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A Population Dynamics Model for the Rampancy of AI Dependency

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We construct and analyze a mathematical model that consists of ordinary differential equations to discuss the population dynamics associated with AI dependency. We particularly focus on the significance of reputation and popularity in AI usage, which are deemed crucial factors in enhancing user satisfaction with their intended purposes and subsequently reinforcing the transition to AI dependency. Based on the mathematical results obtained from our model, we emphasize the importance of effective fundamental literacy in AI usage among users. Such literacy is essential for preparing and implementing preventive measures to mitigate the potential serious consequences stemming from the increasing popularity of AI usage in our society.

KEYWORDS: population dynamics, ordinary differential equation model, digital addiction, generative artificial intelligence (AI)

1. Introduction

Diffusion of an innovative technology could change people's lifestyle. We have major historical examples like metal type printing, automobile, plane, telegraphy, etc. Some of such innovations brought not only benefits but also new problems to our societies, for example, environmental pollution, global warming, etc. Drug disasters can be considered some of the most severe and prominent cases, such as congenital malformation with thalidomide [1, 2], subacute myelo-optico-neuropathy (SMON) induced by clioquinol [3], retinopathy resulting from chloroquine use [4], and hepatitis and HIV infections transmitted through blood transfusions [5, 6]. Over the past decade, similar scenarios have emerged and become increasingly serious across various aspects of digital technologies [7–11].

WHO [12] acknowledged addiction to internet gaming as a real disorder, called by *Gaming disorder, predominantly online*, sometimes mentioned now as Internet Gaming Disorder (IGD), which is generally defined as "Persistent and recurrent use of the internet to engage in games, often with other players, leading to clinically significant impairment or distress" [13], although the concept of IGD has been questioned [14–16]. The criteria for an individual to be classified with IGD are given by Diagnostic and Statistical Manual of Mental Disorders (DSM-5) ([17]; albeit not intended for clinical use; also see [15]). As the number of internet users appears to steadily increase each year [18], IGD is bound to increase as well [13, 14, 19–25]. In recent years, a broader spectrum of internet addictions has gained attention, including social media addiction, screen addiction, and smartphone addiction [26–38].

Today, as is the current trend, the rapid proliferation and popularity of generative artificial intelligence (AI) is raising behavioral concerns among users, despite its undeniable impacts on our lives [11, 39–50]. Generative AI Addiction Syndrome (GAID) is a novel form of digital dependency recognized as a behavioral addiction following compulsive and uncontrollable nature to induce distress, while its classification remains subject to debate [11, 40, 51–55]. Unlike conventional digital addictions, it is typically characterized by passive consumption, which can result in heightened anxiety, depression, impaired decision-making, and disrupted interpersonal relationships [48, 56–58]. This nature is similar to the IGD. However, GAID can be regarded as an active and creative engagement process [54, 59]. Users with GAID exhibit excessive engagement with AI not only for entertainment or utility purposes but also for self-expression and companionship [39, 60, 61]. The distinction between productive use and compulsive engagement becomes blurred, rendering such disorders difficult to identify and challenging to self-regulate [62]. The current tendency to anthropomorphize AI exacerbates the complexity and concern surrounding such situations [11, 40, 44, 45, 55, 63, 64]. The extremal case may result in social withdrawal, preferring AI interaction over human engagement [65, 66].

In this paper, we examine a mathematical model that consists of ordinary differential equations to discuss the population dynamics related to AI dependency and addiction. We particularly focus on the role of reputation and popularity in AI usage, which are considered crucial factors in enhancing user satisfaction with their intended purposes and subsequently reinforcing the transition to AI dependency (see the above cited references).

There have been previous studies with population dynamics models related to addictions (for instance, [67–73] on

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online gaming and social media addictions, and [74, 75] on drug addiction). Most of these studies are simple modifications of mathematical models used to study the epidemic dynamics of transmissible diseases (as for the mathematical modeling and models about the epidemic dynamics, for example, see [76–79]).

In contrast, the nature of AI dependency is distinct in some ways. AI usage can enhance the quality of life by improving work results and efficiencies, or reducing anxiety and loneliness. Even if the user is highly dependent on AI usage, this nature can be considered a benefit. For this reason, at least today, while the reputations of AI usage are rapidly spreading among people, AI dependency would still be little cautioned. Even after some cases of AI addiction are reported to require social attention (see the references cited in the above), AI dependency would not be heavily criticized until now. It is clear, however, that AI dependency can potentially lead to AI addiction, which may cause social disorders as previous studies discussed. Once the stronger recognition of AI dependency appears in people, it becomes more likely that society will develop a system to care for such AI-dependent users. Today, growing concerns about AI dependency begin with being aware of the necessity for a public health measure to it. In fact, the number of published studies on various aspects of AI dependency rapidly increases (for instance, see [11]).

Consequently, when discussing the impact of increased AI usage on user behavior, two key aspects must be considered. Firstly, the growing popularity of AI usage leads to a larger number of users becoming dependent on it. Secondly, a larger number of AI-dependent users increases the likelihood of available social support to mitigate this dependency. These two aspects are related to population dynamics according to AI user behavior. The first aspect is analogous to the spread of a transmissible disease, while the second aspect is specific to the spread of AI dependency. In other words, a larger number of AI-dependent users can lead to higher popularity of AI usage, which in turn accelerates the increase of AI-dependent users. At the same time, it may also strengthen the caution surrounding AI usage and improve the efficiency of recovery treatments. Notably, the second aspect has not been considered in most previous mathematical models regarding addiction distinct from AI dependency or other digital dependencies, which are analogous to epidemic dynamics models. It may overlook an important factor that can influence the spread of AI dependency. In contrast, [72] attempted to incorporate this specific aspect into a mathematical model for online gaming addiction. The author is unaware of any previous work on the spread of AI dependency to date. Subsequently, in this paper, we construct a simple population dynamics model that considers these two aspects of AI dependency and attempt to discuss how the rampancy of AI dependency in the AI user community could be influenced by these aspects.

