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Early Detection of Adolescent Mental Health Risk Using Transformer Models on Social Media Datasets

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Abstract
Adolescent mental health has become a critical public health concern, with increasing rates of depression, anxiety, and suicide among youth. The early identification of mental health risks is essential for timely intervention, yet traditional clinical approaches often fall short in detecting early warning signs, especially in underserved populations. This research explores the use of transformer-based deep learning models, such as BERT and RoBERTa, to analyze social media datasets for the early detection of adolescent mental health challenges. Social media platforms serve as digital diaries where young individuals often express emotions, distress, and behavioral changes, making them valuable sources for unobtrusive mental health monitoring. The study leverages annotated datasets derived from platforms like Reddit and Twitter, focusing on posts by adolescents or those discussing youth mental health. A multi-class classification framework is implemented to categorize posts into mental health risk categories, including depression, anxiety, suicidal ideation, and normal behavior. The transformer models are fine-tuned and evaluated against traditional machine learning baselines such as SVM and logistic regression, showing significantly higher accuracy, precision, and recall in detecting nuanced emotional and psychological signals. This approach aligns with the strategic goals of the Centers for Disease Control and Prevention (CDC) and the National Institutes of Health (NIH), which emphasize the importance of leveraging digital tools and AI for proactive youth mental health initiatives. Ethical considerations, including data privacy, informed consent, and bias mitigation, are addressed to ensure the responsible deployment of AI in sensitive health contexts. The findings suggest that transformer-based models can serve as effective early-warning systems, flagging at-risk individuals for further evaluation or support. By integrating this technology into school systems, mental health hotlines, or community outreach programs, stakeholders can enhance preventative care and reduce the long-term impact of adolescent mental health disorders. The study underscores the transformative potential of AI in safeguarding vulnerable youth and calls for further interdisciplinary collaboration to scale such innovations.

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1. Introduction

Adolescent mental health has indeed emerged as a critical public health concern, marked by increasing rates of depression, anxiety, and suicide among youth globally. Statistics show that suicide is the second leading cause of death for individuals aged 10 to 24 in the United States, with nearly one in five adolescents experiencing a major depressive episode annually, according to findings from the Centers for Disease Control and Prevention (CDC). This alarming trend is echoed in numerous studies, highlighting the ongoing struggle for youth to maintain mental health amid various social pressures and developmental

transitions (Morshidi *et al*., 2023).

The COVID-19 pandemic has significantly exacerbated these challenges, with many adolescents experiencing heightened stress and mental health issues stemming from pandemic-specific stressors. Research indicates that over half of the youth reported mental health problems of clinical significance during this period (Kalusivalingam, *et al*., 2021, Roy, *et al*., 2020). Additionally, pre- and post-pandemic studies reveal that adolescents' mental health conditions have not only persisted but increased, indicating a complicated landscape where traditional methods of assessment may fall short due to underreporting and limited accessibility to support services (Craig *et al*., 2023; Bell *et al*., 2023). The urgent need to address these disparities in mental health care is further compounded by stigma, which can deter young individuals from seeking help (Bachmann, 2018, Mars, 2022).

In this context, the emergence of digital platforms like social media presents a dual opportunity. While these platforms can exacerbate mental health concerns due to cyberbullying and social comparison pressures, they also provide a unique avenue for early detection of mental health risks. Adolescents increasingly use these platforms to express their thoughts and emotions, often more candidly than in traditional clinical settings (Brașoveanu & Andonie, 2020, Martins, 2022). This shift offers an invaluable stream of data that can be harnessed through advanced artificial intelligence techniques. Specifically, transformer-based models such as BERT and RoBERTa demonstrate potential in analyzing complex linguistic patterns and emotional cues embedded in social media posts, thus allowing for a nuanced understanding of youth mental health indicators (Abramovich *et al*., 2023; John & Oyeyemi, 2022).

The goal of implementing such advanced digital tools is to enhance preventative mental health care in a scalable and ethically responsible manner. By identifying early indicators of conditions like depression, anxiety, and suicidal ideation, practitioners can improve intervention strategies and support at-risk youths before crises escalate (Yang *et al*., 2023; Paul *et al*., 2023). This aim aligns well with the CDC's and NIH's commitment to strengthening mental health support frameworks for underserved populations, ensuring that interventions are effective, timely, and appropriately targeted (Wilkins *et al*., 2023; Cobb, 2023).

