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Title of Research Report: Peer Influence, Present Bias, and Digital Self-Control: A Dynamic Network Model of Problematic Smartphone Use

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Abstract

Problematic smartphone use is often studied as an individual self-control problem, but individuals' behaviour may also be shaped by their peers, their ability to anticipate their own future behaviour, and the availability of self-control tools. This paper develops a dynamic network model that examines how peer influence, present bias, and digital self-control interact to shape smartphone use. The model distinguishes between naive and sophisticated individuals and incorporates self-control adoption as a behavioural choice that limits smartphone use. Monte Carlo simulations are conducted on a Watts–Strogatz small-world network with 100 individuals observed over 20 periods.

The results show that smartphone use gradually declines and stabilises over time, while self-control adoption remains relatively stable. Naive individuals have slightly higher long-run smartphone use and lower self-control adoption than sophisticated individuals. However, counterfactual experiments show that peer-use spillovers have a substantially larger effect on aggregate smartphone use than naivety under the baseline parameterisation. Further sensitivity analysis shows that this relative difference persists across the tested range of positive values of the peer-use coefficient, although the magnitude of the effects varies. Sensitivity analysis also shows that stronger naivety effects consistently increase smartphone use and reduce self-control adoption, while changes in network rewiring have little effect on long-run outcomes under the baseline model.

These findings suggest that problematic smartphone use may reflect not only individual present bias and self-control limitations, but also the social environment in which behavioural decisions are made. The results also highlight the importance of accounting for network spillovers when studying digital self-control and designing interventions.

Keywords: Problematic smartphone use; Peer influence; Present bias; Digital self-control; Naivety; Social networks; Behavioral economics

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Table of Contents

Section 1: Introduction **1**
Section 2: Literature Review **3**
2.1 Peer Influence Across Age Groups 3
2.2 Present Bias, Naivety, and Self-Control 5
2.3 Digital Self-Control and the Adoption Decision 6
Section 3: Methodology **8**
3.1 Model Framework 8
3.2 Present Bias and Intertemporal Decision-Making 9
3.3 Naivety and Sophistication 10
3.4 Lagged Peer Exposure to Smartphone Use 11
3.5 Digital Self-Control Tool Adoption 12
3.6 Smartphone Use Outcome 14
3.7 Dynamic Timeline 15
3.8 Simulation Design 17
Section 4: Results **18**
4.1 Baseline Dynamics 18
4.2 Naive versus Sophisticated Individuals 20
4.3 Counterfactual Experiments 22
4.4 Estimator Performance on Simulated Data 24
4.5 Sensitivity to the Naivety Effect and Network Structure 26
Section 5: Conclusion **29**
References **31**
Acknowledgements **34**

2026 S.-T. Yau High School Science Award
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Section 1: Introduction

Problematic smartphone use (PSU) has emerged as a growing problem in contemporary society. The term PSU is defined as the inability to control or regulate smartphone use (Ndayambaje & Okereke, 2025). As technology advances, smartphones are becoming a larger part of daily life, leading not only to negative physical effects such as body pain and eye strain, but also to mental health effects such as increased levels of depression, anxiety, and mood disorders (Devi & Singh, 2023). Candussi et al. (2023) summarized in their systematic review that 37% to 66% of university students suffer from PSU. This shows that PSU has become an increasingly concerning issue.

In China, as of July 2026, the number of smartphone users stood at 1.304 billion, representing an increase of 46 million from the previous year (Statista, 2026). With the rapid growth in the number of smartphone users and the increasing number of individuals connected to the internet, developing healthy smartphone use habits has become more important than ever. However, simply recognizing the problem is not sufficient. To effectively understand and address PSU, it is necessary to examine the factors that influence individuals' smartphone use and their ability to regulate it.

One important factor is the influence of peers. Individuals do not make decisions about smartphone use in isolation, as their behaviors may be shaped by the habits and expectations of people within their social networks. In other words, the extent of smartphone use of an individual's peer would also influence the individual's own usage. At the same time, smartphone use involves an important trade-off between immediate benefits and future costs. The immediate entertainment, social interaction, and convenience provided by smartphones may be particularly attractive to individuals with stronger present bias, who place greater weight on immediate rewards than on future consequences. Finally, even when individuals recognize the potential negative consequences of excessive smartphone use, their ability to regulate their behavior may depend on the digital self-control methods available to them.

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Therefore, this research examines PSU through three closely connected, and influential perspectives: peer influence, present bias, and digital self-control. By incorporating these social, behavioral, and individual regulatory factors, this research aims to provide a more comprehensive understanding of why problematic smartphone use occurs and how it may be mitigated.

The rest of this paper is structured as follows. Section 2 provides an in-depth review of the existing literature on peer influence, present bias, and digital self-control, with particular attention to their relationships with problematic smartphone use and the gaps in existing research. Section 3 introduces the methodology of the study, including the theoretical framework, model structure, and the operationalization of the independent and dependent variables. Section 4 presents and discusses the results, focusing on how peer influence, present bias, and digital self-control shape individuals' smartphone use and the development of problematic smartphone use within a dynamic social network. Finally, Section 5 concludes the paper by summarizing the key findings, discussing their implications, and outlining the limitations of the study and directions for future research.

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Section 2: Literature Review

This paper sits within three closely connected branches of literature: peer influence, present bias, and digital self-control. Research on peer influence has primarily examined how social environments affect decision-making and behavior among students and adolescents, while comparatively less attention has been given to adults and broader everyday settings. The literature on present bias focuses on how individuals may place disproportionate weight on immediate rewards relative to future consequences, providing a behavioral framework for understanding decisions involving self-control. Finally, research on digital self-control examines how individuals regulate their engagement with digital technologies and resist immediate digital rewards. Together, these three branches provide the theoretical foundation for understanding how social influence and individual preferences may shape decisions regarding problematic smartphone use and digital self-control.

2.1 Peer Influence Across Age Groups

Peer influence is defined as changes in an individual's thoughts or behaviors that may result from experiences and interactions with friends and other affiliates (Laursen & Veenstra, 2021), and it is a pervasive and influential force during adolescence. Moreover, peer influence increases resemblance among social affiliates, driving both beneficial habits and problematic behaviors. Therefore, understanding how peer influence operates within social networks is important when seeking to understand and address specific problematic behaviors.

According to Laursen and Veenstra (2021), adolescents have high levels of conformity and are particularly susceptible to peer influence. This can be partly explained by changes in their social environments. Upon entering adolescence, individuals gradually shift from environments closely monitored by parents and other adults to schools, where peer interaction becomes more frequent and important. Peers may provide companionship, guidance, and social norms; therefore, adolescents may feel the need to conform to their peers, especially when nonconformity can

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result in negative social consequences. This susceptibility to peer influence is particularly relevant to smartphone use because smartphones are highly social devices, and individuals may be influenced by the usage patterns and behaviors of those around them. Xu et al. (2023) found that peer pressure on mobile phone use significantly predicted mobile social media addiction among adolescents, demonstrating a relationship between peer influence and problematic smartphone use.

Although the influence of peers during adolescence is well established, less attention has been given to whether and how peer influence persists into adulthood. Chown and Inoue (2025) examined peer influence in the workplace and found that peer influence manifests in convergence when physicians perform deliveries. Pike et al. (2026) demonstrated that peer influence is also observed in body dissatisfaction. Candussi et al. (2023) showed that smartphone overuse is prevalent among university students, suggesting that problematic smartphone use is not limited to adolescents. However, Xiong and Vang (2023) argued that the extent to which adults are affected by peer influence may decrease with age. In their experiment, as the age of the participants increased, they became less susceptible to taking risks in the presence of peers. This suggests that although peer influence can affect adults, its effects may vary across different stages of life.

Taken together, existing literature suggests that peer influence is relevant across age groups, but its strength and manifestation may differ between adolescents and adults. However, important gaps remain in the literature. Firstly, much of the literature has focused on adolescent behaviors such as bedtime decisions and smoking and alcohol trends, while less attention has been given to problematic smartphone use. Moreover, existing research on peer influence among adults has examined contexts such as the workplace, with less attention given to everyday behaviors such as smartphone use. Therefore, limited research has examined how peer influence affects problematic smartphone use across different age groups. This provides a basis for considering peer influence as an important factor in explaining differences in smartphone use and digital self-control.

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2.2 Present Bias, Naivety, and Self-Control

While peer influence emphasizes the role of the social environment, individual preferences also play an important role in explaining problematic smartphone use. According to O'Donoghue and Rabin (1999), people prefer to "experience rewards soon" and "delay costs until later". This constitutes a self-control problem, as individuals may choose immediate rewards despite recognizing the greater benefits of delaying them. Broadly in line with this perspective, Deng et al. (2024) defined present bias as "a preference for positive events to be now rather than not-now".

