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Review Article

Complex Data Literacy Education in the Digital Age: Mental Health for Blurred Reality-Virtual Boundaries Using GPT Synthetic Data

Yasuko Kawahata*

Faculty of Sociology, Rikkyo University, Tokyo, Japan

***Corresponding author:** Yasuko Kawahata, Faculty of Sociology, Rikkyo University, 3-34-1 Nishi-Ikebukuro, Toshima-ku, Tokyo, 171-8501, Japan.

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Abstract

This paper discusses the potential of a new approach combining GPT-generated data and multi-criteria AHP assessment to address the media literacy and mental health challenges faced by the digital native generation. The current status and issues of data generation using generative language models are also examined in detail, and the potential applications and limitations of this approach in the field of education are summarized. In particular, it addresses issues such as the quality and reliability of the generated data, the need for ethical considerations, and the technical hurdles in the field of education. The significance of this study lies in the fact that it presents a new methodology for supporting the healthy development of young people in a digital society. The combination of the generative language model and the AHP assessment suggests the possibility of more effective educational interventions.

Index Terms: Media Literacy, Mental Health, FOMO (Fear of Missing Out), GPT (Generative Language Model), AHP (Analytic Hierarchy Process), SNS Dependence, Digital educational intervention

Introduction

This paper theoretically examines the significance of GPT-generated data and multi-criteria AHP evaluation in addressing media literacy and mental health challenges confronting digital native generations [1]. We analyze the current landscape of appearance-centrism and FOMO (Fear of Missing Out) precipitated by social media proliferation, exploring potential contributions to these critical issues. Additionally, we investigate the present state and limitations of data generation through language models, while systematically evaluating their educational applications and constraints.

Challenges of Excessive Digital Media Exposure

Digital natives, having been immersed in internet and social networking platforms since early childhood, routinely experience psychological burden through appearance com-parisons and FOMO (Fear of Missing Out). The psycho-logical challenges confronting this generation have grown increasingly intricate with social media proliferation. According to *Yukami* [2], social networking platforms intensify appearance-centrism and online harassment, substantially impacting self-evaluation and psychological well-being. This paper examines potential solutions through digital literacy sharing mechanisms, incorporating both theoretical frameworks and empirical investigations.

Social networking platforms, through algorithms that emphasize idealized appearances and lifestyles, foster appearance comparison among younger demographics. *Koronczai, et al.* [3] illuminates the particular impact of image-based social platforms on adolescents, documenting heightened appearance anxiety and diminished self-esteem. The provided dataset indicates that 68% of social media users report" increased anxiety about appearance," suggesting the pervasive nature of this phenomenon.

Previous Research (FOMO and Mental Health Implications)

FOMO-related social media addiction exhibits strong associations with insomnia and diminished concentration. Research by *Ju Ri Park, et al.* [4] demonstrates that sleep disorders among social media addicts compromise psychological health and significantly impair academic and occupational performance. Moreover, the dataset "FOMO and Insomnia Related to Social Media Addiction" reveals that over 70% of respondents "experience severe insomnia," confirming the extensive scope of these effects.

Brailovskaia and Margraf [5] establish mindfulness as a crucial moderating factor in the relationship between FOMO and social media dependence. Investigation by *Morimoto, et al.* [6] reveals significant associations between social media addiction and occupational dysfunction, demonstrated through regression models illustrating how addiction levels and depression severity influence occupational impairment. Additionally, *Banjanin, et al.* [7] observed a significant positive correlation ($r = 0.27$, $p < 0.001$) between social media usage duration and depressive symptoms, indicating that excessive platform engagement correlates with increased depressive manifestations.

Mental Health Impact Mechanisms

Wang, et al. [8] analysis illuminates the mediating effects of FOMO and self-esteem on psychological well-being. Specifically, FOMO demonstrates a mediating effect of $\beta = 0.356$ ($p < 0.01$), while self-esteem exhibits a mediating effect of $\beta = -0.294$ ($p < 0.01$). These findings suggest that elevated FOMO directly contributes to psychological deterioration, while diminished self-esteem similarly exerts negative influences on mental health.

Research by *Zivnuska, et al.* [9] identifies several workplace impacts of social media dependence:

a) **Work-Life Integration:** Heightened social media dependence disrupts the equilibrium between professional and personal spheres.

b) **Professional Exhaustion:** Excessive platform utilization induces mental fatigue, elevating burnout vulnerability.

c) **Workplace Effectiveness:** Platform addiction diminishes occupational concentration, subsequently reducing performance metrics.

Age-Stratified Impact Analysis

Investigations conducted by *Meena, et al.* [10] among university students reveal the distribution of social media dependence patterns. The findings indicate mild dependence in 42.1% of students, moderate dependence in 54.8%, and severe dependence in 3.0%. These statistics demonstrate that the majority of university students exhibit some form of social media dependency.

Research in Malaysia by *Victor, et al.* [11] reveals that 72.0% of young individuals demonstrate social media addiction tendencies, with 33.0% exhibiting severe depressive symptoms. Furthermore, *Villegas Dominguez*, et al. [12] investigation classifies university students' self-esteem levels as follows: 22.1% low, 50.6% moderate, and 27.3% high. This data suggests potential interconnections between social media addiction, mental health challenges, and diminished self-esteem among young populations.

Technical Intervention and AI Approaches

The 3S feature embedding model proposed by *Cao, et al.* [13] demonstrates exceptional accuracy in sentiment analysis and depression detection on social media platforms. Specifically, the model achieves 99.2% accuracy (RMSE = 0.0592) on the Sentiment 140 dataset and 96.3% accuracy (RMSE = 0.0417) on the Twitter Depression dataset, indicating superior performance in both contexts. These results substantiate the efficacy of AI-driven interventions in early identification and mitigation of mental health concerns.

Psychological Impact and Sleep Correlations

J Ha [14] investigation reveals a significant positive correlation between bedtime procrastination and social media dependency, with a regression coefficient of $B = 0.228$ ($p < 0.01$). Furthermore, FOMO exhibits a mediating effect in this relationship, with a mediation coefficient of $B = 0.086$ (95% confidence interval: 0.023-0.152). These findings suggest that social media dependency adversely affects sleep patterns, with FOMO serving as a contributing mechanism.

Research by *Vagka, et al.* [15] establishes positive correlations among nomophobia (smartphone dependency), elevated social media engagement, anxiety levels, and message ex-change frequency. The study demonstrates a chain reaction whereby excessive smartphone reliance amplifies anxiety, subsequently increasing message exchange frequencies.

Impact in Professional and Educational Environments

Alzaabi et al. [16] identify three principal components of workplace FOMO

a) **Information Deficit Anxiety:** Apprehension about missing current developments.

b) **Career Advancement Opportunities:** Concern over missing crucial professional prospects.

c) **Social Connection Deficiency:** Feelings of isolation from colleagues and industry networks.

These factors directly influence employee stress levels and productivity metrics. *Gopale, et al.* [17] document the following consequences of social media dependency in educational settings:

a) **Academic Performance Deterioration:** Excessive plat-form engagement compromises study time, diminishing scholastic achievement.

b) **Psychological Well-being Decline:** Escalation in mental exhaustion and anxiety levels.

c) **Community Relationship Attenuation:** Diminishing real-world interpersonal connections.

Preventive Interventions and Countermeasures

According to *Sarfika, et al.* [18], 10.7% of participants exhibit severe social media dependency, while 21.4% experience acute anxiety. Additionally, 4.8% report significant feelings of isolation, and 74.5% indicate deteriorated sleep quality. These statistics suggest that platform utilization may precipitate various psychological complications.