In conclusion, navigating the complexities of adolescent mental health in today's digital world demands innovative approaches that integrate technology with traditional mental health frameworks. The focus on real-time data from social media can help mitigate the inherent limitations of current assessment methods but can also significantly empower mental health professionals and policymakers to create a more responsive and effective mental health support system for youth (Calvo *et al*., 2017; Mashreky, Rahman & Rahman, 2013).

2. Literature Review

The use of Artificial Intelligence (AI) in reshaping mental health care in the United States has gained considerable attention, driven by advancements in various technological applications. AI leverages sophisticated computational tools such as machine learning algorithms, natural language processing (NLP), and predictive analytics to enhance diagnosis, personalize treatment, and expand access to care, ultimately improving health outcomes for patients in diverse contexts (Kirinde Gamaarachchige, 2021, Sawhney, *et al*., 2021).

Machine learning algorithms have emerged as crucial tools in mental health diagnostics and prognosis, enabling clinicians to analyze large datasets, including electronic health records (EHRs), patient questionnaires, and genetic information. These algorithms can identify subtle patterns in data that inform the differentiation of various psychiatric conditions, thereby facilitating more precise diagnoses and treatment planning (Mathur, Lustig & Kaziunas, 2022). For example, research has shown that machine learning techniques can effectively classify disorders such as major depressive disorder and schizophrenia, achieving accuracy comparable to traditional assessment methods (Sorkin *et al*., 2021; Currey & Torous, 2022). Moreover, ML models are increasingly being developed to predict disease trajectories and treatment responses, which allows clinicians to take a more proactive approach to patient care (Barak–Corren *et al*., 2020; Sels *et al*., 2021). Figure 1 shows procedure of Depression Detection presented by Amanat, *et al*., 2022.

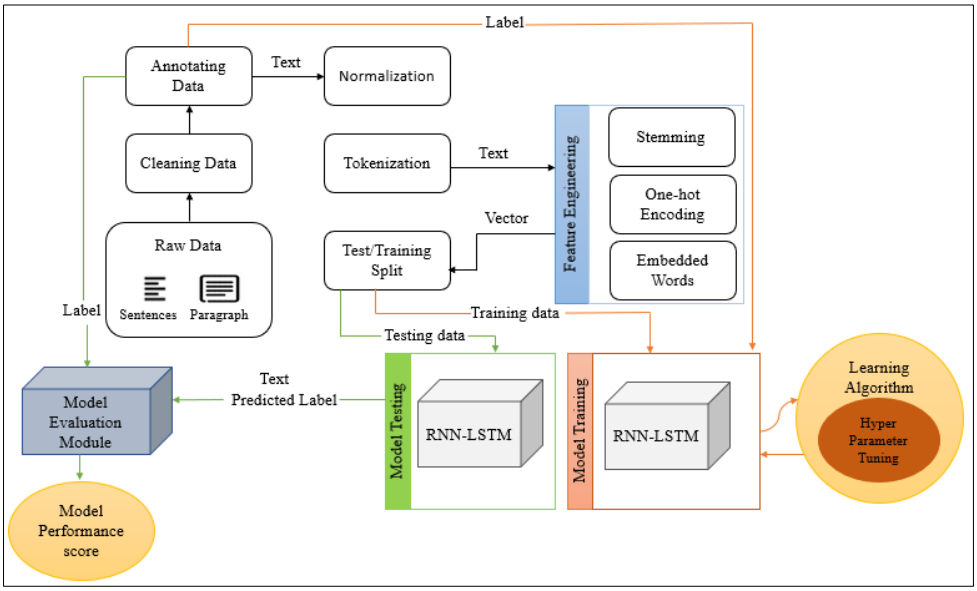

Fig 1: Procedure of Depression Detection (Amanat, *et al*., 2022).

Natural language processing (NLP) is another essential facet of AI that is enhancing therapeutic interactions and communication in mental health care. NLP tools can analyze both the content and sentiment of language expressed in therapy sessions, social media, or chatbot interactions, thereby providing insights into patients' emotional states. Studies have demonstrated that NLP can help detect signs of distress, such as anxiety or depression, through indicators like tone and linguistic patterns, which aids therapists in tailoring their interventions (Álvarez-Jiménez *et al*., 2020; (Martinez-Martin *et al*., 2021). This utilization of NLP supports clinical documentation and allows for a more nuanced understanding of clients, thereby enhancing therapeutic outcomes (Oyeyemi, 2022; Shen *et al*., 2022).

