What makes AI addictive? The role of discounting, risk aversion and self-regulation

Abstract. AI-enabled technology, with its capabilities of parsing large data sets and adaptively tuning its learning capabilities, has the potential to keep users "hooked". However, this poses a problem for child users, since their ongoing cognitive development is not adequately primed to implement self-regulation. In this paper, we evaluate the impact of technology overuse by studying its impact on limited attention resources among children. We examine the factors that make AI-enabled technology addictive for children, specifically the impact of the short-term and long-term discounting tendencies and the degree of risk-aversion prevalent among child users. Our work in this paper illustrates the unique attributes of child users of technology, and therefore calls for technology design that can enhance the user experience of children by avoiding negative outcomes associated with the over-usage and addiction of AI-enabled technology.

Keywords: Addictive AI, Future discount, Risk Aversion.

1 Introduction

The scope of technology's reach into modern childhood is broad. According to recent estimates, one in three Internet users is a child [21]. The impact of technology on our society has created increasingly seamless avenues for children to interact with technology. For example, work in [2] found that the top three most popular uses of smart speakers were for search, streaming music, and IoT device control. These applications lend themselves to be used by both children and adults, and it may be inferred that the nature of technology's interactions with children are different than those with adults. As AI technology matures, the nature of interactions with such smart applications continues to evolve. AI-powered applications continuously refine their operations by sifting through millions of queries, ratings and use cases to achieve robust interactions with the humans who use them. For example, the Pew Internet Report statistics [26] indicate that the algorithms driving YouTube's recommendations encourage users to watch progressively longer and more popular content. Additionally, a fifth of the most-recommended videos were determined by researchers to be oriented toward children.

Several reasons have been posited for technology addiction, including but not limited to the efficiency of recommendation algorithms, intuitive and seamless interface design, and low barrier to entry and participation [1]. Ongoing research into

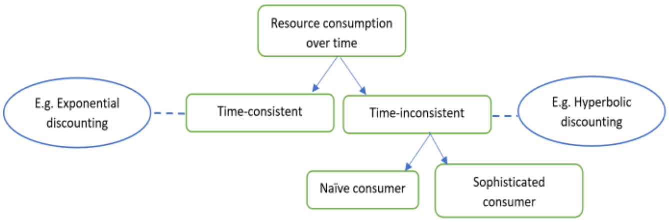

Fig. 1. Resource consumption profiles over time.

the adverse impacts of overusing Internet technologies has described the negative effects on academic work [14], as well as on social and personal performance [15]. Work in [14] described how immediate gratification afforded by social media use was a significant driver in the tendency toward developing Internet addiction. Our work in this paper seeks to quantify the impact of instant gratification and the myopic decisions that prefer short-term outcomes leading to over-usage of technology among children. In this paper, we study how self-regulation of limited attention resources, tendency to discount the future and risk-aversion impacts the decision to use technology. We propose an economic model based on discounting that studies three types of technology users: naïve users (who are unaware of their self-regulation problem), sophisticated users (who are aware of their self-regulation problem and act accordingly to maximize their utility) and time-consistent users who follow an initial disciplined plan of technology usage (see Fig. 1). We model the utility of technology usage according to an iso-elastic utility function, which has been used to study addiction and habit formation [24, 25]. Our findings indicate a clear difference between the value derived from technology usage by naïve and time-consistent users. We show that the naivete of children and their lower risk-aversion are key factors in their reduced self-regulation of limited resources. Finally, we highlight key directions for future research – explainable AI as a tool for learning with technology, regulation and accountability and the need for developing technologies that enhance the cause of ethical AI for children.

2 Related Work

Much like drugs and alcohol, Internet addiction has been studied as a clinical disorder [34]. Technology addiction has far-reaching consequences among children and adults, extending deep into their brains [9]. Neuroscientific evidence pointing to Internet addiction has shown that certain processes in the prefrontal cortex related to working memory and executive functions were reduced, similar to the outcomes in other behavioral addictions such as gambling [6]. Related research into how Internet addiction rewires structures deep in the brain and shrinks surface-level matter was described in [23]. Additional work in [8] confirmed that Internet addiction was related to impulsivity (urgency, lack of perseverance) and obsessive passion. While the vast majority of studies about Internet and technology addiction among children have been conducted from the perspective of adults, work in [31] looked at the interaction between children and technology from the perspective of children. Physical health experiences reported by children ranged from headaches, poor vision and fatigue, while mental health experiences documented included the inability to focus, adverse effects of seeing vivid imagery, aggression, and sleep problems. Although it might seem that limiting a child's access to technology might be a solution, differing guidelines on best practices can leave parents and educators at crossroads. Screen time limits, long seen as guidelines for best practices, have seen conflicting interpretations. Is an educational app excluded from screen time? Going back further, what makes an app, device or website "educational"? In [12], some children described that, in the absence of specific parental restrictions on usage, they would prefer to use the tablet "until they got tired" or "until it died".