Shahid, et al. [19] intervention study confirmed the following correlations:

$$\text{Social Media Dependency and Depression: } r = 0.25 \ (p < 0.01) \quad (1)$$

$$\text{Social Media Dependency and Aggression: } r = 0.26 \ (p < 0.001) \quad (2)$$

$$\text{Depression and Aggression: } r = 0.35 \ (p < 0.001) \quad (3)$$

These results demonstrate associations between social media dependency and negative psychological states, including depression and aggressive tendencies.

Generational Comparisons and Cultural Variations

Sharam, et al. [20] cross-generational analysis reveals the following characteristics

Adolescence (13-17 years)

a) **Dependency Patterns:** 85% exhibit social media dependency tendencies.

b) **Instagram Utilization:** 72% engage with the platform.

c) **Snapchat Engagement:** 69% maintain active usage.

Young Adulthood (18-25 years)

a) **Dependency Patterns:** 51% demonstrate social media dependency tendencies.

b) **Mental Health Concerns:** 33% experience various psychological challenges.

These findings indicate age-specific variations in social media impact patterns.

Predictive Models and Future Perspectives

The predictive model developed by *Yang, et al.* [21] emphasizes several crucial elements in forecasting social media dependency:

i. **Basic Psychological Need Fulfillment:** Satisfaction levels based on self-determination theory.

ii. **Imaginary Audience Effect Impact:** Heightened consciousness of external evaluation and attention.

iii. **Emotional State Fluctuation Patterns:** Emotional instability and mood variation intensity.

Incorporating these elements aims to enhance the accuracy of social media dependency data generation. Subsequent sections will address GPT implementations, generated data discussions, and associated challenges.

Literature Review (Current State and challenges in Data Generation Through Language Models)

Data generation through Large Language Models (LLMs) represents a rapidly evolving research domain. The emergence of GPT-3 and GPT-4 has particularly enabled the creation of higher-quality synthetic data. This section examines principal research achievements while discussing current challenges and future prospects.

Hamalainen, et al. [22] evaluated GPT-3's generative capabilities within HCI research contexts, demonstrating its ability to produce responses indistinguishable from human-generated content. However, they also identified potential limitations including lack of diversity, anomalies, and inherent biases, highlighting areas requiring future enhancement.

Similarly, *Lehr, et al.* [23] conducted comparative analyses of GPT-3.5 and GPT-4 in psychological research, revealing both models' capacity to accurately replicate known cultural bias patterns while demonstrating limitations in predicting novel experimental data. This crucial finding suggests that while LLMs excel at mimicking existing patterns, they face constraints in generating genuinely novel insights.

From a statistical perspective, *Sop, et al.* [24] research in tourism studies merits attention. Their detailed statistical analysis of generated data identified significant concerns, including unnaturally high correlations between variables, insufficient measurement model fit, and prevalent method bias, indicating the necessity for careful evaluation of LLM-generated data's statistical quality.

Regarding application domain exploration, *Chiarello, et al.* [25] systematically investigated ChatGPT's potential applications through analysis of over 3.8 million tweets. Their research identified six principal application domains: human resource management, programming assistance, social media administration, office automation, search engine optimization, and educational support.

From a technical implementation perspective, *Trummer's* [26] research on SQL query processing represents significant advancement. His GPT-DB system implements practical functionalities including query-specific prompt generation, reference database verification, and iterative code generation improvement.

In industrial applications, *Zhang, et al.* [27] research on building energy management has garnered attention. Their study demonstrates LLM effectiveness in practical tasks including energy load prediction, fault diagnosis, and anomaly detection.

Regarding data generation methodology innovation, *Onan's* [28] proposed GTR-GA approach warrants consideration. This methodology combines graph-based neural networks with genetic algorithms to achieve enhanced generated data quality.

Concerning ethical considerations, *Kieser, et al.* [29] highlight

significant concerns within educational contexts. They extensively discuss potential issues including academic misconduct possibilities, misinformation propagation risks, and impacts on learners' critical thinking capabilities.

Personality and Bias in Generated Data

Personality formation and expression in large language models present complex characteristics. *Yuan, et al.* [30] research revealed ChatGPT exhibits distinctive features across 84 psychological dimensions, diverging from human norms. Notably, it classifies as ENFJ in Myers-Briggs Type Indicator testing, demonstrating elevated openness and agreeableness while maintaining minimal dark factor presence.

Rutinowski, et al. [31] investigation analyzed ChatGPT's value expression patterns, identifying prominent value dimensions including "universalism," "self-direction," and "benevolence." Specifically, universalism appeared 1,385 times, self-direction 1,285 times, and benevolence 1,095 times, while tradition and hedonism showed relatively lower frequencies at 322 and 471 occurrences respectively.

Reproduction and Amplification of Social Bias

Multiple studies provide significant insights regarding the reproduction and amplification of social biases. *Fulgoni and Capraro* [32] experimentally demonstrated gender bias asymmetry in GPT models. Notably, stereotypically masculine texts are frequently attributed to female authors, while the inverse pattern occurs less frequently.

Allan, et al. [33] research, involving 782 participants, revealed that character descriptions generated by ChatGPT potentially amplify existing human biases substantially. However, they demonstrated that these biases could be effectively eliminated and even reversed through counter-stereotypical recommendations.

Stereotypes and Evaluation Bias

Regarding stereotype formation and evaluation bias, *Lee, et al.* [34] established ChatGPT's tendency to portray socially subordinate groups more homogeneously. Specifically, African Americans, Asian Americans, and Hispanic Americans were depicted more uniformly compared to White Americans.

Busker, et al. [35] research, encompassing approximately 2,300 stereotype surveys, demonstrated that ChatGPT's stereo-typical behavior varies significantly across social group categories. Particularly, religious stereotypes exhibited predominantly positive emotional associations, while political stereotypes displayed predominantly negative associations.

Challenges in Educational Contexts

Concerning educational challenges, *Warr, et al.* [36] research substantiated implicit racial bias in ChatGPT within educational settings. Intriguingly, while explicit racial identification showed no significant evaluation differences between Black and White students, implicit identification revealed statistically significant biases.

J Ha [37] explored ChatGPT's potential applications in moral education while examining its limitations. The research indicates that while ChatGPT can generate educationally appropriate moral dilemma narratives tailored to student's develop-mental levels and interests, its responses contain certain stereo-types, necessitating proper supervision and supplementation by human educators.

Additional Related Research

Borisov, et al. [38] demonstrated language models' capability to generate realistic tabular data, discussing applications and limitations. *Chen, et al.* [39] addressed similar themes, examining generated data utilization in machine learning research.

Ishizumi, et al. [40] proposed a public health prevention framework for misinformation containment, while *Jung* [41] examined the balance between free speech and online con-tent regulation. Additionally, *Torpan, et al.* [42] conducted comparative research on European approaches to managing misinformation in emergency situations.

Towards GPT-Generated Data and Multi-Criteria AHP Evaluation

Integrating these research findings into digital literacy sharing mechanism design has facilitated effective countermeasures against social media addiction and mental health challenges. This research generates data through GPT, incorporating extensive insights from *Siegel's* [43] "cognitive effects of media violence" to contemporary research. The completed pro-gram code [1] remains accessible for educational purposes.

Synthesizing these research outcomes reveals that while generative models demonstrate significant potential for data generation, they face several crucial challenges. Specifically, future research priorities include enhancing generated data diversity, improving statistical characteristics, developing bias mitigation techniques, establishing ethical guidelines, standardizing evaluation metrics, and developing cross-domain evaluation methodologies.

