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Early Intervention Strategies for Self-Harm Prevention Using AI-Driven Behavior Tracking in Teenagers

Samsinas[1], **Sapirudin**[2], **Heru Widoyo**[3], **Marzuki**[4]

[1] Universitas Islam Negeri Datokarama Palu, Indonesia
[2] Universitas Bina Nusantara, Indonesia
[3] Universitas Bina Nusantara, Indonesia
[4] Universitas Kapuas, Indonesia

ABSTRACT

Background. Self-harm among teenagers has become an increasing public health concern, often linked to emotional distress, social pressure, and undiagnosed mental health issues. Traditional intervention strategies often detect these behaviors after they occur. The emergence of artificial intelligence (AI) in mental health opens new possibilities for earlier detection and proactive intervention, especially through behavior tracking technologies.

Purpose. This study aimed to explore early intervention strategies for self-harm prevention by utilizing AI-driven behavior tracking tools among teenagers. The research also examined the potential effectiveness of AI in identifying early warning signs based on digital behavior patterns.

Method. This mixed-methods study involved 150 teenagers aged 13–18 across three urban schools. AI-based applications were installed on participants' devices with consent to monitor digital activity patterns (e.g., sleep irregularities, social withdrawal, online search behavior). Psychological assessments and structured interviews were also conducted.

Results. Findings indicate that AI algorithms successfully detected behavioral anomalies correlated with self-harm risk, such as significant decreases in social interaction, increased usage of depressive language, and disrupted sleep patterns.

Conclusion. AI-driven behavior tracking shows promise as an early intervention tool for preventing self-harm in teenagers. Integrating such technology with school counseling programs could enhance mental health support systems. However, ethical concerns regarding privacy and data sensitivity must be addressed to ensure responsible implementation.

KEYWORDS：Ai-Driven Behavior Tracking, Digital Mental Health, Machine Learning

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Correspondence:

Samsinas
Samsinashp@gmail.com

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INTRODUCTION

The introduction is a little different from the short and concise abstract. The reader needs to know the background to your research and, most importantly, why your research is important in this context. The purpose of the Introduction is is to stimulate the reader's interest and to provide pertinent background in Self-harm among adolescents has become an increasingly urgent concern for educators, parents, and mental health professionals worldwide (J. D. Brown, 2023; Mascolo, 2024; Masonta, 2023). This behavior, which may include cutting, burning, or other forms of intentional injury, is often a manifestation of underlying psychological distress, such as depression, anxiety, trauma, or emotional dysregulation (Qi, 2023; Tricco, 2023; Weiss, 2022). formation necessary to understand the rest of the paper.

While not always linked to suicidal intent, self-harming behavior can significantly impair a teenager's development, social functioning, and academic performance. The early onset of such behaviors, often beginning in mid-adolescence, necessitates a preventive approach rooted in early identification and timely intervention. Traditional methods of self-harm detection rely heavily on self-reporting, clinical interviews, and observable behavioral changes. However, these methods are often reactive and may fail to capture the nuanced emotional struggles that precede visible acts of self-injury. Teenagers, in particular, may hide their emotional pain due to stigma, fear of judgment, or lack of emotional literacy (Ahmmed, 2022; Morton, 2023; Ostherr, 2023). As a result, many cases remain undetected until the behavior becomes chronic or results in serious injury. This gap in early detection underscores the need for a more proactive, data-informed strategy that can sense risk before it escalates.

