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Mathematical Model Formulation and Analysis on Social Media Addiction Among Federal University Dutsin-Ma Students

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ABSTRACT

Social Media is a serious problem in society today and many students are addicted to Media. Social media has become an indispensable part of contemporary issues in Federal University Dutsin-Ma, influencing how students communicate, share information, and build relationships. The advent of these platforms such as Facebook, Instagram, Twitter, and others has revolutionized the way students interact and consume information. However, this transition has also given rise to concerns about the addictive nature of social media usage and its potential impact on mental health and well-being. The concern over social media addiction is not only limited to its impact on individual well-being but also extends to its broader societal implications. While existing research has provided valuable insights into the qualitative aspects of social media addiction, there is a noticeable gap in the literature regarding the development and application of mathematical models to analyze and predict addictive behaviors in the digital realm. In this research, we developed deterministic models for Social Media Addiction driven by the Social Media User in Federal University Dutsin-Ma Students taking into consideration factors such as social media usage pattern, factors contributing to social media addiction. Two approaches were developed, one which is descriptive analysis, where data from 200 students in the university were collected using Goggle Form as instrument, and then analyzed. The other which is the Mathematical Model formulation and Analysis on Social Media Addiction. The models were analyzed through the determination of the model's steady states and their respective stabilities analysis in terms of the Social Media Addiction reproduction numbers R0. The analysis shows that Social Media Addiction-free equilibrium (SMAFE) is locally asymptotically stable if $R0 < 1$ and unstable if $R0 > 1$. The SEARC model simulation examines the dynamics of social media user and addiction among Federal University Dutsin-Ma students. The model considers five states: Susceptible (S), Exposed (E), Addicted (A), Recovered (R), and Self-controlled (C). The numerical simulation reveals that social media addiction is a significant concern, with a high proportion of students becoming addicted. The model also highlights the importance of self-control and recovery in mitigating the negative impacts of social media addiction. The sensitivity analysis of the model parameters was done to determine where the campaigns and interventions should be targeted for effective control of the addiction. The results from the simulations therefore, illustrated that increasing the rate of interventions reduces the number of social media addicts in the University. The model also highlights the importance of self-control and recovery in mitigating the negative impacts of social media addiction. Demographic changes and other factors can influence the prevalence of social media addiction. In summary, results showed that mass media awareness against social media user reduces Social Media Addiction. From the study, it was concluded that if social media intervention is emphasized and mass media campaign is also regulated then social media addiction will be reduced from the University. The study suggested that the Students should be encouraged to engage in offline activities and hobbies to reduce their reliance on social media.

Keywords. SEARC Model, Reproduction Number, Social Media, Addiction, Social Media Addiction, Addiction-Free Equilibrium

1. Introduction

A. *Overview*

Social media has now become the indispensable part of contemporary society, influencing how individuals communicate, share information, and build relationships. The advent of these platforms such as Facebook, Instagram, Twitter, and others has revolutionized the way people interact and consume information. This shift towards digital communication has brought about numerous benefits, fostering global connectivity and facilitating the rapid dissemination of information. However, this transition has also given rise to concerns about the addictive nature of social media usage and its potential impact on mental health and well-being.

The exponential growth of social media platforms over the past decade has led to an increase in the time individuals spend engaging with these digital spaces. The ease of access, constant connectivity, and the allure of social validation through likes, comments, and shares contribute to the immersive nature of social media experiences. As a result, researchers and psychologists have turned their attention to understanding the psychological and behavioral aspects of social media usage, particularly the phenomenon of social media addiction.

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Numerous studies have highlighted the negative consequences associated with excessive social media use. For instance, Kuss and Griffiths (2017). pointed out that social media addiction can lead to adverse effects on mental health, including increased levels of anxiety and depression. Similarly, Anderson and Smith (2018) found a correlation between addictive social media use and negative outcomes such as sleep disturbances and reduced academic performance.

The concern over social media addiction is not only limited to its impact on individual well -being but also extends to its broader societal implications. Issues such as cyberbullying, online harassment, and the spread of misinformation are amplified in the context of social media, raising questions about the overall health of the digital society. Consequently, there is a pressing need for comprehensive research that goes beyond qualitative assessments and delves into the quantitative aspects of social media addiction.

Understanding the dynamics of social media addiction requires a multidimensional approach that encompasses psychological, sociological, and technological factors. While existing research has provided valuable insights into the qualitative aspects of social media addiction, there is a noticeable gap in the literature regarding the development and application of mathematical models to analyze and predict addictive behaviors in the digital realm.

The integration of mathematical modeling into the study of social media addiction offers a unique opportunity to quantify the intricate relationships between various variables. By employing mathematical frameworks, researchers can gain a more nuanced understanding of the factors that contribute to addiction, the tipping points that lead to problematic usage, and the potential trajectories of addictive behaviors over time.

This research aims to bridge this gap by focusing on the mathematical formulation and analysis of social media addiction. By leveraging mathematical models, the study seeks to provide a systematic and quantitative exploration of the patterns and dynamics associated with social media addiction. This approach is anticipated to offer new perspectives on the temporal evolution of addictive behaviors, the identification of critical influencing factors, and the development of predictive models that can aid in intervention strategies. Social media is an application that has the ability to share ideas, activities, feelings and many more within their networks. As the millennium began, social networking were introduced at a fairly rapid rate. Most of social media system needs us to create a profile, established linkages with other or interact with others in an easier form. Connecting with people requires little effort within a modern world. According to Urban Dictionaries (2018), young adult is the person between the ages of 18 to 35. These people are in the early process of getting a secondary education, struggling to graduate, finding jobs, striving to keep the jobs, building careers, learning about the relationship and many more. This age group they will realize that they have commitment issues and struggle with making an adult decision on a daily basis. During the 1970s, psychologist Paul Eckman identified six basic emotions that he suggested were universally experienced in all human cultures. The emotions he identified were happiness, sadness, disgust, fear, surprise, and anger. He later expanded his list of basic emotions to include such things as pride, shame, embarrassment, and excitement.

Addiction is characterized by inability to consistently abstain, impairment in behavioural control, and craving, diminished recognition of significant problems with one's behaviours and interpersonal relationships, and a dysfunctional emotional response. Like other chronic diseases, addiction often involves cycles of relapse and remission (ASAM, 2011).There is general fact of agreement on this young adults nowadays frequent use of social media which some research suggest that today generation of young adults actively mashing, contributes content, creating and like combining of information content from multiple sources that they found to be share toward social media sites where they can participate actively (Dye, 2007). and by doing that they prefer to stay connected in social media and multitask

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through technology (Rawlins et al. 2008). On the other hand, studies of university students (a subset of Gen Y) suggest that they spend a considerable amount of time simply consuming 4content like just scrolling and looking at their social media (Christakis and Fowler, 2007)., just like other generations. In addition, young adults today uses social media for the same purposes as other members which is for leisure, study, information, or entertainment, for socializing, experimenting and experiencing a sense of community (Valkenburg et al., 2006 and the most important is for staying in touch with family and friends (Lenhart and Madden, 2007). The fact that the individual's internet addicted to four main factors. It is possible to revise these factors as a social media addiction factor. These factors have been grouped into four categories which are Social Support Need, Living Conditions, Sexual Adultness and Creating a New Character.

The excessive and maladaptive use of social media platforms is often referred to as social media addiction or social networking addiction. Individuals who excessively use social media display similar, hallmarked symptoms that are present with substance use and behavioral addictive disorders, such as salience, tolerance, mood, modification, conflict, withdrawal and relapse (Griffiths and Meredith, 2009).

The effects of this problematic social media use can be significant been linked to job loss, psychological distress, impaired daily functioning, poor mental health and poor academic performance (McCarroll, 2021).

Stakeholders in education sector have attributed this poor academic performance in Nigeria to the lack of adequate of awareness to the reading of culture, inadequate library facilities, poor access to books and other reading materials and the growth in television viewership culture. Due to very often accessible to the social media by its user via numerous devices including the mobile phones, have brought another dimension to the already this situation. Ahmed (2019). state that social media have contributed to the decline of reading culture among students and district from reading their books in the sense that they always use most of their time chatting or listening to music or watching videos. This show that many of these students will have no longer over control over the use of their application which result to the tendency for social media addiction.

Therefore, this motivated us to examine and formulate a mathematical model that will be use to asses and analysis of social media addiction.

B. Paper structure

The study will employ the survey method for statistical analyses. An online survey, such as Google Forms, will be administered to 1500 students from Federal University Dutsin-Ma, Katsina state. The data collected will be analyzed using graphical charts. Also, The SEARC model will be visually represented as a flowchart, depicting the transitions and interactions between the different compartments of the population.

2. Overview of Literature

This section will describe the theoretical frame work of this present research as well as explicate the concept of social media addiction. It will extent to demonstrate previous research on social media addiction.

The behavior of drug addiction among Nigeria adolescents using a five-compartment model that led to the formulation of a systems of ODEs. The drug addiction free equilibrium point was obtained, which had been proved to be locally and globally asymptotically stable especially if the model threshold quantity is less than one. The implication is that addiction to drugs can be eliminated from the human population when substantial measures are taken (Fatokun et al.2023). The numerical simulation conducted shows that rehabilitation of drug addicts plays an indispensable role in controlling drug misuse among adolescents. Those who are rehabilitated should be completely separated from their previous mates or gangs whether light or heavy users; otherwise, they will keep cycling between

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drug users, treatment, recovery, and back to addiction again. Therefore, it becomes impossible to eliminate the drug abuse in the society and among the adolescent in Nigeria (Fatokun et al.2023).

