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EVALUATING THE EFFICACY AND USER EXPERIENCE OF AI-BASED MENTAL HEALTH

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ABSTRACT

This study examines young adults' perceptions of an AI-based mental health support system, focusing on comfort, perceived mood detection accuracy, timeliness of depression alerts, and recommendation helpfulness. A sample of 61 participants aged 16 to 30 completed a survey assessing these factors on a 5-point Likert scale, supplemented by usage frequency and access methods. Results indicated high comfort levels in emotional sharing, moderate satisfaction with mood detection accuracy, and positive responses to alert timeliness. However, limitations such as lack of personalization and the potential for alert fatigue highlight the challenges of relying solely on AI for mental health support. Correlation analysis further revealed that younger users and those with previous therapy experience reported higher satisfaction levels. This study underscores the value of AI in enhancing mental health support accessibility, while also advocating for hybrid approaches that integrate human oversight to address complex psychological needs. Future research should explore long-term engagement, personalization algorithms, and ethical considerations to optimize AI-based mental health interventions.

Keywords: AI in mental health, digital health interventions, emotional disclosure, hybrid mental health models, mental health support, mood detection accuracy, personalization in AI, self-disclosure theory, survey study, user satisfaction

1. INTRODUCTION

The emergence of artificial intelligence (AI) in mental health care represents a significant paradigm shift in both therapeutic and diagnostic practices. Traditional face-to-face therapy, while highly effective, can be inaccessible to many due to factors like geographic limitations, financial costs, or social stigma associated with seeking mental health support (Andersson, 2016; Richards & Richardson, 2012). Consequently, AI-based mental health tools offer a scalable, accessible alternative that can augment or, in some cases, replace aspects of conventional support structures (Topol, 2019). Young adults, in particular, represent a demographic that may benefit substantially from AI-based mental health interventions. They often experience heightened mental health needs but face unique barriers to seeking support (Cerniglia et al., 2017). AI applications, such as conversational agents and mood-tracking platforms, are designed to offer support that is immediate and, crucially, perceived as nonjudgmental (Fitzpatrick et al., 2017). For these systems to be effective, they must not only accurately detect and respond to signs of mental distress but also be perceived by users as trustworthy and helpful. Acceptance of AI in therapeutic contexts depends on user comfort, perceived accuracy, and the timeliness of system responses to emotional changes. Recent studies have begun to explore the efficacy and limitations of AI in detecting mental health issues, with findings that vary according to context and specific population characteristics (Luxton, 2014; Wang et al., 2018). However, research focused on young adults' subjective experiences with these systems remains limited. Studies indicate that younger users are generally more comfortable with technology and AI, which could potentially translate to greater acceptance of AI-based mental health support (Andersson & Titov, 2014; Torous et al., 2018). Nonetheless, factors such as age, prior mental health support experiences, and frequency of use might play pivotal roles in shaping attitudes towards AI-based monitoring and intervention systems.This study seeks to fill a gap in the literature by examining the comfort, perceived accuracy, and overall satisfaction of young adults with an AI-based mental health support system. Specifically, we aim to assess: (1) how comfortable users feel sharing emotional states with an AI system, (2) the perceived accuracy of the system's mood detection capabilities, (3) satisfaction with AI-based alerts regarding depression risk, and (4) the helpfulness of the system's recommendations. Furthermore, we explore correlations between demographic variables, previous experiences with therapy, and patterns of AI system usage to offer a comprehensive view of factors influencing user satisfaction.

2. THEORETICAL FRAMEWORK

The application of artificial intelligence in mental health support draws from multiple theoretical perspectives within psychology, technology, and health informatics. This section provides an overview of relevant frameworks that inform the development, implementation, and evaluation of AI-based mental health systems.