2. Assumptions

While some may view today's situation of AI usage as the dawn of a new digital era, we should also consider its rapid popularization and penetration into our daily lives [45]. For our modeling in this paper, we assume a community where AI use has become prevalent and widely adopted.

2.1 AI user state

We categorize AI user behavior into three states based on their usage patterns: moderate, dependent, and addicted (see Fig. 1). The moderate state signifies a stage where the user maintains control over their AI usage. The dependent state indicates excessive AI usage, leading to an "always-on" behavior lacking proper self-control akin to the DSM-5 definition of addiction [17]. Nonetheless this state could potentially be alleviated through effective interventions, which may recover such users to the moderate state. These interventions encompass psychological therapy and exercise, medication, parental guidance, and support groups. We suppose that there are chances for AI-dependent users to receive such effective interventions after recognizing their dependency, either through self-awareness or through guidance from neighbors.

In contrast, we characterize here the AI-addicted user by a reluctance to accept intervention or a limited response to such interventions. This user exhibits cognitive, emotional, and social impairments. The rehabilitation of such an AI-addicted user necessitates a customized treatment plan implemented by the community to incorporate available interventions [80]. We assume that while such a treatment may rehabilitate an AI-addicted user, they cannot simply return to a moderate state. Instead, the rehabilitated user enters a dependent state, and thus, they may relapse into the addicted state while they could return to the moderate state with further therapeutic interventions.

This categorization of AI-dependent and AI-addicted users can be compared to the early and later stages of the Interaction of Person-Affect-Cognition-Execution (I-PACE) model proposed by [56] for internet and other addictions.

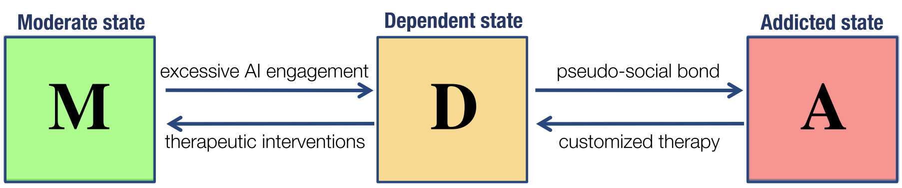

Fig. 1. State transitions of AI user in our modeling.

Note that while their model serves as a conceptual framework to elucidate the psychological and neurobiological processes underlying the development and perpetuation of addicted states, our model specifically focuses on the prevalence of AI dependency and addiction among its users.

2.2 State transitions

The transition of AI user state between the moderate and the dependent stages depends on the extent to which users engage with the AI for both professional and personal purposes. Promoting AI engagement can be facilitated by positive social perceptions of the benefits and comfort associated with its use for certain tasks. Conversely, excessive AI use predisposes users to compulsive work behaviors [48, 81, 82]. Criticism of excessive AI use can foster a sense of repulsion. Therefore, we assume that the likelihood of transitioning from a moderate to a dependent state is positively correlated with the number of dependent and addicted users, as their activities contribute to promoting AI use. In contrast, we assume that the transition from a dependent to an addicted state occurs independently of the number of users. This suggests that the AI-dependent user has already engaged excessively with the AI, and the transition to an addicted state may be driven by a pseudo-social bond with the AI, as discussed in [48]. The likelihood of this bond depends on the personal traits and circumstances of the AI-dependent user [50, 56].

The transition from a dependent to a moderate state is facilitated by certain interventions aimed at relaxing excessive AI usage by the user. The application of such interventions becomes feasible only after the user's AI dependency gains attention from others or is self-identified. The increased number of identified addicted users may enhance the motivation to recognize AI dependency, as news about AI addiction is readily disseminated on the internet today and easily accessible to the public. Hence, we assume a positive correlation between the likelihood of transitioning from a dependent to a moderate state and the number of AI-addicted users. Conversely, we assume that the likelihood of transitioning from an addicted to a dependent state is independent of the number of any users. This assumption arises because rehabilitation must be customized for each individual with AI addiction, and the duration of rehabilitation varies depending on the patient's personality traits and specific circumstances. On the other hand, this assumption could be considered a mathematical simplification in our modeling of a basic population dynamics model in this paper.

3. Model

3.1 Generic model

Following the assumptions described in Sect. 2, we consider the following system of ordinary differential equations as our model for population dynamics, as illustrated in Fig. 2 regarding the fluxes of AI users based on their behavior patterns:

$$\begin{aligned} \frac{dM}{dt} &= -f(D+A)M + g(A)D \\ \frac{dD}{dt} &= f(D+A)M - g(A)D - \mu D + \rho A \\ \frac{dA}{dt} &= \mu D - \rho A, \end{aligned} \tag{3.1}$$

where $M = M(t)$, $D = D(t)$ and $A = A(t)$ are respectively the population sizes of moderate users, dependent users, and addicted users, respectively, at time t. Parameters μ and ρ are positive constants, while $f(D+A)$ and $g(A)$ are functions of $D+A$ and A. Positive parameters μ and ρ are the transition rate from addicted to dependent state and the inverse transition rate, respectively. As we assumed in Sect. 2.2, the transition from dependent to addicted state is driven by the personal circumstances. Hence, it is now given as a constant rate μ for the population dynamics governed by (3.1). Similarly, the transition from addicted to dependent state relies on the rehabilitation tailored for each addicted user, and thus the transition rate is given as a constant ρ. It is worth noting that the total population size is a positive constant independent of time t: $M(t) + D(t) + A(t) = N > 0$ for any $t \geq 0$. We disregard here any demographic changes in the population of AI users because we assume a community where AI use has become prevalent and widely adopted, as described at the beginning of Sect. 2. As a reasonable initial condition, we assume that generally $M(0) > 0$, $D(0) \geq 0$ and $A(0) \geq 0$, and specifically $M(0) = N$, $D(0) = 0$ and $A(0) = 0$.