Another research revealed that the four factors which are accessibility of the internet, Lack of time management. Second, social utility describes the need to act on a way that is both efficient and significant within that social world. Third, is a surveillance, or needing to understand one's social environment. Lastly, the need for an escape, or to get away from social environment when one feels overwhelmed. Social media allows users to fulfill all of these needs in some way and allow them to observe the behaviors and published personalities of others without them even knowing, thus gauging the social environment (Sandra Ball-Rokrach and Melvin Deflear). Users who used social media to gain recognition or gratification from others were more likely to develop a social media addiction due to low self-esteem or other factor that user who have negative self-perceptions use social media to feel better (Ahmed, 2019). The social media and it's relationship to anxiety is one of the most interesting phenomena that occurs. Like discussed with motivational frame works, social media is commonly used as a coping skill to deal with stress, yet it ends up creating more anxiety in the future, then psychological description has been observed with the employment on social media as a negative coping skill. Uses and gratification theory was created in the 1940s, when researchers began to look into why certain people choose to get their information from certain forms or genes of media over other. The theory states that people are motivated to seek out form of media to satisfy their psychological and social needs.

Although originally conceptualized before the present technological advances and the existence of social media, this theory can easily encapsulate motivation for social media usage and help to explain the thread of addiction with the conclusion of social media in this Theoretical frame work, users have access a variety of platforms to use to suit their needs. If the user is more image-driven, they would best communicate through a platform like Instagram, but if a user is text-driven, Facebook may be better options to fulfill his or her needs. Mc Quail (2010) explain in his book "....... Those who use mass media for their own purpose do hope for some effect (such as persuasion or selling) beyond attention and publicity, gaining the latter remains the immediate goal and is often treated as a measure of success or failure. From a Theoretical standpoint, this implies that users are constantly looking for their social media presence to have an effect, whether it be selling something or simply gaining attention. In current research on social media, uses and gratification theory has not been fully adopted as an important conceptualization. However, it is very applicable when given the nature of social media and the potential motivation for usage.

3. Social Media Usage Patterns and Addiction

Understanding social media usage patterns is integral to unraveling the complexities of addiction. The significance of frequency and duration in social media use as key indicators of addictive behaviors. The repetitive nature of engagement and the time spent on these platforms contribute to the development of addictive tendencies (Kuss and Griffiths, 2017).

Social media, as a platform for social comparison Vogel et al. (2014) intensifies addiction risk. Users engage in constant comparisons with others, leading to a heightened desire for social validation and reinforcement. Festinger's Social Comparison Theory (1954) elucidates how individuals evaluate their worth based on social comparisons, contributing to addictive patterns as users seek affirmation through online interactions.

The study by Macy et al. (2017) delves into network models to analyze the spread of addictive behaviors within social networks. It highlights the interconnected nature of social

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addiction, indicating that behaviors can propagate through social ties, influencing individuals within a network.

In summary, the literature underscores that social media addiction is closely linked to patterns of usage, with frequency, duration, and the social comparison dynamics playing crucial roles. The interconnected nature of social networks further amplifies the spread of addictive behaviors.

3.1 Factors That Contributes to Social Media Addiction

The literature on social media addiction has highlighted several factors that contribute to the addiction.

The literature discusses internet access on smartphones is seen as the biggest issue to social media dependency and contributes to social networking addiction. Individuals spend most of their time on social networking sites which then becomes a habit. The desire and demand to be online become the catalyst for the release of endorphins (hormones of satisfaction and pleasure), like people who experienced alcohol addiction. They will not realize how many hours they spend long hours scrolling and later become addicted (Meena et al., 2021). Social media sites are regarded as a necessity for filling a person's free time. The concept of 'free time is what drives them to use the internet indefinitely, resulting in addiction. The absence of social media makes them feel "empty".

In addition, most of parents introduce their children to social media sites at a young age because they are preoccupied with their careers, causing their children to be neglected and deprived of love. As a result, children have their social site without parental supervision as early as the age of five. They conclude these conditions can lead to addiction in children, resulting in a variety of health problems and intruding with the individual's life such as working or spending time with family.

Furthermore, the literature mentions how the current global economic situation in developed countries affects personal financial circumstances and family comfort. The cost of a computer is now more affordable, allowing many people to use it indefinitely with the help of Internet networks. In addition, the market price of smartphones is affordable to everyone regardless of age. This indirectly contributes to the addiction to social media sites. Menayes (2015) on the dimensions of social media addiction among university students examines three factors that are associated with addiction. Factor 1 represents a decline in school performance, driving, not meeting friends, and thinking about social media when not using them. Factor 2 states social media overuse, neglecting schoolwork, feeling irritable, and lack of sleep due to social media usage. Factor 3 is dealing with boredom and the need to use social media. Results indicate the amount of time spent using social media is positively correlated with all factors of social media addiction. It describes when the individual will show symptoms of addiction when they spend more time using social media. Experience with social media was positively correlated with two of the three factors while negatively correlated with factor 3. This means that when a person has more experience with social media, the more likely he or she will be addicted to them.

3.2. Psychological Variables

Psychological factors play a pivotal role in the manifestation of social media addiction. [48] introduce the concept of Fear of Missing Out (FOMO), a psychological variable associated with increased social media use. FOMO reflects the anxiety individuals experience when they perceive others enjoying rewarding experiences, compelling them to stay constantly connected to avoid missing out. The study by Andreassen (2016) delves into the intricate relationship between self-esteem, narcissism, and social media addiction. It reveals that individuals with lower self-esteem may be more prone to seeking affirmation and validation on social media platforms, contributing to addictive behaviors.

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Narcissistic tendencies can further drive individuals to engage in self-promotion and attention-seeking activities online, intensifying social media addiction. Understanding the psychological dynamics is essential in the context of Festinger's Social Comparison Theory (1954). The theory elucidates how users assess their self-worth through social comparisons, a process amplified on social media platforms. The constant comparison with others can lead to addictive patterns as individuals seek external validation and approval in the digital space (Vogel et al., 2014).

In summary, psychological variables such as FOMO, self-esteem, and narcissism significantly influence the development and perpetuation of social media addiction. These factors underscore the intricate interplay between individual psychological characteristics and addictive behaviors in the online environment.

3.3. Social Influences

Social influences play a crucial role in shaping social media addiction, encompassing peer interactions, social support, and the impact of group dynamics. Tajfel and Turner's Social Identity Theory (1979) provides a theoretical lens to understand how individuals define their identities within social groups. In the context of social media, users form digital communities around shared interests or identities, influencing their online interactions and engagement patterns. Hawi and Samaha (2017) study emphasizes the role of normative beliefs within online social networks as a significant factor in the development of addictive behaviors. Users are influenced by the perceived norms of their online communities, affecting their own behavior. The study underscores the importance of considering the social context and peer influence in understanding social media addiction dynamics. The interconnected nature of social networks is explored by (Macy et al. 2015), who utilize network models to analyze the spread of addictive behaviors within these networks. The study highlights how behaviors can propagate through social ties, influencing individuals within a network. This interconnectedness reinforces the social nature of addiction on social media platforms.

In summary, social influences, guided by Social Identity Theory and normative beliefs within online networks, significantly contribute to the development and reinforcement of social media addiction. Recognizing the role of peer interactions and group dynamics is vital for understanding the social dimensions of addictive behaviors in the digital space.

3.4. The Relationship between Social Media Addiction and Academic Performance

From an educational perspective, previous research shows their respective result of the relationship between social media and academic performance. Hou et al. (2019) conclude that addiction is negatively correlated with academic performance. It is based on the result of the self rank measure of academic performances that was negatively associated with social media addiction. There are 3 reasons underlying this result. Firstly, social media addiction may indicate more time spent online and less study time. Students' time management disrupted and affected academic performance. Secondly, social media addiction interfered with the work of students, distracted them from staying focused. Studies have shown that multitasking harms the execution of specific tasks. Thirdly, students have difficulties encoding and remembering what they are learning. Azizi et al. (2019) also reported the same findings. It is based on the result of the correlation between social networking addiction and GPA in study samples. The study describes the higher the excessive use of social networks, decrease the academic performance. The result is consistent with the past studies, it states social networking addiction affects academic performance by producing academic procrastination, reducing sleep quality, and escalating academic stress. Overuse of social networks can decrease the level of academic engagement and students' grades although the platform can be a learning tool for the student to improve their academic engagement. However, Roehl et al. (2021)

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found out that there is no significant relationship between Social Media Addiction and Academic Performance. The findings show that excessive use of social media did not harm their academic performance. The student's performance remained unchanged despite their addiction to social media platforms. These findings are consistent with past studies that found that there was no significant relationship between social media usage and academic performance. The study explains the main factor that led to poor academic performance was students' behavior and poor time management.

Another reason was that students' use of social media positively influences them. 53.2% of students agree that using social media has helped them improve their grades, and half of the students can still perform well in academics even if they discontinue using social media (Othman et al., 2017).

3.5. The Gender Differences of Social Media Addiction

Some of the previous research has found a correlation between these variables. [3] state lower age, being a woman, current relationship, being a student, low-level education, low income, lower self-esteem, and narcissism parameters have high addiction. It indicates that being a female is one of the criteria of having high addiction to social media. In addition, a separate study by (Diekmann 1998) reveals that females share more selfies on social media. This study is consistent with that of Tutgun-Ünal who describes that female use more social media than males to receive emotional support, and males are negatively affected by social media. These findings reported the gender difference in terms of the purpose of the individual using social media. An analysis by (Diekmann et al., 2010) about the relationship between social networking addiction and academic performance in Iranian students found out male students were significantly more addicted than female students. They conclude the gender differences of addiction were based on the time spent on social media

The study shows there are no significant differences between genders based on the SMAS (Social media addiction scale) result while significant differences are seen conflict factor from the 6 component of addiction that was evaluated. The scholar explains male students neglect their homework and activities. On the other hand, females choose to use social media to communicate with existing friends and for shares which are not considered problematic social media usage.