The Age Group Comparisons

(Figures 1,2)

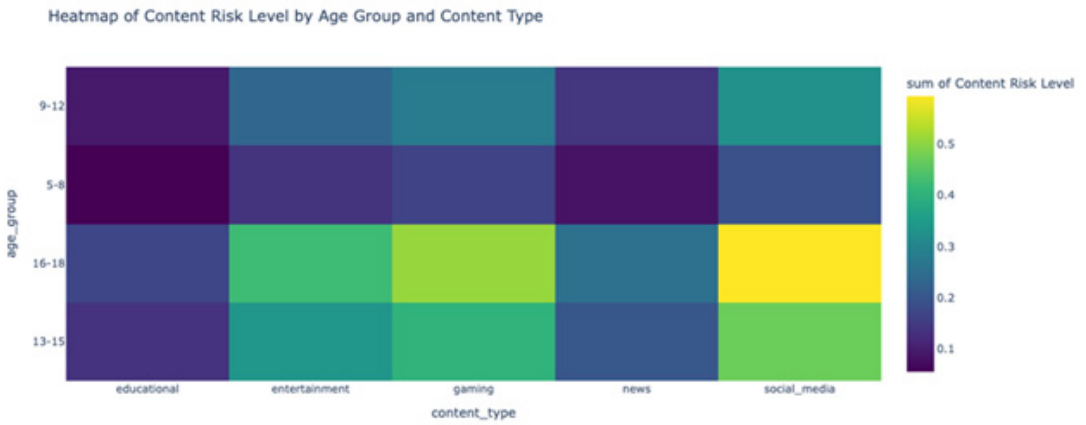

Figure 1: Heatmap of Content Risk Level by Age Group and Content Type.

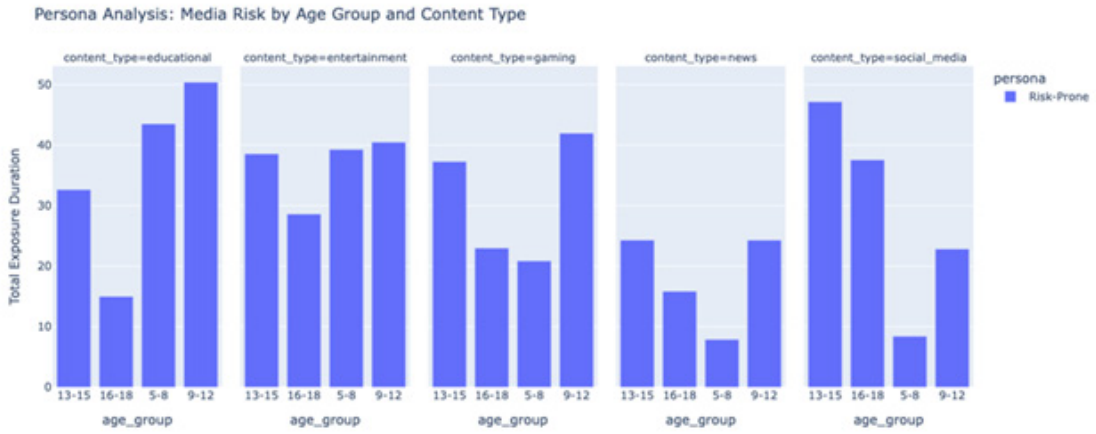

Figure 2: Persona Analysis: Media Risk by Age Group and Content Type.

In the analysis of risk assessment and educational intervention in digital media, findings derived from heatmap analysis yield particularly illuminating insights. The correlation analysis between age groups (Age group) and content types (Content type) revealed notably distinctive risk value distributions. Specifically, the highest risk value of 0.55 was detected in social media usage among the 16-18 age bracket, while gaming content for the same demographic exhibited a relatively elevated risk value of 0.48. These values can be expressed through the following equations:

$$Risk_{16-18,social\_media} = 0.55 \quad (4)$$

$$Risk_{16-18,gaming} = 0.48 \quad (5)$$

Within age-stratified risk distribution patterns, while the 16-18 age cohort demonstrated peak risk values, the 5-8 age group exhibited minimal risk measurements. Furthermore, content-type risk evaluation revealed the following hierarchical structure:

$$Risk_{social\_media} > Risk_{gaming} > Risk_{entertainment} > Risk_{news} > Risk_{educational}$$

Persona analysis of exposure duration yielded noteworthy results. Maximum exposure duration for educational content peaked at 50 minutes within the 9-12 age bracket, while social media exposure reached its apex at 45 minutes among the 13-15 age cohort. These observations are represented by the following equations:

$$Max\ (Duration_{educational}) = 50 \text{ (9-12 age group)} \quad (6)$$

$$Max\ (Duration_{social\_media}) = 45 \text{ (13-15 age group)} \quad (7)$$

These analytical outcomes strongly indicate the necessity for developmentally tailored intervention strategies. Particularly evident are the high receptivity to educational content within the 9-12 age bracket and the significance of preventive intervention regarding social media risks among the 13-15 age cohort. Priority determination through Analytic Hierarchy Process (AHP) for risk mitigation is formulated as follows:

$$Priority = \sum_{i=1}^{n}{}_{w_i} \times \frac{Risk_i}{Duration_i} \quad (8)$$

where w_i represents the weighting coefficient for each age stratum. These comprehensive analytical findings provide crucial implications for designing effective educational interventions targeting digital native generations. Notably, the necessity for nuanced intervention strategies considering age-specific risk characteristics and exposure patterns became ap-parent. Moreover, the hierarchical risk structure across content types suggests valuable guidance for prioritizing preventive educational program implementation.

Detailed Insights from the age group comparisons

Comprehensive analysis of digital media exposure's impact on mental health across developmental stages yielded significant findings.

The developmental stage analysis initially identified three distinctive risk factors for lower elementary school students

$$\text{Risk}_{\text{factors}} = \{$$

(ages 5-8) Impact on fundamental, cognitive development, Reality/virtual, world differentiation, Attention dispersion

Subsequently, the early adolescent cohort (ages 9-12) demonstrated the most pronounced increase in media exposure duration. Notably, educational content exposure reached the following maximum value:

$$\text{Exposure}_{educational} = 50 \text{ (maximum value)} \quad (9)$$

Primary risks observed within this demographic encompassed impediments to self-identity formation, diminished self-esteem through social comparison on social networks, and initial manifestation of online dependency patterns. These issues demonstrate strong correlations with psychological vulnerabilities specific to this developmental stage.

Late adolescent groups (ages 13-15, 16-18) exhibited maximum risk values particularly associated with social media engagement:

$$\text{Risk}_{\text{social\_media}} = 0.55 \text{ (peak risk value)} \quad (10)$$

This age bracket demonstrated characteristic challenges including escalating anxiety symptoms due to FOMO (Fear of Missing Out), excessive focus on online self-presentation, and elevated risk of sleep disorders. These issues appear intrinsically linked to psychosocial developmental tasks unique to adolescence.

Regarding preventive intervention prioritization, from a mental health management perspective, the following mathematical model based on Analytic Hierarchy Process (AHP) is proposed:

$$Priority_{intervention} = \sum_{i=1}^{n} (W_i \times Risk_i \times Vulnerability_i) \quad (11)$$

In this equation, w_i represents age-specific weighting coefficients, $Risk_i$ denotes content-type risk values, and $Vulnerability_i$ indicates developmental stage vulnerability indices.