This tendency is particularly relevant to smartphone use because smartphones provide immediate rewards, such as entertainment and social interaction, while many of the negative consequences of excessive use occur in the future. Present bias can therefore contribute to self-control problems and influence individuals' decisions regarding smartphone use. Individuals experiencing problematic smartphone use may suffer from physical discomfort as well as mental health problems such as anxiety, depression, and sleep disturbances (Ndayambaje & Okereke, 2025; Zhu et al., 2025), negatively affecting their wellbeing and daily lives. The conflict between immediate rewards and future consequences may make it difficult for individuals to reduce their smartphone use even when they recognize these negative consequences.

However, individuals do not experience present bias and self-control problems in exactly the same way. Hoong (2021) identified sophisticated and naive individuals based on differences between their predicted and actual future behavior. The difference between a sophisticated individual's ideal future use and real future use is relatively small, while that of a naive individual is larger. This suggests that sophisticated individuals have a better understanding of their own future behavior and self-control, whereas naive individuals may have greater difficulty recognizing their own self-control problems. Research shows that naive individuals are more likely to procrastinate, while sophisticated individuals are more likely to preproperate given the same opportunities (Freeman, 2021). Therefore, accounting for differences in naivety may be important when examining how individuals respond to attempts to reduce smartphone usage.

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2.3 Digital Self-Control and the Adoption Decision

Given these differences in self-control, several methods have been proposed to mitigate present bias and problematic smartphone use. Self-control tools, such as digital "detox" programs, smartphone usage tracking applications, and physical time lock boxes, have been proposed to reduce the negative impact of PSU (Ndayambaje & Okereke, 2025). "Detox" programs provide individuals with time away from their digital devices. This method has demonstrated that even reducing screen time by a small amount every day can produce benefits for overall wellbeing (Georgetown University, 2025). Usage tracking applications, on the other hand, primarily track phone usage, informing individuals about their usage patterns and helping them recognize the steps that may be taken to form better online habits. This method may be particularly useful for more sophisticated individuals, as it increases awareness while still allowing them to retain autonomy over their behavior. Physical time lock boxes, however, may create poor user experiences and may sometimes even backfire (Lu et al., 2024).

However, in these studies, the tool is almost always provided by the researcher. Participants are assigned to a detox program, given a tracking application, or provided with a lock box, and researchers examine how their screen time changes as a result. Hoong (2021), for example, studies soft commitment devices experimentally, but the device is still introduced by the researcher rather than chosen by the individual. What has received less attention is why individuals choose to adopt these tools in the first place. Whether a person decides to install a screen time limit, and whether they continue using it, may itself depend on how well they understand their own future self-control, as well as the behavior of people around them. This is the gap that the model in Section 3 aims to address by treating the adoption of digital self-control tools as an individual decision rather than something imposed externally.

These differences between self-control interventions highlight the importance of examining digital self-control as a distinct behavioral mechanism. Unlike physical interventions, digital self-control tools can be directly connected to smartphone usage and measured through changes in screen time and usage behavior. Therefore, digital self-control provides a measurable way to examine how individuals respond to self-regulation mechanisms while accounting for differences

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in present bias and naivety. This makes digital self-control an important third component of the theoretical framework of this research.

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Section 3: Methodology

3.1 Model Framework

This study develops a dynamic network model to examine how peer influence and present bias jointly shape problematic smartphone use and the adoption of digital self-control tools. The model integrates three mechanisms that are often examined separately in the existing literature: individuals' intertemporal preferences, their awareness of future self-control problems, and the peer influences within a social network. Rather than treating smartphone use as a purely individual decision, the model assumes that individuals make decisions within an interconnected social environment in which both smartphone use and self-control behaviors can diffuse through peer networks. Moreover, this model captures the characteristics of both adolescents and adults, addressing a gap in the existing literature, where relatively limited research has focused on PSU among adults.

The model consists of three components. First, individuals differ in their degree of present bias and in their awareness of their future self-control problems. Second, at the beginning of each period, individuals observe lagged peer behavior and decide whether to adopt a digital self-control tool. Third, conditional on their level of present bias, peer exposure, and availability of self control tools in the previous and current periods, individuals determine their smartphone use during the current period. The realized smartphone use and self-control adoption decisions then become the state variables that influence decisions in the following periods.

This structure allows the model to capture individual-level behavioral tendencies, dynamic social interactions, and cross-period trends. In particular, peer influence enters the model with a one-period lag, reflecting the assumption that an individual's peers' behavior in the previous period can affect their own decisions in the current period.

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3.2 Present Bias and Intertemporal Decision-Making

The first component of the model concerns present bias, which determines how individuals evaluate trade-offs between immediate and future utility. Following the quasi-hyperbolic discounting framework proposed by Laibson (1997) and O'Donoghue and Rabin (1999), individual i's total utility at time t is represented as

$$V_{i,t} = u_{i,t} + \beta_i \sum_{k=t+1}^{T} \delta_i^{k-t} u_{i,k}$$

where $V_{i,t}$ denotes the total utility perceived by individual i at time t, $u_{i,t}$ represents current-period flow utility, β_i is the individual's present-bias parameter, and δ_i is the standard long-run discount factor. Both parameters are assumed to satisfy $0 < \beta \leq 1$ and $0 < \delta \leq 1$.

The parameter β_i captures the additional weight placed on immediate utility relative to future utility. Therefore, a lower value of β_i represents a stronger present bias, meaning that the individual places relatively greater importance on immediate gratification. In contrast, δ_i captures the individual's conventional long-run discounting of future utility.

This distinction is particularly relevant to problematic smartphone use. Smartphone use can generate immediate utility through entertainment, social interaction, or information consumption, while excessive use may create future costs such as reduced productivity or difficulty in maintaining intended usage limits. Consequently, an individual with stronger present bias may place disproportionately high value on the immediate benefits of smartphone use and insufficient weight on its future consequences.

Importantly, present bias is incorporated into the individual's intertemporal utility and represented in the smartphone-use equation through the term $1 - \beta_1$, rather than being treated as

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an ad hoc explanatory variable. This allows the model to represent present bias as a behavioral mechanism underlying the individual's decision-making process.

3.3 Naivety and Sophistication

The model further distinguishes individuals according to their awareness of their own future self-control problems. According to O'Donoghue and Rabin (1999) and Hoong (2021)'s research, individuals may differ not only in their actual present bias but also in their beliefs about how present-biased their future selves will be.

Let β_i denote individual i's actual present-bias parameter and $\hat{\beta}_i$ denote the individual's predicted future present-bias parameter. The degree of naivety is defined as

$$N_i = \hat{\beta}_i - \beta_i$$

Under this formulation, a sophisticated individual correctly anticipates their future self-control problem, such that

$$\hat{\beta}_i = \beta_i$$

and therefore $N_i = 0$. A naive individual underestimates the extent of their future present bias, such that

$$\hat{\beta}_i > \beta_i$$

resulting in $N_i > 0$.

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This distinction is important because the perceived need for digital self-control may depend not only on the individual's actual difficulty in resisting immediate rewards, but also on whether the individual recognizes this difficulty in advance. A sophisticated individual who anticipates future self-control problems may be more likely to adopt a digital self-control tool before excessive smartphone use occurs. In contrast, a naive individual may underestimate their future difficulty in controlling smartphone use and consequently delay or avoid adoption.

Thus, naivety and sophistication enter the model as a determinant of the digital self-control adoption decision rather than directly determining smartphone use.

3.4 Lagged Peer Exposure to Smartphone Use

To incorporate social interactions, the model represents individuals as nodes within a weighted social network. Let w_{ij} denote the network weight between individual i and peer j, capturing the strength or relevance of their social connection. Peer influence is modeled using lagged peer behavior rather than contemporaneous behavior.

The weighted exposure of individual i to peer smartphone use in period t is defined as

$$P_{i,t} = \sum_{j} w_{ij} \, c_{j,t-1}$$

where $P_{i,t}$ represents individual i's exposure to peers' smartphone use during the previous period, w_{ij} is the network weight between i and j, and $c_{j,t-1}$ is peer j's smartphone use duration in period $t-1$. The summation is taken over all peers connected to individual i.

The use of lagged peer exposure serves two purposes. First, it reflects the dynamic nature of social influence: individuals respond to behaviors that their peers have previously exhibited rather than simultaneously determining each other's behavior. Second, it prevents the model

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from mechanically assuming that peer behavior and individual behavior are determined at exactly the same moment.

The equation is consistent with research suggesting that smartphone-related behaviors can be influenced by social environments and peer behavior (Liu et al., 2017; Ran et al., 2024). A higher value of $P_{i,t}$ indicates greater exposure to smartphone use within the individual's social network and is therefore expected to increase the individual's current smartphone use, holding other factors constant.