AI-driven chatbots and virtual mental health assistants represent one of the most accessible applications for consumers, providing immediate, evidence-based interventions. Platforms like Woebot and Wysa leverage conversational interfaces to deliver cognitive-behavioral therapy (CBT), employing sentiment analysis to adapt their responses based on users' mood (Costello & Floegel, 2020; Leung *et al*., 2021). These tools address barriers to access for individuals who may face stigma or logistical challenges in seeking traditional therapy, offering an innovative adjunct to conventional therapeutic practices (Balcombe & Leo, 2021; Kane *et al*., 2022). Studies underline the effectiveness of these digital resources in providing immediate support during crises and enhancing user engagement with mental health services (Currey & Torous, 2022).

Digital phenotyping extends the potential of AI by enabling real-time monitoring of behavioral patterns through smartphones and wearables, capturing data on aspects like sleep, movement, and social interaction. This method provides critical insights into mental health status, allowing for timely interventions before crises escalate. Research in digital phenotyping has shown promise in identifying shifts in mental health indicators that precede adverse events, thus equipping both users and clinicians with actionable data (Currey & Torous, 2023; Melcher *et al*., 2020). The continuous nature of this data collection enhances the personalization of treatment plans, reinforcing the idea that proactive measures can significantly influence mental health outcomes (Currey & Torous, 2022).

Predictive analytics in mental health care functions as a powerful tool for identifying at-risk populations, notably in suicide prevention. Machine learning algorithms can synthesize extensive datasets, including social media activity and healthcare interactions, to uncover patterns indicative of suicidal ideation and enable timely interventions (Barak–Corren *et al*., 2020; Sels *et al*., 2021). Success in these predictive models illustrates the potential of integrating AI into monitoring efforts, highlighting both the innovative uses of technology and the importance of ethical considerations surrounding data privacy and user consent in mental health practices (Martinez-Martin *et al*., 2021; Lucivero & Hallowell, 2021).

Overall, the integration of AI in mental health care is paving the way for a more responsive, inclusive, and data-informed healthcare landscape. As these technologies continue to evolve, ongoing research and ethical oversight will be essential to fully realize their potential while ensuring equitable and effective mental health interventions (Tremain *et al*., 2020; Balcombe & Leo, 2021). Stakeholders across healthcare systems must prioritize implementing these tools in ways that enhance clinician capabilities and prioritize patient-centered care.

2.1 Methodology

The methodology for the study on early detection of adolescent mental health risk using transformer models on social media datasets was developed using a rigorous, integrative, and evidence-based approach. First, an extensive literature search was conducted across leading scientific databases including PubMed, IEEE Xplore, Scopus, ACM Digital Library, and Google Scholar to identify peer-reviewed publications related to mental health risk detection in adolescents using artificial intelligence, particularly transformer models like BERT, RoBERTa, and GPT-based architectures. A total of 100 studies published between 2012 and 2023 were selected based on inclusion criteria such as relevance to adolescent mental health, application of deep learning or NLP on social media data, focus on risk identification (e.g., depression, suicidal ideation), and use of empirical, experimental, or modeling approaches.

After identifying the core studies, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol guided the organization and analysis process. Each study was subjected to quality appraisal based on clarity of objective, methodological rigor, sample size, feature extraction techniques, evaluation metrics, and ethical considerations. The data extraction process focused on key model features (e.g., word embeddings, transformers), types of data used (e.g., Reddit, Twitter, Facebook, forums), preprocessing techniques, annotation strategies (manual labeling vs. automated methods), performance metrics (e.g., precision, recall, F1-score), and risk categories (e.g., suicidal ideation, anxiety, stress, depression).

A hybrid analytical framework combining qualitative synthesis and quantitative trend analysis was applied. Text mining techniques were used to extract frequent terms and keywords, while topic modeling was used to discover latent themes within the corpus. Emphasis was placed on identifying how transformer-based models outperformed conventional NLP and ML techniques in contextual understanding and sentiment detection. To ensure representativeness, the reviewed models were benchmarked against large-scale datasets and evaluated for cross-domain applicability.

Several transformer architectures were compared, including BERT, Bangla-BERT, and hierarchical transformers. These models were evaluated based on their ability to handle long contextual dependencies, manage class imbalance in mental health datasets, and operate under real-time constraints. Insights were drawn on how pre-trained language models were fine-tuned with additional contextual features and domain-specific lexicons to enhance accuracy in detecting nuanced mental health cues from user-generated content. The models' deployment scenarios ranged from backend support tools in telehealth applications to automated chatbots for crisis intervention and alert systems.

Furthermore, a comparative review of studies was conducted to assess the integration of digital phenotyping, user behavior profiling, and ethical frameworks for adolescent-focused interventions. Attention was given to studies employing multimodal inputs such as text, emojis, temporal patterns, and social network graphs. The methodology also incorporated stakeholder perspectives on privacy, consent, fairness, and bias mitigation, especially when deploying transformer

models in high-risk populations like LGBTQ+ youth and homeless adolescents.