3.6. The Gender Differences in Academic Performance

(Halkitis et al., 2011) found that there is no significant gender difference in students' and academic performance. It is based on data analysis of the survey Students' Academic Performance Aptitude Test (SAPAT). T test result reveals a small score that differentiates males and females. Thus, it achieves the objective of the studies. However, other studies have different findings. A study found out that girls can outperform boys in secondary college training in two ways: they score better in standardized tests, and they drop out at a lesser rate (Halkitis et al., 2011) . There is a positive affiliation of performance in standardized tests, normal marks, and exact study habits with university enrolment. The better performance of female students compared to male college students is the answer for the gender gap in education, each in Malaysia and abroad. In the same vein, (Keeling et al., 2011) in their current study is to explore students' performance in special subjects according to their gender. The quantitative data are used to analyze the possible difference in academic achievement between males and females from the different subjects of several fields of study such as statistics and computing science representing science, fertilization and animal feeding represent agricultural subjects, and sociology and English for human sciences and language (Keeling and Rohani 2011) . Observation shows that female educational achievement is changing in terms of number and performance. Female college students presently now not only outnumber male students but additionally get

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better grades in all the classes of subjects. They conclude that the gender variable is no longer become a barrier in gaining knowledge of or educating college subjects. These scholars' proof that females are performed than males' students in achieving a better result in the class although in different studies courses.

3.7. Existing Mathematical Models

While the literature on social media addiction provides rich insights into psychological and sociological aspects, the exploration of mathematical models in this context is limited. (Macy, 2015) contribute to this domain by employing network models to analyze the spread of addictive behaviors within social networks. Their study reveals the interconnected nature of social media addiction, emphasizing how behaviors can propagate through social ties and influence individuals within a network. The study highlights the need for mathematical models to capture the dynamics of social media addiction systematically. Network models, in particular, offer a valuable approach to understanding how addictive behaviors spread and manifest within digital communities. These models can provide insights into the emergence of addictive patterns, identify influential nodes within networks, and offer a quantitative understanding of the social aspects of addiction. However, the literature reveals a gap in comprehensive mathematical models that integrate various influencing factors. The absence of models that consider both psychological and social dimensions limits our ability to predict and intervene effectively in cases of social media addiction. Addressing this gap is essential for developing holistic models that can inform targeted interventions and preventative strategies.

In summary, while existing research has started to explore network models for understanding the spread of addictive behaviors within social networks, there is a notable gap in comprehensive mathematical models that encompass the multifaceted nature of social media addiction.

The literature review has provided a comprehensive overview of the existing research on social media addiction, encompassing social media usage patterns, psychological variables, social influences, and existing mathematical models. The identified gaps in the literature, particularly the limited application of mathematical modeling in understanding social media addiction, underscore the need for the current research. The focus of this study is to bridge this gap by developing a robust mathematical model that captures the complex dynamics of social media addiction and contributes to the broader understanding of this phenomenon.

4. Methodology

The third chapter of this research is dedicated to outlining the robust statistical approach employed for analyzing social media addiction. In the contemporary digital age, understanding the intricate dynamics of social media addiction is paramount, necessitating a comprehensive and quantitative approach. The introduction emphasizes the importance of adopting a mathematical model, SEARC, as a sophisticated tool for systematically dissecting the prevalence and nature of social media addiction within a population.

The significance of employing a mathematical model for studying social phenomena is well-established in literature (Smith, 2015; Anderson and Smith, 2018) . Mathematical models provide a structured framework that allows for the representation of complex interactions within a system, facilitating a deeper understanding of the underlying dynamics (Anderson and Smith, 2018) .

4.1. Method of Data Collection

The instrument used for this study was Google Form for the purpose of data collection from respondents as descriptive analysis which designed by researcher with aid of Mathematics Department, Federal University Dutsin-Ma Katsina State. The instrument was validated and sent to 1000 students across the Federal University Dutsin-Ma, but only 200 responses were collected and analyzed. For the instrument reliability, the revised instrument was first

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administered to 150 students who were also students from other universities of Nigeria as a pilot assessment but were not included in the subjects of the study.

4.2. Model Formulation and Description

The SEARC model divides the total population N(t), into five compartments, each representing distinct states in the context of social media addiction. The compartmentalization allows for a nuanced examination of how individuals transition through different states regarding social media addiction. This mathematical approach is rooted in epidemiological modeling, where the spread of diseases among different populations is commonly studied using compartmental models (Keeling & Rohani, 2011).

The assumptions underlying the SEARC model include a continuous positive recruitment (η) into the susceptible class, representing the influx of individuals through birth or immigration. This recruitment process is fundamental to demographic modeling [29]. Additionally, a proportion (K) of the susceptible population displays self-control, aligning with behavioral assumptions derived from addiction psychology literature [59]. A natural death rate (μ) is applied uniformly to all individuals throughout the study, reflecting a standard demographic parameter (Diekmann et al., 2010) .

The transitions between compartments are defined by rates and probabilities. The transmission of addiction (ρ) per contact between susceptible and addicted individuals is a critical parameter, and its consideration aligns with research in social network analysis and addiction dynamics Christakis, and Fowler, 2007) . The progression of exposed individuals to addiction (δ) and the subsequent awareness of the adverse effects (ψ) contribute to the realism of the model, drawing on insights from addiction research and health communication studies (Halkitis et al., 2011; Duke et al., 2014). The SEARC model integrates the concept of recovery, where individuals transition from addiction to recovery at a rate determined by ψ. This aligns with the principles of recovery-oriented systems of care (Kelly and White, 2011) . Recovered individuals may relapse (θ) or demonstrate self-control (ϵ), contributing to the dynamic nature of the model. This formulation is informed by addiction relapse literature and self-control theories(Baumeister et al., 1998).

4.3. Schematic Representation of the SEARC Model

The SEARC model can be visually represented as a flowchart, depicting the transitions and interactions between the different compartments of the population. Below is a textual description of how you might articulate the schematic representation:

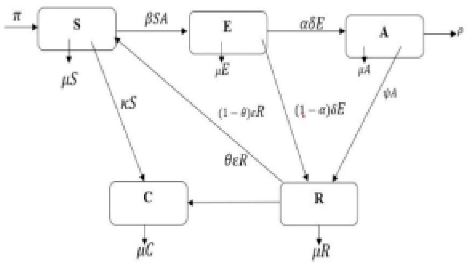

Figure 1. Schematic Representation of the Model

The SEARC model's schematic representation is structured as a flowchart, illustrating the dynamic transitions of individuals through various states related to social media addiction. The flowchart encompasses five main compartments: Susceptible (S), Exposed (E), Addicted (A), Recovered (R), and Self-control (C).

Susceptible (S): Represented as the starting point in the flowchart, individuals in this compartment are susceptible to social media addiction. They can transition to the Exposed compartment upon contact with addicted individuals.

Exposed (E): Individuals move to this compartment when exposed to addicted individuals but have not yet engaged in addiction. From here, a proportion progresses to addiction (A), while the remainder moves to the Recovered compartment (R).

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Addicted (A): Individuals in this compartment are actively engaged in social media addiction. Some gain awareness of the adverse effects and transition to the Recovered compartment (R), while others may continue in the addicted state.

Recovered (R): Representing individuals who have successfully overcome social media addiction, this compartment includes those who have consciously stopped using social media. From here, some may relapse and return to the Susceptible compartment, while others exhibit self-control and move to the Self-control compartment.

Self-control (C): This compartment represents individuals who, even if exposed, can control themselves when using social media, preventing addiction. A proportion of individuals from the Susceptible, Exposed, and Recovered compartments may join the Self-control compartment.

Arrows connecting the compartments signify the directional flow of individuals through different states, capturing the essence of the SEARC model's dynamic nature. The parameters described in Table 3.1 influence the rates of these transitions, shaping the overall dynamics of social media addiction within the population.

4.4. Description of Parameters of the Addiction Model

Susceptible individuals are individuals are recruited through admission in to the population at rate. These susceptible individuals become exposed to the addition at a rate of $\frac{BAS}{N}$ with a small interval $(t, t+\Delta t)$, where β is a positive constant number representation the product of the contact frequency and addition transmission probability pre contact. Some susceptible individuals join to subpopulation (control class) that does not permanently use social media at a rate K. Those in the exposed class have engaged to the social media usage but not get addicted. We assume that $\alpha\delta E$ is the rate at which ah individuals in the exposed class become addicted and other recovered at the rate of $(1-\alpha)\delta E$. Through orientation program in the school and/or treatment, the addicted individuals move to the recovery class at a rate of ψA, or died due to addition at a rate of P. The recovered individuals can totally stop using social media control class at a rate of $\theta\varepsilon R$ or go back to susceptible class again at a rate $(1-\theta)\varepsilon R$.

Table 1. Description of Parameters of the Addiction Model

Parameters	Description
ρ	Death rate due to addiction
β	Contact rate of addicted individuals to the susceptible individuals
δ	Rate at which exposed individuals become addicted
ψ	Rate at which exposed individuals become recovered
ε	Immigration rate from recovered individuals
π	Recruitment rate of susceptible class
K	Proportion of individuals that joins the self-controlled population from susceptible class
μ	Death rate of all population (all classes)
α	Proportion of individuals that joins the addicted subpopulation from the exposed compartment
θ	Proportion of individuals that joins the self-controlled subpopulation from the recovered compartment

Model Assumptions

The whole population has an average death rate of μ and π is the recruitment rate through admission in to the school and the population is assumed to be constant.

Susceptible individuals do not become addicted initially but enters in to the exposed class with conditional transition parameters B

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and that individuals become addicted immediately after exposure.

The model assume that the population is not structured by age, gender, or other demographic factors and that individuals interact with each other uniformly regardless of location and other spatial structure.