Since modern devices are increasingly enmeshed in some kind of network, children are not able to translate the implications of their local interaction with digital technology contained in toys and other devices to a global network. Work in [5] studies exactly this conundrum, where they outline the core issues of child users – impact of digital identity on the life course of children, and data generated by child users that is analyzed by "indeterminate algorithms, for indeterminate identities". The authors also discuss how the issue of children's understanding of data persistence, tracking, and data mining is inadequate, and does not account for realistic informed consent practices.

The addiction caused from the over-usage of digital technology by children can be attributed to two broad factors. First, the design of AI-enabled technology is purposely addictive. User profiles are continuously tuned and refined to adapt to the user's activities and "reward" the user with recommendations for indulging in more of those activities, such as the endless newsfeeds, videos and notifications made available through inviting interfaces [30]. Second, children's brains work differently than adults when it comes to projecting long-term outcomes from present activity. Work in [28] studied how adolescents favor short-term outcomes in decision making. In their work, the authors described how children learn little from negative outcomes, thus advocating for the use of effective deterrents in a proactive rather than reactive learning mechanism. Since negative consequences do not serve as capable learning experiences for children, the notion of invulnerability and consequent risk-taking is higher in children. One of the key findings of their work illustrates how adolescents exhibit an optimistic bias, where they view their own risks as lesser than those of peers. Multiple factors were identified as causes of this optimistic bias, including incomplete brain maturation, as well as cognitive and developmental differences.

Our work builds upon these notions of myopic decision-making among children when it comes to interaction with AI-enabled technology, thus leading to ineffective long-term use of limited attention resources. This paper quantifies the adverse impacts of choosing the short-term outcomes of gratification from over-usage of technology by children. We use tools from economics and game theory to study how time-inconsistent behaviors by child users to study the utility of technology usage over a period of time. In the next section, we present our model for studying the behavior of child users who exhibit

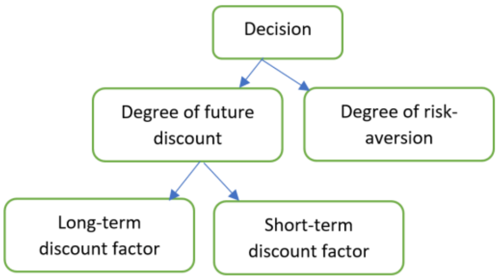

Fig. 2. Factors impacting the decision to use technology

naïve time-inconsistent behavior, and contrast it with it that of an adult who exhibits sophisticated time-inconsistent behavior or better yet, time-consistent behavior when it comes to regulating technology usage over time.

3 Model

Consider a budget of K that reflects sparse attention resources that must be allocated to a technology activity. We consider a child to be a naïve player who is unable to project the shortcomings of spending all her time and attention resources on the technology in the current instant. Consider that our consumer receives a stream of payoffs $x_1, x_2, \ldots, x_T$ over the periods $t = 1, 2, \ldots, T$, and evaluates per-period utility function as $u(x)$. We assume three time periods, which includes the current time period t_1 and the future time periods t_2 and t_3. The allocation of the total available resources K is allocated among these three time periods is denoted as x_1, x_2 and x_3, where $x_1 + x_2 + x_3 = K$. We denote the utility of consuming x_i resources during the current time period t_i as $v_i(x_i)$.

The discounted sum of future payoffs, as evaluated in period $t = 1$ is evaluated as below, where, $\delta \in (0, 1)$ is the player's discount factor, which she uses to discount future payoffs.

$$v(x_1, x_2, \ldots, x_T) = u(x_1) + \delta u(x_2) + \ldots + \delta^{T-1} u(x_T) = \sum_{t=1}^{T} \delta^{t-1} u(x_t) \quad (1)$$

Equation (1) reflects the behavior of a time-consistent player who consistently uses the value of δ to discount payoffs from future time periods. This discounting rule, also known as exponential discounting, describes consumers who will stick to their plan for future time periods. This time-consistent behavior is in contrast to hyperbolic discounting, where a player uses an additional discount factor of $\beta \in (0, 1)$ to discount all of the future compared to present consumption.