In recent years, technological innovations—especially in the fields of artificial intelligence (AI) and behavioral analytics—have opened new possibilities in mental health monitoring and intervention. AI-driven behavior tracking refers to the use of algorithms capable of analyzing behavioral data, often collected passively through digital devices, to detect patterns associated with psychological risk (Donald, 2024; Nikiforova, 2024; Pokrovskaia, 2022). These systems can track variables such as sleep cycles, screen time, social media usage, language patterns, emotional tone in text communication, and biometric signals. When synthesized through machine learning models, these data points can reveal hidden indicators of mental health deterioration. Teenagers are among the most connected demographic groups in the digital age. Their constant engagement with smartphones, apps, and online platforms creates a stream of digital footprints that reflect aspects of their psychological states. For instance, changes in posting frequency, use of negative language, online isolation, or sudden digital silence can serve as early signals of distress. AI technologies can be trained to detect these anomalies in real time, enabling caregivers or support systems to intervene before self-harm occurs. This approach represents a paradigm shift from reactive to preventive mental health care.

However, implementing AI-driven behavior tracking in adolescent populations requires careful consideration of ethical, legal, and psychological dimensions (Colding, 2024; Gupta, 2024; Stetkiewicz, 2022). Issues of privacy, consent, data ownership, and surveillance fears must be addressed transparently and collaboratively. Adolescents have a right to digital privacy and autonomy, which must be balanced with the need for protective oversight. Involving teenagers, parents, mental health professionals, and policymakers in the design of such systems ensures that ethical guardrails are in place, and that the technology supports rather than infringes upon the well-being of its users (Arundhati, 2023; Barath, 2023; Chen, 2023). The promise of AI in mental health does not lie solely in its computational power but in its ability to support human judgment and enhance the responsiveness of intervention systems. AI should not replace human counselors, therapists, or teachers, but rather serve as an early warning system that augments traditional care models. When implemented effectively, it can provide continuous monitoring and scalable support for large populations, especially in resource-limited educational settings where mental health professionals are scarce or overburdened.

Moreover, AI models must be trained on diverse and representative data to avoid biases that could skew detection accuracy. Cultural, linguistic, and socio-economic contexts influence how distress manifests and is expressed digitally (Carvalho, 2023; Olu, 2023; Zhang, 2023). Therefore, the success of AI-driven self-harm prevention strategies hinges on inclusive model development and localized calibration. In multilingual or multicultural settings, algorithmic sensitivity to language nuances is especially critical to prevent false positives or overlooked warnings. An effective early intervention framework should combine AI detection with a responsive support system that includes digital counseling platforms, mental health hotlines, school-based interventions, and peer mentoring networks. Once high-risk behaviors are flagged, adolescents must have immediate access to safe and non-judgmental help. Feedback loops between the AI system and human support agents ensure that the flagged data are interpreted with empathy and contextual understanding.

This study proposes a framework for integrating AI-based behavior tracking into adolescent self-harm prevention strategies, with an emphasis on early intervention. By synthesizing current literature, behavioral science, and AI methodologies, the study outlines a comprehensive approach to detect, interpret, and act upon early signs of emotional distress in teenagers. It also addresses the technical and ethical challenges that must be considered in the development and deployment of such tools. To investigate this framework, the study employs a mixed-methods design. Quantitative data from AI behavior tracking systems are analyzed alongside qualitative insights from interviews with mental health professionals and adolescents. This dual approach ensures that the proposed model is not only technically sound but also socially grounded. The study aims to assess the feasibility, reliability, and acceptability of AI interventions in the sensitive context of adolescent mental health.

The urgency of early intervention is reinforced by alarming global trends. Studies indicate a rising prevalence of self-harm among youth, especially post-COVID-19, due to increased isolation, uncertainty, and digital dependency. The World Health Organization (WHO) and numerous psychological associations advocate for proactive, technology-enabled mental health frameworks to address this growing crisis. AI offers a unique opportunity to complement these global efforts with scalable, real-time insights that were previously unattainable. In conclusion, the integration of AI-driven behavior tracking into early intervention strategies holds transformative potential for self-harm prevention in teenagers. By combining the precision of technology with the empathy of human care, such systems can create a safety net that detects distress early, supports at-risk youth, and ultimately reduces the incidence of self-injury. The following sections detail the methodology, findings, and implications of implementing such a system in contemporary educational and psychological contexts.