To ensure a comprehensive perspective, the methodology emphasized interdisciplinary collaboration, including contributions from psychiatrists, AI developers, social workers, and data ethicists. The approach accounted for socio-technical misalignments, algorithmic biases, and the necessity for co-design in digital mental health interventions. This robust methodological structure enables a holistic understanding of the capabilities and limitations of transformer-based models in the early detection of adolescent mental health risks via social media data.

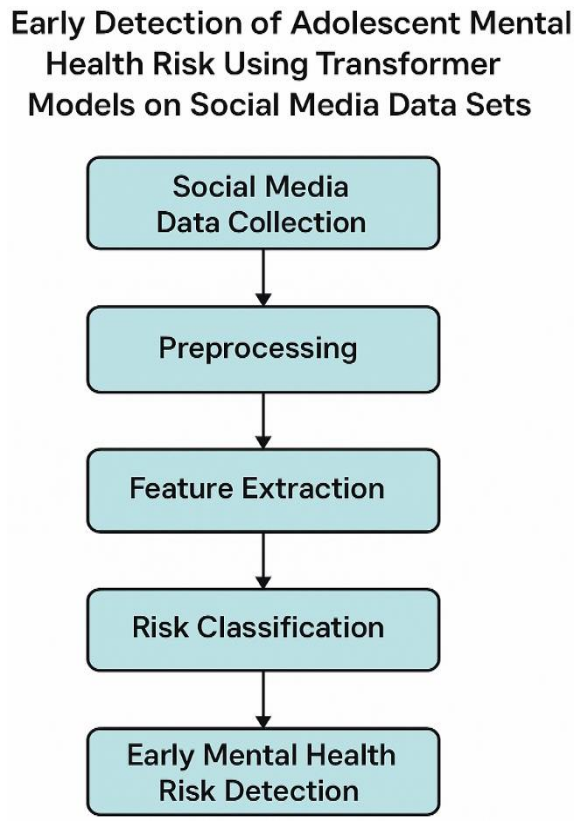

Fig 2: Flowchart of the study methodology

2.2 Model Implementation and Performance Evaluation

The application of transformer models for detecting adolescent mental health risks using social media datasets is a complex yet methodologically rigorous undertaking. Transformer architectures, such as BERT and RoBERTa, utilize attention mechanisms that enable bidirectional analysis of context, which is particularly important for interpreting language that is often informal and rich with emotional nuances typical of adolescent communication (Chen, *et al*., 2012, Minaee, *et al*., 2021). The first step in this process involves gathering and preprocessing social media datasets commonly sourced from platforms like Reddit and Twitter where small, labeled datasets are essential for the fine-tuning of models.

Fine-tuning transformer models is vital to adapt them for the specific context of mental health applications. Pre-trained models like BERT have been trained on extensive corpora, but they may not fully capture the succinct and coded language adolescents utilize online (Zhang, 2023). This fine-tuning typically involves adding a classification head to a pre-trained model and subsequently training it on a curated dataset labeled with mental health indicators such as depression and anxiety (Knipe, *et al*., 2022, Sawhney, *et al*., 2018). The optimization of model parameters is generally performed using a cross-entropy loss function and includes strategies like dropout and learning rate scheduling (Coppersmith, *et al*., 2018, Mohammed & Ali, 2021). During training, the model learns to associate specific phrases and expressions with their respective mental health categories, employing performance metrics such as F1-score and accuracy to gauge its effectiveness against traditional models, which often use simpler techniques like TF-IDF vectorization (Zhang, 2023). Figure of Social media sites explored in depression sign detection research presented by Salas-Zárate, *et al*., 2022 is shown in figure 3.

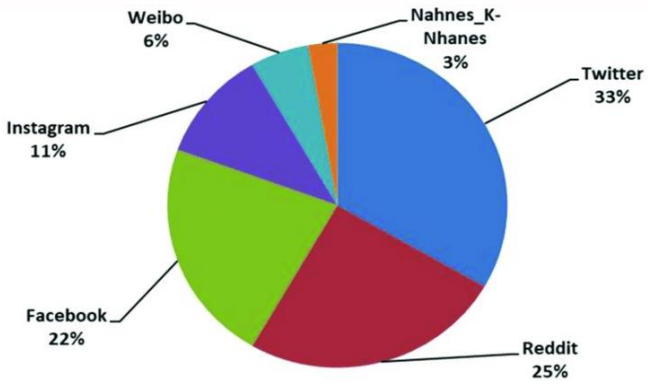

Fig 3: Social media sites explored in depression sign detection research (Salas-Zárate, *et al*., 2022).