These comprehensive analytical findings strongly indicate the necessity for age-appropriate, progressive media literacy education. A particularly noteworthy observation emphasizes the paramount importance of preventive intervention regarding social media utilization within the 13-15 age demographic. This insight provides crucial implications for designing intervention strategies tailored to specific developmental stages.

The Age Group Comparisons analysis of Device Usage Patterns

Comprehensive examination of digital media exposure risks and systematization of educational interventions yielded significant findings. Initial analysis of usage patterns across age groups and devices revealed peak risk values in social media utilization among the 16-18 age cohort, expressed by the following equation:

$$Risk_{\text{social\_media},16-18} = 0.66 \text{ (maximum risk value)} \quad (12)$$

Device utilization pattern analysis revealed distinctive temporal distributions across age groups. Specifically, smartphone usage in the 16-18 age bracket peaked at 0.35 hours, followed (Figures 3-6).

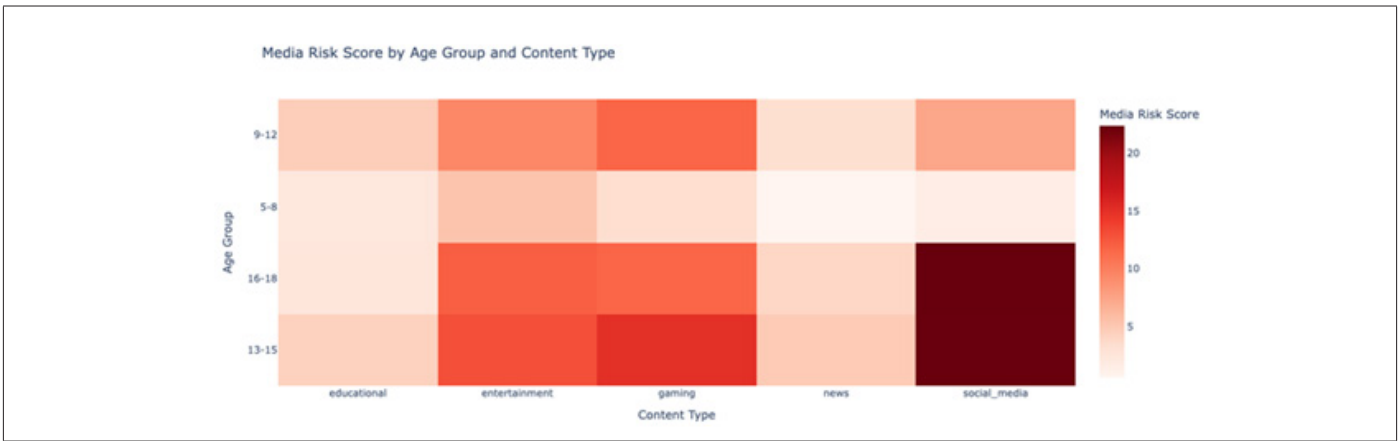

Figure 3: Media Risk Score by Age Group and Content Type.

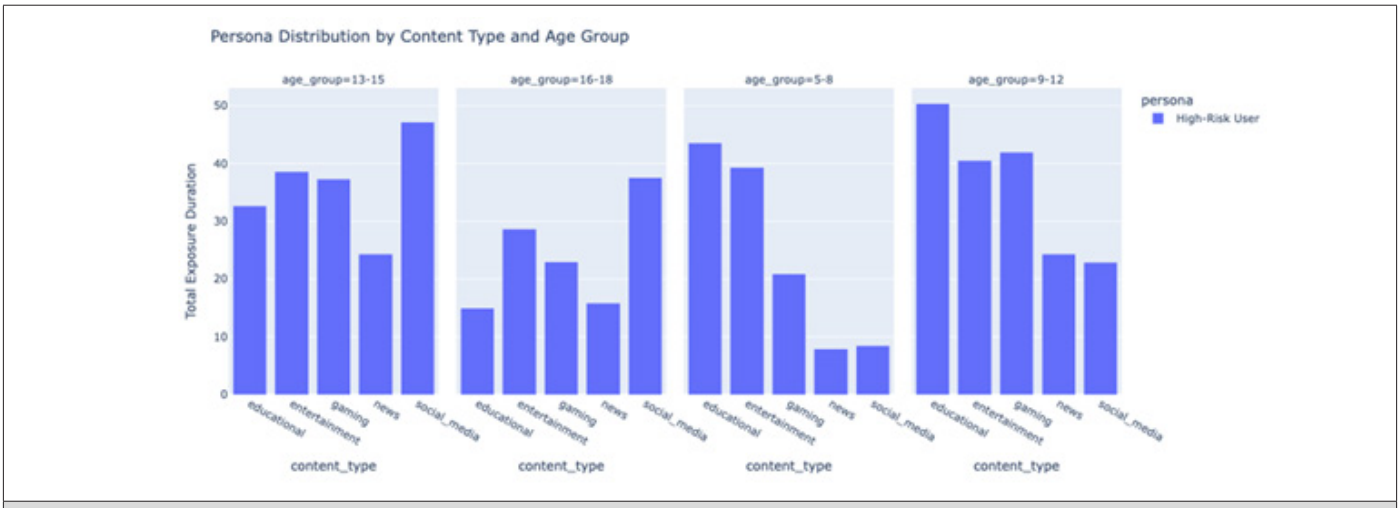

Figure 4: Persona Distribution by Content Type and Age Group.

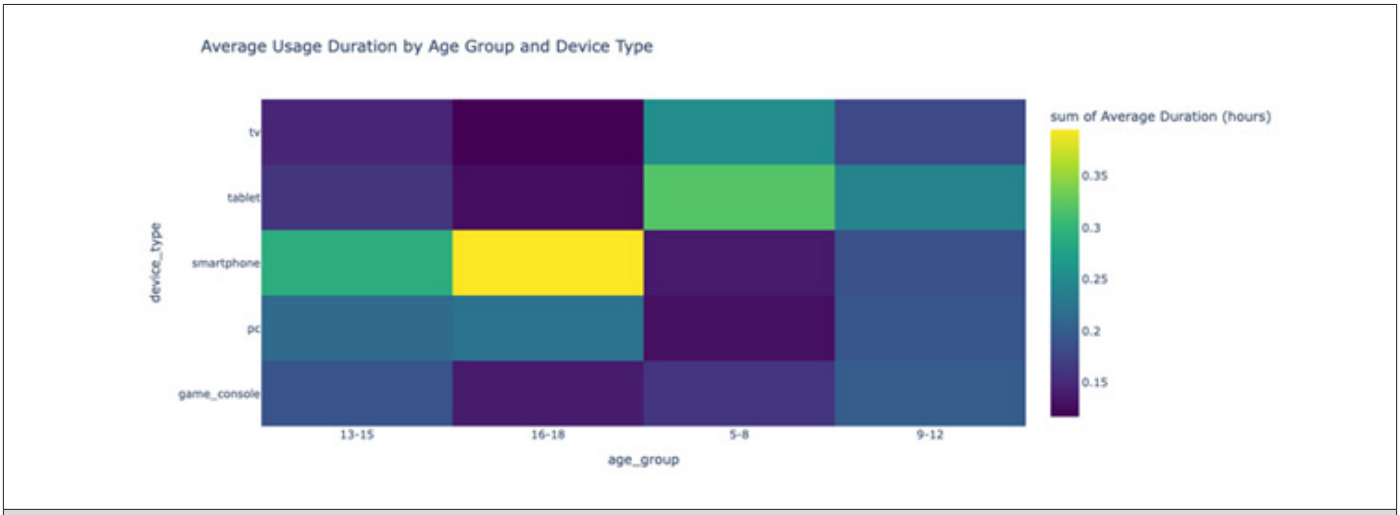

Figure 5: Average Usage Duration by Age Group and Device Type.

