Technological Tribulations: How Does User Interface and Advertising Lead Towards Addiction?

PSY338

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Introduction

According to a report published by the marketing agency We Are Social and social media management firm Hootsuite, people ages 16 to 64 use the internet for 6 hours and 58 minutes a day on average (Kemp, 2022). Because digital devices and the internet provide us easy and quick access to information, this instant gratification can lead to dependency and addiction regarding electronics. Given this behavior, companies can take advantage of user interface and advertising strategies to engage consumers to purchase more items and/or spend more time on websites and applications.

Our paper seeks to explore the underlying mechanisms of digital interfaces and how they impact brain activity and behavior, leading consumers to spend more time and money while interacting with platforms such as web pages, mobile apps and social media. With an increasingly digital everyday life, we tend to seek out more of our daily rewards, including shopping, entertainment, and social interactions, through digital platforms like our phones. But how is our brain actually involved in internet addiction? What is it specifically that draws us to repeated usage and interactions with different websites and apps? And can compulsive app or website interactions be explained through a model of addiction? We will briefly answer the first question with an overview of the brain, and then we will explore the second question primarily through personality-based models and the third through computational models of addiction involving drugs and learning systems. See **Appendix** for a walkthrough example of how the two types of models can be applied in a real life scenario.

Throughout the paper, we will see evidence indicating that obsessive and compulsive interactions with digital interfaces appear to show certain symptoms that align with substance addiction. However, other properties of substance addiction might be difficult to match, even for the most sophisticated digital interfaces and their most excessive users.

The Brain and Addiction

We will begin by briefly exploring the parts of the brain regions involved in addiction. One area of the brain that may implicate much of control and decision making regarding internet addiction is the prefrontal cortex, which is part of the cerebral cortex and covers the frontal lobe. The prefrontal cortex plays a role in planning cognitive behavior, personality and social behavior, and decision making. As reviewed by Brand, Young, and Laier (2014), Internet-related cues may interfere with these control processes performed by the prefrontal cortex, impacting working memory and other executive functions. Thus, a reduction of prefrontal control processes can lead to the development of Internet addiction.

Another important part of the brain that plays a role in addictive behavior is the basal ganglia, a set of nuclei in the brain that are heavily influenced by dopamine, a neuromodulator generated in the midbrain. Dopaminergic projections from the ventral tegmental area (VTA) to the the nucleus accumbens (NAc) in the ventral striatum have major implications for how signaling from the cortex, including the prefrontal cortex, influence downstream projections from the NAc to other regions (such as the prefrontal cortex). This rather complicated feedback loop between cortex and NAc, modulated by dopamine, is important for the way in which we learn about rewards and punishments in the environment, as increased dopamine levels signal unexpected rewards. The impact it has on the cortex, including the prefrontal cortex, might alter the ways in which we process stimuli such as digital interfaces. The models explored in this paper focus heavily on the effects of these regions of the brain and dopamine specifically, since dopamine has a quite substantial influence on addictive behavior.

Personality-Based Model

Now, to answer our second question about what it is specifically that draws us to repeated usage and interactions with different websites and apps, we will review two personality-based models describing internet and cell phone addiction by De-Sola Gutiérrez, Rodríguez de Fonseca, and Rubio (2016) and Billieux et al. (2015). De-Sola Gutiérrez, Rodríguez de Fonseca, and Rubio (2016) review a breadth of studies that have been previously conducted on cell phone addiction. In the review, the authors look at how the five-factor model, which uses extraversion, openness, conscientiousness, agreeableness, and neuroticism as five dimensions of measuring a person's personality, has been applied to cell phones. In general, phone addiction related to sending text messages is associated with high extraversion and low self-esteem, while phone addiction related to social media is associated with high extraversion as well as high neuroticism. Additionally, excessive phone use was generally negatively correlated with conscientiousness, agreeableness, and openness.

A different paper, Billieux et al. (2015), examines phone addiction through a pathway-based personality model. In his paper, he identifies three main pathways: the excessive reassurance pathway, the impulsive-antisocial pathway, and the extraversion pathway. In the excessive reassurance pathway, risk factors such as low self-esteem and high neuroticism can lead an individual to call and message others excessively, resulting in an addictive pattern of phone use and SMS dependency. In the impulsive-antisocial pathway, poor impulse control can result in antisocial patterns of phone use like cyberbullying, phone use in inappropriate contexts, and excessive video gaming/gambling. Finally, in the extraversion pathway, a constant desire to socialize with others or build new relationships can result in an individual excessively relying on social media and messaging apps to stay connected to other and can also lead to risky patterns of phone use such as texting while driving.