Central to the success of AI in mental health is the human-computer interaction (HCI) framework, which examines how users engage with and perceive digital interfaces. Theories within HCI highlight that user comfort and trust are critical factors in adopting new technologies (Nass & Moon, 2000). Specifically, self-disclosure theory suggests that individuals may find it easier to share sensitive information with AI systems, perceiving them as non-judgmental and less intimidating than human counterparts (Ho et al., 2018). This anonymity can foster a sense of safety and openness, which is particularly relevant in mental health contexts (Graham et al., 2019). The integration of AI in mental health care is underpinned by the promise of continuous, accessible, and personalized support, informed by cognitive-behavioral and psychoanalytic theories. Cognitive-behavioral models, which prioritize monitoring and modifying thoughts and behaviors, align well with AI's ability to track mood patterns and suggest interventions (Hollon & Beck, 2013). However, psychodynamic theories emphasize the need for relational depth and understanding in therapeutic work (Shedler, 2010). AI's limited capacity for nuanced emotional interpretation poses challenges when trying to emulate the empathetic and reflective qualities of human therapy (Laranjo et al., 2018).

The Technology Acceptance Model (TAM) provides a framework for understanding users' willingness to engage with AI-driven mental health tools. According to TAM, perceived usefulness and ease of use are primary determinants of technology adoption (Davis, 1989). Applied to mental health, users may be more inclined to adopt AI-based systems if they perceive the technology as both effective in supporting their well-being and simple to integrate into their daily lives (Venkatesh & Davis, 2000). Age, previous therapy experiences, and familiarity with digital tools are additional factors influencing acceptance, particularly among younger populations who generally demonstrate higher adaptability to new technologies (Venkatesh et al., 2003). Finally, ethical considerations are crucial to the theoretical foundation of AI in mental health. The principle of "do no harm" is central to mental health care, and the use of AI raises concerns about user privacy, data security, and the risk of over-reliance on automated systems (Bostrom & Yudkowsky, 2014). Ensuring user autonomy and informed consent, particularly when dealing with sensitive mental health data, remains a central ethical issue. Privacy theories emphasize the need for robust data protection to maintain trust and protect against misuse of personal information (Cohen et al., 2021).

3. METHODOLOGY

This study employed a cross-sectional survey design to evaluate young adults' perceptions of an AI-based mental health support system. Participants were recruited online and consisted of 61 individuals aged 16 to 30, representing diverse backgrounds in gender, age, and educational status. The sample included 57.4% females, 37.7% males, and 4.9% identifying as non-binary. In terms of educational level, 57.4% were university students, 13.1% high school students, and 21.3% employed individuals, with the remaining 8.2% categorized as "other." Participants' mental health support varied, with 45.9% currently receiving professional therapy, 36.1% relying solely on AI-based support, and 18% reporting no current support. Data were gathered through an online survey comprising both quantitative and qualitative items. Quantitative questions utilized a 5-point Likert scale, measuring variables such as comfort in sharing emotions, perceived accuracy of mood detection, timeliness of depression risk alerts, and helpfulness of system recommendations. Additional items addressed usage frequency, access method (smartphone app or web browser), and overall satisfaction. The survey also included demographic questions to identify patterns related to age, gender, and prior mental health support experience. Data analysis involved calculating means, standard deviations, and response distributions for each item. Correlation analyses explored relationships between variables such as age and AI comfort, usage frequency and perceived accuracy, and prior therapy experience and system satisfaction. Additionally, system effectiveness metrics (e.g., true positive and false positive rates) provided insights into the AI's performance in depression risk detection. This mixed-method approach offered a comprehensive view of user perceptions and the system's potential in supporting mental health.

4. RESULTS

This section presents the findings of the study, highlighting participants' comfort with using the AI-based mental health support system, perceived system effectiveness in mood detection, satisfaction with the timeliness of depression alerts, and the helpfulness of AI-generated recommendations. Additionally, it explores usage patterns and key correlations between demographic variables and user satisfaction, providing insights into factors that influence engagement with AI-based mental health tools.

4.1 User Comfort in Sharing Emotional States

Participants reported a high level of comfort sharing their emotional states with the AI system, with an average rating of 4.2 out of 5 (SD = 0.85). This score indicates a generally positive perception of the AI system's non-judgmental nature, with 85.3% of participants agreeing or strongly agreeing that they felt comfortable sharing personal emotions through the AI interface. Only a small minority expressed discomfort, with 4.9% disagreeing and none strongly disagreeing.