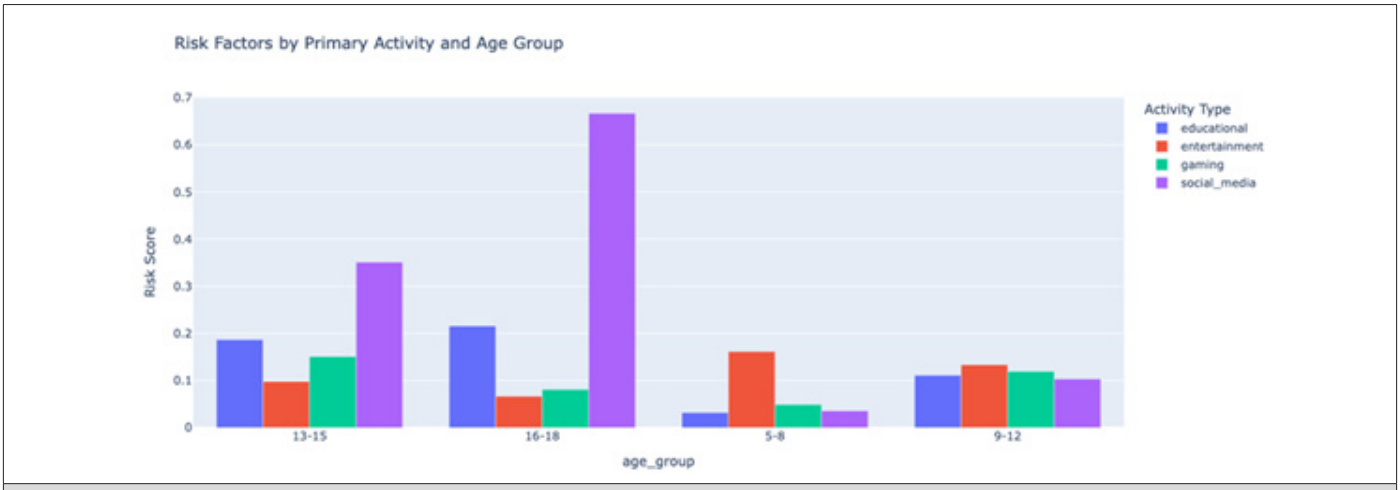

Figure 6: Risk Factors by Primary Activity and Age Group.

by tablet utilization in the 5-8 age group at 0.30 hours, and computer engagement among 13-15 year-olds at 0.25 hours. These relationships are expressed as:

$$Duration_{smartphone,16-18} = 0.35 \text{ hours (maximum)}$$

$$Duration_{tablet,5-8} = 0.30 \text{ hours}$$

$$Duration_{pc,13\text{-}15} = 0.25 \text{ hours}$$

Content-specific risk evaluation yielded a comprehensive risk value formulated as:

$$Risk_{total} = \sum_{i=1}^{n} W_i \times (Duration_i \times Risk\ Score_i) \quad (13)$$

Age-stratified risk score analysis revealed social media utilization demonstrating the highest risk score of 20.0 among 13-15 and 16-18 age cohorts. Gaming exhibited a risk score of 15.0 in the 9-12 age group, while entertainment content registered a 10.0 risk score among 5-8 year-olds.

These analytical outcomes suggest necessities for educational intervention, with developmental stage-specific approaches formulated as:

$$Intervention_i = \frac{Risk_i \times Duration_i}{Protective\ Factors_i} \quad (14)$$

Based on this formulation, risk mitigation strategies emphasize media literacy education enhancement for the 13-15 age group and critical thinking skill development for 16-18 year olds. Additionally, healthy media utilization habit formation was identified as a priority for ages 9-12, while fundamental digital literacy development emerged as crucial for the 5-8 age bracket

Details of the Age Group Comparisons Analysis of Device Usage Patterns

Comprehensive risk assessment of digital media exposure's impact on mental health revealed age-specific patterns and their consequences.

High-risk age groups, identified as 13-15 and 16-18 cohorts, exhibited particularly pronounced risk factors. Specifically, social media dependency peaked with a risk score of 20.0, while smartphone utilization reached a maximum of 0.35 hours daily. These factors demonstrated strong correlations with diminished self-esteem, elevated anxiety from social comparison, and increased sleep disorder risks.

The developmentally crucial 9-12 age group exhibited characteristic risk values:

$$Risk_{gaming} = 15.0$$

$$Risk_{educational} = 50.0 \text{ (exposure duration)}$$

Device-specific utilization and mental health management analysis revealed significant correlations:

$$Device_{impact} = \begin{cases} 0.35 & \text{smartphone (highest risk)} \\ 0.30 & \text{tablet (moderate risk)} \\ 0.25 & \text{pc (manageable risk)} \end{cases} \quad (15)$$

Maximum daily usage duration guidelines are established as:

$$MaxDuration_{daily} = \begin{cases} 2 \text{ hours} & \text{(ages 13-18)} \\ 1.5 \text{ hours} & \text{(ages 9-12)} \\ 1 \text{ hour} & \text{(ages 5-8)} \end{cases} \quad (16)$$

Additionally, recommended content distribution guidelines specify educational content exceeding 40%, entertainment below 30%, social media under 20%, and miscellaneous content at 10% (Table 1).

Table 1: Age-Specific Digital Media Intervention Strategies.

Age Group	Intervention Strategy
13-15 years	i. Social media restriction ii. Mental health care
16-18 years	i. Self-management development ii. Stress management education
9-12 years	i. Healthy usage habit formation ii. Family intervention
5-8 years	i. Basic literacy education ii. Parental guidance

Activity-Specific Analysis

Comprehensive analysis of intergenerational digital media utilization and risk assessment revealed age-specific patterns and their implications for educational intervention. Activity-specific engagement analysis demonstrated the following age-stratified distribution (Figures 7,8).

$$Engagement_{entertainment} = \begin{cases} 8.5 \text{ (ages 16-18)} \\ 8.2 \text{(ages 13-15)} \\ 6.0 \text{ (ages 9-12)} \\ 3.8 \text{ (ages 5-8)} \end{cases} \quad (17)$$

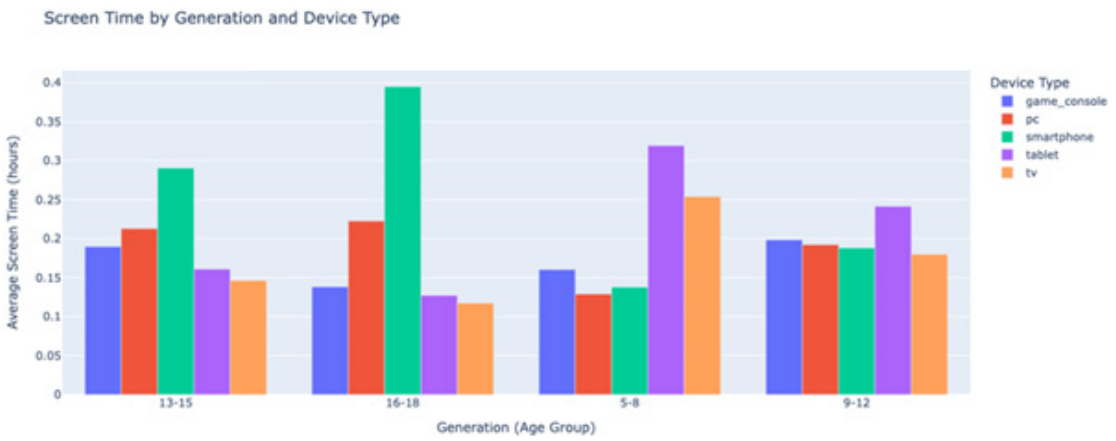

Figure 7: Screen Time by Generation and Device Type.