Comparing substance use disorders (SUD), one of the most extensively studied forms of addiction, with phone addiction, there seems to be a lot of overlap between the personality types of people who are more predisposed to drug addiction and technology addiction. In a large meta-analysis by Kotov et al. (2010), people with SUDs tended to show high levels of neuroticism and low levels of conscientiousness, similar to the findings by De-Sola Gutierrez et al. (2016). Additionally, Kotov et al. (2010) found that SUD was correlated with lower levels of agreeableness, another trend that was found by De-Sola Gutierrez et al. (2016) for people showing higher levels of compulsive phone usage.

These two different personality-based models of phone addiction highlight ways in which an individual's personality can influence not only their likelihood of phone addiction but also affect the ways that phone addiction manifests itself. The personality trends for people with SUDs show that there is quite substantial overlap between the personalities of those who develop substance addiction and those who develop phone addiction. This overlap may indicate that compulsive phone and internet usage could similarly be explained through the lens of an addiction model.

Computational-Based Model

As the personality models focus on personality aspects that make some of us more susceptible towards technology addiction, we now turn towards two computational models to answer our third question of whether compulsive online interactions can be explained through a model of addiction. First, we will look at an addiction model involving drugs and learning systems and show how technology addiction can be modeled similarly to these drug addiction models. Then, we will discuss user interface and advertising from the company side and present the computational models behind their advertising techniques.

Computational Addiction Model

Drug addiction may utilize the same pathways as natural learning systems. As such, current models using temporal-difference reinforcement learning (TDRL) can also be applied to addiction models. In a TDRL model, dopamine drives a reward-error signal, which is intended to be minimized. In addiction models, we can add a drug- (or in our case, technology-) induced dopamine increase and so actions that lead to receiving drugs/technology are overcompensated.

In Redish (2004), the transient increase in dopamine from addictive drugs was modeled by assuming that the drugs induce an increase in achieved to expected reward independently of the change in the value function. As a result, the agent is unable to learn a value function that cancels out with the increase in dopamine reward. The equations that represent this addiction temporal-difference reinforcement learning model are as follows:

$$\delta = max\left\{ y^{d}[R(S_{t}) + V(S_{t})] - V(S_{k}) + D(S_{t}),\ D(S_{t}) \right\}$$

$$V(S_{k}) \leftarrow V(S_{k}) + \eta_{V}\delta$$

where $R(S_t)$ is the reward at state S_t (where time = t), γ^{d} indicates raising the discounting factor by the delay d, and η is the learning rate. If $D(S_t) = 0$, then this model returns to the original temporal difference reinforcement learning model. Connecting this model to technology usage, dopaminergic reward from using technology can also be modeled through this type of TDRL model. One small change from the model that Redish proposed is that continuous interaction with a specific aspect of a digital interface may not bring ever-increasing dopaminergic activity, potentially because the “pull” of technology addiction may not be as strong as that from an illegal drug. Future work can define what constitutes addiction level and furthermore, what characterizes socially acceptable addictions.

Personalized Advertising Computational Techniques

As technology continues to improve, the marketing and advertising domain becomes more interconnected with strategies such as artificial intelligence, semantic web, and machine learning techniques. Industries rely on the personal and contextual knowledge of a user to determine the best time and place for advertisements. With more streamlined and personalized systems, customers are more likely to increase their click-through rate and build interactive relationships between consumer and business.

There are two main models that advertisers follow to better understand their customers and increase their ad personalization. The first and most popular category includes user context models, which use factors about an individual, such as age, gender, device location, and device type to predict one's click through rate in a collection of advertisements. The first step for this process is to collect useful information to be utilized as inputs in the model. Next, computational techniques are applied to rank the advertisements for each individual. Some common methods include classification (Bayes, logistic regression, support vector machines, factorization-based models), clustering (k-means, fuzzy clustering), filtering techniques for ranking (matrix factorization, principal component analysis), and neural networks (deep Boltzmann machines, deep reinforcement learning). These methods clean the data, help locate patterns, and fit the data to advertisements to determine the best choice to be shown to the user.

