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Research Article

Algorithmic Pollution and Its Impact on Mental Health: Provisional Study Evaluating the Risks of Induced Reliance on Short-Form Video Content

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Abstract

This study examines the multifaceted impact of short-video platforms-specifically their underlying recommendation algorithms on users' mental health and psychological dependencies. We introduce the concept of "algorithmic pollution," referring to the unforeseen negative consequences that algorithmic design and operation can have on individuals and society. Such issues include ethical challenges, bias, lack of transparency, and social influence, all of which potentially foster psychological dependencies and filter-bubble effects that limit exposure to diverse viewpoints. Furthermore, the continuous presentation of negative or appearance-idealized content can exacerbate behaviors like "doomscrolling" and body dissatisfaction, contributing to the deterioration of users' mental health and, in some cases, promoting eating disorders.

The research employs both theoretical and empirical frame- works to understand how algorithmic personalization intensifies psychological vulnerabilities. We develop a data-driven simulation program to empirically assess the risks associated with algorithmically guided dependence on short-video platforms. This program models user behaviors-such as viewing duration, interaction density, and engagement patterns-under varying algorithmic influence factors, including personalization intensity and content diversity. Through time-series analysis and persona- based user segmentation, we identify that younger audiences, especially students, are more susceptible to rapid increases in dependency levels and are disproportionately affected by algorithm-induced echo chambers.

Our findings underscore the importance of ethical algorithmic design, enhanced transparency, and regulatory interventions. Interdisciplinary approaches, including digital literacy education and mental health–aware recommendation strategies, can mitigate these risks. By quantifying algorithmic influence and clarifying the correlating factors of psychological stress, this study offers a foundation for responsible algorithm governance. Ultimately, this work aims to support healthier user experiences, preserve mental well-being, and ensure that digital ecosystems can sustainably co-exist with social values and ethical standards.

Keywords: Algorithmic pollution, Short-video platforms, Mental health, Psychological dependency, Ethical algorithm de- sign, Bias, Transparency, Digital literacy, Doomscrolling, Body dissatisfaction, Echo chambers, Content personalization

Introduction

This paper provides a multifaceted analysis of the effects that the widespread diffusion of digital media has on mental health. In particular, it focuses on the ethical dilemmas, biases, lack of transparency, societal repercussions, and psychological dependencies engendered by algorithmic design and implementation [1,2,3]. The notion of "algorithmic pollution" has attracted significant concern as it appears frequently across various media environments. The current state of affairs increasingly necessitates both objective and subjective literacy in interpreting these data-driven indicators. This concept encompasses the unintended negative consequences that algorithmic architectures and operations impose on individuals and societies. Similar to environmental contamination, its influence may extend across a broad range of domains.

To examine how these factors shape personal psychological well-being from both theoretical and empirical standpoints, we developed a validation program that utilizes generated data. By doing so, we aimed to create a self-study platform enabling users to empirically assess risks associated with algorithmic dependency-be they objectively quantifiable or subjectively perceived-from a data analytic perspective. As a concrete example, we devised a tool under the theme of "algorithmically induced dependency risk assessment," capable of multilayered analysis of short-video platform reliance and performing Analytic Hierarchy Process (AHP) evaluations that consider mental health and social alienation [4-8]. In contemporary society, digital media have become central conduits for information sharing and communication. Against this backdrop, this paper employs data-driven case studies to comprehensively document the ethical challenges, social ramifications, and psychological dependencies arising from algorithmic design and operation, and to analyze their implications.

Algorithm Design and Ethical Issues

Algorithms and personalized recommendations, which traverse public networks daily in the digital ecosystem, target delivering content aligned with individual tastes by leveraging user behavioral histories and attributes. Although this approach potentially enhances the user experience and stimulates purchasing intentions, it must be acknowledged that relying on past behaviors and preferences to recommend content may cause users to be exposed primarily to homogeneous information. As a result, they risk being confined within a "filter bubble" that reinforces their existing beliefs and values, and subsequently reduces opportunities to encounter divergent perspectives and alternative sources of knowledge. Moreover, from a health-oriented perspective within the contemporary digital landscape, concerns have been raised that frequent recommendations of negative content can unconsciously lead individuals into "doomscrolling"-the prolonged consumption of distressing news. Such patterns are reported to increase anxiety, elevate stress levels, and in some instances aggravate depressive symptoms.

In addition, when algorithms suggest content without considering a user's emotional state, there is a possibility that inappropriate materials will be delivered during periods of heightened emotional sensitivity, resulting in adverse mental health outcomes. For instance, if users experiencing sadness or stress continually receive negative material, their emotional condition may deteriorate further [9,3]. To mitigate these issues, designers of recommendation systems should incorporate considerations for users' mental well-being. Potential strategies include detecting emotional cues and presenting content accordingly, as well as curating information reflecting a diverse range of viewpoints to prevent the formation of filter bubbles.

In summary, while recommendations and algorithms guided by personalized data can contribute to improved user satisfaction, it is essential to recognize their latent ramifications for psychological health and implement appropriate designs and operational frameworks. Although algorithms are intended to streamline and automate decision-making processes, design choices made during their initial formulation may introduce complex ethical dilemmas. In recent years, explainable Artificial Intelligence (XAI) has emerged with the aim of enabling users to comprehend the reasoning processes behind algorithmic decisions. However, if such explanations are merely appended post hoc, responsibility may be displaced onto the algorithm itself, complicating the accountability of its developers [1,2,10].

Dependence on Data

At the most fundamental level, algorithms rely heavily on their input data. Their performance hinges on the quality, quantity, and structure of the datasets employed for training and evaluation. Several aspects are particularly crucial [11].

Data Quality: Any bias or incompleteness within the underlying data directly influences the algorithmic output. For example, if a dataset unequally represents certain attributes (e.g., gender, age, ethnicity), the algorithm may internalize that skew. This asymmetry can be quantified as:

$$Bias\ Ratio = \left(\frac{P(Positive\,Outcome - Group\ A)}{P(Positive\,Outcome - Group\ B)} \right)$$

A Bias Ratio = 1 signifies underlying bias, potentially leading to imbalanced outcomes.

Dependence on Data Volume: Although ample data enhance algorithmic accuracy, they also escalate the costs of data collection and raise the threat of privacy infringements [10-12]. In machine learning applications, the volume of data crucially affects generalization capabilities.