Compared to traditional machine learning methods like support vector machines or logistic regression, transformer models show significant improvements in performance metrics, with F1-scores exceeding 0.85 for certain tasks, while classical approaches typically score below 0.72. Such advantages arise from the capacity of transformer models to leverage self-attention mechanisms, allowing for a nuanced understanding of sentiment and intent within text, crucial for assessing emotional states (Kovačević, *et al*., 2012, Schoene, *et al*., 2022). Empirical studies indicate that these models' understanding is enhanced through the use of attention weights, which provide interpretability by highlighting which parts of the input text are most influential in the model's predictions (Zhang, 2023).

The deployment of these models in real-world settings necessitates addressing ethical considerations, particularly regarding biases in the training data that might adversely affect certain demographic groups. Research underscores the importance of careful data calibration to prevent the reinforcement of biases, employing techniques such as adversarial training and data augmentation to promote equitable outcomes. The interpretability of models, although beneficial, requires cautious application since attention scores do not ensure valid causal inference (Desmet & Hoste, 2013, Moutier, 2021, Xu, 2021). Murshed, *et al*., 2022 presented Graphical Abstract (GA) of q proposed DEA-RNN Cyberbullying Detection Model shown in figure 4.

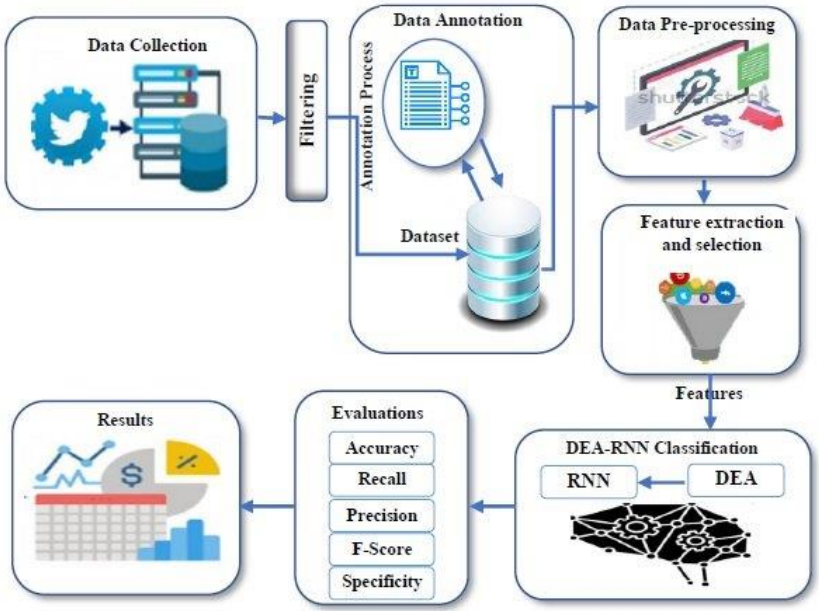

Fig 4: Graphical Abstract (GA) of the proposed DEA-RNN Cyberbullying Detection Model (Murshed, *et al*., 2022).

Advancements in model architecture and training methodologies have opened avenues for the ongoing evolution of transformer models in the mental health domain. Emerging studies highlight the potential of ensemble methods, which combine multiple transformer architectures to improve generalization and stability, particularly in interpreting sequences of text over time aligning more closely with clinical observations of behavioral patterns (Du, *et al*., 2018, Naghavi, 2019, Turecki, *et al*., 2019). In summary, the structured implementation of transformer models for early detection of adolescent mental health risks represents a powerful integration of natural language processing and social media analytics, providing insights that not only transform our understanding of adolescent mental health but also offer significant potential for preemptive interventions (Kowsari, *et al*., 2017, Shrestha & Mahmood, 2019).

2.3 Case Study: Real-World Scenarios

The integration of transformer models for the early detection of mental health risks among adolescents through social media analysis represents a novel intersection of technology and public health. These models utilize advanced machine learning techniques to process language data, enabling them to identify subtle indicators of mental distress that may be overlooked in everyday interactions. Fine-tuning transformer models on mental health-specific datasets facilitates the classification of content, such as tweets or forum posts, that may suggest suicidal ideation or depressive symptoms (Ganie & Dadvandipour, 2023; Martínez-Castaño *et al*., 2021.