The model assumes that there are external interventions, such as public health campaigns or policy changes with conditional transmission parameter ψ, that could affect the continuous spread of social media addition. n

From the assumptions and the flow diagram of the model is shown in fig 3.1 above, the following model equation are derived

$$N(t) = S(t) + E(t) + A(t) + R(t) + C(t) \quad 1$$

$$\frac{dN}{dt} = \frac{dS}{dt} + \frac{dE}{dt} + \frac{dA}{dt} + \frac{dR}{dt} + \frac{dC}{dt} \quad 2$$

$$\frac{dS}{dt} = \pi + (1-\theta)\varepsilon R - (\beta A + \mu + K)S \quad 3$$

$$\frac{dE}{dt} = \beta SA - (\mu + \delta)E \quad 4$$

$$\frac{dA}{dt} = \alpha\delta E - (\mu + \psi + \rho)A \quad 5$$

$$\frac{dR}{dt} = \psi A + (1-\alpha)\delta E - (\mu + \varepsilon)R \quad 6$$

$$\frac{dC}{dt} = KS + \theta\varepsilon R - \mu C \quad 7$$

With the initial condition

$$S(0) > 0, E(0) \geq 0, A(0) \geq 0, R(0) \geq 0,$$
$$C(0) \geq 0 \quad 8$$

E. Invariant Region

Let's define the invariant region Ω as:

$$\Omega = \{S, E, A, R, C\epsilon R^5 | S + E + A + R + C = N, S(0) > 0, E(0) \geq 0, A(0) \geq 0, R(0) \geq 0, C(0) \geq 0\}$$

Where N is the total population size

So, Ω is closed because the system of equations (3)-(7) are continuous and boundaries of Ω are defined by the equations themselves.

The following theorem ensures the boundedness of the model (3)-(7)

Theorem 3.1: if the initial conditions of the model equation (3)-(7) are with in

$$\Omega = \left\{(S, E, A, R, C)\epsilon R^5 : 0 < N(t) \leq \frac{\pi}{\mu}\right\} \quad 9$$

Then the solution of $\{S(t) + E(t) + A(t) + R(t) + C(t)\}$ are all positive for $t \geq 0$. Boundedness refers to the region in which solution of the system is bounded in $\Omega \subset R^5{}_+$.

The population of interest at time t from equation (1) and (2)

$N(t) = S(t) + E(t) + A(t) + R(t) + C(t)$ and $\frac{dN}{dt} = \frac{dS}{dt} + \frac{dE}{dt} + \frac{dA}{dt} + \frac{dR}{dt} + \frac{dC}{dt}$ respectively.

Substituting equations (3)-(7) in equation (2) yield

$$\frac{dN}{dt} = \pi - \mu S - \mu E - \mu A - \mu R - \mu C - \rho A \quad 10$$

But $N = S + E + A + R + C$

$$\frac{dN}{dt} = \pi - \mu N - \rho A \quad 11$$

If there is no death due to the social media addiction, equation (3.10) becomes

$$\frac{dN}{dt} = \pi - \mu N \quad 12$$

The equation is a first order differential equation by integrating equation (12) we have

$$\int \frac{dN}{dt} \leq \int (\pi - \mu N) \quad 13$$

$$\int \frac{dN}{\pi - \mu N} \leq \int dt \; \frac{ln\, ln\, (\pi - \mu N)}{\mu} \leq t + K$$

$$ln\, ln\, (\pi - \mu N) \leq -\mu(t + K)$$

Let $B = e^{-\mu K}$

$$\pi - \mu N \leq Be^{-\mu t} \quad 14$$

At $N(0) = S(0)$

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$\pi - \mu N \leq Be^{-\mu(0)}$

$\pi - \mu N = B$

, so that equation (14) become

$\pi - \mu N \leq (\pi - \mu N(0))e^{-\mu t}$

$$N(0) \leq \frac{\pi}{\mu} - \left[\frac{\pi - \mu N(0)}{\mu}\right] e^{-\mu t}$$

As $t \to \infty$, the size of population $N \to \frac{\pi}{\mu}$.

This implies that, $0 \leq N \leq \frac{\pi}{\mu}$ and $N(t) \leq \frac{\pi}{\mu}$

Positive Solutions of the SMA Model.

It is important to establish that all of the state variables in the equations of the model (1)-(7) are non-negative for future time, $t > 0$ for it to have epidemiological significance. To prove the positivity of the model solution we considered the following theorem.

Theorem 3.2: Given that the initial values then

$S(0) > 0, E(0) > 0, A(0) > 0, R(0) > 0, C(0) > 0$

the solution $S(t), E(t), A(t), R(t), C(t)$ of the system (1-3.7) are positive for all the model $t \geq 0$

Proof. From the equation 3.3 of the model

$$\frac{dS}{dt} = \pi + (1 + \theta)\varepsilon R - (\beta A + \mu + K)S \quad 16$$

$$\frac{dS}{dt} + (\mu + K)S \leq \pi$$

Let $P = (\mu + K) and\ Q = \pi$

I.F $= e^{\int Pdt}$

$$\int Pdt = \int (\mu + K)dt$$

$$\int Pdt = (\mu + K)t$$

Then,

$I.F = e^{(\mu+K)t}$

So, we have

$$S(t)e^{(\mu+K)t} = \int \pi e^{(\mu+K)t}dt + B \quad 18$$

At $t = 0$

$$S(0) = \frac{\pi}{\mu+K}e^{(\mu+K)t} + S(0) - \frac{\pi}{\mu+K}$$

$$B = S(0) - \frac{\pi}{\mu+K}$$

Then, we have

$$S(t)e^{(\mu+K)t} = S(0) - \frac{\pi}{\mu+K} + \frac{\pi}{\mu+K}e^{(\mu+K)t}$$

$$s(t)e^{(\mu+K)t} = S(0) - \frac{\pi}{\mu+K} + \frac{\pi}{\mu+K}e^{(\mu+K)t}$$

$$S(t)e^{(\mu+K)t} = S(0)e^{-(\mu+K)t} + \frac{\pi}{\mu+K} + \frac{\pi}{\mu+K}e^{-(\mu+K)t}$$

$$S(t)e^{(\mu+K)t} = S(0)e^{-(\mu+K)t} + \frac{\pi}{\mu+K}(1 + e^{-(\mu+K)t})$$

$$S(t)e^{(\mu+K)t} = S(0)EXP^{-(\mu+K)t} + \frac{\pi}{\mu+K}(1 + EXP^{-(\mu+K)t}) \quad 19$$

As $t \to \infty$

We obtain

$$0 \leq S(t) \leq \frac{\pi}{\mu+K}$$

Therefore,

$$S(t) \geq S(0)EXP^{-(\mu+K)t} \geq 0$$

By the same procedure, we obtained

$$E(t) \geq E(0)EXP^{-(\mu+\delta)t} \geq 0,$$

$$A(t) \geq A(0)EXP^{-(\mu+\psi+P)t} \geq 0,$$

$$R(t) = R(0)EXP^{-(\mu+\varepsilon)t} \geq 0,$$

$$C(t) = C(0)EXP^{-\mu t} \geq 0.$$

This indicate that the solution of model (3-7) are positive. Hence all feasible solutions of system (3-7) lies in the region Ω. Thus, the model is epidemiologically meaningful and mathematically well posed.

Existence Uniqueness of SMA Models Solution

The general 1st order ODE has the following form:

$$\frac{dy}{dx} = F(x,y)$$

Where $x(t_0) = y_0$ 21

The following inquiries will be interest to one: What conditions allow us to declare that the solution of equation (21) exists?

Under what conditions allow us to declare that there is a unique solution to equation (21)?

For this let

$$F_1 = \pi(1-\theta)\varepsilon R$$

$$-(\beta A + \mu + K)S \qquad 22$$

$$F_2 = \beta SA - (\mu + \delta)E \qquad 23$$

$$F_3 = \propto \delta E - (\mu + \psi + \rho)A \qquad 24$$

$$F_4 = \psi A + (1-\propto)\delta E - (\mu + \varepsilon)R \qquad 25$$

$$F_5 = KS + \theta\varepsilon R - \mu C \qquad 26$$

The existence and uniqueness of our SMA model's solution are shown using the given theorems.

Theorem 3.3: All the solutions of the model (3-7) are unique.

Let Ω represent the domain defined in

$$\Omega = \left(|t-t_0| \le a, |x-x_0| \le b, y = (y_1, y_2, y_3, \dots y_n), \; y_0 = (y_{10}, y_{20}, y_{30}, \dots y_{n0})\right) \qquad 27$$

And assume that $g(t,y)$ satisfies the Lipschitz condition:

$$\|g(t,y_1) - g(t,y_2)\| \le L\|y_1 - y_2\| \quad 28$$

And when ever $(t,y_1),(t,y_2) \in \Omega,$ where K represent any positive constant value. Then $\exists a\delta > 0$ such that system (21) in the interval $|(t,t_0)| \le \delta.$ it is important to remember that equation (3.28) is achieved by the condition that:

$$\frac{\partial F_i}{\partial y_j}, i,j = 1,2,3, \dots n \qquad 29$$

Be continuous and bounded in the Ω

Considering the model equation (3-7), we are interested in the region $0 \le \propto \le R, .0 < R < \infty.$ we look for the bounded solution in the region and whose partial derivatives satisfy $F \le \propto \le 0.$ where $\propto$ and δ positive constant are.

Theorem 3.4: All the solution of the model equation (3-7) are exists in the domain Ω defined in equation (27) such that equation (28) and $0 \le \propto \le R$ hold. Then $\exists$ a solution of (3-7) which is bounded in the domain Ω.