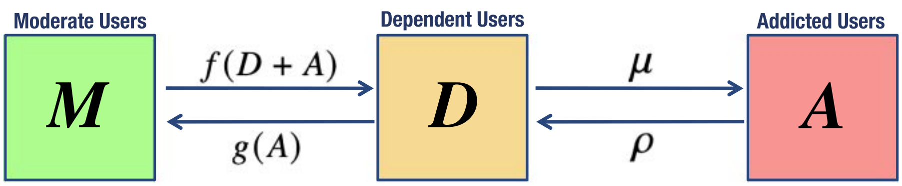

Fig. 2. AI user fluxes based on their behavior patterns in our model (3.1).

Functions $f(D+A)$ and $g(A)$ in (3.1) give the transition rate from moderate to dependent state and the inverse transition rate, respectively. These functions $f(x)$ and $g(y)$ are assumed to satisfy the following features:

- ▹ $f(x)$ and $g(y)$ are positive, differentiable, and monotonically increasing for $x > 0$ and $y > 0$;
- ▹ $f(0) = f_0 > 0$ and $g(0) = g_0 > 0$;
- ▹ The right derivatives $f'(+0) := \lim_{x\to+0} \frac{f(x)-f(0)}{x}$ and $g'(+0) := \lim_{y\to+0} \frac{g(y)-g(0)}{y}$ are non-negative and finite.

The third feature is assumed for a mathematical convenience to omit certain specific cases.

The first feature follows the assumptions given in Sect. 2.2. Positive constants $f_0 = f(0)$ and $g_0 = g(0)$ represent the intrinsic transition rates from moderate to dependent states and vice versa, respectively, when dependent and addicted users do not influence these transitions. These constants f_0 and g_0 signify the likelihoods of those transitions, driven by the AI's attractive nature, and by the user's inherent tendency to overcome addiction on their own. With a positive constant g_0, we assume here that AI-dependent users have the potential to overcome addiction on their own. Such self-recovery from addiction may depend on a concept known as "self-reflexivity" or "self-reflection," which serves as a phase of self-regulation [42].

Conversely, as the AI usage becomes more user-friendly through its development for commercial/business purposes by the developers, its attractive nature intensifies, further accelerating the transition from moderate to dependent states. However, this increased attractiveness also makes it more challenging to overcome AI dependency. Since regular AI usage has a characteristic that drives users toward dependency, we assume that the intrinsic transition rate to AI dependency $f(0) = f_0$ is positive, as described in the second feature. Based on these arguments on the relationship between the attractive nature of AI usage and these transitions between moderate and dependent states, it is possible that the parameters f_0 and g_0 have a negative correlation.

We can get the following lemma concerning the boundedness of the solution $(M(t), D(t), A(t))$ to the system (3.1):

Lemma 3.1. *The solution $(M(t), D(t), A(t))$ of (3.1) with any initial condition $(M(0), D(0), A(0))$ with $M(0) > 0$, $D(0) \geq 0$, and $A(0) \geq 0$ stays in the set $(0,N)\times(0,N)\times(0,N)$ for any $t > 0$.*

This lemma can be easily proved by showing that $dM/dt|_{t=0} < 0$; $dD/dt|_{t=0} > 0$; $dA/dt|_{t=0} = 0$, and then $dM/dt|_{M=0} > 0$; $dD/dt|_{D=0} > 0$; $dA/dt|_{A=0} > 0$ for any finite $t > 0$, while $dM/dt|_{(M,D,A)=(N,0,0)} < 0$, $dD/dt|_{(M,D,A)=(0,N,0)} < 0$, and $dA/dt|_{(M,D,A)=(0,0,N)} < 0$ for any finite $t > 0$, where we used the constraint that $M(t) + D(t) + A(t) = N$ for any $t \geq 0$. We do not provide a detailed proof here. This result demonstrates that $M(t)$, $D(t)$, and $A(t)$ are positive and bounded for any finite $t > 0$.

We can easily find that the "pathological" equilibrium with $D > 0$, $A > 0$ and $M = 0$ never exists for the system (3.1). Similarly, the "healthy" equilibrium $(M, D, A) = (N, 0, 0)$ also does not exist. Conversely, for the system (3.1), we can obtain the following result on the existence of the "undesirable" equilibrium $(M, D, A) = (M^*, D^*, A^*)$ with $A^* > 0$ and $D^* > 0$, and $M^* > 0$ (Appendix B):

Lemma 3.2. *At least one undesirable equilibrium $(M, D, A) = (M^*, D^*, A^*)$ exists for the system (3.1) such that $A^* > 0$ and $D^* > 0$, and $M^* > 0$.*

Since the system (3.1) can be reduced to a two dimensional system of (D, A) with $M(t) + D(t) + A(t) = N$ for any $t \geq 0$ (Appendix A), we can apply the Poincaré-Bendixson Theorem (for example, refer to [79, 83–88]), along with Lemma 3.1 and the above result showing that there is no equilibrium point on the boundary of the set $\overline{\Omega}_2 := \{(D, A) \mid 0 \leq D + A \leq N\}$. Consequently, we have the following result:

Theorem 3.3. *For the system (3.1) with the initial condition such that $M(0) > 0$, $D(0) > 0$, and $A(0) \geq 0$, the solution asymptotically approaches an undesirable equilibrium or a periodic solution where the values of D and A remain positive.*

This theorem demonstrates that, based on the system (3.1), subpopulations of dependent and addicted users persist. It is important to note that this theorem does not necessarily preclude the possibility that the system eventually approaches an asymptotically stable periodic solution.