3.5 Digital Self-Control Tool Adoption

The second behavioral decision concerns whether an individual adopts a digital self-control tool. Let

$$A_{i,t} \in \{0,\ 1\}$$

where $A_{i,t} = 1$ indicates that individual i adopts a digital self-control tool in period t, while $A_{i,t} = 0$ indicates that the individual does not adopt one.

The adoption decision is modeled probabilistically as

$$Pr(A_{i,t} = 1) = \Lambda(\alpha_0 + \alpha_1 N_i + \alpha_2 R_{i,t} + \alpha_3 c_{i,t-1})$$

where $\Lambda(\cdot)$ denotes a logistic function. The expected signs of the coefficients are

$$\alpha_1 < 0, \alpha_2 > 0, \alpha_3 > 0$$

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Here, N_i represents the individual's degree of naivety, $R_{i,t}$ represents lagged peer exposure to self-control tool adoption, and $c_{i,t-1}$ represents the individual's own smartphone use in the previous period.

The first explanatory variable, N_i, captures the role of awareness. A higher degree of naivety indicates a larger discrepancy between an individual's actual and predicted future present bias. Under the model, greater naivety is expected to reduce the probability of adopting a self-control tool, reflected by $\alpha_1 < 0$. This also makes intuitive sense as individuals who underestimate their future self-control problems may perceive less need to take preventive action.

Peer influence is incorporated into adoption through

$$R_{i,t} = \sum_j w_{ij} A_{j,t-1}$$

where $R_{i,t}$ represents individual i's exposure to peers' previous-period adoption of digital self-control tools. A higher value of $R_{i,t}$ indicates that an individual's peers previously adopted self-control tools carry greater proportion. The model assumes $\alpha_2 > 0$, implying that self-control behavior may diffuse through the network: individuals are more likely to adopt a tool when their peers have previously done so.

Finally, previous smartphone use $c_{i,t-1}$ enters the adoption decision with an expected positive coefficient, $\alpha_3 > 0$. Individuals who experienced higher smartphone use in the previous period are assumed to have a greater perceived need for intervention and are therefore more likely to adopt a self-control tool.

This specification allows adoption to arise from three distinct mechanisms: individual awareness of one's self-control problems, peer influence, and one's previous behavior.

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3.6 Smartphone Use Outcome

Following the behavioral framework proposed by Yu (2026), current smartphone use is modeled in two steps. First, a latent level of smartphone use is determined by previous smartphone use, lagged peer exposure, the individual's present-bias parameter, and unobserved factors:

$$c_{i,t}^{*} = \kappa_0 + \rho c_{i,t-1} + \lambda P_{i,t} + \theta(1 - \beta_i) + \varepsilon_{i,t}$$

Second, actual smartphone use is determined by whether the individual adopts a digital self-control tool:

$$c_{i,t} = \max\{0, (1 - A_{i,t}) c_{i,t}^{*} + A_{i,t} \min(c_{i,t}^{*}, L_i)\}$$

Here, $c_{i,t}^{*}$ represents the individual's latent smartphone use before the effect of self-control is applied, while $c_{i,t}$ represents actual smartphone use in period t. The lagged use term $c_{i,t-1}$ captures persistence in smartphone use, while $P_{i,t}$ represents lagged peer exposure to smartphone use. The present-bias term $1 - \beta_i$ captures the effect of present bias on smartphone use, and $\varepsilon_{i,t}$ captures unobserved factors affecting the outcome. $A_{i,t}$ indicates whether the individual adopts a digital self-control tool, and L_i represents the usage limit imposed by the tool.

When $A_{i,t} = 0$, actual smartphone use is equal to the latent level $c_{i,t}^{*}$. When $A_{i,t} = 1$, smartphone use is restricted to the lower of the latent level and the individual's limit L_i. The outer $\max\{0, (\cdot)\}$ ensures that predicted smartphone use cannot be negative.

The model therefore imposes the following restriction:

$$c_i(1) \leq c_i(0)$$

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with $c_i(1) < c_i(0)$ when the self-control tool is binding. Here, $c_i(1)$ represents smartphone use when individual i adopts a self-control tool, while $c_i(0)$ represents smartphone use when the individual does not adopt one. Thus, adoption can reduce smartphone use by imposing a limit on the individual's latent level of use.

This structure separates the decision to adopt a self-control tool from the subsequent outcome of smartphone use. Adoption is a behavioral choice influenced by the individual's naivety, peer self-control adoption, and past smartphone use. Once adopted, the self-control tool affects actual smartphone use by limiting the individual's latent level of use when that level exceeds L_i.

3.7 Dynamic Timeline

The model operates recursively across discrete time periods. At the end of period $t - 1$, smartphone use $c_{i,t-1}$ and digital self-control adoption $A_{i,t-1}$ are realized for every individual in the network. These outcomes become the state variables entering period t.

At the beginning of period t, the model first calculates two forms of lagged peer exposure:

$$P_{i,t} = \sum_j w_{ij} c_{j,t-1}$$

and

$$R_{i,t} = \sum_j w_{ij} A_{j,t-1}$$

The first equation captures exposure to peers' previous smartphone use, while the second captures exposure to peers' previous adoption of self-control tools. Given these network

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exposures, together with their individual characteristics and previous smartphone use, individuals make their adoption decisions $A_{i,t}$.

During period t, individuals then determine their smartphone use $c_{i,t}$, conditional on their current adoption status and peer exposure. Their intertemporal preferences, including present bias and long-run discounting, determine how they evaluate immediate versus future consequences of this choice.

At the end of period t, the realized values of $c_{i,t}$ and $A_{i,t}$ update the model state:

$$S_t = (c_t, A_t)$$

This updated state is then used as the input for period $t + 1$, allowing the model to continue over time.

Overall, the model can be summarized as:

$$(c_{t-1}, A_{t-1}) \rightarrow (P_t, R_t) \rightarrow A_t \rightarrow c_t \rightarrow (c_t, A_t)$$

This recursive structure allows the model to examine how individual characteristics and peer interactions affect smartphone use over time. In particular, it provides a framework for studying whether excessive smartphone use can reinforce itself through both past and present individual behavioral persistence and peer effects, and whether digital self-control tools can interrupt this process. At the same time, the inclusion of naivety and sophistication allows the model to distinguish between individuals who accurately anticipate their future self-control problems and those who underestimate them, providing a behavioral foundation for heterogeneous adoption decisions.

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3.8 Simulation Design

To examine the dynamics generated by the model, a simulation of 100 individuals over 20 periods is conducted. Individuals are embedded in a Watts-Strogatz small-world network with six neighbours per node and a rewiring probability of 0.2. Each row of the adjacency matrix is normalised so that peer weights sum to one. For each individual, the present-bias parameter β_i is drawn; β_i is equal to $\hat{\beta}_i$ ($N_i = 0$) for sophisticated agents, and below $\hat{\beta}_i$ for naive agents ($N_i > 0$). Initial values of smartphone use and self-control adoption are also assigned.

In each period, lagged use and adoption generate peer exposure $P_{i,t}$ and $R_{i,t}$. These variables, together with naivety and lagged own use, determine the adoption probability through the logistic adoption equation, from which binary adoption $A_{i,t}$ is drawn. Smartphone use then follows the use equation, including an i.i.d. normally distributed shock. All baseline parameters are illustrative values chosen for theoretical sign consistency and are not empirically estimated.

The baseline simulation is first conducted to examine the behavior of the model under the main parameter settings. Two counterfactual scenarios are then considered: one in which all individuals are sophisticated $N_i = 0$, and another in which peer influence on smartphone use is removed $\lambda = 0$. A sensitivity analysis is also conducted by varying the naivety coefficient α_1 and the network rewiring probability.

To reduce the effect of random variation, each simulation setting is repeated 500 times, while each cell in the sensitivity analysis is repeated 200 times. The simulations use the same network structure across repetitions, while behavioral shocks are independently generated in each run. The mean outcomes and 95% Monte Carlo intervals are then reported.

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Section 4: Results

All results are based on 500 Monte Carlo replications (seeds 1000–1499), with 100 individuals observed over 20 periods on a fixed Watts–Strogatz small-world network ($k = 6$, rewiring probability $p = 0.2$). The network remains fixed across replications, while the behavioural random draws vary. The intervals reported in the text and tables, as well as the shaded areas in the figures, represent the 2.5th–97.5th percentiles of the Monte Carlo distribution. These intervals show the variation across simulation replications rather than sampling uncertainty from empirical data. All parameter values are illustrative simulation choices rather than empirical estimates. Therefore, the results focus mainly on the mechanisms and relative size of the effects rather than their real-world magnitudes.