Dependence on Algorithmic Design: The interpretability and trustworthiness of results substantially depend on the chosen algorithmic model. For instance, while black-box methods such as deep learning may achieve high accuracy, they are often difficult to explain, hindering comprehension of their internal logic.

Dependence On Operational Context: Algorithmic performance relies substantially on its operational environment. Factors such as computational resources, user interactions, and regulatory frameworks all play pivotal roles [3,13].

Deficiencies in Transparency and Accountability: Many systems remain "black boxes," rendering the decision- making processes opaque. This lack of transparency erodes confidence in the algorithm's outputs and further obscures the locus of accountability.

For example:

i. Users find it challenging to contest erroneous decisions when they cannot grasp the algorithm's reasoning [11].

ii. Developers may evade responsibility for unanticipated system behaviors.

As shown in Table 1, the absence of transparency precipitates numerous tangible repercussions.

Table 1: Concrete Effects Stemming from a Lack of Transparency.

Effect	Example
Dispersed responsibility	Ambiguity regarding accountability in erroneous decisions
Difficulty in filing objections	Limited means for users to prove unfairness due to inaccessible decision criteria
Erosion of trust	Users may refrain from adopting algorithms they cannot trust, restricting the system's broader acceptance

Algorithmic Complexity

One crucial factor underlying the challenges discussed is the increasing complexity of algorithms. Advanced techniques such as deep learning often result in models whose behavior even developers themselves cannot fully comprehend. Consequently, this lack of transparency hinders accountability.

Impact of Computational Complexity: In more intricate models, the computational burden can grow exponentially. For instance, the computational complexity of a neural network can be expressed as:

$$o\left(n^2.d\right),$$

where n denotes the input data size and d represents the network depth. Such an increase in computational effort adversely affects operational efficiency.

Insufficient Regulation and Governance

The absence of clear regulations and governance frame- works for algorithms constitutes another fundamental problem. This lack of oversight can lead to issues such as:

i. Ambiguous accountability for incorrect decisions.

ii. Inadequate regulations concerning privacy and data usage [12].

Since algorithmic deployment strongly depends on legal, regulatory, and ethical frameworks, the absence of well- defined standards governing data privacy and accountability may impede the proper utilization of algorithms. Understanding this premise is essential in the context of digital data [10].

Data Bias and Fairness Concerns

Because algorithms make decisions based on input data, data bias exerts a direct influence on outcomes. If skewed datasets are employed, certain groups risk being treated un- justly. Consequently, enhancing literacy and awareness regarding the provenance and logging of data is imperative [13].

For example, potential challenges include:

i. Disproportionate outcomes for specific racial or gender groups.

ii. In the medical field, algorithms might undervalue certain patient groups, resulting in inadequate treatment.

Contextual Bias Stemming from Operational Environments

The environment in which algorithms are deployed can itself induce biases. In particular, the social context or operational policies shaping the algorithm's use may disadvantage certain populations.

Biases Originating from Datasets: A large share of algorithmic bias originates from input data. If datasets reflect societal prejudices, the algorithm may replicate and potentially amplify these biases.

Quantifying Bias: The "Disparate Impact Ratio" is one metric employed to quantify bias:

$$Disparate\ \mathrm{Im}\,pact\ Ratio = \left(\frac{P(Positive\,Outcome - Group\ A)}{P(Positive\,Outcome - Group\ B)}\right)$$

A ratio in the range 0.8 Disparate Impact Ratio 1.25 is generally considered fair.

Concrete Examples: In a recruitment algorithm, if historical hiring data favor male candidates, the algorithm may undervalue female applicants. Consequently, the hiring rate of women could decline.

Bias Arising from Model Design: Bias may also emerge during algorithm design. For ex- ample, if certain features are weighted inappropriately, the resulting output may be skewed.

Table 2: Impacts of Operational Bias.

Impact	Example
Unequal Service Provision	A medical algorithm delivering un suitable diagnoses for certain ethnic groups

Emergence of Legal/Ethical Issues	A criminal justice algorithm un fairly classifying residents of a particular region as high-risk
Erosion of Trust	Users lose faith in algorithmic decisions, delaying system adoption

Impacts of Operational Bias: Operational bias can produce the following outcomes, which must not be overlooked (Table 2).

Algorithmic Contamination

"Algorithmic contamination" denotes unforeseen negative repercussions arising from the design and deployment of algorithms on individuals and societies. Similar to environmental pollution, it can produce wide-ranging effects, notably:

i. Inappropriate collection and usage of personal data, in- fringing on privacy [12].

ii. Encouragement of socially undesirable behaviors.

Moreover, misuse of algorithms in areas like healthcare or education can cause irreversible harm or biases at both individual and community levels [4]. Algorithmic bias originates from data, design, and the environment. If training data are skewed, such distortions surface in the algorithm's output. For instance, a crime prediction algorithm might consistently classify historically over-monitored regions as "high risk" [1,2].

$$Bias\left(D\right) = f\left(H, S, P\right)$$

Here, D is data, H is human judgment, S is the data collection method, and P is the processing technique.

Additionally, prioritizing certain objectives during algorithm design can internalize bias. For example, popularity bias in recommendation systems leads to disproportionately promoting specific products or content [1].

$\text{Bias} = \alpha \cdot \text{Objective}_1 + \beta \cdot \text{Objective}_2$

Here, Objective1 represents accuracy, Objective2 fairness, and α, β their respective weights.

The environment and user behavior can also induce bias. For example, public policy usage of algorithms could excessively target certain populations [4].

Algorithmic Dependence and Psychological Effects

Excessive reliance on algorithms poses concerns in education and academia. Overdependence on generative AI may reduce creativity and critical thinking [5].

$$D = a.S + b.E$$

In this equation, D is the degree of dependence, S is stress level, and E is expectation. Coefficients a and b represent the weights of these factors. If the algorithm functions as a "black box" with opaque in- ternal processes, accountability and transparency are compromised. This lack of interpretability undermines both fairness and reliability [4].

Causes and Consequences of Errors

Errors in algorithmic decision-making, which may emerge from data imperfections, algorithmic limitations, or operational issues, can severely affect fairness and trustworthiness.

Data Errors: Incomplete datasets, noise, or inaccurate labeling lead to erroneous algorithmic outputs. Such errors are reflected in accuracy metrics:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Samples}$$

Low accuracy suggests the influence of data errors

Model Limitations: Algorithmic performance hinges on model selection. Simple models fail to capture complex patterns, while highly sophisticated ones risk overfitting.