Proof:

Suppose

$$F_1 = \pi(1-\theta)\varepsilon R - (\beta A + \mu + K)S$$

$$F_2 = \beta SA - (\mu + \delta)E$$

$$F_3 = \propto \delta E - (\mu + \psi + \rho)A$$

$$F_4 = \psi A + (1-\propto)\delta E - (\mu + \varepsilon)R$$

$$F_5 = KS + \theta\varepsilon R - \mu C$$

We show that: $\frac{\partial F_i}{\partial y_j}, i,j = 1,2,3,4,5$ are continuous and bounded in the region Ω. For each of the model equations we investigated the following partial

From equation (3.22-3.26)

$$\left|\frac{\partial F_1}{\partial s}\right| = |-(\beta A + \mu + K)| < \infty, \left|\frac{\partial F_1}{\partial E}\right| = |0| < \infty, \left|\frac{\partial F_1}{\partial A}\right| = |-\beta S| < \infty, \left|\frac{\partial F_1}{\partial R}\right| = |(1-\theta)\varepsilon| < \infty, \left|\frac{F_1}{\partial C}\right| = |0| < \infty$$

$$\left|\frac{\partial F_1}{\partial s}\right| = |-(\beta A + \mu + K)| < \infty, \left|\frac{\partial F_1}{\partial E}\right| = |0| < \infty, \left|\frac{\partial F_1}{\partial A}\right| = |-\beta S| < \infty, \left|\frac{\partial F_1}{\partial R}\right| = |(1-\theta)\varepsilon| < \infty, \left|\frac{F_1}{\partial C}\right| = |0| < \infty$$

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$\left|\frac{\partial F_2}{\partial s}\right| = |-(\beta A)| < \infty$, $\left|\frac{\partial F_2}{\partial E}\right| = |-(\mu+\delta)| < \infty$, $\left|\frac{\partial F_2}{\partial A}\right| = |\beta S| < \infty$, $\left|\frac{\partial F_2}{\partial R}\right| = |0| < \infty$, $\left|\frac{F_2}{\partial C}\right| = |0| < \infty$

$\left|\frac{\partial F_3}{\partial s}\right| = |0| < \infty$, $\left|\frac{\partial F_3}{\partial E}\right| = |\propto \delta| < \infty$, $\left|\frac{\partial F_3}{\partial A}\right| = |-(\mu+\psi+\rho)| < \infty$, $\left|\frac{\partial F_3}{\partial R}\right| = |0| < \infty$, $\left|\frac{F_3}{\partial C}\right| = |0| < \infty$

$\left|\frac{\partial F_4}{\partial s}\right| = |K| < \infty$, $\left|\frac{\partial F_4}{\partial E}\right| = |(1-\propto)\delta| < \infty$, $\left|\frac{\partial F_4}{\partial A}\right| = |\psi| < \infty$, $\left|\frac{\partial F_4}{\partial R}\right| = |-(\mu+\varepsilon)| < \infty$, $\left|\frac{F_4}{\partial C}\right| = |0| < \infty$

$\left|\frac{\partial F_5}{\partial s}\right| = |0| < \infty$, $\left|\frac{\partial F_5}{\partial E}\right| = |0| < \infty$, $\left|\frac{\partial F_5}{\partial A}\right| = |0| < \infty$, $\left|\frac{\partial F_5}{\partial R}\right| = |\theta\varepsilon| < \infty$, $\left|\frac{F_5}{\partial C}\right| = |\mu| < \infty$

These show that partial derivatives exist, continuous and bounded.

Hence from the uniqueness theorem of SMA model's solution that there is only one solution to the model equation (3.3-3.7) in the domain Ω.

$$\frac{dS}{dt} = \pi + (1-\theta)\varepsilon R - (\beta A + \mu + K)S \qquad 30$$

$$\frac{dE}{dt} = \beta SA - (\mu+\delta)E \qquad 31$$

$$\frac{dA}{dt} = \propto \delta E - (\mu+\psi+\rho)A \qquad 32$$

$$\frac{dR}{dt} = \psi A + (1-\propto)\delta E - (\mu+\varepsilon)R \qquad 33$$

$$\frac{dC}{dt} = KS + \theta\varepsilon R - \mu C \qquad 34$$

For the equilibrium point S^* where $\frac{dS}{dt} = 0$

$$\pi + (1-\theta)\varepsilon R - (\beta A + \mu + K)S = 0$$

$$\pi + (1-\theta)\varepsilon R = (\beta A + \mu + K)S$$

$$S^* = \frac{\pi + (1-\theta)\varepsilon R}{\beta A + \mu + K}$$

For the equilibrium point E^* where $\frac{dE}{dt} = 0$

$$\beta SA - (\mu+\delta)E = 0$$

$$\beta SA = (\mu+\delta)E$$

$$E^* = \frac{\beta SA}{\mu+\delta}$$

$$E^* = \frac{\beta A}{\mu+\delta}\left[\frac{\pi + (1-\theta)\varepsilon R}{\beta A + \mu + K}\right]$$

For the equilibrium point A^* where $\frac{dA}{dt} = 0$

$$\propto \delta E - (\mu+\psi+\rho)A = 0$$

$$\propto \delta E = (\mu+\psi+\rho)A$$

$$A^* = \frac{\propto \delta E}{\mu+\psi+\rho}$$

$$A^* = \frac{\propto \delta E}{\mu+\psi+\rho}\left[\frac{\beta A^*}{\mu+\delta}\left(\frac{\pi + (1-\theta)\varepsilon R}{\beta A + \mu + K}\right)\right]$$

For the equilibrium point E^* where $\frac{dR}{dt} = 0$

$$\psi A + (1-\propto)\delta E - (\mu+\varepsilon)R = 0$$

$$R^* = \frac{\psi A + (1-\propto)\delta E}{\mu+\varepsilon}$$

$$R^* = \frac{\psi\left[\frac{\propto\delta}{\mu+\psi+\rho}\right]\left[\frac{\beta A}{\mu+\delta}\left(\frac{\pi+(1-\theta)\varepsilon R}{\beta A+\mu+K}\right)\right] + (1-\propto)\delta\left[\frac{\beta A}{\mu+\delta}\left(\frac{\pi+(1-\theta)\varepsilon R}{\beta A+\mu+K}\right)\right]}{\mu+\varepsilon}$$

For the equilibrium point C^* where $\frac{dC}{dt} = 0$

$$KS + \theta\varepsilon R - \mu C$$

$$KS + \theta\varepsilon R = \mu C$$

$$C^* = \frac{KS + \theta\varepsilon R}{\mu}$$

$$C^* = \frac{K\left[\frac{\pi+(1-\theta)\varepsilon R}{\beta A+\mu+K}\right] + \theta\varepsilon R}{\mu}$$

4.5. Social Media Addiction-Free Equilibrium (SMAFE)

Let E_0 denote the addition-free equilibrium and we need to set an $= 0$ in absence of the addiction of social media (no addicted individuals).

From the equation (30-34)

$$\frac{dS}{dt} = \pi + (1-\theta)\varepsilon R - (\beta(0) + \mu + K)S$$

Where

$(A = 0)$

$\frac{dE}{dt} = \beta S(0) - (\mu + \delta)E$ Where $(A = 0)$

$\frac{dR}{dt} = \psi(0) + (1 - \propto)\delta E - (\mu + \varepsilon)R$

$(A = 0)$

$\frac{dC}{dt} = KS + \theta\varepsilon R - \mu C$

Since $\frac{dS}{dt} = 0$

$\pi + (1 - \theta)\varepsilon R - (\mu + K)S = 0$

$S = \frac{\pi + (1-\theta)\varepsilon R}{\mu + K}$

But since $A = 0$ with time $R = 0$ 35

$$S = \frac{\pi}{\mu + K} \quad 36$$

Also $\frac{dE}{dt} = 0$, then

$-(\mu + \delta)E = 0$

$(\mu + \delta)E = 0$

But $(\mu + \delta) \neq 0$

$$E = 0 \quad 37$$

Also $\frac{dR}{dt} = 0$, then

$(1 - \propto)\delta E - (\mu + \varepsilon)R = 0$

From equation (3.36) $E = 0$

$-(\mu + \varepsilon)R = 0$

Since $\mu + \varepsilon \neq 0$

Then $R = 0$

Therefore equation (35) holds.

Also $\frac{dC}{dt} = 0$ then

$KS + \theta\varepsilon R - \mu C = 0$

Where

Since $R = 0$

$\mu C = KS$

$$C = \frac{KS}{\mu} \quad 38$$

Substitute $S = \frac{\pi}{\mu + K}$ in C

$$C = \frac{K\left(\frac{\pi}{\mu + K}\right)}{\mu} \quad 39$$

Then it follows that $A = E = R = 0$ from equations (3.37 and 3.35)

Where $S = \frac{\pi}{\mu + K}$ and $C = \frac{K\left(\frac{\pi}{\mu + K}\right)}{\mu}$ from equation 3.36 and equation 3.39 respectively.

Therefore the components of social media addiction-free equilibrium are given by

$$E_0 = (S, E, A, R, C) = \frac{K}{\mu}\left(\frac{\pi}{\mu + K}\right) \quad 40$$

Addiction Reproduction Number (R_0)

This represents the average number of new addicted individuals generated by single addicted individuals in a fully susceptible population.

To analyze the stability of the equilibrium points, the basic addiction reproduction number (R_0) of the model is important.