4.1 Baseline Dynamics

Average smartphone use decreases over time, from 2.71 units in the first period (interval: 2.45–2.95) to a long-run level of 1.97 units, measured as the average of the last five periods (interval: 1.84–2.09; Figure 1). The decline is strictly monotonic through period 5, after which the average use becomes relatively stable. Average use is 1.99 in period 5, 1.97 in period 8, and remains at 1.97 in period 20. There is no overshooting or oscillation, which is consistent with the stable autoregressive root of $\rho = 0.6 < 1$. The long-run level is within 10% of the period-5 value, suggesting that the model reaches convergence within roughly one quarter of the simulation period.

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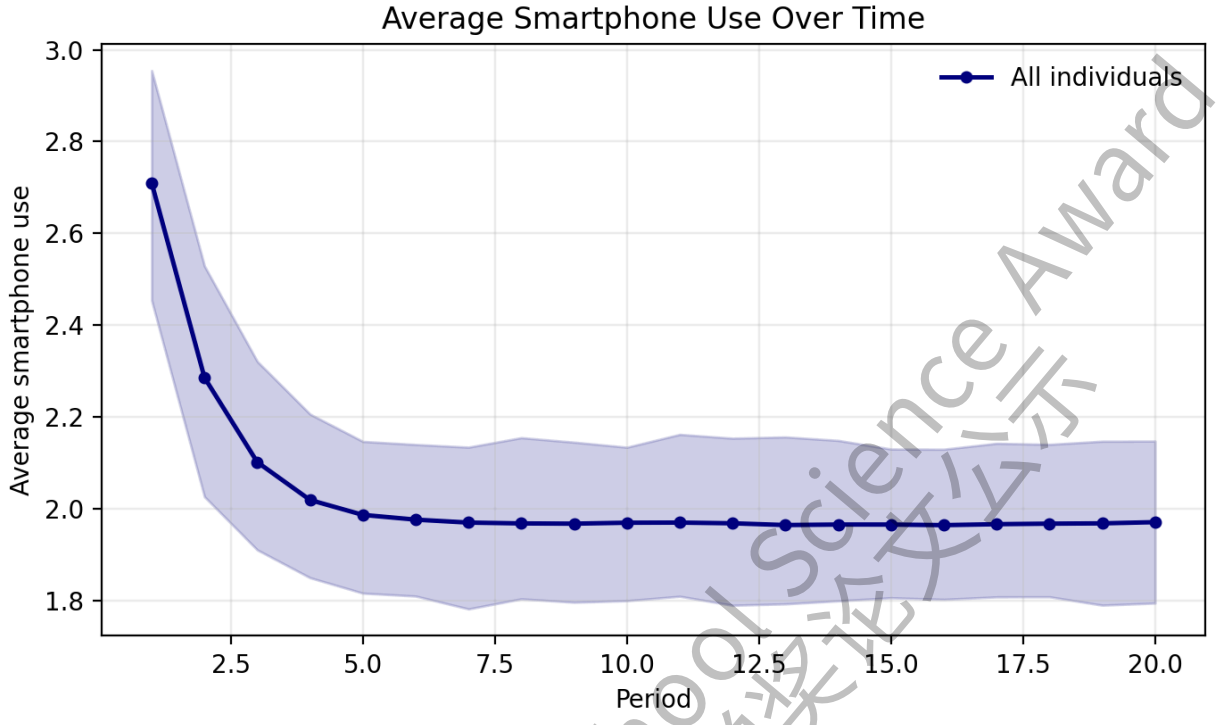


Figure 1. Average smartphone use over time. The solid line represents the mean across 500 Monte Carlo replications, and the shaded area represents the 2.5th–97.5th percentile range.

The positive long-run level of smartphone use comes from three main parts of the model. First, the latent-use intercept $\kappa_0 = 0.5$ provides a positive baseline level of use. Second, the present-bias term $\theta(1 - \beta_i)$, with $\theta = 1.0$ and $\beta_i \sim U(0.5, 1.0)$, contributes an average of 0.25 units to latent use. Third, the non-negativity constraint $\max(c, 0)$ prevents negative values from entering observed use. Actual use is also affected by the self-control limit. When $A_{i,t} = 1$, observed use is given by $\min(c_{i,t}^{*}, L_i)$ instead of $c_{i,t}^{*}$, where $L_i \sim U(0.5, 2.0)$ is an individual-specific cap. Since long-run adoption is around 0.38, approximately 38% of individuals are subject to this cap in a given period.

The aggregate self-control adoption rate starts at 0.40 and stabilises at around 0.38 in the long run (interval: 0.33–0.43; Figure 2). Unlike smartphone use, adoption does not show a clear upward or downward trend. This is because two effects work in opposite directions in the adoption equation. Higher peer self-control encourages adoption because $\alpha_2 > 0$, while lower

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own use gradually reduces the incentive to adopt because $\alpha_3 > 0$. By period 20, the Monte Carlo interval for adoption is approximately 0.33–0.43. Relative to the mean, this interval is about 24% of the long-run adoption rate, compared with about 13% for smartphone use. This suggests that adoption varies more across simulations, which is expected because adoption is a binary decision while smartphone use is a continuous outcome with autoregressive dynamics.

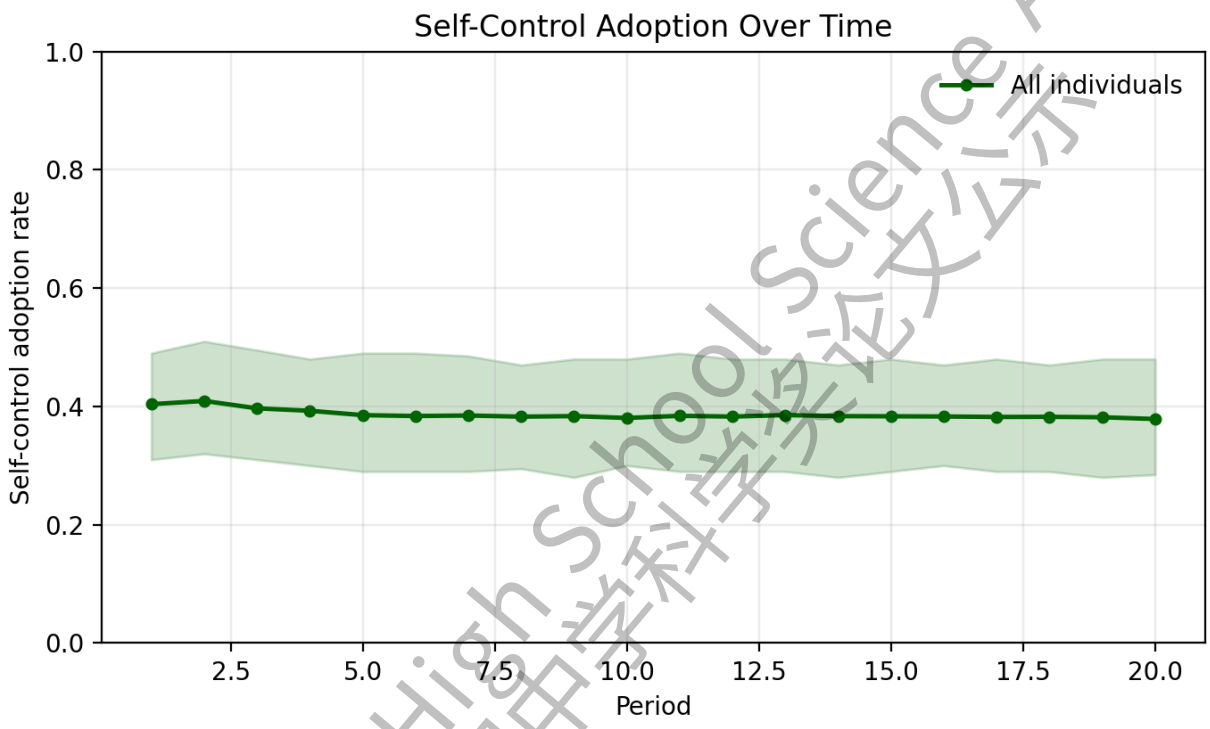


Figure 2. Aggregate self-control adoption rate over time.

4.2 Naive versus Sophisticated Individuals

Naive and sophisticated individuals begin with the same distribution of initial conditions. Mean smartphone use in period 1 is 2.77 for naive individuals and 2.65 for sophisticated individuals. The two groups differ only in their naivety gap N_i. Therefore, the later difference between the two groups is generated by the model's dynamics rather than by different initial conditions.

By period 20, naive individuals have an average use of 2.01 units (interval: 1.77–2.25), compared with 1.93 units for sophisticated individuals (interval: 1.72–2.17; Figure 3). This gives

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a use gap of 0.07 units. The corresponding adoption rates are 0.36 for naive individuals and 0.40 for sophisticated individuals, giving an adoption gap of −0.04. The difference between the groups appears within the first five periods and then remains relatively stable.