Impacts: Errors have extensive implications: (Table 3)

Table 3: Impacts of Errors.

Impact	Example
Reduced Decision Accuracy	A financial algorithm making in correct lending decisions
Increased Social Costs	Rising medical expenses due to misdiagnoses
Loss of User Trust	Systems plagued by frequent errors are avoided

Mitigating algorithmic errors and biases calls for:

- Enhancing transparency in data collection processes.

i. Implementing model designs that consider fairness.

ii. Adapting algorithms to the contextual needs of their operational environments.

Societal Implications and the Need for Regulation: For algorithms to gain social acceptance, improved transparency and the establishment of ethical guidelines are essential. Such efforts include stakeholder collaboration and the introduction of regulations mindful of sustainability and social responsibility [1,2].

The Diffusion of Negative Content: On short-video platforms, harmful remarks and hostile messages tend to proliferate readily, making users more susceptible to psychological distress and heightened anxiety [14]. To address the mental health challenges that digital media pose, several measures are essential. First and foremost, it is important to introduce educational initiatives that enhance users' understanding of algorithmic mechanisms and inherent limitations, thereby enabling them to engage with social media responsibly while sustaining self-esteem [15]. Moreover, rendering the algorithmic decision-making processes more interpretable can alleviate users' apprehensions and foster greater trust in these systems [1].

The Intensification of Comparison Culture: The comparison culture reinforced by social networks is a significant driver of perceived isolation. Evaluating oneself against others' achievements or appearances exacerbates feelings of social estrangement [15]. In particular, younger demo- graphics influenced by such a culture exhibit a pronounced tendency to depend on social media validation, making them more vulnerable to experiences of loneliness and detachment when confronted with negative appraisals or peer comparisons [16].

Table 7 shows the efficacy of concrete intervention measures (Table 4).

Table 4: Improvement Rates of Preventive and Interventional Strategies.

Intervention	Improveme (%)	Source
SNS Literacy Education	45%	*Ye, et al.,* (2023) [14]
Family and Community Support	50%	*Dumitrascu, et al.,* 2021 [9]
Limiting SNS Usage Time	40%	*Delgado- Rodrıguez, et al.,* (2022) [15]
Online Bullying Prevention Programs	30%	*Fioravanti, et al.,* (2023) [16]

Table 5: Risk Factors Linking Sns Use to Psychological and Physical Health Issues.

Factor	Quantitative Measure	Source
SNS Use and Eating Dis orders	More than 2 hours/day in creases risk by 30%	[12]
Social Comparison and Body Dissatisfaction	Correlation coefficient: 0.75	[12]
SNS Dependence and Stress	10% increase in dependence score raises psycho- logical stress by 5	[7]

Additionally, Tables 5 provides exemplary data on risk factors associated with SNS use. Synthesizing these case studies confirms that engagement with SNS and other media has profound repercussions on both psychological and physiological well-being.

Key Considerations for Short-Video Applications: The Case of Short-Video Platforms

As mentioned in the preceding section, a prominent short- video platform, developed by ByteDance in 2017, has rapidly gained popularity worldwide, especially among younger audiences. Naturally, these platforms do not solely generate negative outcomes. On the positive side, they can serve educational purposes, nurture creativity, enable self-expression, offer entertainment, and even facilitate mutual support communities that improve conditions for individuals with mental health is- sues. Nevertheless, critics have identified negative dimensions, including algorithmic dependency, apprehensions related to surveillance societies, inadequate media literacy, impacts on mental health, and concerns over copyright infringements.

Implications For Mental Health

Short-video platform usage can severely affect users' mental health. At the same time, these services can function as venues for psychological support and educational content. Specifically, high levels of content consumption coupled with algorithmic influence can lead to cognitive overload [17], while reliance on parasocial relationships may weaken real- world interpersonal networks [18]. Conversely, recent attention has centered on influencers who leverage these platforms to promote mental health awareness and offer assistance [19]. However, certain users experience heightened social exclusion or loneliness, exacerbated by features of the platform itself. For example, highly personalized content can hinder face-to-face interactions [20], and downward self-comparisons based on others' appearances or achievements reduce self- esteem [21].

Data Privacy and A Surveillance Society

The manner in which short-video platforms collect and utilize user data has sparked ethical debates. Concerns that the Chinese government may access this information have intensified anxieties regarding the possible emergence of a pervasive surveillance state [7].

Psychological Concerns: Short-video platform usage significantly influences users' cognitive styles and emotional conditions. The rapid swiping of brief video clips encourages intuitive, automatic (Type 1) thinking while impeding analytical, reflective (Type 2) thought processes. Additionally, the promotion of "doomscrolling," (Table 6).

Table 6: Major Challenges and Their Specific Manifestations.

Issue	Details
Mental Health	Cognitive strain, loneliness, psychological dependence
Social Alienation	Inhibited offline interaction, diminished self-appraisal
Data Privacy	Opaque data collection, surveillance concerns
Copyright	Unauthorized use, insufficient legal safeguards

i.e., persistently viewing negative content, has been empirically observed [17]. This phenomenon could undermine the depth of information processing and erode critical reasoning abilities. Furthermore, self-presentation and self-surveillance on these platforms highlight new dimensions of modern supervision technologies, as reflected in Foucault's panopticon framework and Mathiesen's synopticon concept [7]. Users may feel perpetually scrutinized, potentially intensifying inhibitions and anxiety related to self-expression.

Case Study: Short-Video Platforms and Eating Disorders: Short-video platforms, which are particularly popular among younger demographics, employ algorithms to tailor content recommendations based on user interests and behaviors. As a result, the risk of propagating idealized body images or pro-ana content that may foster eating disorders is heightened [22,23]. Aesthetic ideals and diet-related materials prevalent on these platforms can adversely affect users' self-image, thereby increasing the likelihood of developing or aggravating eating disorders [22].

Case Study: Short-Video Platform Algorithms and Mental Health: The recommendation algorithms underpinning short-video platforms prioritize content aligned with users' preferences, making echo chamber formation more likely. This effect strengthens homogenous opinions and values while diminishing exposure to contrasting viewpoints [23].