Thus, for three time periods, the discount factor between the current time period ($t = 1$) and the next period ($t = 2$) is $\beta\delta$. The discount factor for the future time periods, i.e. between time periods $t = 2$ and $t = 3$ is δ. Since $\beta\delta < \delta$, a consumer following hyperbolic discounting discounts the payoffs from future time period in a weaker form (δ) than that in the current time period ($\beta\delta$). Hyperbolic discounting leads consumers

to believe that they will follow a disciplined mode of consumption, but who will ultimately act to revise their plan of consumption. Thus, this player can be acting according to time-inconsistent behavior ($\beta < 1$), be either aware of this self-control problem, or be unaware of it. The former case where a time-inconsistent consumer is aware of her self-control problem is known as a sophisticated player ($\hat{\beta} = \beta$), and the latter case where the time-inconsistent consumer is unaware of her self-control problem is known as a naïve player ($\hat{\beta} = 1$). These factors used in our model (discount factors and risk aversion) that are involved in the decision to use technology are shown in Fig. 2.
Let $v(x)$ be the iso-elastic utility function given as follows, where $\rho < 1$.

$$v(x) = \frac{x^{1-\rho}}{1-\rho} \qquad (2)$$

Equation 2 represents the iso-elastic utility function. The iso-elastic utility function belongs to a class of functions known as Constant Relative Risk Aversion (CRRA), where the relative risk aversion of a utility function $u(x)$ is given by [3] as follows.

$$\text{Relative risk aversion} = -x\frac{u''(x)}{u'(x)} \qquad (3)$$

A CRRA function such as the iso-elastic utility function is used to model scenarios where, as the resources increase, the consumer holds the same percentage of resources in risky assets. The use of the iso-elastic CRRA utility function has been shown to explain habit formation models [7, 29]. For our three-period scenario, the consumer's hyperbolic discounted consumption problem is given by

$$\max_{x_2,x_3} v(K - x_2 - x_3,\ x_2, x_3) = \frac{(K-x_2-x_3)^{1-\rho}}{1-\rho} + \beta\delta\frac{x_2^{1-\rho}}{1-\rho} + \beta\delta^2\frac{x_3^{1-\rho}}{1-\rho} \qquad (4)$$

Thus, the optimization problem for allocation of limited attention resources (K) can be formulated as follows:

$$\max_{x_2} v_2(x_2, K_2 - x_2) = \frac{x_2^{1-\rho}}{1-\rho} + \beta\delta\frac{(K_2-x_2)^{1-\rho}}{1-\rho} \qquad (5)$$

For best response, set $\frac{dv_2}{dx_2} = 0$, and re-arranging to solve for x_2, we get

$$x_2 = \frac{K_2}{1+(\beta\delta)^{1/\rho}} \qquad (6)$$

Since allocation during the third time period is given by $x_3(K_2) = K_2 - x_2$, from equation (6), we get

$$x_3(K_2) = \frac{K_2\,(\beta\delta)^{1/\rho}}{1+(\beta\delta)^{1/\rho}} \qquad (7)$$

Backtracking to find the maximum utility during the current time period, our optimization problem is defined as

$$\max_{x_1} v_1(x_1,\ x_2, x_3) \qquad (8)$$

Substituting equations (6) and (7) into (8), we get,

$$\max_{x_1} v_1(x_1,\ x_2, x_3)\ = \frac{x_1^{1-\rho}}{1-\rho} + \frac{\beta\delta}{1-\rho}\left(\frac{K-x_1}{1+(\beta\delta)^{1/\rho}}\right)^{1-\rho} + \frac{\beta\delta^2}{1-\rho}\left(\frac{(K-x_1)(\beta\delta)^{1/\rho}}{1+(\beta\delta)^{1/\rho}}\right)^{1-\rho} \qquad (9)$$

Setting $\frac{dv_1}{dx_1} = 0$ in equation (9), and rearranging to solve for x_1, we get

$$x_1 = K\left\{1 + \frac{(\beta\delta)^{1/\rho}}{\left[1+(\beta\delta)^{1/\rho}\right]^{\frac{1-\rho}{\rho}}}\left[1 + \delta(\beta\delta)^{\frac{1-\rho}{\rho}}\right]^{\frac{1}{\rho}}\right\}^{-1} \qquad (10)$$