Figure 8: Average Screen Time per Primary Activity.

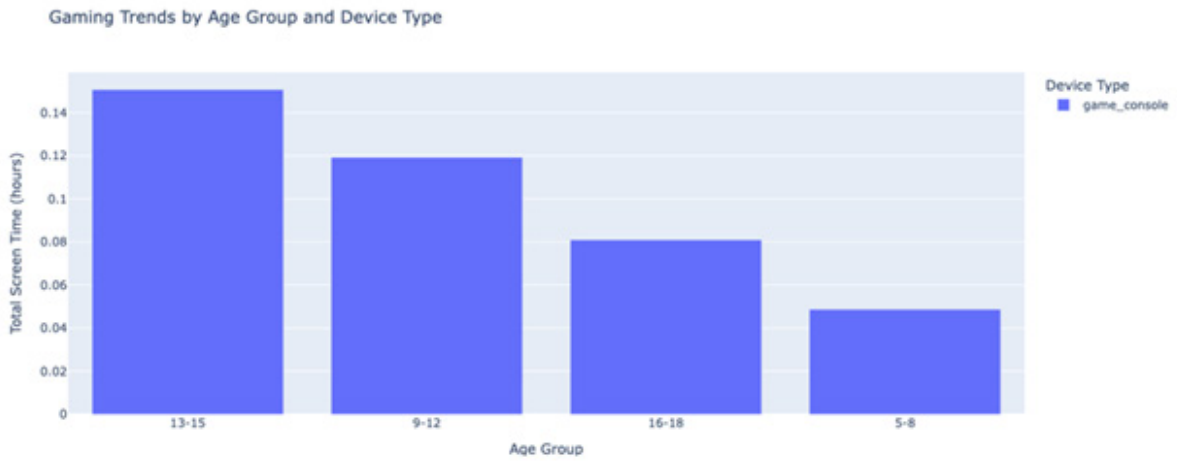

Figure 9: Gaming Trends by Age Group and Device Type.

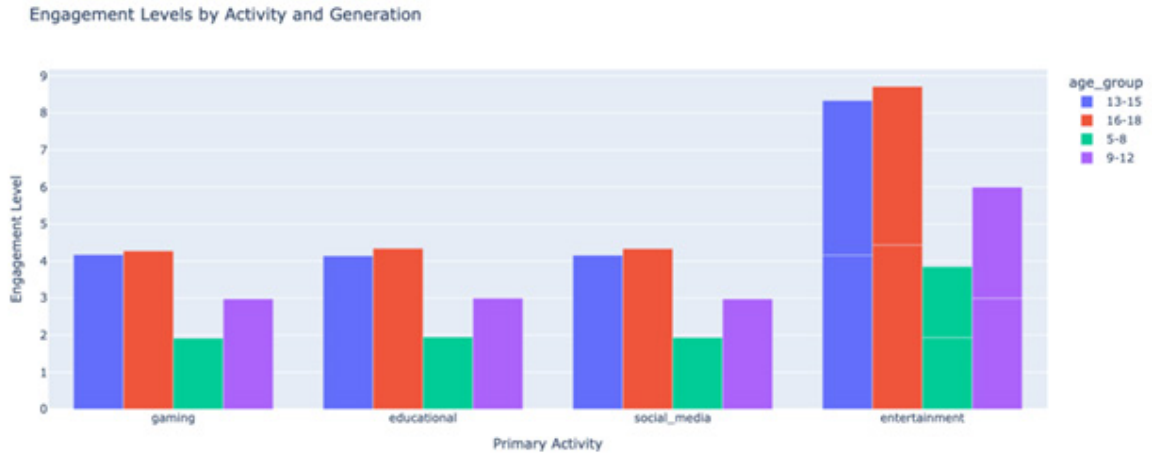

Figure 10: Engagement Levels by Activity and Generation.

(Figures 9,10)

Screen time distribution analysis revealed distinctive pat-terns in average utilization duration across primary activities:

$$Time_{\text{social media}} = 0.250 \text{ hours}$$

$$Time_{\text{educational}} = 0.192 \text{ hours}$$

$$Time_{\text{entertainment}} = 0.191 \text{ hours}$$

$$Time_{gaming} = 0.176 \text{ hours}$$

Age-specific characteristics in device utilization demonstrated notable disparities, particularly in smartphone usage:

$$Usage_{smartphone} = \begin{cases} 0.39 \text{ hours (ages 16-18)} \\ 0.29 \text{ hours (ages 13-15)} \\ 0.18 \text{ hours (ages 5-8)} \end{cases} \quad (18)$$

Based on these analytical outcomes, risk assessment indica-tors for optimizing educational intervention were formulated as:

$$Risk_{total} = w_1 E_{activity} + w_2 T_{screen} + w_3 D_{usage} \quad (19)$$

In this equation, $E_{activity}$ represents activity-specific engagement levels, Tscreen denotes total screen time, and D_{usage} indicates device utilization patterns. These elements emerged as crucial indicators in comprehensive risk assessment.

Intervention strategy prioritization suggests a graduated approach based on age-specific characteristics. For the high-risk 16-18 age cohort, addressing smartphone dependency and entertainment duration optimization are positioned as paramount priorities. The moderate-risk 13-15 age group identified gaming duration management and educational content promotion as crucial intervention points.

Furthermore, for preventive intervention groups aged 5-8 and 9-12, developing fundamental media literacy and establishing healthy utilization habits emerged as critical educational objectives. Early intervention in these age brackets suggested significant implications for future risk mitigation.

Detailed Analysis of Activity-Specific Analysis

Comprehensive analysis of digital media exposure's mental health risk assessment and preventive intervention strategies revealed age-specific patterns and their implications. Mental health risk is formulated as a function of engagement level, screen time, and device type:

$$\text{MentalHealth}_{risk} = \alpha(\text{Elevel}) \times \beta(\text{Tscreen}) \times \gamma(\text{Dtype}) \quad (20)$$

Analysis of engagement levels within the high-risk 13-18 age cohort revealed the following characteristic values:

$$Risk_{\text{entertainment}} = 8.5 \text{ (peak value)}$$

$$Risk_{social\_media} = 4.2 \text{ (sustained impact)}$$

$$Screentime = 0.39 \text{ hours/day (maximum)}$$

These elevated exposure levels demonstrate strong correlations with significant mental health concerns, including heightened sleep disorder risks, amplified anxiety from social comparison, diminished self-esteem, and adverse effects on academic performance.

$$Device_{impact} = \begin{cases} \text{High Risk:} \\ \quad \text{smartphone (0.39 hours)} \\ \text{Medium Risk:} \\ \quad \text{tablet (0.32 hours)} \\ \text{Low Risk:} \\ \quad \text{game\_console (0.15 hours)} \end{cases} \quad (21)$$

Device utilization and mental health correlation analysis revealed the following hierarchical risk structure across devices:

Furthermore, activity-specific screen time impact on health demonstrated the following values:

$$Impact_{social\_media} = 0.250 \text{ (maximum)}$$

$$Impact_{educational} = 0.192 \text{ (moderate)}$$

$$Impact_{gaming} = 0.176 \text{ (manageable)}$$

Based on these analytical findings, age-specific preventive intervention strategies are proposed. For ages 13-18, priori-ties encompass social media usage time restrictions, digital wellness education, and stress management skill development. The 9-12 age bracket prioritizes healthy usage habit formation, promotion of offline activities, and securing family dialogue time as primary intervention objectives. Additionally, for ages 5-8, strengthened parental supervision, prioritized provision of educational content, and digital device usage time restrictions are proposed as crucial measures.