Propagation of Pro-Ana Content: Short-video platforms readily recommend Pro-Ana (pro- anorexia) materials through their algorithms, thereby con- tributing to the onset and exacerbation of eating disorders [23]. Eating disorders are known to worsen under the influence of digital media. In particular, platforms such as short-video services frequently circulate content endorsing idealized body images and extreme dietary behaviors, which intensify the severity of these conditions [22,23]. Dissatisfaction with one's own physical appearance triggers psychological stress, initiating a detrimental cycle that adversely affects eating

behaviors [24].

$$Stress = \alpha.Body\ Dissatifaction + \beta.Social\ Comparsion$$

$$Eating\ Behavior = \gamma.Stress + \delta.Media\ Influence$$

Additionally, users exhibiting strong SNS dependency show an average increase of 5 points in their body dissatisfaction scores [14].

Case Studies of Worsening Eating Disorders: Eating disorders exhibit a tendency to deteriorate due to the pervasive impact of digital media. As previously noted, short-video platforms, in particular, contain abundant con- tent promoting unattainable body ideals and extreme dieting behaviors, ultimately contributing to the escalation of these conditions [22,23].

Psychological Stress and the Aggravation of Disordered Eating: Discontent with one's appearance generates psychological strain, which in turn worsens maladaptive eating patterns [24]. Furthermore, users with significant SNS dependency show an average increase of 5 points in body dissatisfaction scores [14]. Numerous studies have documented a close relationship between SNS use and heightened anxiety [14]. In fact, individuals with strong SNS dependency exhibit anxiety scores approximately 20% higher than their less-dependent counter- parts.

Intensification of Depressive Symptoms: Research reports that exposure to SNS posts displaying idealized lifestyles and body images diminishes self-assessments, consequently exacerbating depressive tendencies [25-31]. The idealized appearances and life scenarios frequently showcased on SNS significantly undermine self-esteem among younger audiences, leading to serious repercussions for mental health. Nocturnal SNS usage habits result in reduced sleep duration and diminished sleep quality. Dumitrascu et al. [9] have demonstrated that each additional hour of nighttime SNS usage decreases sleep quality by 30%. The virtual connections provided by SNS can weaken face-to-face relationships, increasing feelings of isolation [24].

Implementation of Enhanced Regulations: (Table 7)

Table 7: Effectiveness of Preventive and Interventional Strategies.

Measure	Improvement (%)	Source
Enhanced User Education	45%	[5]
Increased Transparency	50%	[1]
Strengthened Regulations	40%	[3]

Governments and regulatory bodies have begun establishing standards for algorithmic design and operation, introducing rules aimed at ensuring fairness and transparency [4,9].

Description of the Simulation Algorithm for Analyzing Dependency Tendencies on Short-Video Platforms

This section explains the code designed to generate and analyze data for assessing user dependency trends on short- video platforms. The program is structured to correlate user behavior patterns with algorithmic influence factors. The following subsections elucidate the primary functions of the code [6].

Overall Design of the Data Generation Algorithm

This system generates user-specific behavioral data to evaluate dependency levels and the influence of algorithms. The main components of the code are summarized below:

a. **Algorithmic Factors:** A dictionary defining at- tributes of each algorithmic factor (e.g., content personalization, infinite scrolling). It stores characteristic values and corresponding weights for their influence.

b. **Content Categories:** Definitions of fundamental engagement rates and the propensity for addiction across various content types.

c. **Tiktok algorithmic user Class:** Manages algorithmic profiles and usage histories at the user level and is responsible for generating session data.

Functions of the TikTok Algorithmic User Class: This class simulates user behavior, producing data for each session. Below are key methods and their intended purposes.

_INITIALIZE_ALGORITHMIC_PROFILE

This function initializes a user's algorithmic profile by randomly generating parameters:

i. **Content Preferences:** Randomly assigned inclinations for various content categories.

ii. **Engagement Patterns:** Behavioral patterns such as scrolling speed, viewing time, and interaction frequency.

iii. **Session Duration Model:** Baseline session durations and their variance.

iv. **Dopamine Response:** Baseline dopamine reaction levels and adaptation rates.

This setup ensures that each user model reflects distinct behavioral characteristics.

CALCULATE_ALGORITHMIC_INFLUENCE

This function calculates the impact that the algorithm exerts on user behavior. Four factors are considered:

$$
\begin{aligned}
Influence = &\left(content\_personalization \, \mathrm{X} \, w_1\right) \\
&+\left(\inf inite\_scroll \, \mathrm{X} \, w_2\right) \\
&+\left(recommendation\_accuracy \, \mathrm{X} \, w_3\right) \\
&+\left(novely\_factor \, \mathrm{X} \, w_4\right)
\end{aligned}
$$

Here, w1, w2, w3, w4 represent the weights of each factor.

GENERATE_SESSION_DATA

This method generates data for a single session through the following steps:

i. **Calculating Baseline Session Duration:** Use of gamma distributions to randomly generate viewing times.

ii. **Applying Algorithmic Influence:** Incorporating the algorithmic influence score into the session duration.

iii. **Generating Interaction Data:** Employing beta distributions to compute "likes," comments, and **Shares.**

iv. **Updating Dopamine Response and Dependency:** Adjusting dependency and dopamine levels based on viewing times and interactions.

The generated data are stored in the format shown in Table 8.

Table 8: Description of Each Data Attribute.

Attribute	Description
user id	User identifier
persona	User persona
timestamp	Session starts time
duration minutes	Viewing duration of the session (in minutes)
algorithmic influence	Degree of algorithmic impact
dependency level	Dependency score
interaction count	Total number of user interactions
dopamine level	Dopamine level
session type	Session type (e.g., binge watching)

Explanation of Analysis Functions: The following outlines the set of functions designed to analyze the generated data.

ANALYZE_DEPENDENCY_PATTERNS

This function evaluates users' dependency tendencies. It calculates various indicators, including daily usage patterns, interaction density, and the frequency of prolonged viewing sessions.

A N A L Y Z E_A L G O R I T H M I C_I M P A C T

This function examines trends in algorithmic influence and investigates correlations with user behavior. It places particular emphasis on the relationship between algorithmic impact and user engagement.

C A L C U L A T E_C O N T E N T_D I V E R S I T Y

This function measures the diversity of session types using entropy. Higher diversity implies that the user engages with a broader array of content categories. By modeling user behavior and algorithmic influence factors, and subsequently generating and validating data on dependency trends, the analysis conducted herein moves closer to providing empirical insights for discussions on algorithmic transparency and ethical design.