We assume three kinds of players – a child (fully naïve player), a sophisticated player that follows hyperbolic discounting, and a disciplined player (follows exponential discounting). For a disciplined player, exponential discounting with $\beta = 1$ results in

$$x_1 = K\left\{1 + \frac{(\delta)^{1/\rho}}{\left[1+(\delta)^{1/\rho}\right]^{\frac{1-\rho}{\rho}}}\left[1 + \delta(\delta)^{\frac{1-\rho}{\rho}}\right]^{\frac{1}{\rho}}\right\}^{-1} \qquad (11)$$

For a time-inconsistent player, replace β with $\hat{\beta}$ to denote the level of time-inconsistency in equation (15), we get

$$x_1 = K\left\{1 + \frac{\left(\hat{\beta}\delta\right)^{1/\rho}}{\left[1+\left(\hat{\beta}\delta\right)^{1/\rho}\right]^{\frac{1-\rho}{\rho}}}\left[1 + \delta\left(\hat{\beta}\delta\right)^{\frac{1-\rho}{\rho}}\right]^{\frac{1}{\rho}}\right\}^{-1} \qquad (12)$$

A sophisticated player differs from a naïve player in that $\hat{\beta}$ equals 1 for a fully naïve player, but she actually acts according to a value of $\beta < 1$. On the other hand, a sophisticated player is aware of her shortcomings when it comes to efficiently allocating sparse attention resources. Thus, $\hat{\beta} = \beta$, and $\beta < 1$ for the sophisticated time-inconsistent player. In equation (12), we denote the term (βδ)^(1/ρ) as the plasticity, P, of the limited attention resources available in any given time period. The next section presents our findings of the role of discount factors (β, δ), the degree of risk aversion (ρ), and the plasticity (P) on the utility derived from consuming limited attention resources.

4 Findings

From Fig. 3, we see that as the long-term discount β increases, the plasticity increases. Similarly, as the short-term discount, δ increases, the plasticity increases. This shows that the plasticity is directly proportional to the long-term and short-term discount factors. The increase in plasticity shows that the limited attention resources are not self-regulated – they can be spent on demand in as much quantity as required in the given time period. However, once spent, they cannot be recovered and subsequent time periods will suffer from a limited quantity of attention resources.

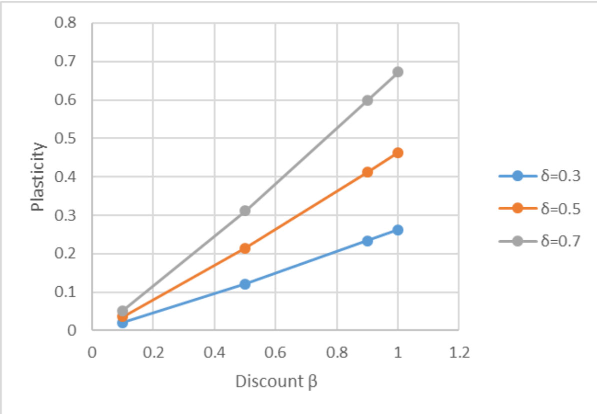

Fig. 3. Plasticity as a function of the long-term discount factor β. Higher the value of β, the higher the plasticity of limited attention resources.

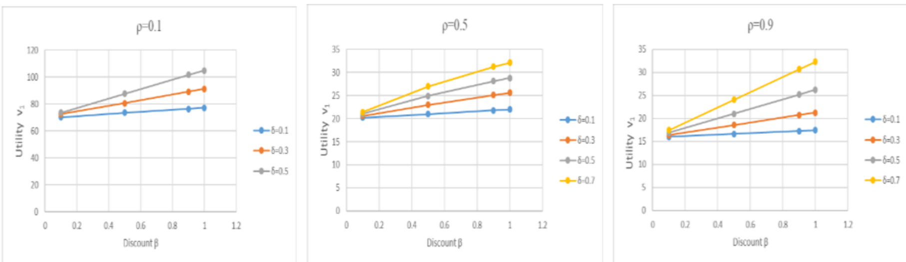

Fig. 4. The utility of consuming a resource in the current time period (v_1) as a function of the long-term discount factor β.