3.2 A simple model

In this section, we consider a mathematically simplest version of (3.1) with the following linear functions f and g:

$$f(D+A) = f_0\left(1 + \beta\frac{D+A}{N}\right); \quad g(A) = g_0\left(1 + \sigma\frac{A}{N}\right), \tag{3.2}$$

where positive parameters β and σ are the coefficients to reflect the effectivity of available information in enhancing the transitions from moderate to dependent states and the inverse transition respectively. The three-dimensional system (3.1) with (3.2) is equivalent to a closed two-dimensional system of (D, A) as shown in Appendix A. This equivalence is achieved using the relation $M(t) = N - D(t) - A(t)$ for any $t \geq 0$. To simplify the mathematical analysis, we can employ the mathematically equivalent two-dimensional system to explore the nature of the system (3.1) with (3.2).

As outlined in Appendix C, we can readily derive the undesirable equilibrium $(M, D, A) = (M^*, D^*, A^*)$ with $A^* > 0$ and $D^* > 0$, and $M^* > 0$ for (3.1) with (3.2), as

$$P^* := D^* + A^* = \frac{1}{2} \cdot \frac{1}{\beta + sg_0/f_0} \left[\beta - 1 - \theta \frac{g_0}{f_0} + \sqrt{\left(\beta - 1 - \theta \frac{g_0}{f_0}\right)^2 + 4\left(\beta + s\frac{g_0}{f_0}\right)} \right] N; \tag{3.3}$$

$D^* = \theta P^*$; $A^* = (1-\theta)P^*$; $M^* = N - D^* - A^*$, where

$$\theta := \frac{\rho}{\mu + \rho}; \quad s := \theta(1-\theta)\sigma.$$

It can be easily found that $P^*/N < 1$. Consequently, the undesirable equilibrium is unique (see Appendix C):

Lemma 3.4. *The undesirable equilibrium* (M^*, D^*, A^*) *always uniquely exists in* $\Omega_3 := \{(M, D, A) \mid M > 0, D > 0, A > 0, M + D + A = N\}$ *for the system* (3.1) *with* (3.2).

For the stability of the undesirable equilibrium of the system (3.1) with (3.2), we can obtain the following result (Appendix C):

Theorem 3.5. *For the system* (3.1) *with* (3.2)*, the undesirable equilibrium* $(M, D, A) = (M^*, D^*, A^*)$ *with* $A^* > 0$*,* $D^* > 0$*, and* $M^* > 0$ *is globally asymptotically stable.*

As a result, we have found that the population dynamics by (3.1) with (3.2) eventually converges to an undesirable equilibrium (see Fig. 3). This result also implies that the system (3.1) with (3.2) does not have any periodic solution.

As seen in Fig. 4, D^* and A^* at the undesirable equilibrium are monotonically increasing in terms of β, and they converge to θN and $(1-\theta)N$ respectively as $\beta \to \infty$, while $P^* \to N$ and $M^* \to 0$ as $\beta \to \infty$. In contrast, D^* and A^* are monotonically decreasing in terms of σ, and $(M^*, D^*, A^*) \to (N, 0, 0)$ as $\sigma \to \infty$. Furthermore, we can easily find that D^* and A^* are monotonically decreasing in terms of g_0/f_0, and converge to 0 as $g_0/f_0 \to \infty$, while $M^* \to N$ as $g_0/f_0 \to \infty$. Conversely, as $g_0/f_0 \to +0$, D^* and A^* converge to positive finite values, respectively:

$$\lim_{g_0/f_0 \to +0} \frac{D^*}{N} = \theta; \quad \lim_{g_0/f_0 \to +0} \frac{A^*}{N} = 1 - \theta,$$

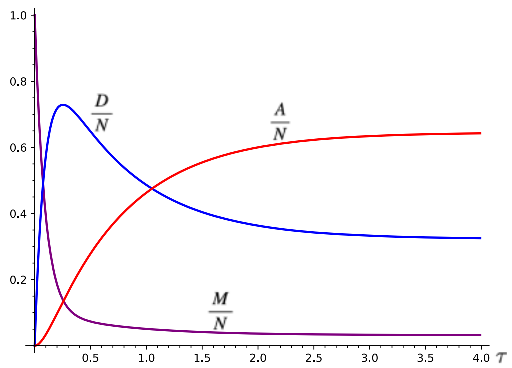

Fig. 3. Temporal variation of $(\frac{M}{N}, \frac{D}{N}, \frac{A}{N})$. Numerically drawn by the mathematically equivalent two-dimensional system (A·4) in Appendix A with $\tau = \mu t$; $\phi_0 = f_0/\mu = 10.0$; $\beta = 0.01$; $r = \rho/\mu = 0.5$; $\gamma_0 = g_0/\mu = 1.0$; $\sigma = 0.01$; $(\frac{M(0)}{N}, \frac{D(0)}{N}, \frac{A(0)}{N}) = (1.0, 0.0, 0.0)$. For these parameter values, $(\frac{M^*}{N}, \frac{D^*}{N}, \frac{A^*}{N}) = (0.032, 0.323, 0.645)$.