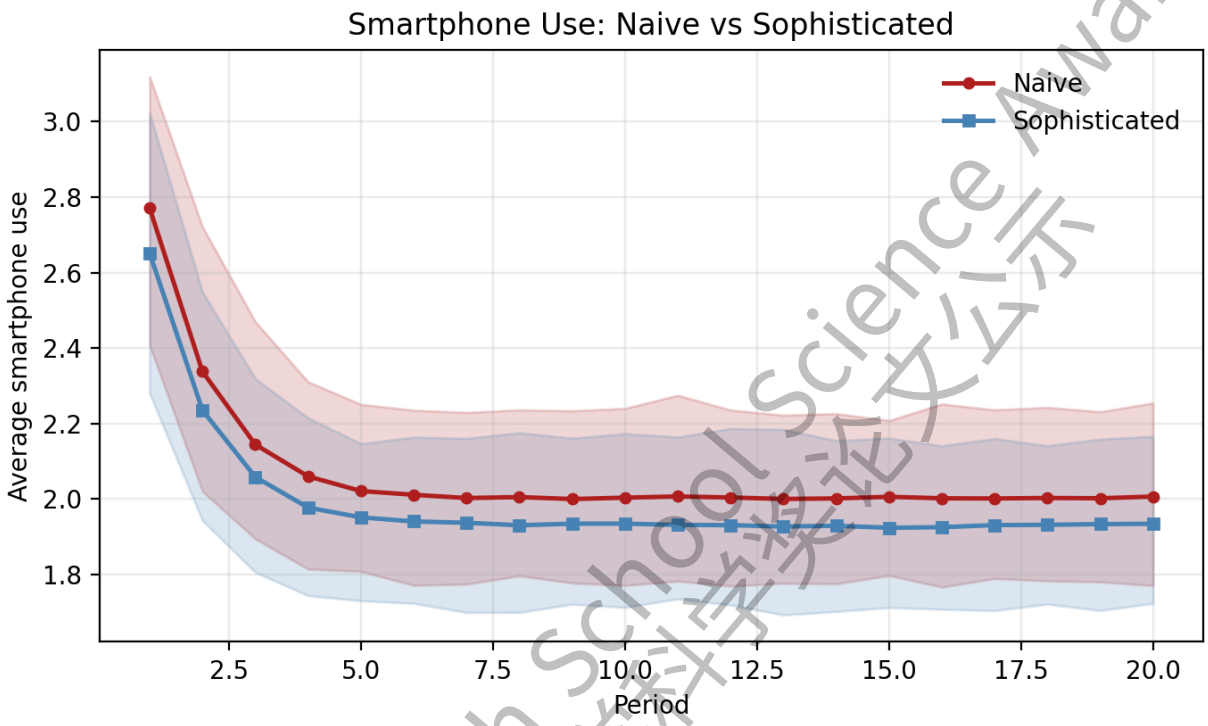


Figure 3. Average smartphone use by behavioural type.

The model provides two main pathways through which present bias affects observed smartphone use. First, the present-bias parameter β_i directly enters the latent-use equation through $\theta(1-\beta_i)$. Individuals with lower β_i, and therefore stronger present bias, have higher latent use $c_{i,t}^{*}$. This effect applies to both naive and sophisticated individuals. Second, the naivety gap $N_i = \hat{\beta}_i - \beta_i$ affects the probability of adopting self-control through $\alpha_1 = -1.0$. Naive individuals underestimate their present bias and therefore have a lower probability of adopting self-control.

Because adoption limits use through the $\min(c_{i,t}^{*}, L_i)$ mechanism, lower adoption means that naive individuals are more likely to remain uncapped. This increases the difference in observed use between the two groups. Importantly, the use equation itself does not include a direct naivety

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term. Therefore, the difference in observed use between naive and sophisticated individuals is generated through their different rates of self-control adoption. The Monte Carlo intervals of the two groups overlap in every period, so the result should be interpreted as a difference in average behaviour and its underlying mechanism rather than a complete separation between individual trajectories.

4.3 Counterfactual Experiments

Two counterfactual experiments are used to examine the importance of naivety and peer influence. In the first scenario, all individuals are assumed to be sophisticated ($N_i = 0$). In the second, the peer-use spillover is removed by setting $\lambda = 0$. Each counterfactual is compared with the baseline using the same random seed in each replication. This paired design reduces the effect of common simulation noise. Table 1 reports the long-run outcomes and paired treatment effects, while Figures 4 and 5 show how the outcomes change over time.

Eliminating naivety reduces long-run smartphone use by 0.06 units (paired interval: −0.10 to −0.01), corresponding to a reduction of approximately 3%. At the same time, long-run self-control adoption increases by 0.023 (0.006 to 0.044). In contrast, removing the peer-use spillover reduces long-run smartphone use by 0.49 units (−0.57 to −0.42), or approximately 25%. This effect is about nine times larger than the effect of eliminating naivety. Adoption also decreases slightly by 0.021 (−0.040 to −0.004). When peer-driven use is removed, individuals have lower own use, which reduces the incentive to adopt self-control because $\alpha_3 > 0$. Both treatment-effect intervals exclude zero.

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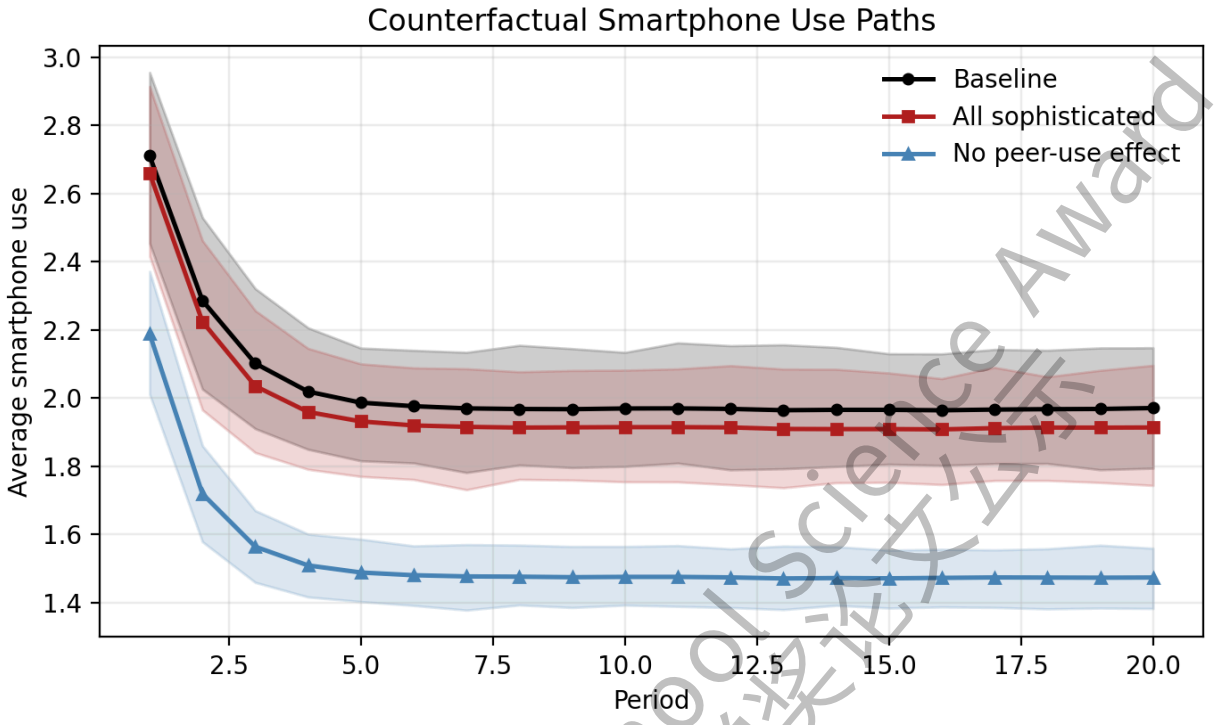


Figure 4. Counterfactual smartphone-use paths.