So, it is obtained by the next-generation matrix method technique and according to the approach, equation (4-6) can be expressed as

$\frac{dE}{dt} = \beta SA - (\mu + \delta)E$

$\frac{dA}{dt} = \propto \delta E - (\mu + \psi + \rho)A$

$\frac{dR}{dt} = \psi A + (1 - \propto)\delta E - (\mu + \varepsilon)R$

Then we have

$F = (\beta SA\,0\,0), v = ((\mu + \delta)E\ -\propto \delta E + (\mu + \psi + \rho)A\ - \psi A - (1 - \propto)\delta E + (\mu + \varepsilon)R)$

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Where F and v are the rate of appearance of new addicted individuals in compartment and the transfer of individuals into and out of compartment by all other means respectively. Using the linearization method, the associated matrices at social media addition-free equilibrium (SMAFE) and after taking partial derivatives as defined by

$$\Delta F(E_0) = (F\ 0\ 0\ 0)\ \ and\ \Delta v(E_0) = (v\ 0\ J_3\ J_4)$$

Where F is non negative and v is a non-singular matrix, in which both are the $M \times M$ matrices defined by

$$F = \left[\frac{\partial F_i}{\partial F_j}(E_0)\right],\ and\ v = \left[\frac{\partial v_i}{\partial v_j}(E_0)\right] \quad \text{With } 1 \le i, j \le m$$

and m is the number of infected classes. In particular $m = 3$

$$\frac{\partial F}{\partial x} = \left[\frac{\partial F_1}{\partial E}\ \frac{\partial F_1}{\partial A}\ \frac{\partial F_1}{\partial R}\ \frac{\partial F_2}{\partial E}\ \frac{\partial F_2}{\partial A}\ \frac{\partial F_2}{\partial R}\ \frac{\partial F_3}{\partial E}\ \frac{\partial F_3}{\partial A}\ \frac{\partial F_3}{\partial R}\right] \text{ And}$$

$$\frac{\partial v}{\partial x} = \left[\frac{\partial v_1}{\partial E}\ \frac{\partial v_1}{\partial A}\ \frac{\partial v_1}{\partial R}\ \frac{\partial v_2}{\partial E}\ \frac{\partial v_2}{\partial A}\ \frac{\partial v_2}{\partial R}\ \frac{\partial v_3}{\partial E}\ \frac{\partial v_3}{\partial A}\ \frac{\partial v_3}{\partial R}\right]$$

$$\frac{\partial F}{\partial x} = [0\ \beta S\ 0\ 0\ 0\ 0\ 0\ 0\ 0] \quad \text{And}$$

$$\frac{\partial v}{\partial x} = [\mu + \delta\ \beta S\ 0\ \ {-\propto \delta}\ \ \mu + \psi + \rho\ 0\ \ -(1 - \propto)\delta\ \ -\psi\ \ \mu + \varepsilon]$$

$$F = \left[0\ \frac{\beta\pi}{\mu + K}\ 0\ 0\ 0\ 0\ 0\ 0\ 0\right]\ \ and$$

$$v = [\mu + \delta\ 0\ 0\ \ {-\propto \delta}\ \ \mu + \psi + \rho\ 0\ \ -(1 - \propto)\delta\ \ -\psi\ \ \mu + \varepsilon]$$

$C_{11} = (\mu + \psi + \rho)(\mu + \varepsilon)$, $C_{12} = (-\propto \delta)(\mu + \varepsilon)$, $C_{13} = (\propto \psi\delta) + \delta(1 - \propto)(\mu + \psi + \rho)$

$C_{21} = 0$, $C_{22} = (\mu + \delta)(\mu + \varepsilon)$ $C_{23} = (-\psi)(\mu + \delta)$

$C_{31} = 0$, $C_{32} = 0$, $C_{33} = (\mu + \delta)(\mu + \psi + \rho)$

Adj.

$$v = [(\mu + \psi + \rho)(\mu + \varepsilon),\ 0\ 0\ (-\propto \delta)(\mu + \varepsilon),\ \ (\mu + \delta)(\mu + \varepsilon)\ \ 0\ (\propto \psi\delta) + \delta(1 - \propto)(\mu + \psi + \rho)\ (-\psi)(\mu + \delta)\ (\mu + \delta)(\mu + \psi + \rho)\ ]$$

$$|v| = C_{11}V_{11} + C_{12}V_{12} + C_{13}V_{13}$$

$$|v| = (\mu + \delta)(\mu + \varepsilon)(\mu + \psi + \rho)$$

$$v^{-1} = Adj(v) \times \frac{1}{|v|}$$

$$v^{-1} = \left[\frac{1}{\mu+\delta}\ 0\ 0\ \frac{\propto\delta}{(\mu+\delta)(\mu+\psi+\rho)}\ \frac{1}{\mu+\psi+\rho}\ 0\ \frac{\propto\psi\delta+\delta(1-\propto)(\mu+\psi+\rho)}{(\mu+\delta)(\mu+\varepsilon)(\mu+\psi+\rho)}\ \frac{\psi}{(\mu+\varepsilon)(\mu+\psi+\rho)}\ \frac{1}{\mu+\varepsilon}\right]$$

$$Fv^{-1} = \left[0\ \frac{\beta\pi}{\mu+K}\ 0\ 0\ 0\ 0\ 0\ 0\ 0\right] \left[\frac{1}{\mu+\delta}\ 0\ 0\ \frac{\propto\delta}{(\mu+\delta)(\mu+\psi+\rho)}\ \frac{1}{\mu+\psi+\rho}\ 0\ \frac{\propto\psi\delta+\delta(1-\propto)(\mu+\psi+\rho)}{(\mu+\delta)(\mu+\varepsilon)(\mu+\psi+\rho)}\right.$$

Then, the next generation matrix denoted by Fv^{-1} is given as

$$Fv^{-1} = \left[\frac{\beta\pi \propto \delta}{(\mu + K)(\mu + \delta)(\mu + \psi + \rho)}\ \frac{\beta\pi}{(\mu + K)(\mu + \psi + \rho)}\ 0\ 0\ 0\ 0\ 0\ 0\ 0\right]$$

Eigen values of Fv^{-1} by setting the determinant $|Fv^{-1} - \lambda I| = 0$

$$\begin{bmatrix} \frac{\beta\pi\propto\delta}{(\mu+K)(\mu+\delta)(\mu+\psi+\rho)} - \lambda & \frac{\beta\pi}{(\mu+K)(\mu+\psi+\rho)} & 0 \\ 0 & -\lambda & 0 \\ 0 & 0 & -\lambda \end{bmatrix} \quad 3.42$$

Before, the characteristics equation given as

$$\left(\frac{\beta\pi \propto \delta}{(\mu + K)(\mu + \delta)(\mu + \psi + \rho)} - \lambda\right)(\lambda^2) = 0 \quad 43$$

$\lambda^2{}_{1,2} = 0$ Or $\frac{\beta\pi}{(\mu+K)(\mu+\psi+\rho)} - \lambda_3 = 0$

$\lambda_1 = 0\ or\ \lambda_2 = 0\ \ or\ \lambda_3 = \frac{\beta\pi\propto\delta}{(\mu+K)(\mu+\delta)(\mu+\psi+\rho)}$

We will define the stability of the SMA model equilibrium point's disease-free equilibrium point

$$E_0 = (S^0, E, A, R, C)$$

The addiction reproduction number R_0 of SMA is given as:

$$R_0(S, E, A, R, C) = \frac{\beta\pi\propto\delta}{(\mu+K)(\mu+\delta)(\mu+\psi+\rho)}, \quad \text{where } (\mu + K)(\mu + \delta)(\mu + \psi + \rho) \ne 0$$

Epidemiologically,

If $R_0 < 1$, the occurrence of the disease will decrease

$R_0 = 1$,

If $R_0 > 1$, the occurrence of the disease will increase

In view of these remarks on our model, we have

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If $\beta\pi \propto \delta < (\mu+K)(\mu+\delta)(\mu+\psi+\rho)$ the occurrence of the addiction will decrease

If $\beta\pi \propto \delta = (\mu+K)(\mu+\delta)(\mu+\psi+\rho)$ the occurrence of the addiction will be constant

If $\beta\pi \propto \delta > (\mu+K)(\mu+\delta)(\mu+\psi+\rho)$ the occurrence of the addiction will increase

Solving the characteristic equation (43) for the Eigen values $\lambda_1, \lambda_2\ and\ \lambda_3$, we obtained

R_0 Is the maximum of the three Eigen values $\lambda_1, \lambda_2\ and\ \lambda_3$.

Hence the addiction reproductive number is the dominant Eigen values of Fv^{-1}. Thus we have that

$$R_0 = \frac{\beta\pi \propto \delta}{(\mu+K)(\mu+\delta)(\mu+\psi+\rho)} \qquad 44$$

Local Stability of the Addiction-Free Equilibrium of the Model

To study the behavior of the system (3-7) around the addiction-free equilibrium

$E_0 = \left(\frac{\pi}{\mu+K}, 0,0,0, \frac{K}{\mu}\left(\frac{\pi}{\mu+K}\right)\right)$ From equation (40), we resort to the linearized stability approach.

Recall equation (22-26)

$$F_1 = \pi + (1-\theta)\varepsilon R - (\beta A + \mu + K)S$$

$$F_2 = \beta SA - (\mu+\delta)E$$

$$F_3 = \propto \delta E - (\mu+\psi+K)A$$

$$F_4 = \psi A + (1-\propto)\delta E - (\mu+\varepsilon)R$$

$$F_5 = KS + \theta\varepsilon R - \mu C$$

$$J = \begin{bmatrix} -\beta A-\mu-K & 0 & -\beta S & (1-\theta)\varepsilon & 0 \\ \beta A & -\mu-\delta & \beta S & 0 & 0 \\ 0 & \propto\delta & -\mu-\psi-\rho & 0 & 0 \\ 0 & (1-\propto)\delta & \psi & -\mu-\varepsilon & 0 \\ K & 0 & 0 & \theta\varepsilon & -\mu \end{bmatrix} \qquad 3.45$$

Evaluating equation (3.45) at $E_0 = \left(\frac{\pi}{\mu+K}, 0,0,0, \frac{K}{\mu}\left(\frac{\pi}{\mu+K}\right)\right)$, we get

$$J_{E_0} = \begin{bmatrix} -\mu-K & 0 & -\frac{\beta\pi}{\mu+K} & (1-\theta)\varepsilon & 0 \\ 0 & -\mu-\delta & \frac{\beta\pi}{\mu+K} & 0 & 0 \\ 0 & \propto\delta & -\mu-\psi-\rho & 0 & 0 \\ 0 & (1-\propto)\delta & \psi & -\mu-\varepsilon & 0 \\ K & 0 & 0 & \theta\varepsilon & -\mu \end{bmatrix} \qquad 3.46$$

From the equation (3.46) of matrix above, some of the negative Eigen values are

$-\mu, -(\mu+K), -(\mu+\varepsilon), -(\mu+\delta)$

The other Eigen values are obtained from quadratic equation.

$$\lambda^2 = \eta_1\lambda + \eta_2 = 0 \qquad 3.47$$

From the equation (46) of matrix above, some of the negative Eigen values are

$-\mu,\ -(\mu+K),\ -(\mu+\varepsilon),\ -(\mu+\delta)$

The other Eigen values are obtained from quadratic equation.