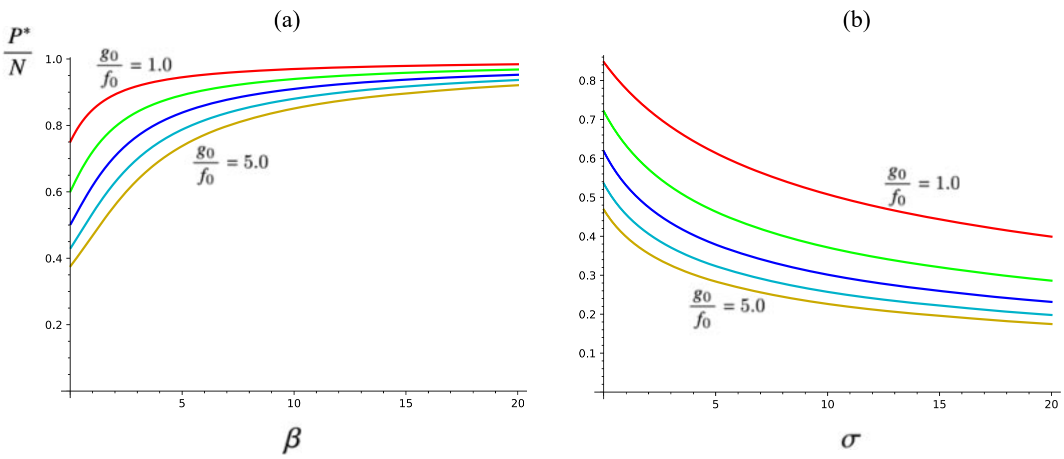

Fig. 4. Parameter dependence of the population size of AI-dependent users $P^* = D^* + A^*$ at the undesirable equilibrium. Numerically drawn for $g_0/f_0 = 1.0, 2.0, 3.0, 4.0, 5.0$, respectively with $r = \rho/\mu = 0.5$, and (a) $\sigma = 0.0$; (b) $\beta = 10.0$.

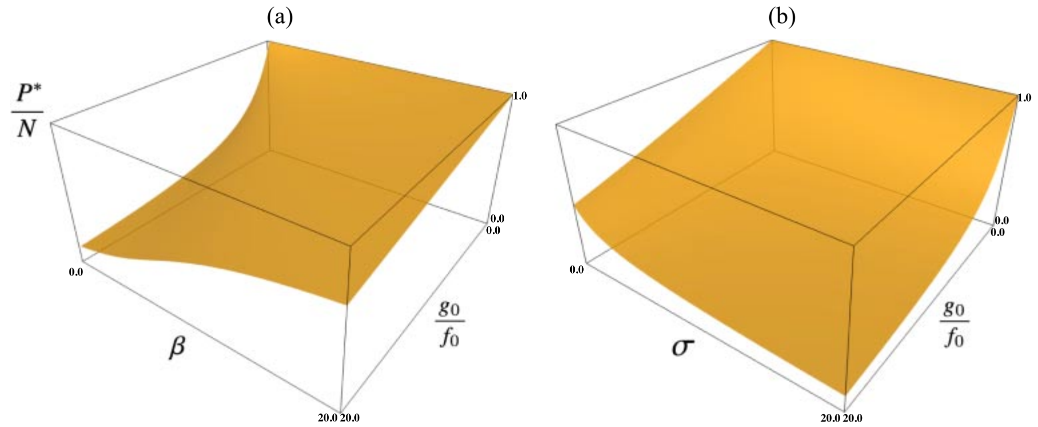

Fig. 5. Parameter dependence of the population size of AI-dependent users $P^* = D^* + A^*$ at the undesirable equilibrium. Numerically drawn with $r = \rho/\mu = 0.5$, and (a) $\sigma = 0.0$; (b) $\beta = 10.0$.

where $P^* = D^* + A^* \to N$ and then $M^* \to 0$ (see Fig. 5).

As described in Sect. 3.1, the parameter f_0 represents the inherent likelihood of excessive AI use leading to AI dependency for a user. This tendency can be influenced by the appealing virtual personality of generative AI, its feature fueling personal relevance and self-specificity. Additionally, the competent AI assistance in various tasks, whether for business or daily life, can further promote this tendency [48]. Especially once the AI assistants are recognized as competent and the rewards of their use are perceived, the work-reward cycle can potentially escalate. This escalation can lead users to invest excessive time and energy into work, thereby increasing the likelihood of transitioning to AI dependency. In today's digital landscape, current AI users find themselves in such a situation. Therefore, for the current reality of AI users, the parameter f_0 would be positive and may even be increasing.

In contrast, the user's inherent potential to overcome AI dependency, represented by the positive parameter g_0 in our model, would remain relatively small in the current real situation. This is because of a potential negative correlation between f_0 and g_0 as mentioned in Sect. 3.1. Most of users, as mentioned above, are now attracted to the competent AI assistance. Therefore, we may hypothesize that the value of g_0/f_0 is small and less than one, which corresponds to the current real situation.

Moreover, we can hypothesize that the value of σ is very small near zero, or alternatively, it is equal to zero. Parameter σ represents the effectivity of online information in enhancing the recovery from AI dependency, as explained in Sect. 3.1. As we assumed there, this enhancement is achieved through the recognition of AI addiction by the AI users. However, today, such information to alert users about the risks of addicted AI use appears to be quite limited.

Under these hypotheses, we can find the following features regarding the parameter dependence of the population size of AI-dependent users $P^* = D^* + A^*$ at the undesirable equilibrium (Appendix D):

$$\left|\frac{\partial P^*/\partial\beta}{\partial P^*/\partial(g_0/f_0)}\right| < 1 \quad \text{and} \quad \left|\frac{\partial P^*/\partial\sigma}{\partial P^*/\partial(g_0/f_0)}\right| < 1. \tag{3.4}$$

For a given set of parameter values, the value of $\partial P^*/\partial\beta$ represents the sensitivity of the equilibrium value P^* to a slight change in the value of parameter β (for example, refer to [89]). The same concept applies to the corresponding formula for the other parameter. These features of sensitivities of the equilibrium value P^* in (3.4) indicate that it is the most sensitive to changes in g_0/f_0. Therefore, based on the scenario we hypothesized, a change in the value of g_0/f_0 could most efficiently decrease the population size of AI-dependent users at the undesirable equilibrium.