Moving onto the next time period, once again, the remainder of attention resources can be spent in an unregulated fashion, by consuming as much as required in that time period. The consequence of this direct relationship between the discount factors and the plasticity P is that fewer and fewer resources are available for consumption during subsequent time periods. The resulting impact on the consumer (whether naïve, sophisticated or disciplined) is that the utility of the resource decreases in subsequent time periods, which is a prime factor in addiction. Poor self-regulation causes the consumer to consume more and more of a scarce resource without thought for the future [4, 11].

We also see that as ρ increases, the plasticity P decreases. The plasticity is related to the amount of self-regulation of attention resources over current and future time periods. Here, ρ denotes the degree of relative risk aversion in the utility function. As ρ increases, it denotes a higher risk-averse consumer whose profile becomes increasingly cautious of the consumption and therefore seeks to regulate it. Thus, the inversely proportional relationship between ρ and the plasticity P offers insights into the behavior of a naïve consumer (child) and contrasts it with increasing abilities for regulation such as those found in sophisticated consumers or time-consistent consumers.

Fig. 4 shows the utility during the current time period, v_1, as a function of the long-term discount factor β. Consistent with the findings in Fig. 3 above, we see that an increase in β leads to an increase in the utility obtained by a consumer in the current time period, which ultimately leads to lower resources available for future time periods. Similarly, with an increase in δ, the utility of resource consumption during the current time period increases resulting in fewer available resources for the future. Also, as ρ increases, the utility decreases in the current time period signifying the higher risk aversion behavior exhibited with sophisticated and time-consistent consumers.

5 Discussion

The decision to devote limited attention resources to a certain task is a consequence of several factors. In this work, we studied how short-term and long-term discount factors, as well as the degree of risk aversion contributes to the plasticity of self-regulation of expending limited attention resources and the corresponding utility derived from the spending of these resources on AI-enabled technologies. We found that, children who typically exhibit behavior similar to that of naïve consumers, discount the future heavily in favor of the present time period, which leads to increased spending of attention on the AI technology in the current time period leaving fewer attention resources for the future. Naïve users are unaware of their time-inconsistent behavior, and their lower risk-aversion tendencies translate into addictive behaviors toward technology. In contrast, sophisticated consumers – perhaps, a child or adult with higher self-regulation capabilities – still exhibits time-inconsistent behavior, but is aware of their self-control issues. Thus, a sophisticated consumer will regulate her own future behavior in order to derive higher value from their patterns of resource consumption. On the other hand, a time-consistent consumer follows a planned course of attention expenditure corresponding to a discount factor. As the discount factor increases, more of the resources are consumed in the initial time period. When the future is completely discounted, all of the resources are consumed during the current time period.

Our work classifies children as naïve users, although, adults exhibiting limited self-control could also be classified as naïve users. The reverse is also true – some children might exhibit greater awareness of their time-inconsistent behavior and therefore behave as sophisticated consumers or time-consistent consumers do with limited resources. One example of this is the Stanford marshmallow experiment [22] which suggested that children who exhibited delayed self-gratification were more capable of success in later life. This suggests that self-regulation is not entirely the domain of a certain age group, but rather is a combination of internal traits and environmental stimuli [33]. While both time-consistent and time-inconsistent users are faced with the task of self-regulation of technology consumption, the difficulty of accomplishing this over a period of time is compounded by the addictive nature of the AI-enabled technology itself.

While a sophisticated or time-consistent consumer might be able to withstand the temptation to watch another video or play the game one more time, a naïve user might find it challenging to do so [32]. The phrase "technologization of childhood" first made popular in [27] studied technology usage of children within the home, and found that parents were getting more and more comfortable with their children's increasing competence with the technology. Parents reported feeling conflicted over regulating their children's usage, and not being able to discern the right balance of technology usage. This raises important questions about the nature of regulation. Should prevalent screen time guidelines contain warnings about the impact of over-usage by children? Should the developers of technology create auto-shut off features that detect an age-appropriate user and limit activity? If this is true, it raises concerns about technology overreach leading to issues in privacy, surveillance, censorship and ultimately user freedoms. Additionally, the role of algorithmic biases cannot be overlooked. The development of technology that implements an auto-shutoff feature based on computed thresholds may be impacted by biases, errors and malfunction. Children are especially vulnerable to the adverse impacts of these effects. Proponents of early digital literacy would argue that since humans live in a networked world populated by devices, introduction to technologies should begin in childhood to ensure competence and fluency. Thus, the ethics of the relationship of children's interaction with the burgeoning AI-enabled technology in their environment is a nuanced one, whose urgency is pressing with the arrival of every new technological artifact.

