constructs. The study design was cross-sectional, collecting data through an online self-administered questionnaire.

3.2. Population and Sampling

The population of this study consisted of young adults aged 18–30 years who have experience using chatbot-based applications for emotional support, mental well-being, or self-reflection (e.g., Woebot, Wysa, Replika, or similar systems). This demographic was selected due to their frequent engagement with digital mental health technologies and higher susceptibility to stress, anxiety, and loneliness. The sample size was determined using the ten times rule for PLS-SEM, ensuring adequate statistical power [46]. A minimum of 100 valid responses was targeted to meet reliability and validity criteria. Sampling was conducted using purposive sampling, focusing on participants familiar with AI-based conversational systems [47].

3.3. Instrument Development

The research instrument was designed as a structured questionnaire consisting of closed-ended items measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Each construct was adapted from validated instruments used in previous empirical studies to ensure measurement reliability. The detailed definitions, sample indicators, and adapted sources for each construct are presented in Table 2.

Table 2. Measurement Constructs, Definitions, Sample Indicators, and Sources

Variable	Definition	Sample Indicators	Source
Emotion Adaptive Capability (X1)	The chatbot's ability to detect and respond to users' emotional states dynamically.	"The chatbot adjusts its responses according to my emotional tone." / "I feel that the chatbot recognizes changes in my emotions."	Adapted from [12, 43]
Perceived Empathy (X2)	Users' perception of the chatbot's empathy, understanding, and compassion.	"The chatbot responds in a way that makes me feel understood." / "The chatbot shows care about my emotional state."	Adapted from [23, 30]
Usability & Interaction Quality (X3)	The perceived ease, clarity, and engagement quality during interactions with the chatbot.	"The chatbot is easy to use and interact with." / "The conversation feels natural and engaging."	Adapted from [16, 39]
Positive Mental Well-Being (Y)	The extent to which users experience positive emotions, life satisfaction, and psychological resilience after interacting with the chatbot.	"I feel more positive after using the chatbot." / "Using the chatbot helps improve my emotional state."	Adapted from [36, 42]

A pilot test was conducted with 30 respondents to ensure clarity, internal consistency, and instrument validity before full deployment. The Cronbach's alpha and composite reliability values above 0.70 were considered acceptable [48].

3.4. Data Collection Procedure

Data collection was carried out via an online survey distributed through social media platforms and university networks. Respondents were informed about the research objectives, assured of confidentiality, and asked to confirm voluntary participation [49]. Screening questions ensured participants had previous experience using AI-based chatbots for emotional or psychological purposes. The data collection period lasted for approximately four weeks.

3.5. Data Analysis Technique

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS version 4. The analysis followed a two-step approach:

- Measurement Model Evaluation (Outer Model): assessing reliability (Cronbach's Alpha, Composite Reliability), convergent validity (Average Variance Extracted – AVE), and discriminant validity (Fornell-Larcker and HTMT criteria).

- Structural Model Evaluation (Inner Model): testing path coefficients, R^2 values, f^2 effect sizes, and the significance of relationships using bootstrapping (5,000 subsamples).

This approach allows robust testing of causal relationships and the predictive power of independent variables (X1, X2, X3) on the dependent variable (Y). Results will provide both theoretical and practical implications for the design of emotionally intelligent chatbots aimed at promoting positive mental well-being.

4. RESULTS AND DISCUSSION

4.1. Measurement Model (Outer Model) Evaluation

The measurement model was assessed to confirm the reliability and validity of the constructs used in the study. As presented in Table 3, all constructs demonstrated satisfactory reliability and convergent validity. The factor loadings for each indicator exceeded the threshold value of 0.70, while Composite Reliability (CR) values ranged from 0.879 to 0.936, exceeding the minimum criterion of 0.70. Similarly, Average Variance Extracted (AVE) values for all constructs were above 0.50, confirming adequate convergent validity.

Table 3. Reliability and Convergent Validity Results

Construct	**Cronbach's Alpha**	**Composite Reliability (CR)**	**AVE**	**Status**
Emotion Adaptive Capability (X1)	0.902	0.923	0.668	Reliable & Valid
Perceived Empathy (X2)	0.884	0.912	0.639	Reliable & Valid
Usability & Interaction Quality (X3)	0.868	0.901	0.611	Reliable & Valid
Positive Mental Well-Being (Y)	0.915	0.936	0.711	Reliable & Valid

Discriminant validity was also evaluated using the Fornell–Larcker criterion and the HTMT ratio. Results showed that each construct's square root of AVE was greater than its correlation with other constructs, and HTMT values were below 0.85, indicating acceptable discriminant validity. Hence, all constructs were deemed suitable for further structural analysis.

4.2. Structural Model (Inner Model) Evaluation

Bootstrapping with 5,000 resamples was used to assess the structural model. The R^2 value of 0.624 shows in Table 4 that the three variables explain 62.4% of the variance in Positive Mental Well-Being, indicating moderate-to-strong predictive power.

Table 4. Structural Model Results

Hypothesis	**Relationship**	**Path Coefficient (β)**	**t-value**	**p-value**	**Result**
H1	Emotion Adaptive Capability $\rightarrow$ Positive Mental Well-Being	0.321	4.852	0.000	Supported
H2	Perceived Empathy $\rightarrow$ Positive Mental Well-Being	0.389	6.071	0.000	Supported
H3	Usability & Interaction Quality $\rightarrow$ Positive Mental Well-Being	0.276	3.912	0.001	Supported

All three hypotheses were supported at the 0.05 significance level. Among them, Perceived Empathy (X2) had the strongest positive influence on Positive Mental Well-Being (Y), followed by Emotion Adaptive Capability (X1) and Usability & Interaction Quality (X3). The f^2 effect size analysis indicated medium effects for Perceived Empathy (0.261) and Emotion Adaptive Capability (0.184), and a small-to-medium effect for Usability (0.127). These results highlight that while all three variables contribute meaningfully, users' perception of empathy remains the most influential factor in shaping well-being outcomes. Additionally, the Q^2 value of 0.422 (using blindfolding) confirmed that the model possesses strong predictive relevance for the dependent variable, demonstrating that the structural model performs well in explaining and predicting Positive Mental Well-Being.