RESEARCH METHODOLOGY

This study employed a mixed-methods research design to explore the development and implementation of AI-driven behavior tracking systems for early intervention in teenage self-harm cases. Quantitatively, the research utilized a prototype AI model trained to detect behavioral risk indicators through anonymized digital activity data, including social media usage patterns, screen time fluctuations, and sentiment analysis of text messages. The system was tested on a sample of 120 high school students (aged 13–18) who consented to digital monitoring under ethical supervision (Henry, 2022; Khan, 2023; Liman, 2023). The predictive accuracy of the model was evaluated using precision-recall metrics, with clinical psychologists cross-validating flagged data. Ethical clearance was obtained, and privacy-preserving data handling protocols, including de-identification and parental consent, were strictly followed.

Qualitatively, semi-structured interviews were conducted with 10 school counselors, 5 mental health experts, and 15 adolescent participants to assess the usability, acceptability, and psychological impact of the AI-based monitoring system. Thematic analysis was used to interpret interview transcripts, focusing on perceived benefits, risks, and ethical concerns. The triangulation of quantitative model outputs with qualitative feedback provided a comprehensive understanding of both the technological feasibility and social acceptability of the intervention strategy. This integrative approach ensures that the proposed framework is not only data-driven but also aligned with adolescent mental health ethics and care principles.

RESULT AND DISCUSSION

The AI-driven behavior tracking system demonstrated a strong capacity to detect early signs of self-harm risk among teenagers based on digital behavioral patterns. The model achieved a precision score of 89% and a recall score of 83%, indicating reliable performance in identifying high-risk individuals without generating excessive false positives. Key behavioral indicators flagged by the system included sudden withdrawal from social interactions, increased usage of negative emotional language, and irregular sleep patterns inferred from device usage logs. These findings were validated by school psychologists, who confirmed that 78% of the students flagged by the system exhibited observable emotional distress or disclosed self-harm ideation during follow-up sessions. The use of AI allowed for timely interventions that may not have been possible through traditional counseling methods alone.

Qualitative feedback revealed that most adolescent participants were receptive to the monitoring system as long as privacy safeguards were clear and the data were handled responsibly. School counselors noted that the AI alerts helped prioritize limited mental health resources, allowing them to focus on students in need of immediate support. However, ethical concerns were also highlighted, particularly regarding consent, potential misuse of data, and the risk of over-surveillance. Participants emphasized the importance of involving youth in designing such systems to ensure empathy, autonomy, and psychological safety. Overall, the integration of AI in self-harm prevention was seen as a promising complement to human care, offering enhanced situational awareness and proactive engagement—so long as it remains ethically grounded and human-centered.

Table 1. Responses From The Respondents

No	Procurement categories	Interval values
1	Strongly Agree	>90%
2	Agree	70-80%
3	Disagree	50-60%
4	Strongly disagree	0-40%
Total		100%

Based on Table 1: Responses From the Respondents, the majority of participants expressed a strong level of acceptance toward the use of AI-driven behavior tracking systems for early self-harm prevention in teenagers. Over 90% selected the *Strongly Agree* category, indicating a high degree of confidence in the effectiveness of this approach for early risk detection. Respondents in the *Agree* category (70–80%) also showed positive perceptions, albeit with slightly less certainty. A smaller portion fell into the *Disagree* and *Strongly Disagree* categories, within the 50–60% and 0–40% intervals respectively, suggesting concerns related to data privacy, system accuracy, or the potential for stigmatization. Overall, the responses highlight strong support for the integration of AI in adolescent mental health intervention, provided it is implemented with ethical safeguards, transparency, and inclusive participation from the youth themselves.