5.1 Limitations

Our model for studying the behavior of naïve (child users) versus sophisticated users, or time-consistent users showed that plasticity, or the self-regulation of limited attention resources depends on the short-term and long-term discount factors as well as the degree of risk aversion. Consequently, the utility of consumers over time varied as a function of the attention resources available to them, especially for the naïve consumers. Some limitations of our work concerning the modeling of resources, the utility function, and plasticity are described below.

First, while the CRRA utility function used in our model has been widely used to model short-term choices over long-term benefits, further research into the use of other classes of functions such as increasing/decreasing absolute risk aversion (IARA/DARA) might reveal insights into the behaviors of various kinds of users. Our model could then be enhanced to study various levels of naivete, to study increasing levels of sophistication in planning and self-regulation of limited attention resources.

Second, our paper studied the allotment of limited attention resources to be allocated over a period of time. However, in practice, children live in environments with a range of spatio-temporal resources. For example, the introduction of a sport, hobby or friends might serve to reduce the time spent with a technology. Similarly, life events, seasonal patterns and broad socio-economic-political factors dictate the different environments of children around the world. Further research will help to determine the true impact of addictive technology on child behavior. For example, long-term comparisons of brain structures of children in environments not exposed to technology versus those heavily exposed to technology will shed light into how technology has altered child behavior.

Lastly, we modeled the plasticity of resource allocation as a function of the risk aversion and discount factors. However, other forms of plasticity might be defined. For example, if the resources are chosen as a combination of attention, working memory and other higher-order executive functions, plasticity of these resources would have to be incorporated into the models presented in this paper.

5.2 Future Work

Although our work has focused on the discounting and risk aversion inherent in the behavior of naïve users, our model can be extended to study how addictive technology can be improved by incorporating explainability, regulation and accountability in developing AI technologies for children. We present some directions below.

Explainable AI as a teaching tool: Our model can be extended to understanding how children learn with humans versus with technology, over a period of time. The discounting and risk aversion factors could be used to study varying levels of naivete. Additionally, since AI-driven technology is capable of learning and improving, discounting and risk-aversion can be applied to the technology as well creating a multi-dimensional model of smart agents and humans with varying levels of discounting and risk aversion. This points to the role of explainable AI not just as a tool for justifying decision-making, but also as a tool for extending the learning paradigm from being technology-assisted to being one that is technology-initiated.

Role of regulation and accountability in ethical AI development: Research over the past three decades has increasingly pointed to the asymmetry of scale inherent in technology. The power of vast networks at our fingertips has far-reaching consequences for information dissemination. Network effects disproportionately affect children, as they are faced with content in apps, social networking sites, and websites for which they might not be developmentally ready. Effective regulation and accountability measures can help to develop significant interventions for the use of technology as a positive force in children's lives.

Distributive justice in technology usage: Although AI technologies heavily influence our lives, the notion of fair resource allocation through technology has not received much attention. Distributive justice, which is defined broadly as fair allocation of resources [18], has heavily influenced work in multiple domains including copyright law [13], environmental law [17], and economic policy [16]. By developing AI algorithms that adapt to children, we can unlock the potential for AI technology to be sensitive to individual differences in variety of children's environments [10, 15]. Future work in this area will require ethical AI frameworks for collocated spaces of adults, children, bots and IoT devices in pervasive networks and will need to address key challenges that result as a consequence of unchecked AI prowess and their impact on children.

6 Conclusions

Choosing consumption of limited attention resources over time is daunting. Discounting the future is one of the reasons that consumption during the current time period seems more appealing than consumption in the future. In this paper, we studied how the consumption of limited attention resources over a period of time is a function of the amount of short-term and long-term discounting as well as the degree of risk-aversion. Characterizing children as naïve users of technology, we showed how limited attention resources would be quickly depleted in the face of low risk aversion and extreme discounting. On the other hand, more disciplined and thoughtful users could mitigate some of the effects of lack of self-regulation and myopic over-consumption in the current time period. The problem of designing technologies that do not encourage discounting the future among child users and consequent addiction is a pressing one due to their ongoing cognitive development. The consequent implications of technology design for children are of increasing importance, where children are inheriting environments embedded with AI-enabled technology of various kinds.

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