Since the parameters f_0 and g_0 represent the inherent nature of AI users to either become dependent on AI or overcome this dependency, as mentioned above and in Sect. 3.1, these values are considered contingent upon the level of fundamental literacy in AI usage. In conclusion, our result underscores the significance of fundamental literacy in AI usage for users. While the current social tendency acknowledges its importance, we should recognize its higher necessity to prevent a serious social problem of AI dependency among the younger generations in future.

4. Concluding Remarks

As highlighted by [31, 38, 43, 48, 50, 54, 90], immediate action is imperative to comprehend, diagnose, and mitigate the consequences of addictions to digital tools, including generative artificial intelligence. This aligns with the results in [72], which employed a mathematical population dynamics model to consider the dissemination of internet gaming addiction. In this paper, our presented mathematical model underscores the importance of fundamental literacy in AI usage for users, suggesting it as a potential preventive measure against the future social issue of AI dependency, although the effectiveness of such literacy remains largely unknown [44].

Our model (3.1) with (3.2) assumes a simple density-dependence of transition rates between moderate and AI-dependent user states. Consequently, the community of AI users eventually approaches an equilibrium state with positive AI-dependent and addicted user subpopulations. However, as mentioned at the last part of Sect. 3.1, the system (3.1) might converge to a periodic solution, depending on the mathematical properties of the functions f and g, which differ from (3.2). We have not mathematically investigated the existence of such a possible periodic solution due to the nature of these functions. While it would be an interesting mathematical problem, it falls outside the scope of our research.

Although our model is simple, actually, we lack specific knowledge about AI dependency. Hence, we cannot make any assumption to further sophisticate it, as there is still limited scientific knowledge on the actual extent of AI dependency [39]. Actually, it is highly probable that the problem of AI dependency may exhibit characteristics influenced by cultural or educational backgrounds for each community [45]. As demonstrated in various theoretical studies using mathematical models for epidemics, the problem of AI dependency will generate a wide range of theoretical subjects that can be explored using mathematical models assuming specific characteristics of different communities. To prepare and conduct preventive measures against the future social issue of AI dependency, we expect further scientific research on AI dependency under an open networking involving researchers and AI developers. After all, AI dependency must be a global issue that requires collective attention and action.

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Appendix A: Mathematically Equivalent Two-dimensional System

Using the relation about (3.1) that $M(t) = N - D(t) - A(t)$ for any $t \geq 0$, we can derive the following two-dimensional closed system mathematically equivalent to (3.1):

$$\begin{aligned} \frac{dD}{dt} &= f(D+A)(N-D-A) - g(A)D - \mu D + \rho A \\ \frac{dA}{dt} &= \mu D - \rho A. \end{aligned} \tag{A·1}$$

With (3.2), this two-dimensional system becomes

$$\begin{aligned} \frac{dD}{dt} &= f_0\left(1 + \beta\frac{D+A}{N}\right)(N-D-A) - g_0\left(1 + \sigma\frac{A}{N}\right)D - \mu D + \rho A \\ \frac{dA}{dt} &= \mu D - \rho A. \end{aligned} \tag{A·2}$$

Further, applying the following transformation of variables and parameters for (A·2):

$$\tau = \mu t; \quad v = \frac{D}{N}; \quad w = \frac{A}{N}; \quad \phi_0 = \frac{f_0}{\mu}: \quad \gamma_0 = \frac{g_0}{\mu}; \quad r = \frac{\rho}{\mu}, \tag{A·3}$$

we get the following system with non-dimensionalized variables and parameters:

$$\begin{aligned} \frac{dv}{d\tau} &= \phi_0\{1 + \beta(v+w)\}(1-v-w) - \gamma_0(1+\sigma w)v - v + rw \\ \frac{dw}{d\tau} &= v - rw. \end{aligned} \tag{A·4}$$

For the non-dimensionalized system (A·4), $u(\tau) := M(t)/N = 1 - v(\tau) - w(\tau) > 0$ is satisfied for any $\tau \geq 0$. From Lemma 3.1, the solution of (A·4) for the initial condition that $v(0) \geq 0$ and $w(0) = 0$ stays in $\overline{\Omega}_2 := \{(v,w) \mid 0 \leq v + w \leq 1\}$ for any $\tau \geq 0$. In this paper, we partially use the non-dimensionalized system (A·4) for the mathematical convenience of our analysis on the system (3.1) with (3.2).

Appendix B: Proof of Lemma 3.2

The undesirable equilibrium (M^*, D^*, A^*) for (3.1) corresponds to the equilibrium (D^*, A^*) for the two-dimensional system (A·1) in Appendix A, where $A^* > 0$, $D^* > 0$, and $D^* + A^* < N$. Since $D^* = \frac{\rho}{\mu}A^*$ and thus $D^* + A^* = (1 + \frac{\rho}{\mu})A^*$ from (A·1), it is necessary that $A^* \in (0, N/(1 + \frac{\rho}{\mu}))$. Now, if the undesirable equilibrium exists, it must be satisfied that

$$\mathcal{H}(D^*, A^*) := f(D^* + A^*)(N - D^* - A^*) - g(A^*)D^* - \mu D^* + \rho A^* = 0$$

from (A·1). The equilibrium value A^* is given as the root of equation $\mathcal{H}(\frac{\rho}{\mu}A, A) = 0$ in terms of $A \in (0, N/(1+\frac{\rho}{\mu}))$. We have $\mathcal{H}(0,0) = f(0)N$ and

$$\mathcal{H}\left(\frac{\frac{\rho}{\mu}N}{1+\frac{\rho}{\mu}}, \frac{N}{1+\frac{\rho}{\mu}}\right) = -g\left(\frac{N}{1+\frac{\rho}{\mu}}\right)\frac{\frac{\rho}{\mu}N}{1+\frac{\rho}{\mu}} < 0. \tag{B·1}$$