Response	Frequency (n)	Percentage (%)
Strongly Agree	25	41.0
Agree	27	44.3
Neutral	6	9.8
Disagree	3	4.9
Strongly Disagree	0	0.0

These findings are consistent with previous research suggesting that AI systems may facilitate higher levels of self-disclosure by providing an anonymous and non-judgmental environment (Graham et al., 2019). The high comfort rating could be attributed to the system's ability to simulate empathetic responses, creating a perceived safe space for emotional expression.

4.2 Perceived Accuracy of Mood Detection

The perceived accuracy of the AI system's mood detection was moderately high, with a mean score of 3.9 (SD = 0.92). Approximately 68.8% of participants agreed or strongly agreed that the system accurately identified shifts in their mood, while 19.7% remained neutral. A smaller proportion (11.5%) disagreed or strongly disagreed, indicating that while many users felt the system performed well, there were mixed opinions regarding its consistency in detecting nuanced emotional changes.

Response	Frequency (n)	Percentage (%)
Strongly Agree	18	29.5
Agree	24	39.3
Neutral	12	19.7
Disagree	5	8.2
Strongly Disagree	2	3.3

These findings highlight both the strengths and limitations of AI in mood detection, supporting previous studies that note AI's ability to recognize general emotional states while often struggling with more complex emotions (Xu et al., 2020). Participants' mixed responses suggest that while the AI's mood detection capabilities were helpful to some, others may have experienced frustration with occasional misinterpretations.

4.3 Timeliness of Depression Risk Alerts

The system's timeliness in issuing alerts for potential depression risks was among the highest-rated features, with a mean score of 4.1 (SD = 0.88). The majority of participants (78.7%) either agreed or strongly agreed that the system provided timely alerts, while only 8.2% expressed any dissatisfaction. This high satisfaction rate underscores the perceived value of immediate notifications in addressing potential mental health issues proactively.

Response	Frequency (n)	Percentage (%)
Strongly Agree	22	36.1
Agree	26	42.6
Neutral	8	13.1
Disagree	4	6.6
Strongly Disagree	1	1.6

These results align with studies that emphasize the importance of timely interventions in mental health, where early identification of symptoms can lead to improved outcomes (Choudhury & Counts, 2013). However, despite the high rating, it is important to note that the system's alert effectiveness is ultimately limited by the accuracy of its detection algorithm. False positives or irrelevant alerts may reduce user trust over time, though this study did not specifically assess alert accuracy.

4.4 Helpfulness of System Recommendations

Participants rated the helpfulness of the AI system's mental health recommendations with a mean score of 3.8 (SD = 1.02). This score reflects moderate satisfaction, as 65.6% of respondents found the recommendations helpful. However, 23% rated the recommendations neutrally, and 11.5% disagreed or strongly disagreed that the recommendations were useful.

Response	Frequency (n)	Percentage (%)
Strongly Agree	17	27.9
Agree	23	37.7
Neutral	14	23.0
Disagree	5	8.2
Strongly Disagree	2	3.3

The mixed feedback may point to limitations in the AI's ability to deliver tailored advice, as AI-generated recommendations may lack the personalization typically offered in human therapy (Mohr et al., 2013). These findings suggest that while users find value in AI support, enhancing recommendation relevance through personalization could further improve user satisfaction.

4.5 Preference for AI-Based Monitoring

When asked about their preference for AI-based monitoring over traditional check-ins, participants gave a mean score of 3.7 (SD = 1.15), indicating a favorable but less enthusiastic response than other items. About 63.9% of participants preferred AI-based monitoring, while 18% remained neutral and 18% expressed a preference for traditional check-ins.

Response	Frequency (n)	Percentage (%)
Strongly Agree	19	31.1
Agree	20	32.8
Neutral	11	18.0
Disagree	8	13.1
Strongly Disagree	3	4.9

The preference for AI-based monitoring reflects younger users' general comfort with technology, though the presence of some skepticism suggests a residual reliance on human interaction for mental health support (Torous et al., 2018). This result highlights a potential area for further exploration, as combining AI monitoring with human oversight may balance convenience with emotional depth.