$\lambda^2 = \eta_1\lambda + \eta_2 = 0$

Where $\eta_1 = \mu + \psi + \rho$ and $\eta_2 = (\mu+\delta)(\mu+\psi+\rho) - \frac{\beta\pi\propto\delta}{\mu+K}$ we applied Routh-Hurwitz criteria in the investigation of negativity of the two roots in the equation (47). It has negative real root if and only if $\eta_1 > 0, \eta_2 > 0$ and $\eta_1\eta_2 > 0.$ it is clear that $\eta_1\ and\ \eta_2$ will be

$$\eta_2 = (\mu+\delta)(\mu+\psi+\rho)\left(1 - \frac{\beta\pi\propto\delta}{(\mu+K)(\mu+\delta)(\mu+\psi+\rho)}\right)$$

$$= (\mu+\delta)(\mu+\psi+\rho)(1-R_0) > 0$$

Hence the social media addiction-free equilibrium point (SMAFEP) is locally asymptotically stable if $R_0 < 1$.

5. Results

This chapter presents the results and discussions from the research on social media addiction and its impact on individuals' psychological and behavioral aspects. The study utilizes a two-fold approach: descriptive analysis of data collected from respondents and modeling simulations based on the SEARC (Susceptible-Exposed-Addicted-Recovered-Controlled) framework. The data analysis section focuses on demographic details, social media usage patterns, addiction levels, psychological factors, and the provides insights into the dynamic behavior of populations as they transition through different states of social media addiction over time.

A. Descriptive Analysis

1. Demographics

The demographic characteristics of the respondents provide an essential backdrop for understanding social media addiction patterns. The results are summarized in Figures 2 to 6:

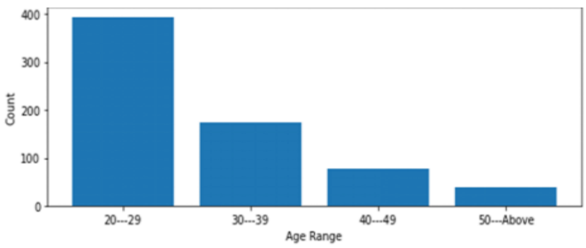


Figure 2: Chart of Demographical representation of Age Group

https://dx.doi.org/10.4314/aujst.v6i2.3

The majority of respondents fall within the age range of 18-30, which aligns with previous studies by (Smith and Thelen, 2003). , who found that younger age groups are more active on social media.

2. Gender Distribution

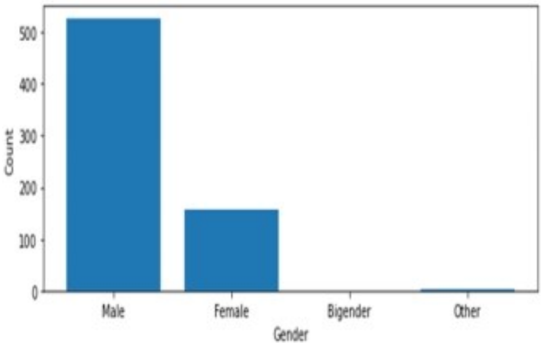


Figure 3: Chart of Demographical representation of Gender Distribution

Female respondents slightly outnumber males, which is consistent with the findings of (Jones, 2020). who observed higher social media engagement rates among women.

3. Occupation

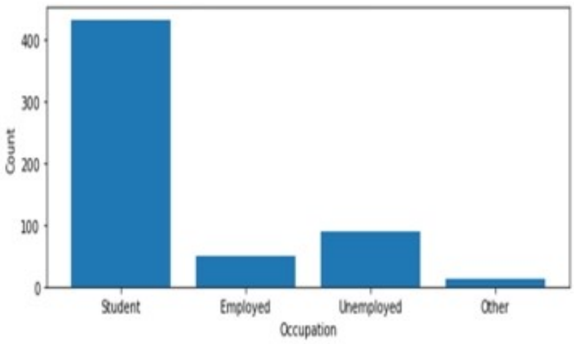


Figure 4: Chart of Demographical representation of Occupation

The data reveals that students make up the largest occupational group, followed by employed individuals. This supports the work of (Duke et al., 2014), who found that students are the most active demographic on social media.

4. EDUCATION LEVEL

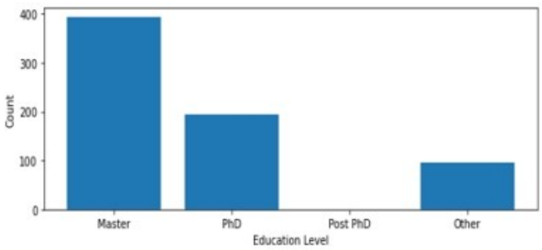
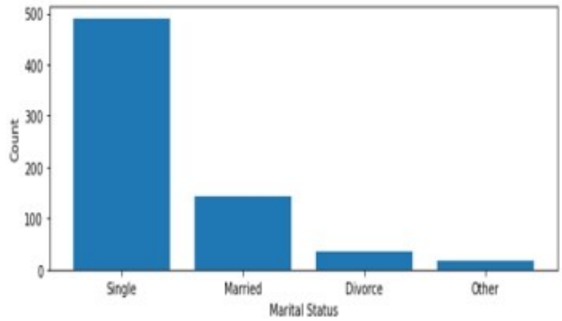


Figure 5: Chart of Demographical representation of Education Level

Most respondents have attained at least a university degree, aligning with studies such as (Greenwood, 2020). which indicate that individuals with higher education levels are more likely to be engaged in online activities.

5. Marital Status



F

Figure 6: Chart of Demographical representation of Marital Status

A majority of the respondents are single, supporting findings by (Valkenburg et al., 2006), who concluded that single individuals tend to spend more time on social media compared to their married counterparts.

2. Social Media Usage Patterns

Figures 7 to 10 summarize the respondents' social media usage patterns.

1. Social Media Platforms

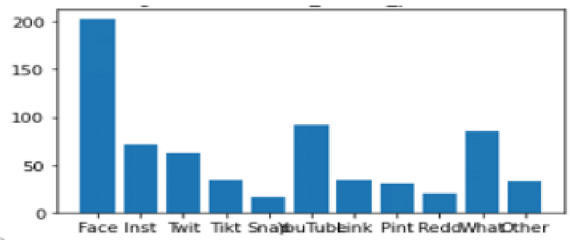


Figure 7: Chart of Social Media Platforms

The results indicate that Instagram and Facebook are the most frequently used platforms, which is consistent with research by (Anderson and Smith, 2018), who also identified these platforms as dominant in the social media landscape.

2. HOURS SPENT ON SOCIAL MEDIA

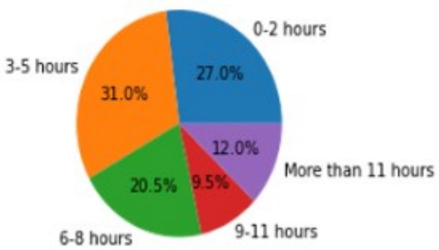


Figure 8: Chart of Hours Spent on Social Media

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Most respondents spend 3-5 hours daily on social media. This corresponds with , who reported similar results regarding daily social media usage.

3. Frequency of Social Media Checks

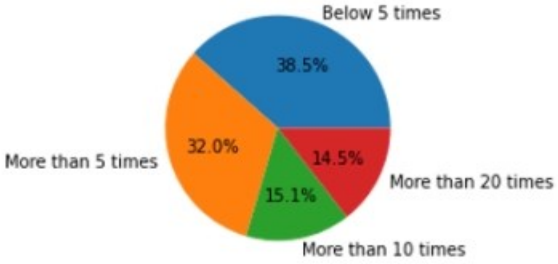

Figure 9: Chart of Frequency of Social Media Checks

Many respondents check their social media accounts multiple times an hour, similar to the findings of (Kuss, and Griffiths, 2012). who observed high levels of frequent social media checking among users.

4. DEVICES Used to Access Social Media

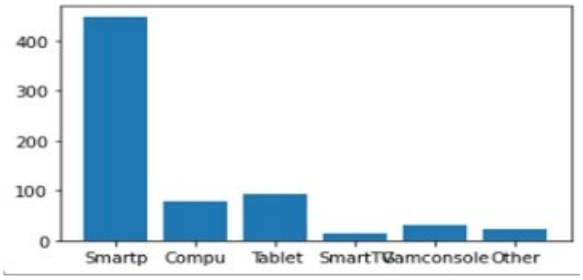

Figure 10: Chart of Devices Used to Access Social Media

Smartphones are the most common device used for social media access, reflecting the trends reported by (Pew Research Center, 2020) .

3. Social Media Addiction Levels

The extent of social media addiction is illustrated in Figures 11 and 12.

1. Social Media Addiction

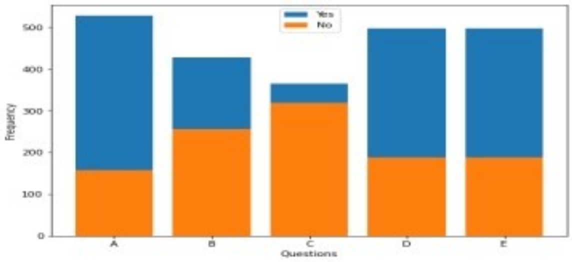

Figure 11: Chart of Social Media Addiction

A significant proportion of respondents show moderate to high levels of addiction. This is consistent with the results of (Kuss and Griffiths, 2017), who reported similar levels of addiction in their studies on social media behavior.