Conceptualizing Algorithmic Influence Factors

The concept of "algorithmic pollution" presented in this paper refers to phenomena in which algorithms exert unintended negative effects on individuals and society, constituting a serious problem in the contemporary world. Addressing this issue requires a multifaceted examination of the ethical dilemmas, transparency deficits, and biases inherent in algorithmic design and operation. In response to the arguments presented in the introduction, we consider three distinct perspectives that highlight the significance of designing algorithmic influence factors.

Visualizing Algorithmic Pollution and Fostering Data- Driven Understanding

Systematically constructing algorithmic influence factors and employing simulations to analyze behavioral patterns and dependency tendencies are crucial in rendering "algorithmic pollution" visible. The simulation algorithm utilized in this study possesses the following characteristics:

i. **Separating and Weighting Influence Factors:** Content personalization, infinite scrolling, recommendation accuracy, and novelty are isolated as distinct factors whose individual impact levels are quantified.

ii. **Data-Driven Dependency Evaluation:** By examining variables such as viewing durations, interaction frequencies, and dependency fluctuations, the simulation enables concrete measurement of how algorithms affect mental health.

Incorporating these elements provides a data-driven foundation for objectively and subjectively understanding the ramifications of "algorithmic pollution." This foundation contributes to the enhancement of digital literacy in today's society.

Modeling User Behavior and Analyzing Psychological Healt Impacts

This simulation meticulously models user-level behavioral data and evaluates fluctuations in dependency levels and algorithmic impact scores. Such modeling is pivotal for assessing the effects on psychological well-being, offering the following advantages:

i. **Time-Series Analysis of Dependency:** Visualizing dependency trends by time of day or over multiple days clarifies the conditions under which dependency intensifies.

ii. **Assessing Algorithmic Sensitivity:** Examining user- specific algorithmic sensitivity (e.g., the effectiveness of recommendations or the influence of content diversity) helps identify factors that increase or decrease psycho- logical strain.

This approach furnishes a new framework for theoretically and empirically examining the consequences of algorithms on mental health.

Empirical Contributions to Digital Ethics and Design Guidelines

Evaluating ethical challenges in algorithmic design necessitates empirical analysis grounded in actual data. This simulation program aids ethical examinations in the following ways:

i. **Enhancing Transparency:** By decomposing algorithmic influence factors and quantitatively assessing their effects, it contributes to improved transparency.

ii. **Guiding Design Improvements:** Providing a basis for proposing concrete design principles that mitigate negative influences on user dependency and psychological well-being.

In doing so, the simulation program seeks to advance empirical analyses aimed at bolstering transparency and social accountability in algorithmic design. In relation to the concept of "algorithmic pollution" outlined in the introduction, this approach contributes from both empirical and practical stand- points. Through a data-driven methodology, it measures the repercussions of algorithmic design on individuals and society, offering a foundation for constructive reform. Such endeavors not only promote deeper digital ethics in contemporary society, but also propose a fresh perspective for harmonizing psychological health and social sustainability.

Discussion

Data Validation

(Figure 1)

This section interprets the code employed to validate and analyze user data from short-video platforms, elaborating on the rationale and implementation details behind each function and visualization technique. The analysis concurrently evaluates user behavior over time, dependency metrics, and algorithmic influences from multiple angles [6].

Figure 1: Dependency and Algorithmic Influence Patterns Over Time of Day.

Data Ingestion and Preprocessing

Data are imported from three CSV files generated by the code above:

i. **tiktok_algorithmic_usage_log.csv:** Session- by-session usage logs.

ii. **tiktok_dependency_analysis.csv:** Statistical data on dependency levels.

iii. **tiktok_algorithmic_impact_analysis.csv:** Data on the analyzed algorithmic influence.

(Figure 2,3)

These datasets are loaded using the pandas library, and columns undergo type conversions and computed additions as needed.

Figure 2: Usage Patterns by Persona.

Figure 3: Distribution of Session Types.

Dependency and Algorithmic Influence Patterns Over Time of Day

Figure 1 presents the average dependency levels (red line) and algorithmic influence scores (blue line) by time of day. The following characteristics are evident:

i. Dependency values fluctuate between approximately 0.64 and 0.68 throughout the day, displaying slightly higher levels between 9:00 a.m. and 3:00 p.m.

ii. By contrast, algorithmic influence remains relatively stable between 0.54 and 0.56, with a modest upward trend in the late afternoon (after 4:00 p.m.).

These observations suggest the existence of daytime intervals during which users are more susceptible to certain algorithmic stimuli.

Usage Patterns by Persona

Figure 2 shows average viewing duration, interaction count, dependency, and algorithmic influence for each persona. The details are as follows: (Figure 3,4)

Figure 4: Time-Series Changes in Dependency.

i. **Viewing Duration:** All personas exhibit remarkably uniform average viewing times of about 150 minutes.

ii. **Interaction Count:** Students register the highest number of interactions (approximately 600), while adults and younger users hover around 500.

iii. **Dependency:** Overall dependency levels remain stable, around 0.6.

iv. **Algorithmic Influence:** Across all personas, influence scores cluster around 0.5.

These results imply that students may be more responsive to algorithmic stimuli, potentially explaining their higher interaction rates.

Distribution of Session Types

Figure 3 shows the distribution of session types by persona:

i. "Binge-watching" sessions dominate across all personas, representing the most common session style.

ii. Although the teenage cohort displays more diverse session types than other groups, binge-watching remains prevalent.

This finding indicates that continuous viewing emerges as the principal mode of content consumption.

Time-Series Changes in Dependency

Figure 4 portrays the temporal changes in dependency for each persona:

i. All personas exhibit an upward dependency trend from November 28 through December 5 (Figure 6).

ii. While dependency among adults increases only gradually, younger users show a more pronounced and rapid escalation

This suggests that younger demographics may cultivate high dependency levels within shorter timeframes.

Relationship Between Interaction and Dependency

Figure 5 presents a scatter plot of the relationship between interaction counts and dependency:

i. Younger users (in orange) tend to have higher interaction rates than other personas.

ii. When interaction counts exceed 500, dependency appears to stabilize within a range of 0.6 to 0.8.

These observations hint that elevated interaction levels may correlate with fixed dependency scores.