Hence, from the continuity of $\mathcal{H}(\frac{\rho}{\mu}A, A)$ in terms of $A \in (0, N/(1+\frac{\rho}{\mu}))$, the Intermediate Value Theorem says that there exists at least one root of equation $\mathcal{H}(\frac{\rho}{\mu}A, A) = 0$ in terms of $A \in (0, N/(1+\frac{\rho}{\mu}))$ since $\mathcal{H}(0,0) > 0$, that is, $f(0) = f_0 > 0$. Consequently Lemma 3.2 has been proven.

Appendix C: Proof of Lemma 3.4 and Theorem 3.5

As the mathematical equivalence, we consider the two dimensional system (A·4) in Appendix A. Regarding the undesirable equilibrium $(v, w) = (v^*, w^*)$ where $v^* > 0$, $w^* > 0$, and $v^* + w^* < 1$, we can easily derive the following equations from (A·4):

$$v^* = \frac{r}{1+r}p^*; \quad w^* = \frac{1}{1+r}p^*; \quad \psi(p^*) := a_0 p^{*2} - a_1 p^* - 1 = 0, \tag{C·1}$$

where $p^* := v^* + w^* = (D^* + A^*)/N = P^*/N$, and

$$a_0 = \beta + \frac{\gamma_0}{\phi_0}\frac{r}{1+r}\frac{\sigma}{1+r}; \quad a_1 = \beta - 1 - \frac{\gamma_0}{\phi_0}\frac{r}{1+r}.$$

Since $a_0 > 0$, $\psi(0) < 0$, and $\psi(1) > 0$, the quadratic equation $\psi(p) = 0$ has a unique positive root less than one. The positive root can be shown as P^* in (3.3). Since $0 < p^* < 1$ and $w^* = p^*/(1+r)$, we have w^* such that $w^* < 1/(1+r)$, which implies that $A^*/N < 1/(1+\frac{\rho}{\mu})$. These arguments prove Lemma 3.4.

Now let us consider the local stability of undesirable equilibrium $(v, w) = (v^*, w^*)$ for the two dimensional system (A·4). We can easily derive the following Jacobi matrix $J(v^*, w^*)$ with respect to the undesirable equilibrium:

$$\begin{aligned}
J(v^*, w^*) &= \begin{pmatrix} \phi_0\{\beta - 1 - 2\beta(v^* + w^*)\} - \gamma_0(1 + \sigma w^*) - 1 & \phi_0\{\beta - 1 - 2\beta(v^* + w^*)\} - \gamma_0\sigma v^* + r \\ 1 & -r \end{pmatrix} \\
&= \begin{pmatrix} \phi_0(\beta - 1 - 2\beta p^*) - \gamma_0\big(1 + \frac{\sigma}{1+r}p^*\big) - 1 & \phi_0(\beta - 1 - 2\beta p^*) - \gamma_0\sigma\frac{r}{1+r}p^* + r \\ 1 & -r \end{pmatrix} \\
&= \begin{pmatrix} -\phi_0\Big[\big(2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}\big)p^* - \big(\beta - 1 - \frac{\gamma_0}{\phi_0}\big)\Big] - 1 & -\phi_0\Big[\big(2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma r}{1+r}\big)p^* - (\beta - 1)\Big] + r \\ 1 & -r \end{pmatrix},
\end{aligned}$$

and find

$$\begin{aligned}
\operatorname{trace} J(v^*, w^*) &= -\phi_0\left[\left(2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}\right)p^* - \left(\beta - 1 - \frac{\gamma_0}{\phi_0}\right)\right] - (1+r); \\
\det J(v^*, w^*) &= r\phi_0\left[\left(2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}\right)p^* - \left(\beta - 1 - \frac{\gamma_0}{\phi_0}\right)\right] + \phi_0\left[\left(2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma r}{1+r}\right)p^* - (\beta - 1)\right] \\
&= (1+r)\phi_0\left[2\left(\beta + \frac{\gamma_0}{\phi_0}\frac{r}{1+r}\frac{\sigma}{1+r}\right)p^* - \left(\beta - 1 - \frac{\gamma_0}{\phi_0}\frac{r}{1+r}\right)\right] = (1+r)\phi_0(2a_0p^* - a_1).
\end{aligned}$$

Since p^* is the larger root of quadratic equation $\psi(p) = 0$, we find that p^* satisfies that $p^* > \frac{a_1}{2a_0}$. Consequently, we can immediately find that $\det J(v^*, w^*) > 0$.