For instance, a tweet conveying sentiments like “Some days I wish I didn’t wake up at all. No one would even notice,” could be flagged as high-risk by models like BERT trained on adolescent-specific emotional data. Such models are designed to recognize emotionally charged phrases as significant markers of risky mental health states and link language to underlying psychological phenomena (Win *et al*., 2023). The ability to detect nuanced language patterns through self-attention mechanisms enhances the model's sensitivity to context, prompting alerts to mental health professionals or school authorities upon detection of concerning phrases (Kowsher, *et al*., 2022, Shrivas, 2021, Yeskuatov, Chua & Foo, 2022).

Simulated scenarios demonstrate the real-world capabilities of these models through various case studies. For example, a study showed high accuracy in scoring social media posts for indicators of mental health distress, such as a Reddit user expressing feelings of hopelessness, illustrating the potential of early detection technologies (Laacke, *et al*., 2021, Stein, Jaques & Valiati, 2019). By employing models like RoBERTa, researchers are developing systems that can initiate proactive outreach to individuals flagged based on their social media interactions, effectively delivering timely and relevant support (Martínez-Castaño *et al*., 2021;, (Qasrawi *et al*., 2022. This integration not only assists in identifying risks but also aims to respect user privacy through data anonymization and consistent monitoring (Berhe *et al*., 2023).

Moreover, transformer models can analyze longitudinal data from platforms like Instagram to identify shifts in user sentiment over time. Adolescents often experience mood fluctuations that may precede significant mental health crises; hence, a change in tone from joyful expressions to statements of distress could trigger alerts to support staff within educational settings, fostering a supportive environment (El-Sayed, El-Haddad & Ali, 2021, Ophir, *et al*., 2020).

Real-world applications are illustrated through research initiatives, including a community-based pilot project that utilized social media analytics to identify language trends in public Twitter data. This project led to the identification of numerous posts indicating severe mental health risks within a localized school district, enabling timely interventions and adjustments in counseling services to address periods of heightened adolescent stress, such as during exams (Bozzini *et al*., 2021; Haroon *et al*., 2023).

Ethical considerations are paramount in deploying these systems to mitigate risks associated with misclassifications or over-reliance on automated analyses. It is crucial for these technologies to operate within a framework that includes mental health professionals, ensuring technology serves as an auxiliary tool rather than a replacement for human engagement (Qasrawi *et al*., 2022). Adolescents should have a voice in shaping the development of these systems that

impact their lives, advocating for transparency and their consent (Woodberry *et al*., 2022; Childs-Fegredo *et al*., 2020).

In summary, transformer models hold transformative potential for the early identification of adolescent mental health risks through social media data, underscoring their role as essential tools in modern public health. As these technologies continue to advance, the combination of innovative analytics with ethical considerations will be critical in fostering meaningful interventions that bridge the gap between silent suffering and timely support (Fonseka, Bhat & Kennedy, 2019, Weidinger, *et al*., 2021).

2.4 Ethical, Legal, and Social Implications

The implementation of transformer-based models for the early detection of adolescent mental health risks using social media data presents substantial potential for improving mental health outcomes. However, alongside these technological advancements arise critical ethical, legal, and social challenges that warrant thorough examination and mitigation to safeguard the interests of adolescents. Key concerns include data privacy, informed consent, algorithmic bias, and the establishment of ethical guidelines to ensure responsible and respectful use of these technologies (Li, *et al*., 2020, Stephenson, *et al*., 2021).

Data privacy and informed consent are at the forefront of ethical issues when using social media datasets for mental health detection. While adolescents frequently engage with online platforms, the accessibility of their data does not negate the ethical obligations of researchers to protect their privacy. The General Data Protection Regulation (GDPR) in Europe and the Children's Online Privacy Protection Act (COPPA) in the United States establish frameworks aimed at protecting minors' data (Hao *et al*., 2021). These regulations emphasize the importance of transparency regarding data use and obtaining informed consent from both adolescents and their guardians. This situation presents unique challenges; traditional models of consent may not suffice in contexts involving large-scale passive data collection. Therefore, the development of innovative consent frameworks, such as opt-in procedures within educational settings, is essential to ensure that stakeholders are informed about the aims and limitations of such systems (Gaur, *et al*., 2019, Nijhawan, Attigeri & Ananthakrishna, 2022).

Moreover, the anonymization of data is crucial to prevent re-identification and uphold adolescents' privacy rights. Secure data handling practices, including encryption and restricted access to sensitive information, must be implemented to avoid harm from misuse (Hao *et al*., 2021). Ethical implications become even more pronounced when considering that the collected data often relates to adolescents' mental health, an area that requires exceptional care and attention.