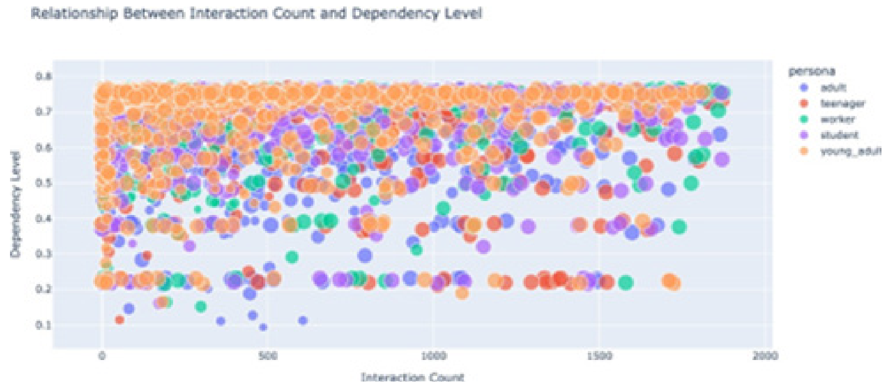

Figure 5: Relationship Between Interaction and Dependency.

Distribution of Algorithmic Sensitivity

Figure 6 displays algorithmic sensitivity by persona:

i. Among students, sensitivity exhibits greater variability, implying that individual responses to algorithms may differ considerably.

ii. Younger and adult cohorts are more stable, showing more consistent reactions to algorithmic inputs.

Synthesizing insights from Figures 1 through 6 yields the following conclusions:

i. User behavior differs by time of day; dependency is notably high during daytime hours.

ii. Students display notably high interaction counts and broad variability in algorithmic sensitivity.

iii. Dependency fluctuates by persona and time of day, suggesting that algorithmic design may influence psychological outcomes.

Figure 6: Distribution of Algorithmic Sensitivity.

Dependency and Algorithmic Influence Patterns by Time of Day

Figure 1 shows dependency gradually increasing from morning to afternoon, then stabilizing. This trend aligns with the time-series changes in dependency illustrated in Figure 4, indicating distinct temporal patterns in user behavior. In particular, the rapid increase in dependency among younger users (see Figure 4) may be linked to comparatively higher midday algorithmic influence.

Persona-Specific Usage Patterns and Dependency

Combining persona-based viewing durations and dependency from Figure 2 with the time-series changes in Figure 4 yields the following insights:

i. The higher viewing durations and interaction counts observed among students (Figure 2) partially explain their abrupt rise in dependency over time (Figure 4).

ii. Although adults maintain steady viewing habits, their dependency levels vary only slightly, highlighting distinct behavioral tendencies among personas.

Session Types and Algorithmic Influence

Figure 3 demonstrates that binge-watching is the predominant session type across all personas. This finding may correlate strongly with the daytime dependency peaks noted in Figure 1. Continuous viewing likely contributes to in- creased dependency, particularly noticeable among students and younger users.

Interaction and Dependency Relationships

The scatter plot in Figure 5 correlates closely with persona-specific interaction counts depicted in Figure 2, confirming high interaction frequencies among students. Coupling these data with the time-series analysis in Figure 4 suggests that personas exhibiting elevated interaction counts are more prone to swiftly rising dependency levels.

Algorithmic Sensitivity Distribution and Diversity

The algorithmic sensitivity distribution in Figure 6 shows that students' sensitivity variability is the widest. This variation aligns with their elevated interaction counts (Figure 2) and the dense distribution observed in Figure 5, implying that algorithm design may produce distinct outcomes for each persona.

Referencing Figures 1 through 6 together leads to the following comprehensive conclusions:

i. Certain times of day correspond to peak dependency levels (Figure 1), which may be strongly linked to particular session types (binge-watching, Figure 3).

ii. Students consistently score highest in viewing duration, interaction count, and algorithmic sensitivity, contributing to rapidly escalating dependency (Figures 2, 4, and 6).

iii. When interaction counts are high, dependency converges to a stable range, indicating that algorithmic configuration influences these dynamics (Figure 5).

iv. Personas with greater sensitivity variability (students) display more diverse behavioral patterns, necessitating persona-tailored algorithmic strategies (Figure 6).

Overall, these outcomes indicate that algorithmic design significantly affects user behavior and psychological impact, underscoring the importance of persona-based optimization (Figure 7).

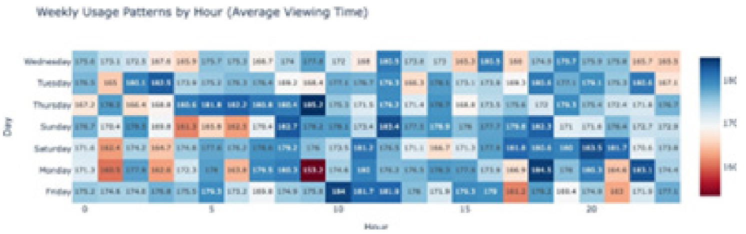

Figure 7: Weekly and Hourly Usage Patterns (Average Viewing Time.

Weekly and Hourly Usage Patterns (Average Viewing Time)

Figure 7's heatmap of mean viewing times by day of the week and hour reveals:

i. Viewing times peak between 10:00 a.m. and 2:00 p.m. on Tuesdays and Thursdays (maximum 185.2 minutes).

ii. The lowest average viewing time occurs on Monday at 10:00 p.m. (153.2 minutes), while usage tends to rise toward the weekend.

iii. Some weekdays show relatively high viewing times even during late-night hours (midnight to 2:00 a.m.).

These findings suggest that viewing behavior depends on both the day and time, with notable clusters on Tuesdays and Thursdays.

Multifaceted Analysis of Algorithmic Influence

(Figure 8) shows content diversity, temporal dependence, engagement correlations, and trends in algorithmic impact:

Figure 8: Multifaceted Analysis of Algorithmic Influence.

i. A negative correlation appears between content diversity and recommendation accuracy (under 0.2).

ii. Scatter plots of time-dependence and adaptation rates show that students and younger users have higher adaptation than other groups.

iii. Engagement correlations reveal that students register the highest values, while teenagers and adults exhibit negative correlations.

iv. The boxplot depicting algorithmic influence trends indicates minor overall variability, but slightly greater dispersion among younger cohorts.

These results suggest persona-specific distinctions in how algorithmic factors manifest.