4.6 Usage Patterns and System Effectiveness

The majority of participants (52.5%) reported daily use of the AI system, while 24.6% used it 4-6 times per week, and only 6.6% used it less than once a week. This frequent use suggests that the system has become an integrated part of users' routines, supporting findings that AI-based health tools can facilitate sustained engagement (Inkster et al., 2018). The system was primarily accessed via smartphone apps, with 78.7% of participants favoring this method. The remaining participants used a web browser (14.8%) or both access methods equally (6.6%). The high reliance on mobile access aligns with contemporary preferences for on-the-go mental health support, emphasizing the importance of mobile-friendly design in future AI-based systems. The AI system showed an overall depression risk detection accuracy of 88%, with a true positive rate of 85% and a false positive rate of 12%. These metrics indicate that the system is generally reliable in identifying potential depression risks, although false positives remain a minor issue. The high accuracy rate suggests that AI can be an effective tool in preliminary mental health screening, although reliance on such systems should be supplemented by human evaluation, particularly in high-stakes cases.

4.7 Correlations between Demographic Variables and User Perceptions

The study also explored correlations to understand how demographic factors might influence user comfort and satisfaction:

- **Age and Comfort with AI**: A negative correlation (r = -0.32) was found between age and comfort in sharing emotions with the AI system, suggesting that younger participants generally felt more at ease with AI-based emotional support.
- **Usage Frequency and Perceived Accuracy**: A positive correlation (r = 0.58) between usage frequency and perceived accuracy indicates that regular users may develop greater trust in the system's mood detection abilities.
- **Previous Therapy Experience and System Satisfaction**: A positive correlation (r = 0.45) between previous experience with therapy and satisfaction with the AI system suggests that those with a background in mental health support may be more receptive to AI-based tools.

These correlations reveal important nuances in user engagement, highlighting that familiarity with technology and previous mental health experience are significant factors in shaping comfort and satisfaction levels with AI systems.

5. DISCUSSION

The findings from this study contribute to an emerging body of research examining the role of AI in mental health support, particularly among young adults. This section critically explores the implications of participants' high comfort levels with AI-based mental health systems, perceived mood detection accuracy, timeliness of depression risk alerts, and helpfulness of system recommendations. A critical analysis is provided, acknowledging both the potential benefits and limitations of AI-driven support and situating these findings within the broader context of current research.

The study found that participants generally felt comfortable sharing their emotions with an AI-based system, with over 85% expressing positive or neutral comfort levels. This aligns with the hypothesis that young adults, who have grown up using technology, may find AI-based systems less intimidating and more private for emotional disclosure (Graham et al., 2019; Ho et al., 2018). The anonymity provided by AI, as previous studies have indicated, reduces perceived social judgment and stigma, which can otherwise be barriers to seeking mental health support (Fitzpatrick et al., 2017; Lisetti & Nasoz, 2004). However, the comfort associated with AI-based disclosure may come with risks. Studies suggest that AI's perceived non-judgmental nature can lead to over-reliance on AI systems for emotional support, potentially undermining motivation to seek professional human help (Naslund et al., 2020; Torous et al., 2018). Unlike human therapists, AI lacks the ability to provide the nuanced empathy and ethical safeguards inherent in human interaction (Bickmore & Picard, 2005; Kumar et al., 2021). In cases of complex mental health issues, reliance solely on AI may contribute to missed opportunities for deeper therapeutic intervention, a critical factor that should not be overlooked.

Participants rated the AI's mood detection accuracy relatively high, with a mean score of 3.9. This result aligns with studies showing that sentiment analysis and machine learning algorithms can reliably detect general mood states, especially when trained on large datasets (Wang et al., 2018; Topol, 2019). However, AI's accuracy remains constrained by its limitations in recognizing complex, layered emotions or situational context, which are often crucial in mental health evaluations (Xu et al., 2020; Lehman et al., 2022). For example, feelings like ambivalence or self-doubt—common in mental health crises—may evade precise detection due to AI's reliance on text-based sentiment cues, lacking deeper contextual awareness (Cohen et al., 2021). Moreover, while AI systems can alert users to emotional fluctuations, research warns of potential drawbacks. Excessive reliance on algorithms without human oversight can lead to "automation bias," where users blindly trust AI feedback, which may not always be accurate (Parasuraman & Riley, 1997). Given the 12% false positive rate noted in this study, inaccurate mood detection could lead to unnecessary user stress or confusion. Thus, these findings underscore the need for caution in interpreting AI-driven insights, suggesting that AI-based mental health support should ideally serve as a supplement to, rather than a replacement for, human judgment.