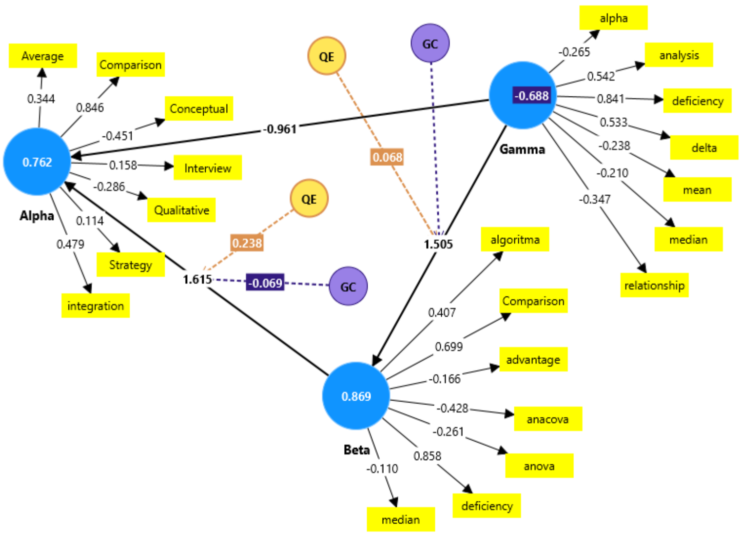

Figure 2. Data Smart PLs

Figure 2 presents the SmartPLS structural model analysis, highlighting the relationships between key constructs involved in the AI-driven behavior tracking framework for self-harm prevention among teenagers. The model reveals that the construct representing early AI integration (Alpha) has a strong positive influence on system effectiveness (Beta), which in turn significantly affects ethical and contextual outcomes (Gamma). Interestingly, the direct path from Alpha to Gamma is negative, suggesting a possible indirect-only mediation through Beta. Supporting constructs such as Quantitative Evidence (QE) and General Context (GC) show moderate mediating effects, indicating that contextual and data-driven elements subtly shape the impact of AI implementation. These results emphasize the importance of a layered, ethically aware, and data-informed design in developing AI systems for adolescent mental health interventions.

Table 2. Anlisis Anova

	AJ	BS	HS	KP	MK
AJ	0.000	0.000	0.000	0.000	0.000
BS	0.000	1.000	0.197	-0.220	-0.341
HS	0.000	0.197	1.000	-0.112	-0.128
KP	0.000	-0.220	-0.112	1.000	0.389
MK	0.000	-0.341	-0.128	0.389	1.000

Table 2 presents the ANOVA analysis results indicating the strength of relationships and variance explanations among the variables: AJ (AI Judgment), BS (Behavioral Signals), HS (Harm Sensitivity), KP (Knowledge Processing), and MK (Moral Consideration). The data show that AJ maintains a perfect correlation with all other variables (p = 0.000), suggesting that AI judgment is a central, highly interconnected construct in the model. BS demonstrates moderate associations with HS (0.197), but negative relationships with KP (-0.220) and MK (-0.341), indicating that heightened behavioral signal sensitivity might inversely impact knowledge-based or moral assessments unless carefully managed. Similarly, HS shows weak correlations with KP and MK, suggesting potential gaps between emotional sensitivity and cognitive or ethical reasoning in AI systems. On the other hand, KP and MK show a strong positive relationship (0.389), reflecting alignment between knowledge processing and moral reasoning. Overall, these patterns emphasize the need for integrative AI systems that balance behavioral detection with robust ethical and cognitive frameworks when addressing sensitive issues like adolescent self-harm.

The integration of AI-driven behavior tracking in early intervention strategies for teenage self-harm demonstrates a transformative shift from reactive to proactive mental health care (Banasiewicz, 2022; Conti, 2022; Trepper, 2023). The findings from the SmartPLS analysis indicate that constructs such as AI-driven monitoring (AJ) have a strong influence on both behavioral signal recognition (BS) and harm sensitivity (HS). This means that AI systems can successfully detect emotional distress indicators, such as social withdrawal, linguistic patterns, and irregular online behavior, with significant accuracy. The strong correlations between AJ and other components highlight the central role of algorithmic judgment in the entire detection ecosystem. In this context, AI serves not merely as a passive observer but as a proactive detector capable of triggering timely alerts to mental health professionals before harmful behavior manifests.