Next, when $\beta - 1 - \frac{\gamma_0}{\phi_0} \le 0$, we immediately have $\operatorname{trace} J(v^*, w^*) < 0$. When $\beta - 1 - \frac{\gamma_0}{\phi_0} > 0$, for

$$\zeta := \frac{\beta - 1 - \frac{\gamma_0}{\phi_0}}{2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}} > 0,$$

we derive

$$\psi(\zeta) = a_0\zeta^2 - a_1\zeta - 1 = -\frac{1}{(2\beta + \frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r})^2}\left\{\left(\frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}\right)^2 + b_1\left(\frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}\right) + b_0\right\}$$

with

$$b_1 = \frac{1}{1+r}(\beta - 1)\left(\beta - 1 - \frac{\gamma_0}{\phi_0}\right) + 4\beta > 0;$$

$$
\begin{aligned}
b_0 &= -\beta\left(\beta-1-\frac{\gamma_0}{\phi_0}\right)^2+2\beta\left(\beta-1-\frac{\gamma_0}{\phi_0}\frac{r}{1+r}\right)\left(\beta-1-\frac{\gamma_0}{\phi_0}\right)+4\beta^2\\
&> -\beta\left(\beta-1-\frac{\gamma_0}{\phi_0}\right)^2+2\beta\left(\beta-1-\frac{\gamma_0}{\phi_0}\right)\left(\beta-1-\frac{\gamma_0}{\phi_0}\right)+4\beta^2=\beta\left(\beta-1-\frac{\gamma_0}{\phi_0}\right)^2+4\beta^2>0.
\end{aligned}
$$

This result implies that $\psi(\zeta)<0$, which means that $p^*>\zeta$, because p^* is the larger root of quadratic equation $\psi(p)=0$. Then, we find that

$$\operatorname{trace} J(v^*,w^*)=-\phi_0\left(2\beta+\frac{\gamma_0}{\phi_0}\frac{\sigma}{1+r}\right)(p^*-\zeta)-(1+r)<0.$$

Therefore, $\operatorname{trace} J(v^*,w^*)<0$ also when $\beta-1-\frac{\gamma_0}{\phi_0}>0$. Finally, we have demonstrated that $\det J(v^*,w^*)>0$ and $\operatorname{trace} J(v^*,w^*)<0$. Hence, every eigenvalue of the Jacobi matrix $J(v^*,w^*)$ has a negative real part. In conclusion, the undesirable equilibrium $(v,w)=(v^*,w^*)$ is locally asymptotically stable.

As described in Appendix A, for the system (A·4), Lemma 3.1 implies that the solution of (A·4) with the initial condition that $v(0)\geq 0$ and $w(0)=0$ remains within $\overline{\Omega}_2=\{(v,w)\mid 0\leq v+w\leq 1\}$ for any $\tau\geq 0$. Since there is no equilibrium point on the boundary of $\overline{\Omega}_2$, and the undesirable equilibrium $(v,w)=(v^*,w^*)$ lies inside $\overline{\Omega}_2$, we can apply the Poincaré-Bendixson Theorem to conclude that the result of Theorem 3.5 holds.

Appendix D: Sensitivity Analysis for $P^*=D^*+A^*$

As described in Appendix C, the equilibrium value $p^*:=v^*+w^*=(D^*+A^*)/N=P^*/N$ is given by the unique positive root of the quadratic equation $\psi(p)=0$ of (C·1). By taking the partial derivative of equation $\psi(p^*)=0$, we can formally derive

$$\frac{1}{p^*}\frac{\partial p^*}{\partial(\gamma_0/\phi_0)}=-\frac{\frac{r}{1+r}(1+\frac{\sigma}{1+r}p^*)}{2a_0p^*-a_1};\quad \frac{1}{p^*}\frac{\partial p^*}{\partial\beta}=\frac{1-p^*}{2a_0p^*-a_1};\quad \frac{1}{p^*}\frac{\partial p^*}{\partial\sigma}=-\frac{\frac{\gamma_0}{\phi_0}\frac{r}{(1+r)^2}p^*}{2a_0p^*-a_1},$$

where a_0 and a_1 are provided in Appendix C. Since the root $p=p^*$ is the larger root of the quadratic equation $\psi(p)=0$, we have $2a_0p^*-a_1>0$.

The inequality

$$\left|\frac{\partial p^*/\partial\beta}{\partial p^*/\partial(g_0/f_0)}\right|=\left|\frac{1-p^*}{\frac{r}{1+r}\left(1+\frac{\sigma}{1+r}p^*\right)}\right|<1 \tag{D·1}$$

is equivalent to

$$p^*>p_1:=\frac{1}{1+r+\frac{r}{1+r}\sigma}.$$

By straightforward calculations, we have

$$\psi(p_1)=a_0p_1^2-a_1p_1-1=\frac{r}{\left(1+r+\frac{r}{1+r}\sigma\right)^2}\left(1+\frac{\sigma}{1+r}\right)\left(\frac{\gamma_0}{\phi_0}-\beta-1-r-\frac{r}{1+r}\sigma\right).$$

From our hypothesis that g_0 is relatively small with large f_0, we have $\gamma_0/\phi_0=g_0/f_0<1$. Thus, we have obtained that $\psi(p_1)<0$. This implies that $p_1<p^*$, because $\psi(p)<0$ for all $p\in(0,p^*)$ based on the properties of the quadratic function $\psi(p)$ for $p>0$. Therefore, the inequality (D·1) holds under the above-mentioned hypothesis. This result demonstrates the first inequality of (3.4).

The inequality

$$\left|\frac{\partial p^*/\partial\sigma}{\partial p^*/\partial(g_0/f_0)}\right|=\left|\frac{\frac{\gamma_0}{\phi_0}\frac{r}{(1+r)^2}p^*}{\frac{r}{1+r}\left(1+\frac{\sigma}{1+r}p^*\right)}\right|<1 \tag{D·2}$$

is equivalent to

$$\frac{1}{1+r}\left(\frac{\gamma_0}{\phi_0}-\sigma\right)p^*<1.$$

Under the hypothesis that σ is sufficiently small near zero (or equal to zero) and $\gamma_0/\phi_0<1$, the left side of this inequality is necessarily less than one because $p^*<1$. Therefore, the inequality (D·2) holds under these hypotheses. Finally, the second inequality of (3.4) can be demonstrated to hold.

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