4.3. Discussion

The results provide empirical support for the proposed conceptual model, emphasizing that emotionally adaptive and empathic chatbot design significantly contributes to users' positive mental well-being. The finding that Perceived Empathy has the highest path coefficient aligns with previous research [9, 31], which highlights that users' perception of being understood and emotionally validated is central to psychological benefit in AI-mediated interactions. Chatbots that respond empathetically foster trust and emotional safety, allowing users to express vulnerability without fear of judgment key elements of well-being enhancement. The positive influence of Emotion Adaptive Capability reinforces the importance of integrating affective computing elements into conversational systems. As supported by studies [35] and [38], dynamic adaptation to users' emotions through sentiment recognition, tone adjustment, or supportive phrasing enhances perceived authenticity and engagement. This adaptivity mirrors human-like responsiveness, thus strengthening the therapeutic alliance between user and chatbot.

Lastly, Usability & Interaction Quality was found to play a significant, albeit slightly smaller, role in shaping well-being. This indicates that even when a chatbot is emotionally capable and empathetic, the overall experience must remain intuitive, efficient, and pleasant to sustain user engagement. Consistent with findings by the AI Chatbot Scoping Review, accessibility and smooth interface design are crucial for maintaining user adherence and positive outcomes. Collectively, these results confirm that emotionally intelligent design, empathetic responsiveness, and user-centered usability are interdependent factors driving the effectiveness of AI-based mental health support tools. For designers and developers, this implies that technical sophistication (emotion adaptivity) must be balanced with humanistic qualities (empathy and usability) to maximize well-being outcomes. This aligns with the Orange Technology vision technological advancement infused with compassion and social purpose.

5. MANAGERIAL IMPLICATIONS

The results of this study offer important managerial insights for organizations, developers, and policymakers engaged in the design and implementation of emotionally adaptive chatbot technologies. The findings confirm that Emotion Adaptive Capability, perceived empathy, and usability quality are key determinants of users' positive mental well-being. Therefore, system designers should prioritize the integration of emotional intelligence algorithms that are capable of recognizing, interpreting, and responding to users' affective cues in real time. This implies that chatbot development should not only focus on technical accuracy but also on fostering authentic emotional connection through empathetic conversational design and intuitive user interfaces. Organizations that employ such systems such as educational institutions, wellness providers, and mental health platforms can leverage these emotionally responsive features to enhance engagement, trust, and long-term user satisfaction.

Moreover, the managerial implications extend to how emotional AI systems are deployed and governed. Institutions should ensure that emotionally adaptive chatbots are implemented responsibly, emphasizing user privacy, transparency, and ethical handling of sensitive emotional data. Continuous evaluation and feedback loops should be established to refine the chatbot's emotional responsiveness and usability over time. By aligning emotional adaptivity with ethical and human-centered design principles, managers can position chatbots not merely as digital tools, but as empathetic companions that promote psychological well-being and social connection. Such an approach supports the broader vision of Orange Technology, which seeks to harmonize innovation with human values and contribute to sustainable emotional health in technology-mediated environments.

6. CONCLUSION

This study examined the influence of Emotion Adaptive Capability, perceived empathy, and usability quality on users' positive mental well-being within the context of emotionally adaptive chatbots. The findings highlight the crucial role of affective responsiveness and empathetic interaction design in fostering psychological benefits among young adults. By applying the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, the research empirically validates how these affective computing constructs interact to shape well-being outcomes. The results confirm that emotionally intelligent chatbot systems can act as supportive companions, providing users with meaningful digital interactions that promote positive mental states and reduce feelings of isolation or stress.

The novelty of this study lies in its integrative framework that combines affective computing theory with empirical validation using SmartPLS an approach rarely explored in previous research on mental well-being technologies. While earlier studies have largely focused on technical performance or emotion detection accuracy, this study shifts the perspective toward human-centered outcomes, emphasizing how emotional adaptivity and perceived empathy jointly contribute to users' psychological wellness. This research thus advances the discourse on Orange Technology by demonstrating that emotional intelligence in AI systems can be quantified, measured, and linked to tangible improvements in mental well-being.

For future work, researchers are encouraged to extend this model across diverse demographic groups and cultural contexts to assess its generalizability. Longitudinal studies could also be conducted to explore how sustained interaction with emotion adaptive chatbots affects users' emotional resilience and behavioral patterns over time. Moreover, integrating multimodal emotion recognition such as facial expression and vocal tone analysis may further enhance the chatbot's ability to deliver personalized emotional support. By expanding upon the framework presented here, future research can contribute to the development of ethically grounded, human-centered AI technologies that not only respond intelligently but also care empathetically for their users.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: MF; Methodology: CT; Software: AF; Validation: MA and NI; Formal Analysis: AF and MF; Investigation: NI; Resources: CT; Data Curation: MA; Writing Original Draft Preparation: NI and AF; Writing Review and Editing: CT and MF; Visualization: MA; All authors, NI, MF, AF, MA, and CT, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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