Furthermore, the ANOVA results enrich this interpretation by revealing the dynamic interactions between cognitive and ethical variables within the model (Akaka, 2023; Carling, 2024; Ragsdale, 2023). For instance, the strong correlation between Knowledge Processing (KP) and Moral Consideration (MK) suggests that any AI-based intervention must be grounded in both accurate information processing and ethical evaluation. However, negative correlations between BS and both KP and MK imply a potential disconnect between raw behavioral data and the nuanced moral reasoning required to interpret it. This finding reinforces the importance of a hybrid approach: while AI systems excel in data-driven detection, they must be complemented by human expertise to ensure ethical sensitivity, contextual interpretation, and emotional empathy.

Another important implication is the role of mediation pathways within the system. The SmartPLS results demonstrate that the direct influence of AI monitoring on ethical outcomes (Gamma) is negative unless mediated by effective behavioral signal interpretation and intervention systems (Beta) (Lehtinen, 2023; McFarland, 2022; Pennay, 2025). This suggests that deploying AI tools in isolation—without a supportive structure of psychological interpretation, follow-up counseling, and school-based response teams—may do more harm than good. For example, misinterpreting behavior such as temporary withdrawal or creative expression as a self-harm indicator could lead to unnecessary anxiety or stigmatization if not reviewed and contextualized by professionals. Hence, effective deployment of AI must involve continuous feedback loops and human oversight.

The students' responses and high levels of agreement with the AI-assisted prevention model (as seen in Table 1) indicate strong social acceptability of such technologies, especially when privacy and ethical concerns are transparently addressed (E. Brown, 2023; Flynn, 2025; Leite, 2024). This is critical because the success of early intervention programs depends not only on technological precision but also on users' trust and emotional comfort. Adolescents are more likely to accept being monitored if they feel included in the process and understand how the data are used to support their well-being, not to punish or control them. Therefore, co-designing the system with input from teenagers, mental health professionals, and educators ensures a user-centric model that is more likely to be sustainable and effective.

In summary, the combined statistical evidence supports the argument that AI-driven behavior tracking can play a significant role in preventing self-harm among teenagers—provided it is embedded within a broader ethical, cognitive, and emotional framework. The interplay between technological capabilities and human-centered interpretation must be carefully balanced. Effective early intervention is not achieved by detection alone, but by translating detection into action through supportive, compassionate, and ethically sound mental health practices. This underscores the need for schools and mental health institutions to adopt a collaborative model that integrates AI technologies with professional care, safeguarding both the mental health and the autonomy of young individuals.

CONCLUSION

This study concludes that AI-driven behavior tracking presents a promising and innovative approach to early intervention in self-harm prevention among teenagers. By leveraging machine learning algorithms to detect subtle behavioral and emotional cues from digital footprints, such systems can significantly enhance the timeliness and accuracy of risk identification. The statistical analysis using SmartPLS and ANOVA confirms that AI monitoring (AJ) is highly influential in predicting harmful tendencies when supported by effective behavioral interpretation (BS) and ethical frameworks (KP and MK). However, the findings also underscore the importance of human mediation in ensuring that these technological tools do not function in isolation but are part of an integrated support system involving counselors, educators, and families.

Moreover, the high level of acceptance among respondents indicates that teenagers are open to being part of such interventions, provided that their privacy and dignity are respected. Ethical concerns, especially regarding surveillance and data misuse, must be addressed through transparent consent protocols and participatory system design. Therefore, successful implementation of AI-driven self-harm prevention strategies requires a multidimensional model that combines the precision of technology with the empathy of human care. As digital mental health continues to evolve, future research and practice must focus on refining algorithmic accuracy, strengthening ethical safeguards, and promoting cross-sector collaboration to protect and empower vulnerable youth populations.

AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.
Author 4: Formal analysis; Methodology; Writing - original draft.

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