2. Social Media Addiction for Yes Responds Only

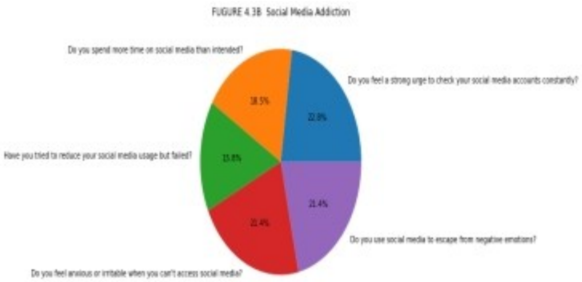

Figure 12: Chart of Social Media Addiction for Yes Responds Only

Many respondents indicated that their addiction had led to negative consequences such as reduced productivity, which mirrors findings by (Andreassen et al., 2017) who documented similar effects of social media addiction.

4. Psychological Factors and Consequences

The psychological impact of social media usage is depicted in Figures 13.

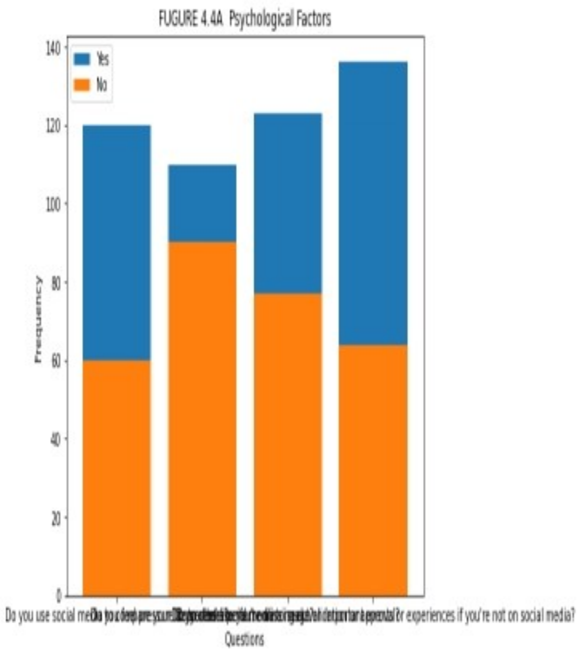

Figure 13. Psychological Factors and Consequences

Anxiety and depression are the most frequently reported psychological effects, which supports findings by (Primack et al., 2017) who concluded that excessive social media use can exacerbate mental health issues.

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Consequences of Social Media Usage

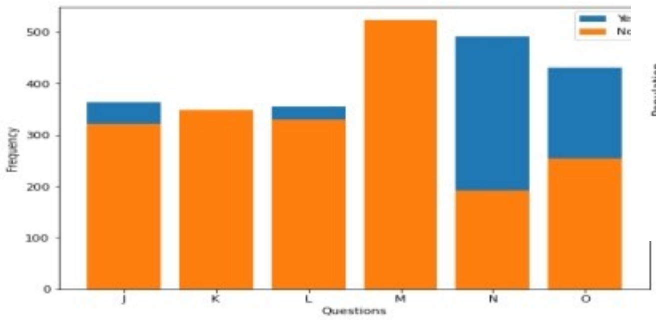


Figure 14: Bar Chart for Consequences of Social Media Usage Many respondents indicated that their addiction has negatively affected their relationships, which is consistent with the research of (Davidson and Yee, 2019) , who found that overuse of social media can lead to social isolation.

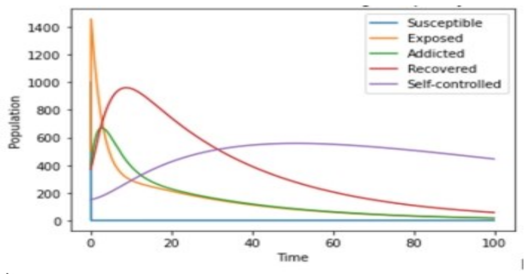
B. Modeling Simulation

The second part of the research involved developing a SEARC model to simulate the spread of social media addiction over time. This model is based on parameters such as recruitment rate, exposure rate, addiction rate, and recovery rate. Figures 15 to 18 show the simulation results for different parameter settings.

Table 1: Parameters and Their Values

Parameters	Values
λ	0.1
β	0.5
δ	0.3
α	0.8
ψ	0.2
ρ	0.05
θ	0.2
κ	0.1
μ	0.01
ε	0.1

1. Case 1: Social media Addiction Frequency



ure 15: Graph that represents Social media Addiction equency

The initial simulation assumes a base exposure rate $\beta =$ **0.5** and a recovery rate $\psi = 0.2$. The results show that the susceptible population initially decreases as more individuals become exposed and eventually addicted. Over time, the recovered and self-controlled populations increase, suggesting the gradual ability of some individuals to regain control over their social media usage. Similar trends were observed by (Han et al., 2019) who modeled behavioral addiction using a comparable approach.

2. Case 2: Social Media Usage Frequency

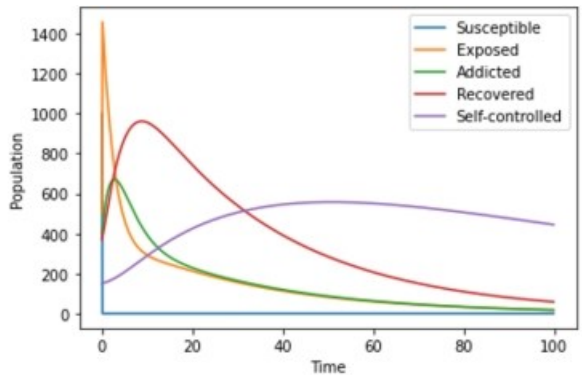
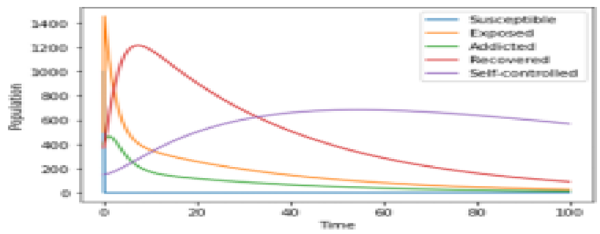


Figure 16 Graph that Represents Social media Usage Frequency

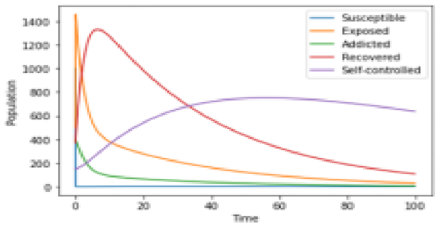
When the exposure rate is increased to $\beta = 1.0$, as shown in Figure 16, the addicted population grows more rapidly, while the susceptible population declines faster. This supports the notion that higher social media engagement leads to quicker addiction, as noted by (Salehan and Negahban 2019) , who examined similar behavioral dynamics.

Case 3: Impact of Social Media Addiction



Figures 17 and 18: Graph that Represents Impact of Social media Addiction

https://dx.doi.org/10.4314/aujst.v6i2.3

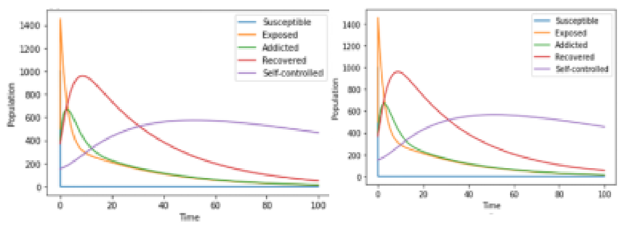


Figures 18: Graph that Represents Impact of

Social media Addiction

Figures 17 and 18 show the impact of varying recovery rates ψ. When the recovery rate is increased from **0.5** (Figure 17) to **1.0** (Figure 18), the addicted population declines significantly faster, indicating that stronger intervention measures can ate covery from social media addiction. This finding is consistent with [13], who demonstrated that behavioral interventions can mitigate social media addiction effectively.

Case 4: Minimization and Control of Social Media Addiction



Figures 19 and 20 Graphs of Minimization and Control

of Social Media Addiction

Figures 19 and 20 examine the effect of self-control rates κ When the self-control rate is increased from **0.5** (Figure 19) to **1.0** (Figure 20), the number of self-controlled individuals rises more quickly, reducing the overall impact of addiction. Similar results were obtained by (Baumeister et al., 1998), who explored the role of self-regulation in managing addictive behaviors.

DISCUSSION

The results from both the descriptive analysis and the simulation modeling highlight the complex interplay between social media usage, addiction, and recovery. The findings indicate that social media addiction is prevalent, particularly among younger demographics, and has notable consequences on mental health and social relationships. The modeling simulation further illustrates the potential effectiveness of recovery and self-control interventions in managing addiction levels. These insights contribute to the growing body of research on digital addiction and provide a foundation for future studies on mitigating its impact.

A. STUDY LIMITATIONS

This study, focuses to examine and develop a mathematical model on the social media addiction, But the study will only be limited to few social media handle (Facebook and WhatsApp) due to their popularity and considering global usage.

6. Conclusion

This study has demonstrated that social media addiction poses a significant challenge among students of Federal University Dutsin-Ma, with a considerable proportion of individuals exhibiting addictive usage patterns. By applying the SEARC mathematical model alongside descriptive analysis, the research highlighted the dynamics of susceptibility, exposure, addiction, recovery, and self-control in shaping addiction outcomes. The findings revealed that interventions that promote self-regulation and increase recovery rates can substantially reduce the prevalence of addiction. Moreover, the results emphasize the importance of awareness campaigns, counseling programs, and institutional policies that encourage healthier digital habits.

Beyond the immediate context, this research contributes to the broader field of behavioral addiction studies by providing a quantitative framework for predicting and controlling social media addiction. However, the study was limited in scope to a few platforms and a relatively small sample size, suggesting the need for broader studies in the future. Future research should focus on refining the model to incorporate demographic and psychological variables, as well as developing predictive tools that can identify high-risk individuals and guide targeted interventions. In conclusion, while social media remains a valuable tool for communication and learning, excessive and unregulated use has far-reaching negative consequences. Addressing this issue requires a balanced approach that combines personal responsibility with institutional and societal interventions.

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