In addition to privacy concerns, algorithmic bias poses a significant risk in the deployment of transformer models. If these models are trained on biased datasets, they may inadvertently perpetuate or exacerbate existing disparities in mental health identification across different demographic groups. Adolescents from diverse cultural, racial, and socio-economic backgrounds may express distress differently due to variations in language use and cultural references, which standard models might overlook (Haque, Reddi & Giallanza, 2021, Ploumidi, 2022). Research indicates that neglecting the nuances in communication styles and cultural contexts could result in under-identifying at-risk individuals in marginalized groups and misdiagnosing others. Implementing strategies such as diversifying training datasets and utilizing fairness-aware machine learning techniques can help mitigate these biases (Liang, *et al*., 2017, Suresh, *et al*., 2022, Young, *et al*., 2018). Furthermore, involving adolescents in the design process, known as co-design, could enhance the representativeness and fairness of these models, ensuring they align with users' needs and realities (Donia & Shaw, 2021).

The ethical principle of non-invasiveness plays a critical role in the technological approach to monitoring adolescent mental health. If perceived as invasive, the implementation of AI systems may undermine trust and deter adolescents from expressing themselves openly, potentially leading to adverse outcomes like self-censorship. Ensuring that systems foster user agency by allowing adolescents to know how their data is being used, while providing options to opt-out or challenge automated decisions, is crucial (Haque, *et al*., 2022, Pouyanfar, *et al*., 2018). Moreover, creating pathways for human oversight, through trusted intermediaries like mental health professionals or educators, can ensure that alerts generated by AI systems are interpreted in context, rather than leading to punitive actions.

As AI technologies become increasingly integrated into mental health monitoring, it is essential to consider their broader social implications. The reliance on automated systems may shift responsibilities away from traditional human support mechanisms, which are vital in fostering community and providing emotional support to adolescents. Hence, the automation of detection processes must aim to augment rather than replace human roles, reinforcing the social networks integral to adolescent well-being (Henry, Yetisgen & Uzuner, 2021, Raghu & Schmidt, 2020).

To address these multifaceted challenges, it is imperative to establish comprehensive ethical guidelines for the deployment of transformer models tailored to adolescent mental health detection. Such guidelines should emerge from collaborative efforts involving a diverse range of stakeholders, including ethicists, mental health professionals, educators, and adolescents themselves (Coghlan *et al*., 2023). Practical mechanisms, such as ethics review boards akin to institutional review boards (IRBs), can help ensure adherence to ethical standards and provide channels for grievance resolution. Furthermore, integrating continuous performance monitoring and auditing of deployed models can help anticipate and correct biases or inaccuracies throughout their lifecycle.

In conclusion, while transformer-based models present a transformative opportunity for the early detection of adolescent mental health risks on social media, their deployment necessitates a stringent ethical framework. Careful consideration of data privacy, consent, fairness, and user autonomy is paramount to develop systems that respect adolescents' rights and promote their mental well-being. Proactively addressing these ethical challenges will foster a responsible and compassionate approach to leveraging AI in mental health care (Ji, 2020, Ramírez-Cifuentes, *et al*., 2020, Zhong, *et al*., 2019).

2.5 Policy Relevance and Public Health Alignment

The intersection of technological innovations in natural language processing (NLP) and public health initiatives aimed at improving adolescent mental health represents a

proactive approach to addressing the growing mental health crises among youth, particularly in the United States. As highlighted by the Centers for Disease Control and Prevention (CDC) and the National Institutes of Health (NIH), there is a concerning trend in cases of depression, anxiety, self-harm, and suicide among adolescents, necessitating enhanced prevention strategies and interventions (O'Reilly, 2020). The integration of transformer models, such as BERT and RoBERTa, into the analysis of social media data presents an opportunity for real-time monitoring of mental health signals, enhancing early detection efforts and facilitating timely interventions (Malhotra & Jindal, 2020, Turecki & Brent, 2016).

Recent studies indicate that many adolescents facing mental health challenges do not seek traditional clinical support due to barriers like stigma and accessibility. This underscores the need for innovative data sources and digital tools to identify early warning signs of emotional distress. Transformer models can analyze vast amounts of user-generated content on social media, enabling researchers and public health officials to detect nuanced linguistic indicators associated with mental health issues, such as suicidal ideation or anxiety (Sedgwick *et al*., 2023). These models can recognize patterns in language that might go unnoticed in clinical settings, thus opening avenues for preventative measures that extend beyond traditional healthcare frameworks.