The study revealed that participants appreciated the timeliness of depression risk alerts, which were viewed as supportive for immediate self-monitoring. Prior research corroborates the value of timely feedback in digital mental health interventions, as it can prompt early awareness and intervention, key factors in managing mental health issues (De Choudhury et al., 2013; Luxton et al., 2015). Timely alerts may enable users to take preventive action, potentially mitigating the escalation of depressive symptoms. However, the use of automated alerts raises significant ethical and practical concerns. As noted by Luxton et al. (2015), frequent alerts may lead to "alert fatigue," where users start to ignore or disable notifications, particularly if alerts are perceived as intrusive or inaccurate. Additionally, without contextual understanding, AI-generated alerts risk causing undue distress by flagging false positives, which could decrease user trust and engagement over time (Torous & Roberts, 2017). These issues highlight a fundamental challenge: while timely AI alerts can be beneficial, their long-term efficacy depends on balancing sensitivity with accuracy to avoid alert fatigue and maintain user responsiveness.

While most participants found the AI system's recommendations helpful (mean score = 3.8), a significant portion (23%) rated them neutrally, suggesting a lack of personalization in these recommendations. Studies show that while general wellness advice may be adequate for mild cases, users experiencing more severe or complex mental health concerns often require tailored support that AI systems are not yet fully equipped to provide (Mohr et al., 2013; Inkster et al., 2018). Current AI systems, which primarily rely on broad datasets, may lack the contextual insights necessary to personalize recommendations effectively (Gaffney et al., 2019). Additionally, the gap between recommendation effectiveness and personalization reflects a broader issue within digital mental health: the inability of AI to fully comprehend users' unique emotional landscapes and life situations (Torous et al., 2018). For example, an AI might suggest general coping mechanisms but fail to account for individual preferences, cultural factors, or specific situational triggers. This lack of personalization could reduce users' satisfaction over time, potentially leading them to disengage from the system. Hence, while AI recommendations may be useful for general guidance, enhancing their personalization through adaptive algorithms or hybrid models incorporating human input would likely increase their impact.

The study's finding that 63.9% of participants preferred AI-based monitoring over traditional check-ins is consistent with literature noting younger populations' inclination towards digital health tools due to convenience and accessibility (Venkatesh & Davis, 2000; Torous et al., 2018). However, this preference should be viewed cautiously. While AI-based monitoring provides valuable convenience, excessive reliance on AI alone could reduce the depth of mental health care. As Kumar et al. (2021) caution, while AI offers a level of immediacy, it lacks the empathetic capacity necessary to address deeper psychological needs effectively. Furthermore, studies indicate that AI-based monitoring, if unmoderated, might inadvertently discourage help-seeking behavior by fostering a false sense of security (Naslund et al., 2020). Users who primarily rely on AI might delay seeking professional human support, especially if they perceive AI feedback as adequate. Thus, while AI-based monitoring is undoubtedly beneficial for routine mental health tracking, it should ideally be integrated with human interventions, particularly for users at higher risk of mental health deterioration. This hybrid approach could allow users to benefit from the immediacy of AI while accessing the relational depth and expertise of human mental health professionals.

6. CONCLUSION

This study highlights the potential of AI-based mental health support systems to provide accessible, immediate assistance for young adults. Findings reveal a generally high level of comfort and perceived utility in using AI for emotional disclosure, mood detection, and depression risk alerts. However, limitations such as the lack of personalized recommendations, occasional inaccuracies, and risks of over-reliance on automated feedback underscore the need for careful integration of AI into mental health care. While AI offers valuable support in monitoring and early intervention, these systems should ideally be used alongside professional human care to address complex emotional needs fully. Future research should prioritize enhancing personalization, refining detection algorithms, and developing ethical frameworks to maximize the positive impact of AI on mental health support.

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