Focus on Peer Influence Dynamics

Comprehensive analysis of correlations between media activities and mental health revealed generation-specific patterns and their implications. The relationship between peer influence and sentiment scores demonstrated the following distinctive distribution (Figures 11-13):

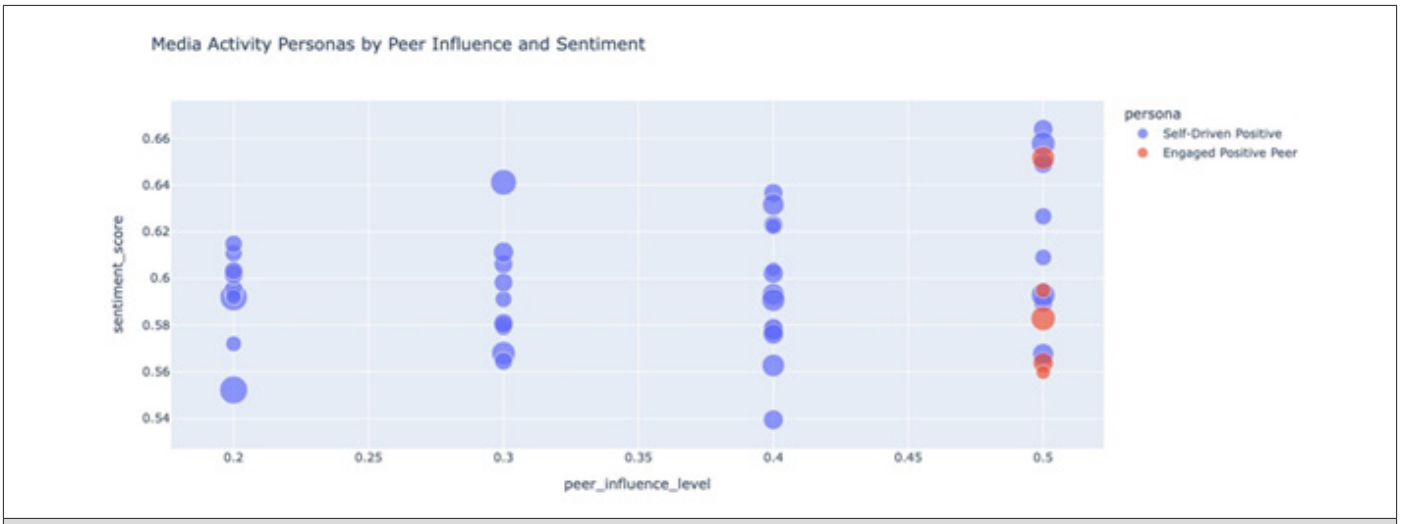

Figure 11: Media Activity Personas by Peer Influence and Sentiment.

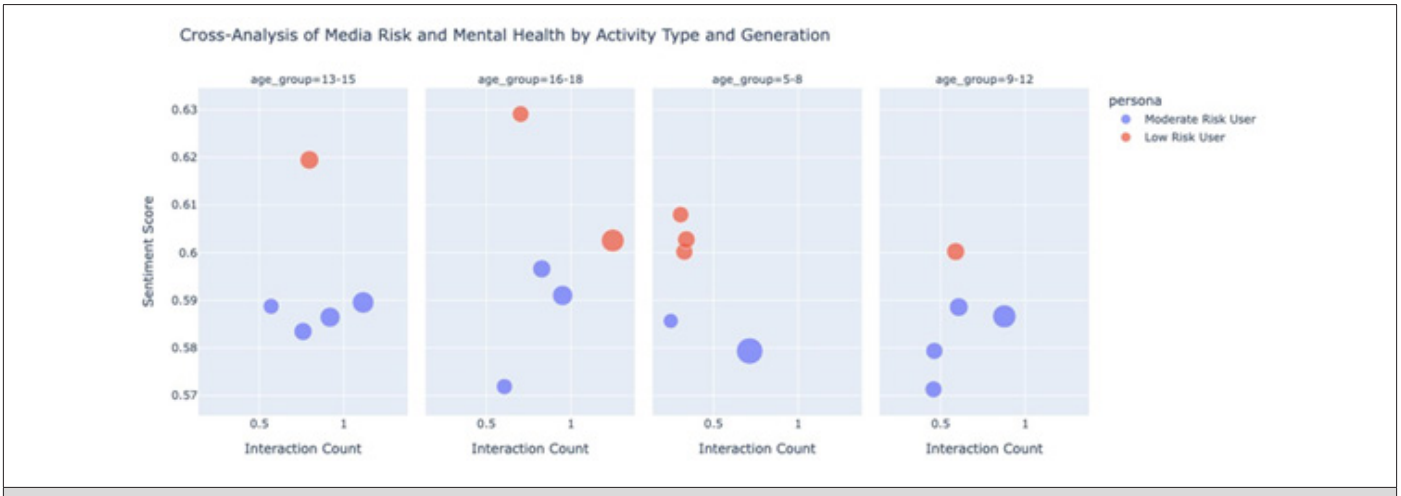

Figure 12: Cross-Analysis of Media Risk and Mental Health by Activity Type and Generation.

Figure 13: Mental Health Risk Analysis by Activity Type.

$$Sentiment_{score} = \begin{cases} 0.66 \text{ (peak value, self-directed)} \\ 0.63 \text{ (peer-influenced)} \\ 0.58 \text{ (minimum value)} \end{cases} \quad (22)$$

Mental health risk assessment across activity types identified moderate risk levels across multiple activity categories. Specifically, browsing, commenting, content creation, and messaging exhibited moderate risk values, while content sharing activities demonstrated comparatively lower risk values (Figure 14):

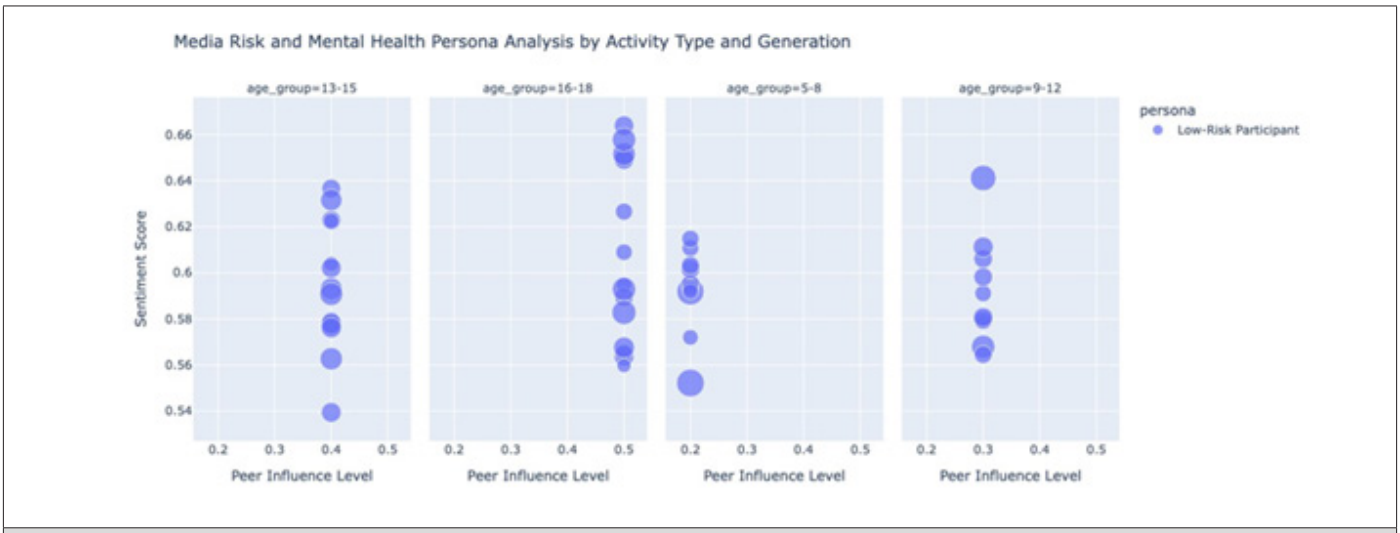

Figure 14: Media Risk and Mental Health Persona Analysis by Activity Type and Generation.