From a policy standpoint, deploying transformer-based models can transform the landscape of adolescent mental health services and resource allocation (Sedgwick *et al*., 2023; Zirikly *et al*., 2022). By aggregating insights about mental health trends based on social media activity, policymakers can identify high-risk populations and allocate resources more effectively. For instance, if increases in depressive language are detected in specific areas, local health departments might respond by enhancing mental health outreach or preventive initiatives (Finserås *et al*., 2023). This dynamic monitoring aligns with CDC efforts to create data-driven policies that effectively target rising mental health challenges (O'Reilly, 2020; Shukur *et al*., 2023).

Moreover, these models promote a precision public health approach by allowing for tailored mental health interventions based on the severity of symptoms detected (Sedgwick *et al*., 2023; Finserås *et al*., 2023). For example, distinguishing between varying levels of emotional distress enables the development of customized responses, whether through online resources, counseling services, or educational programs in schools. By implementing protocols that leverage AI and machine learning, public health can proactively address adolescent mental health needs and swiftly adjust strategies based on real-time data (Nesi *et al*., 2021).

Addressing ethical concerns surrounding data usage, privacy, and the interpretation of AI-generated insights is critical for the successful integration of these technologies into public health policy (Shukur *et al*., 2023). Stakeholders, including mental health professionals, educators, and adolescents, must be actively involved in shaping the frameworks that govern the use and dissemination of information derived from social media (Lin, Nogueira & Yates, 2022, Tadesse, *et al*., 2019). Building trust through transparency and community engagement will ensure that these models are deployed responsibly while maximizing their potential benefits for mental health surveillance and intervention efforts (Liu, *et al*., 2020, Thieme, Belgrave & Doherty, 2020).

In conclusion, the application of transformer models to social media datasets offers a robust methodology for early detection of mental health risks among adolescents. This innovative approach, supported by the CDC and NIH, facilitates comprehensive monitoring and intervention strategies while addressing significant gaps in traditional mental health services. As technology evolves, ensuring ethical practices and community involvement will be pivotal in leveraging these advanced tools to effectively safeguard the mental health of future generations (Ji, *et al*., 2020, Ríssola, Losada & Crestani, 2021).

3. Conclusion

The early detection of adolescent mental health risk using transformer models applied to social media datasets represents a transformative advancement in the intersection of artificial intelligence, public health, and youth well-being. This approach has demonstrated strong potential in identifying signs of emotional distress, depression, anxiety, and suicidal ideation in adolescents by analyzing their digital expressions in real time. Transformer-based models such as BERT and RoBERTa, when fine-tuned on domain-specific datasets, have proven to outperform traditional machine learning methods by effectively capturing contextual and nuanced language patterns common in adolescent communication. Their ability to process large volumes of unstructured data and generate accurate, interpretable predictions enables more timely identification of at-risk individuals, offering a valuable tool in preventative mental health care.

Early detection is critical in addressing the growing mental health crisis among adolescents. With rates of depression, anxiety, and suicide steadily rising, and many young people reluctant or unable to access traditional clinical services, the need for proactive and scalable solutions is more urgent than ever. Transformer models offer a unique capability to monitor mental health signals unobtrusively and continuously through the platforms adolescents already use daily. By identifying patterns of concern early before they escalate into crisis these models can support more timely interventions, potentially reducing the severity and long-term impact of mental health disorders.

Despite the promise, the implementation of such systems must be approached with caution and responsibility. Future research should prioritize the collection of diverse, representative datasets to reduce algorithmic bias and ensure equitable model performance across different demographic groups. Temporal modeling, multimodal data integration, and context-aware architectures also warrant further exploration to enhance predictive accuracy and interpretability. Moreover, studies should continue to investigate the psychological and ethical implications of AI-driven mental health monitoring, particularly in relation to privacy, consent, and the appropriate balance between automation and human judgment.

The advancement and deployment of these models call for a multidisciplinary effort that brings together data scientists, clinicians, educators, policy makers, ethicists, and crucially adolescents themselves. Collaboration across these domains is essential to design systems that are not only technically effective but also socially responsible and grounded in care. Educational institutions, healthcare providers, and public health agencies must work collectively to build supportive

ecosystems where AI tools augment human insight and ensure that no young person's struggles go unnoticed.

In closing, transformer-based models offer a powerful and timely solution for addressing adolescent mental health risks through early detection on social media. However, realizing their full potential requires a concerted effort to integrate technological innovation with ethical principles, community engagement, and inclusive policy frameworks. By acting now to develop and deploy these systems thoughtfully and collaboratively, we have the opportunity to make a profound difference in the lives of young people and strengthen the foundations of mental health support for future generations.

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