Algorithmic Adaptation Patterns by Risk Level

(Figure 9) presents changes in adaptation rates and time- dependence across risk levels, from very low to very high:

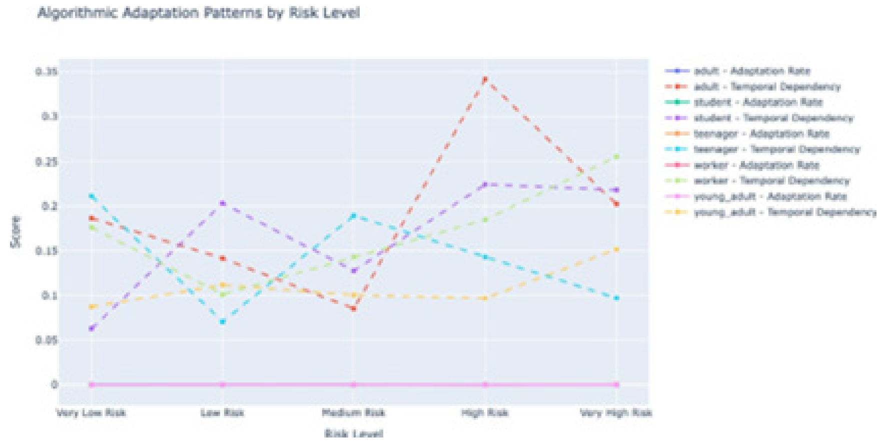

Figure 9: Multifaceted Analysis of Algorithmic Influence.

i. In the high-risk group, students display the highest adaptation rates (above 0.35).

ii. Time-dependence increases markedly between low- and medium-risk scenarios among adults and younger users.

iii. Among teenagers, adaptation rate variations due to risk level are smaller than in other groups.

iv. These findings imply that risk level may serve as a key determinant of algorithmic adaptation rates.

Temporal Behavioral Patterns

(Figure 10) visualizes interaction rates, mean session durations, dependency, and total interaction volumes by time of day:

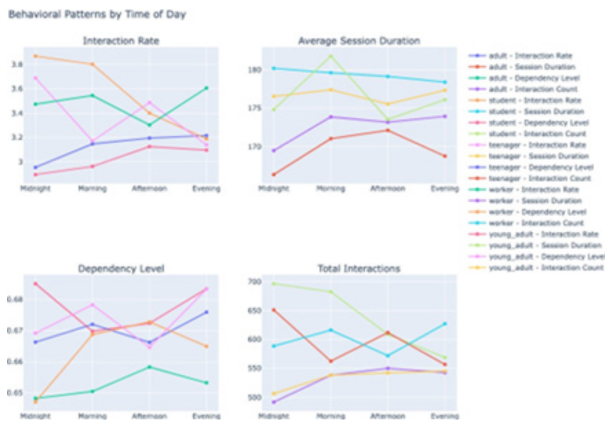

Figure 10: Temporal Behavioral Patterns.

i. Mean session durations are longest during midday (10:00 a.m.–2:00 p.m.), exceeding 180 minutes.

ii. Dependency typically increases after 10:00 p.m., particularly among students.

iii. Total interactions peak during both late-night and daytime hours, notably higher for younger users and students.

These patterns align with day-of-week tendencies illustrated in Figure 10, revealing distinct temporal and persona-based behavioral shifts.

Session Interval Distributions

(Figure 11) shows the distributions of session intervals for each persona:

i. Intervals for binge-watching sessions remain relatively consistent across all personas, with medians ranging from 5 to 10 hours.

ii. “High engagement” sessions appear primarily among adults and are rare in other personas.

iii. “Passive viewing” sessions display the broadest range among teenagers, occasionally exceeding 40-hour intervals.

These outcomes indicate that session intervals depend on both session type and persona.

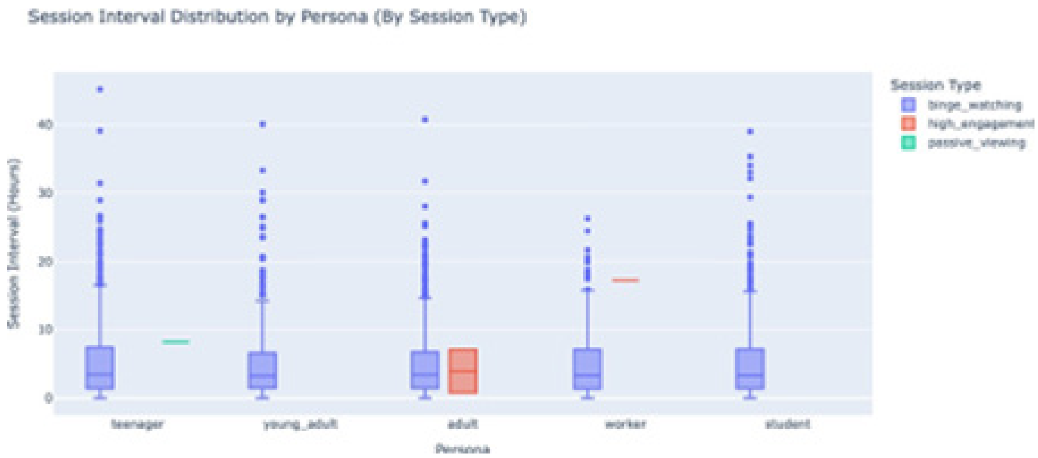

Figure 11: Session Interval Distributions.

Cross-referencing these figures leads to the following key findings:

i. Mean viewing times (Figure 7) and time-of-day behavioral patterns (Figure 4) closely correlate with session interval distributions (Figure 8), particularly for students and younger users.

ii. Algorithmic influence (Figure 8) and adaptation rates by risk level (Figure 9) are vital indicators for personalizing viewing experiences.

iii. Short intervals characteristic of binge-watching likely contribute to nighttime dependency increases (Figure 10).

Conclusion

Algorithmic Dependence and Psychological Impact

This paper aimed to comprehensively evaluate algorithmic dependence and psychological implications by examining user data from short-video platforms. In particular, we concentrated on time-series behavioral data and persona-based usage patterns to analyze how dependency and algorithmic sensitivity influence user psychology and social conduct.

Dependency and Algorithmic Influence by Time of Day

Figure 1 visualized average dependency and algorithmic impact levels by time period. These findings can be interpreted as follows:

i. Dependency peaked between 9:00 a.m. and 3:00 p.m., reaching a maximum of approximately 0.68.

ii. Although algorithmic influence remained relatively stable, it exhibited a slight upward trend after 4:00 p.m.

This suggests that user behavior tends to concentrate during daytime hours, making individuals more susceptible to algorithmic cues in particular temporal windows.