$$Risk_{browsing} = \text{Moderate}$$
$$Risk_{commenting} = \text{Moderate}$$
$$Risk_{content\_creation} = \text{Moderate}$$
$$Risk_{messaging} = \text{Moderate}$$
$$Risk_{sharing} = \text{Low}$$

Analysis of generational interaction patterns revealed the following characteristic distribution in age-specific sentiment

scores:

$$Interaction_{score} = \begin{cases} 0.62 \text{ (ages 13-15)} & \text{high-frequency} \\ 0.63 \text{ (ages 16-18)} & \text{medium-frequency} \\ \text{(ages 5-8)} & \text{low-frequency} \\ 0.59 \text{ (ages 9-12)} & \text{supervised} \end{cases} \quad (23)$$

Based on these analytical findings, educational intervention optimization strategies are proposed. Activities identified as high-risk, including browsing, commenting, and content creation, necessitate particularly focused intervention. Enhancement of protective

factors emphasizes comprehensive media literacy education, establishment of peer support systems, and provision of parental guidance as crucial measures.

Detailed Analysis of Focus on Peer Influence Dynamics

Comprehensive analysis of digital media mental health risk assessment and intervention strategy systematization revealed significant findings regarding correlations between peer in-fluence and psychological well-being. Mental health risk is formulated as a function of peer influence, activity intensity, and sentiment score:

$$\text{MentalHealth}_{risk} = \alpha(P_{influence}) \times \beta(A_{intensity}) \times \gamma(S_{score}) \quad (24)$$

Age-stratified risk characteristic analysis revealed particularly pronounced patterns in the 16-18 age cohort. Specifically, peer influence levels reached a maximum value of 0.5, sentiment scores registered at 0.66, and comprehensive mental health risk positioned within moderate to elevated ranges. Primary concerns identified within this age bracket encompassed heightened anxiety from social comparison, notable self-esteem fluctuations, and elevated stress levels attributable to FOMO (Fear of Missing Out).

Activity-specific mental health impact analysis revealed the following metrics:

$$Impact_{browsing} = 0.60 \text{ (sustained impact)}$$

$$Impact_{messaging} = 0.58 \text{ (social impact)}$$

$$Impact_{creation} = 0.59 \text{ (self-expression impact)}$$

Risk mitigation factor analysis identified content sharing as a relatively low-risk activity, attributable to protective factors including promotion of active social participation, opportunities for positive feedback acquisition, and cultivation of community belonging. Conversely, moderate-risk activities necessitate prevention of excessive immersion, development of time management capabilities, and establishment of healthy utilization patterns.

Preventive intervention strategies propose age-specific a proaches:

$$Intervention_{strategy} = \begin{cases} \text{High-intensity support} & \text{(ages 16-18)} \\ \text{Moderate-intensity support} & \text{(ages 13-15)} \\ \text{Preventive support} & \text{(ages 5-12)} \end{cases} \quad (25)$$

Specific intervention metrics propose utilizing peer influence levels, activity intensity, and sentiment score fluctuations as screening indicators. Protective interventions position enhanced media literacy education, improved stress management capabilities, and support for developing healthy social relationships as crucial measures.

Summary

Digital native generations, having been immersed in internet and social media platforms from early childhood, maintain lives inextricably intertwined with digital media. However, these cohorts face various mental health challenges due to insufficient media literacy and excessive digital media consumption, including psychological burden from appearance comparison and FOMO (Fear of Missing Out). To address these challenges, we introduced novel approaches utilizing data generation through GPT and evaluation methodologies through AHP (Analytic Hierarchy Process), a multi-criteria decision-making method.

GPT (Generative Pre-trained Transformer), a generative language model, possesses capabilities to produce human-like text through extensive training on textual data. This advancement enables synthesis and simulation of previously difficult-to-obtain data, facilitating detailed analysis of digital natives' media utilization patterns [23]. Concurrently, AHP provides decision-making methodologies that hierarchically structure multiple evaluation criteria for quantitative comparison. This approach offers advantages in comprehensively evaluating complex, multifaceted issues such as mental health and media literacy [28]. The integration of GPT-generated data with AHP evaluation enables data enrichment, multifaceted assessment, and objective analysis [22].

Generative language models have evolved rapidly, with the emergence of large-scale models such as GPT-3 and GPT-4. These models extend beyond natural language processing to applications in data generation and simulation [27], with educational applications encompassing automatic learning mate-rial generation and student response evaluation [29]. However, significant challenges persist, including potential reproduction and amplification of social biases and stereotypes [32], reliability concerns regarding generated data's statistical properties [24], and ethical considerations surrounding misinformation generation and privacy violations [41].

Analysis utilizing generated data revealed correlation pat-terns between sentiment scores and peer influence, with self-directed activities demonstrating peak values (0.66), followed by peer-influenced activities (0.63), and minimum values at 0.58. Mental health risk assessment across activity types identified moderate risks in browsing, commenting, content creation, and messaging, while content sharing exhibited lower risk levels. Generational analysis revealed the 16-18 age cohort demonstrating sentiment scores of 0.66 with peak peer influence levels at 0.5. The 13-15 age group recorded sentiment scores of 0.62 with notable social media and gaming influences, while the 9-12 cohort predominantly exhibited supervised usage with sentiment scores of 0.59, and the 5-8 group characterized by tablet utilization showed sentiment scores of 0.60.

The integration of GPT-generated data with AHP evaluation enables individually optimized educational interventions, developmentally appropriate media literacy material generation [37], and objective educational program evaluation. However, limitations persist regarding generated data quality and reliability, ethical considerations for privacy and bias, and technical implementation challenges in educational settings.

These analytical findings suggest that combining GPT-generated data with AHP evaluation presents theoretically and practically promising approaches to addressing media literacy and mental health challenges among digital natives. While enabling data en-

richment and multifaceted evaluation for individualized educational interventions, recognition of limitations including generative model biases, data reliability, and ethical concerns necessitates establishment of appropriate guidelines and evaluation metrics for educational applications [44-64].

Conclusion

The integration of GPT-generated data with multi-criteria AHP evaluation represents a crucial approach to addressing complex psychological and social challenges confronting digital native generations. This paper examined possibilities for knowledge-sharing mechanisms through developing risk assessment systems for media literacy and mental health, while mitigating psychological impacts of social media utilization. Furthermore, we elucidated current circumstances and challenges in generative language model data creation, considering applications and limitations. These technologies may contribute to pursuing fairness and sustainability in digital society.

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Conflict of Interest

None.

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