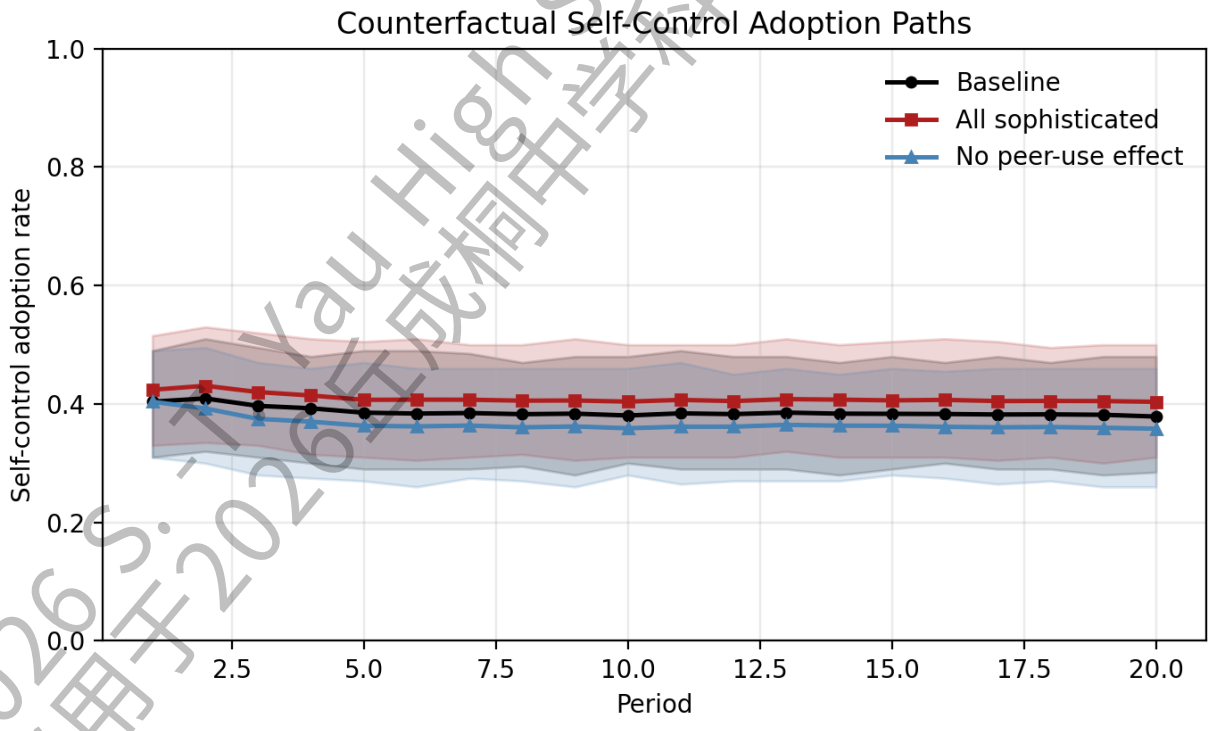


Figure 5. Counterfactual self-control adoption paths.

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Scenario	Long-run use	Δ use (95% interval)	Long-run adoption	Δ adoption (95% interval)
Baseline	1.967	—	0.382	—
All sophisticated ($N_i = 0$)	1.912	−0.055 (−0.102, −0.006)	0.405	+0.023 (0.006, 0.044)
No peer-use effect ($\lambda = 0$)	1.473	−0.494 (−0.573, −0.421)	0.360	−0.021 (−0.040, −0.004)

Table 1. Long-run outcomes and counterfactual effects.

These results suggest two main findings. First, under the parameterisation used in this simulation, the peer-use channel has a much larger effect on aggregate smartphone use than the naivety channel. Removing the peer-use effect produces a reduction in use that is roughly nine times larger than eliminating naivety. Second, the two interventions affect different parts of the model. Eliminating naivety increases self-control adoption, while removing the peer-use channel directly reduces smartphone use and slightly reduces adoption.

The difference between these effects is also related to the $\min(c_{i,t}^{*}, L_i)$ mechanism. Self-control adoption only changes observed use when the individual-specific cap L_i is binding. If latent use is already below the cap, adopting self-control does not change observed use. Therefore, in this simulation environment, the adoption channel has a weaker effect on aggregate use than the peer-use channel.

4.3.1 Sensitivity of Counterfactual Effects to the Peer-Use Coefficient

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A natural concern with the counterfactual results is that the magnitude of the "no peer-use effect" scenario is directly related to the assumed value of λ, since the counterfactual sets λ to zero. To examine whether the relative importance of the two mechanisms depends on the chosen value of λ, the counterfactual experiments are repeated across a range of λ values from 0.05 to 0.60, while keeping all other baseline parameters fixed. For each λ value, a corresponding baseline is simulated using the same random seeds. Therefore, each counterfactual is compared with its own λ-specific baseline rather than a fixed reference point. This paired design helps reduce the influence of common simulation noise when comparing the effects across different values of λ. Table 1A reports the results. At $\lambda = 0.25$, which is the baseline value used throughout the paper, removing the peer-use spillover reduces long-run smartphone use by approximately 25%, consistent with the result in Table 1. Across the tested range, this effect remains negative and becomes larger in magnitude as λ increases, from −5.9% at $\lambda = 0.05$ to −49.9% at $\lambda = 0.60$ (Figure 5A). The "all sophisticated" counterfactual also reduces long-run smartphone use, with the reduction increasing from −1.5% to −5.7% across the same range. However, its magnitude remains substantially smaller than that of the peer-use effect at every value tested.

The 95% Monte Carlo intervals for both effects generally become wider as λ increases, suggesting greater variation in the simulated outcomes when peer-use spillovers are stronger. In addition, the upper bound of the interval for the sophistication effect exceeds zero at some values of $\lambda \geq 0.40$. This indicates that, under these parameter settings, the simulation does not consistently rule out a zero effect of eliminating naivety, even though the average effect remains negative.

These results have two implications. First, the specific effect sizes reported in Table 1 depend on the assumed value of λ and should therefore be interpreted as illustrative simulation outcomes rather than empirical estimates. Second, the peer-use effect remains substantially larger than the naivety effect across the tested range of λ. This suggests that the relative importance of the two mechanisms is not driven solely by the baseline choice of λ. However, this conclusion remains conditional on the other parameter values and assumptions of the model.

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λ	Baseline long-run use	Remove peer-use effect (% change)	Remove peer-use effect (95% MC interval)	All sophisticated (% change)	All sophisticated (95% MC interval)
0.00	1.473	0.0%	—	−1.2%	[−2.4%, −0.3%]
0.05	1.566	−5.9%	[−6.7%, −5.2%]	−1.5%	[−2.9%, −0.4%]
0.10	1.660	−11.3%	[−12.6%, −10.0%]	−1.7%	[−3.3%, −0.4%]
0.15	1.757	−16.2%	[−17.9%, −14.5%]	−2.1%	[−3.9%, −0.5%]
0.20	1.859	−20.7%	[−23.1%, −18.6%]	−2.4%	[−4.5%, −0.3%]
0.25 a	1.967	−25.1%	[−27.5%, −22.7%]	−2.8%	[−5.1%, −0.3%]
0.30	2.084	−29.3%	[−32.3%, −26.3%]	−3.2%	[−6.7%, −0.2%]
0.40	2.338	−36.9%	[−40.9%, −33.0%]	−3.8%	[−8.5%, +1.1%]
0.50	2.621	−43.7%	[−48.1%, −39.4%]	−4.4%	[−12.8%, +4.2%]
0.60	2.947	−49.9%	[−54.8%, −44.8%]	−5.7%	[−17.4%, +6.0%]

Table 1A. Counterfactual effect sizes across different values of λ (500 paired replications per λ).

a Baseline use is reported in raw units, while counterfactual effects are expressed as percentage changes relative to each λ-specific baseline. Intervals represent 95% Monte Carlo intervals.