Usage Patterns by Persona

We classified users into three personas-students, younger adults, and mature adults-then compared their behavioral tendencies. The results highlighted the following points:

i. Average viewing durations hovered around 150 minutes, showing remarkable uniformity.

ii. Students displayed the highest number of interactions (about 600), while both younger adults and mature adults recorded approximately 500.

iii. Students exhibited notably greater algorithmic sensitivity. These observations imply that the student group is most vulnerable to algorithmic prompts and behavioral guidance.

Temporal Changes in Dependency

Visualizing weekly dependency trends revealed that all personas experienced a dependency increase from late November through early December.

i. Students showed a particularly steep rise in dependency compared to other personas.

ii. Adults maintained relatively stable dependency trajectories.

These results indicate that younger cohorts are especially influenced by algorithms, rapidly intensifying their dependency within short intervals.

Distribution of Session Types

Examining the distribution of session types revealed that "binge-watching" was the most prevalent pattern overall. This habit strongly correlated with increases in dependency levels.

Insights From the Generated Data

Synthesizing the above findings, several key points emerge:

i. Algorithmic influence manifests distinctly depending on the time of day and the user's persona.

ii. Students are particularly inclined toward dependency, becoming strongly affected over short periods.

iii. Continuous viewing (binge-watching) contributes to escalating dependency.

iv. Ensuring transparency, ethical considerations, and tailoring algorithmic design to user characteristics is imperative.

Ethical Considerations

Drawing on the analyses presented, we propose the following recommendations to mitigate algorithmic dependence:

i. Algorithmic design should account for users' psychological states and present diversified content recommendations.

ii. Educational initiatives that help users understand the nature and limitations of algorithms are crucial.

iii. Heightened oversight by regulatory bodies is needed to ensure fair and transparent algorithmic operation.

This analysis has clarified the multifaceted nature of user behavior and dependency trends on short-video platforms. Notably, the student demographic exhibited a pronounced risk of algorithm-induced dependence, reinforcing the need for ethically guided algorithmic design. This exploratory study thus provides renewed insight into the importance of ethical frameworks in digital environments.

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Conflict of Interest

None.

References

1. Lima G (2022) The Conflict Between Explainable and Ac- countable Decision-Making Algorithms. ACM FAccT '22.
2. Martin K (2018) Ethical Implications and Accountability of Algorithms. Journal of Business Ethics.
3. Smith J (2021) Algorithms in Mental Health: Opportunities and Challenges. Journal of Medical Systems.
4. Marjanovic O (2018) Algorithmic Pollution: Understanding and Responding to Negative Consequences of Algorithmic Decision-Making.
5. Gao Y, Liu F, Gao L (2023) Echo Chamber Effects on Short Video Platforms. Scientific Reports 13(1): 6282.
6. Kawahata Y (2024) Generating and Validating Anonymity Data: Risk Assessment of Algorithm-Guided Dependence: A Multilayered Analysis of TikTok (Short Video Platform) Dependence - Formative Processes of Mental Health and Social Alienation - Quantitative Evaluation of Causal. Retrieved November 30, 2024, from *https://x.gd/ZjCKR*
7. Galanis P (2024) Determining an optimal cut-off point for TikTok addiction using the TikTok Addiction Scale. International Journal of Education and Research 12(7): July 2024.
8. Hu W (2021) Short video social media dependence. Journal of Social Media Studies 14(2): 84-95.
9. Dumitrascu MC (2021) Anorexia Nervosa: COVID-19 Pan- demic Period. Experimental and Therapeutic Medicine 22(2): 804.
10. Bambauer J, Zarsky T (2018) The Algorithm Game. Arizona Legal Studies. Available at: *https://ssrn.com/abstract=3135949*
11. Waldman AE (2019) Power, Process, and Automated Decision-Making. Fordham Law Review. Available at: *https://ir.lawnet.fordham.edu/flr/vol88/iss2/9*
12. Doe A, Roe B (2020) Privacy Concerns in Mental Health Data Utilization. International Journal of Information Management.
13. Lee C (2019) Addressing Bias in Mental Health Algorithms. Ethics in AI.
14. Ye C (2023) The Influences of Social Media on Eating Disorder Risk. Journal of Education, Humanities and Social Sciences.
15. Delgado Rodrıguez (2022) Social network addiction symptoms and body dissatisfaction in young women. Journal of Eating Disorders.
16. Fioravanti (2023) Problematic Instagram use and eating disorder psychopathology. Social Psychiatry and Psychiatric Epidemiology.
17. Mader (2023) Is (Disordered) Social Networking Sites Usage a Risk Factor for Dysfunctional Eating and Exercise Behavior?" IJERPH.
18. Jiang Q, Ma L (2024) Swiping More, Thinking Less: Using TikTok Hinders Analytic Thinking.
19. Syakiroh A (2024) Parasocial Versus Public Figure on TikTok Social Media: A Psychoanalytic Perspective.
20. Motta M, Liu Y, Yarnell A (2023) Influencing the Influencers: A Field Experimental Approach to Promoting Effective Mental Health Communication on TikTok.
21. Richards A (2024) TikTok: The Darkside of Surveillance.
22. Oktarini NPU (2022) Analysis of the Positive and Negative Impacts of Using TikTok for Generation Z During Pandemic.
23. Bi X, Qian Liang, Guangyan Jiang, Min Den, Hongbo Cui, et al. (2024) The Cost of the Perfect Body: Influence Mechanism of Internalization of Media Appearance Ideals. BMC Psychology 12(1): 138.
24. Gao M (2023) Social Media's Influence on Eating Disorders. Modern Economics & Management Forum.
25. Jankauskiene (2022) Media Pressures, Internalization of Appearance Ideals, and Disordered Eating among Adolescents. Nutrients.
26. Vendeville A (2022) Opening up Echo Chambers via Optimal Content Recommendation. Proceedings of the AAAI Conference on Artificial Intelligence.
27. Richards A (2024) TikTok: The Darkside of Surveillance.

28. Gajo AGE (2023) Sustaining Students' Mental Health Through the Use of TikTok Application.
29. Motta M, Liu Y, Yarnell A (2023) Influencing the Influencers: A Field Experimental Approach to Promoting Effective Mental Health Communication on TikTok. Randomized Controlled Trial 14(1): 5864.
30. Sampathirao P (2016) Overuse of Social Media Affects the Mental Health of Adolescents and Early Youth.
31. Panjaitan WN (2023) Perlindungan Hukum Bagi Pencipta Yang Ciptaannya Digunakan Dalam Aplikasi TikTok Menurut Undang Undang Nomor 28 Tahun 2014 Tentang Hak Cipta.