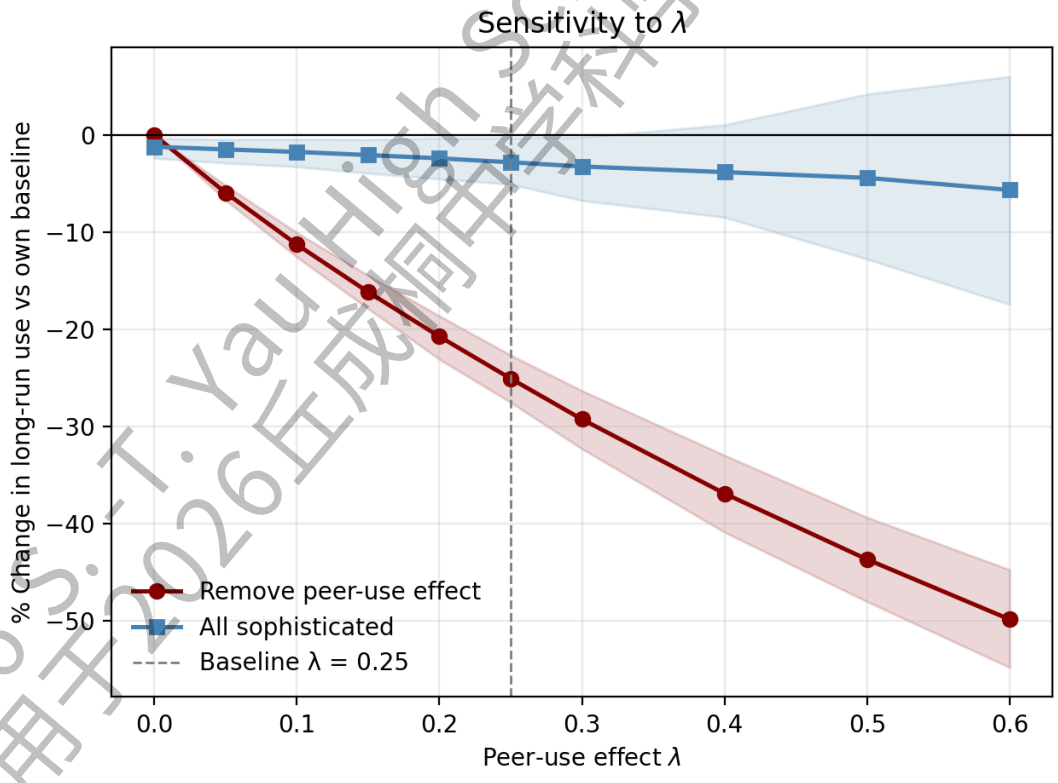


Figure 5A. Counterfactual effect sizes (%) as a function of λ

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4.4 Estimator Performance on Simulated Data

Because the true parameter values are known in the simulation, the model can also be used to evaluate estimator performance. The adoption equation is estimated using logit maximum likelihood, while the latent-use equation is estimated using pooled OLS with the regressors [1, $c_{i,t-1}$, $P_{i,t}$, $1-\beta_i$]. The robustness analysis additionally uses within fixed-effects and Anderson–Hsiao IV estimators for [ρ, λ]. The time-invariant term $\theta(1-\beta_i)$ is absorbed by the within transformation and first-differencing, so its estimate is not directly comparable across these estimators. Table 2 summarises the bias and 95% coverage across 500 replications.

Estimator	**Parameter**	**True**	**Estimate**	**Bias**	**Coverage 95%**
Logit MLE	α_0	−1.0	−1.001	−0.001	0.952
Logit MLE	α_1	−1.0	−1.016	−0.016	0.956
Logit MLE	α_2	0.8	0.790	−0.010	0.944
Logit MLE	α_3	0.15	0.153	+0.003	0.946
Pooled OLS (cluster SE)	ρ	0.6	0.367	−0.233	0.000
Pooled OLS (cluster SE)	λ	0.25	0.205	−0.045	0.824
Within FE (cluster SE)	ρ	0.6	0.242	−0.358	0.000
Within FE (cluster SE)	λ	0.25	0.240	−0.010	0.946
Anderson–Hsiao IV	ρ	0.6	0.287	−0.313	1.000

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Anderson–Hsiao IV	λ	0.25	0.283	+0.033	0.992

Table 2. Estimator performance over 500 Monte Carlo replications.

The logit estimator performs well in recovering the four adoption coefficients. The absolute bias is no larger than 0.016, while 95% coverage ranges from 0.944 for α_2 to 0.956 for α_1. The intercept α_0 also performs well, with a coverage rate of 0.952.

The latent-use equation is more difficult to estimate accurately. Pooled OLS produces substantial downward bias in ρ, with a bias of −0.23 and 0.00 coverage. The estimate of λ shows a smaller bias of −0.045, with coverage of 0.82. The within estimator produces an even larger downward bias in ρ (−0.36) and again has 0.00 coverage. The Anderson–Hsiao IV estimator, a standard instrumental-variables approach for dynamic panel data, also produces a substantial downward bias in ρ (−0.31), although its coverage is 1.00, indicating that its standard errors are relatively conservative.

The downward bias in ρ appears across all three estimators and is related to the structure of the simulated outcome. Observed smartphone use is censored by the self-control limit $\min(c_{i,t}^{*}, L_i)$ when adoption is active and is also bounded below at zero. As a result, the composite error contains a truncation component that is correlated with lagged smartphone use. Therefore, linear estimators cannot fully recover the autoregressive parameter without explicitly modelling the censoring mechanism.

In contrast, the adoption equation is estimated much more accurately. Its regressors, including N_i, $R_{i,t}$, and $c_{i,t-1}$, are predetermined relative to the adoption decision. This helps explain why the logit estimator is able to recover the adoption parameters much more successfully than the linear estimators recover the latent-use parameters.

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4.5 Sensitivity to the Naivety Effect and Network Structure

To examine whether the main findings depend on the choice of naivety effect or network structure, the simulation is repeated over a 5 × 5 grid of the naivety coefficient $\alpha_1 \in \{-2.0, -1.5, -1.0, -0.5, 0.0\}$ and the rewiring probability $p \in \{0, 0.1, 0.2, 0.5, 1.0\}$. Each cell uses 200 replications, with the network held fixed within each cell.

At the baseline rewiring probability of $p = 0.2$, stronger effects of naivety lead to higher long-run smartphone use and lower self-control adoption. When α_1 decreases from 0 to −2, long-run use increases monotonically from 1.91 to 2.02, while long-run adoption decreases from 0.40 to 0.36 (Figure 7). The same pattern is observed across the full grid: stronger naivety penalties reduce adoption and increase smartphone use.

In contrast, changing the rewiring probability has very little effect on long-run outcomes. When $\alpha_1 = -1$, long-run use changes only from 1.964 at $p = 0$ to 1.969 at $p = 1$. The heatmap in Figure 6 also shows that most of the variation comes from changes in α_1 rather than from the network rewiring probability.

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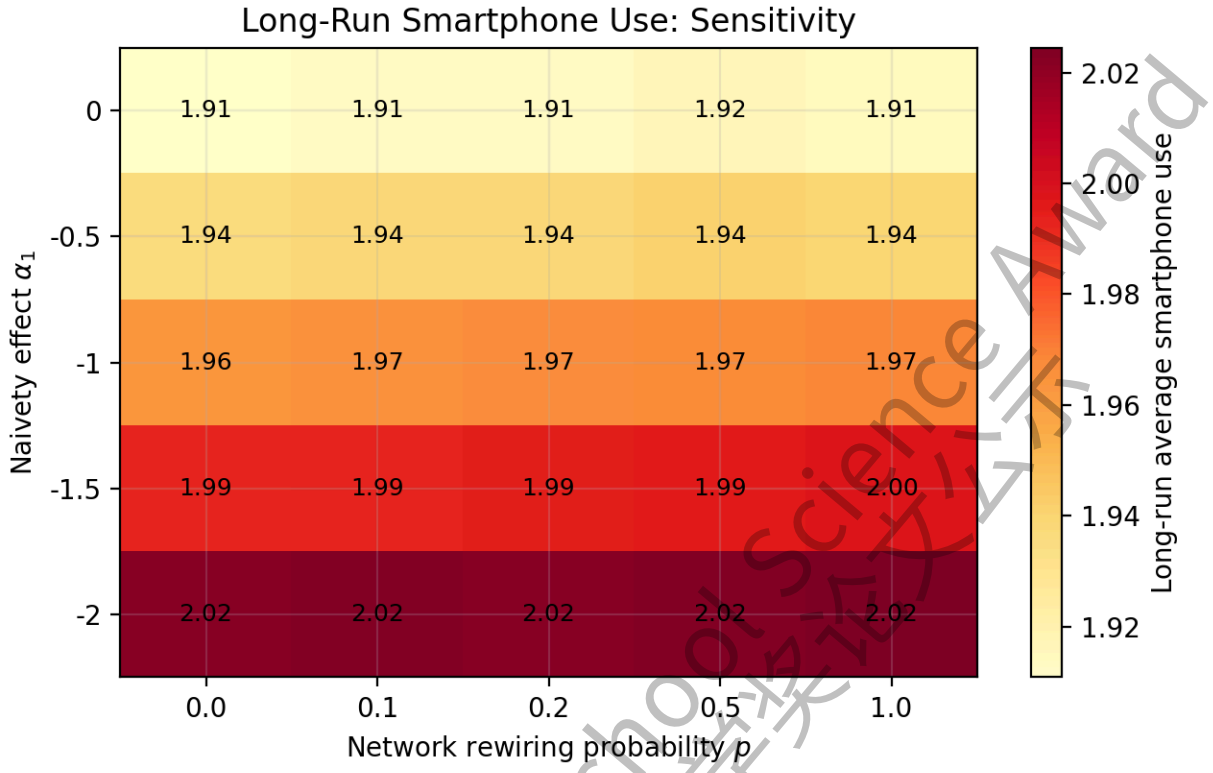
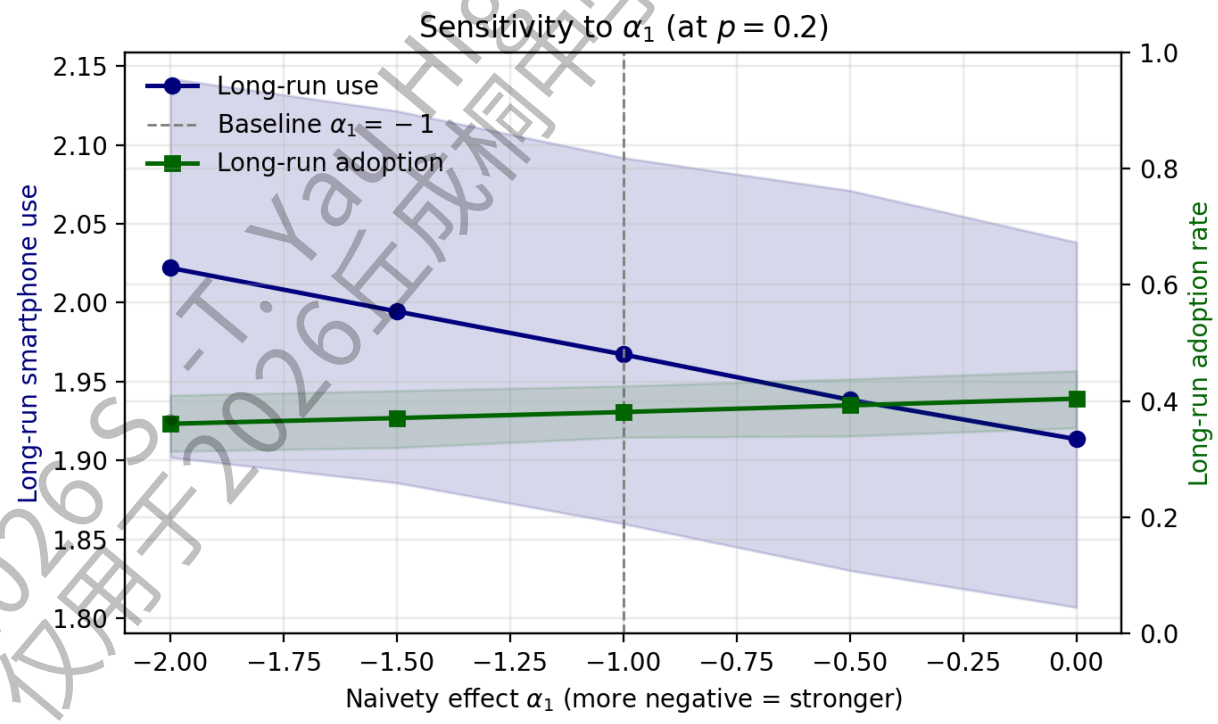


Figure 6. Long-run smartphone use across the naivety-effect and network-structure grid. Cell values represent mean long-run smartphone use from 200 Monte Carlo replications for each combination of α_1 and rewiring probability p.



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Figure 7. Long-run smartphone use and self-control adoption under different naivety effects. Results are shown at the baseline rewiring probability of p = 0.2, with 95% Monte Carlo intervals. The dashed line indicates the baseline value of $\alpha_1 = -1$.

This result suggests that the main conclusions are not strongly dependent on the specific small-world network structure used in the baseline simulation. One reason is that the network weights are row-normalised and the behavioural parameters are homogeneous. As a result, individuals are exposed to the same type of weighted-average peer environment even when the number of long-range connections changes. However, this invariance may not hold if individuals have heterogeneous behavioural parameters or if peer effects depend directly on the number of connections. These provide potential directions for future extensions of the model.

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Section 5: Conclusion

This study develops a dynamic network model to examine how peer influence, present bias, and digital self-control interact to shape problematic smartphone use. By incorporating both behavioural differences between naive and sophisticated individuals and social interactions between individuals, the model provides a framework for examining how individual decision-making and the surrounding social environment can jointly influence smartphone use.

The simulation results suggest that both naivety and peer influence affect smartphone use, but their effects differ substantially in size. Naive individuals show slightly higher long-run smartphone use and lower self-control adoption than sophisticated individuals. However, the counterfactual experiments show that removing the peer-use spillover produces a much larger reduction in long-run smartphone use than eliminating naivety. This suggests that, under the parameterisation used in the model, social exposure is a stronger driver of aggregate smartphone use than differences in individuals' awareness of their own present bias. At the same time, the results show that improving self-control adoption can still reduce use, particularly when the individual-specific self-control limit is binding.

The sensitivity analysis further supports the main findings. Stronger effects of naivety consistently lead to higher smartphone use and lower self-control adoption, while changes in the network rewiring probability have little effect on long-run outcomes. This indicates that the main conclusions are relatively robust to the specific small-world network structure used in the baseline simulation. The estimation results also highlight that while the adoption equation can recover its underlying parameters relatively well, the latent-use equation is more difficult to estimate because observed use is censored by the self-control limit and bounded at zero. An additional sensitivity analysis shows that the peer-use effect remains larger than the naivety effect across all positive values of λ tested. However, the magnitude of both effects changes with λ, reinforcing that the numerical findings are conditional on the parameterisation of the model.

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Several limitations should be considered. First, the parameter values are illustrative simulation choices rather than estimates from real-world data, so the magnitude of the simulated effects should not be interpreted as empirical estimates. Second, the model assumes homogeneous behavioural parameters and a fixed network structure within the simulations. This limits the extent to which the results can capture differences in individual behaviour or changes in social networks over time. Future research could extend the model by incorporating empirical data to estimate the behavioural parameters, and introducing greater heterogeneity across individuals, allowing network structures to evolve.

Overall, the model suggests that problematic smartphone use is not only an individual self-control problem but can also be shaped by the social environment in which decisions are made. Understanding the interaction between present bias, self-control, and peer influence may therefore provide a useful starting point for thinking about interventions that address both individual behaviour and the broader social context.

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Acknowledgements

First of all, I want to thank you, reader, for having read this part. This report explains, to the best of my understanding, the complex dynamics of problematic smartphone use.

I became interested in this topic because of my observations of the troubles in managing screen time that I, as well as many others around me, have in everyday life. The issue has sometimes become so serious that it has affected our lifestyles and health, and that is why I wanted to find a solution, or find out how well solutions work, to mitigate this problem. Throughout the research process, I became particularly interested in how peer influence, present bias, and digital self-control may interact with each other, rather than treating problematic smartphone use as the result of a single factor. This led me to develop a dynamic model in which individual behavior could change over time and be affected by both an individual's own characteristics and the behavior of people around them.

I want to express sincere gratitude to my mentor, Ms. Yizhen Wang, for her unpaid help. Ms. Wang is the economics teacher at my school, and her professional guidance really meant a lot to me throughout my research process. She was extremely supportive from the start, helping me settle on my research topic and research question; during my research process, she offered help with determining the form of the equations, and how they would work not only individually, but also as a dynamic system. In particular, her feedback helped me think more carefully about how peer influence should enter the model, how present bias should be represented in the intertemporal utility framework, and how digital self-control should affect realized smartphone use. The most memorable change in the simulation was the relationship between $c_{i,t}$ and $A_{i,t}$. After a discussion with Ms. Wang, rather than modeling $A_{i,t}$ as a factor that mechanically decreased $c_{i,t}$, I decided to model it as a constraint on the amount of use an individual can realize. This made much more sense, as adoption of digital self-control methods seldom directly and mechanically decreases an individual's screen time.

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The entirety of the research, due to my personal scheduling issues, was conducted in a short amount of time. Despite this, Ms. Wang was always open to questions and provided thoughtful and constructive answers. The research also involved reviewing existing literature on peer influence, present bias, digital self control, and problematic smartphone use, and using these ideas to build and interpret the model. The simulation allowed me to examine how changes in behaviors and assumptions, such as the degree of present bias, peer effects, and the adoption of digital self-control, could influence the dynamics of smartphone use over time. Working through these steps also helped me understand that building an economic model is not simply about putting variables and equations together, but about making sure that the assumptions and relationships represented by those equations make sense both mathematically and intuitively.

AI tools were also used during the research process, primarily for APA citation assistance and grammar correction. Due to my limited coding experience, the code for the model simulation was written by AI with specific human instructions written by myself. I was responsible for determining what the simulation should represent, what assumptions and parameters should be used, and how the results should be interpreted. During the writing process, Ms. Wang also helped me with wording, logic and the structuring of my essay.

This research was my first experience with building a dynamic economic model and conducting a simulation-based analysis. Although there are many aspects of the research that could be further developed with more time and data, the process allowed me to better understand how economic theory can be translated into a formal model and used to explore a real-world problem.

Again, I want to thank Ms. Wang for her help and support, as well as the judges for taking the time to read and evaluate my work.

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