The second type of model uses content-based analysis and text-mining. The first step is similar to the user context model where data about the user is obtained. However, rather than using factual statistics about the user, this method extracts textual information from a webpage, mobile application, or video to better understand the user profile. From the candidate advertisements, keywords are extracted, and the most suitable advertisement is chosen from profile/keyword matching. To extract these entities, natural language processing is a widely used technique. To match profiles and keywords, the aforementioned methods such as classification, clustering, and neural networks can be used to conduct sentiment analysis, aspect mining, topic modeling, or even message generation, and distance functions and weight-based algorithms can be utilized for keyword matching (Viktoratos and Tsadiras, 2021).

Conclusion

The present paper considers the possibility of viewing compulsive phone and technology interactions through the lens of an addiction model. Some evidence, particularly the overlapping personality types of those who develop addictive substance use disorders and those who develop phone addictions, points in the direction that one might label obsessive technology users as addicts. However, unlike Redish's computational model, the presence of an ever-existing increase in dopaminergic activity when consuming the addictive substance (e.g., cocaine) is not present when interacting with a particular aspect of a digital interface. Thus, we will need to further explore whether obsessive technology usage and screen addiction can perfectly fit into an already existing addiction model. However, given what we know about tailored content and targeted advertising, a possibility is that "personalized algorithms" in our technology deliver content that is so in line with our ever-changing preferences that the result is a constant ability to deliver dopamine increase at the onset of the stimulus itself. Of course, this process relies on highly efficient algorithms, and while the evidence laid out in this paper suggests that these algorithms in fact are very good at finding content that we as consumers/users find rewarding, it may be too much to say that personalized content makes our phones like cocaine. As an alternative, the cognitive processes behind technology might work like cocaine with fluctuating potencies, giving pseudo drug-of-abuse-like properties.

Contributions

Each author focused on one section, with Jonas writing the introduction and conclusion, Chloe writing the personality-based model section, and Allison writing the computational model section and appendix. Furthermore, Allison edited the paper and added parts to the introduction. She also added transitions and worked on increasing paper clarity based on the helpful feedback from Rachel Bedder & Yael Niv, co-editors of *The Journal of Learning about Learning*.

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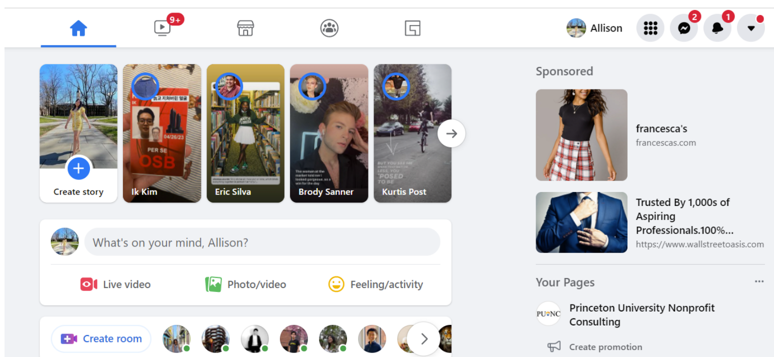
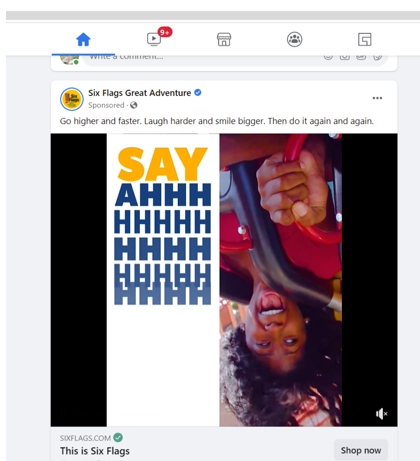
Appendix

In this case study, we will focus on Facebook, a social networking site with almost 3 billion active users as of February 2022. Facebook serves as a popular social media site where users can “friend” others and post both on their own feeds and on their friends’ feeds. Posts include text, pictures, videos, and even links to other posts or websites. Additionally, Facebook charges companies and brands for advertising on their platform. With such a large amount of users on Facebook, it makes sense for companies to want to promote their products there. However, advertising can be costly for the consumer with an average cost of per click of $1.72 across all industries. The amount advertisers are willing to pay truly exemplifies how valuable it is to use Facebook for advertising.





Examples of Ads on Facebook. They appear both on the side of the feed (shown on top) and also when you scroll down the feed (shown on bottom).

First, we will look at how personality-based models can affect advertising and perception of advertisements from consumers. On the advertising side, advertisers can take advantage of the three pathways as described in Billieux et al. (2015) to directly reach consumers. For the excessive reassurance pathway, Facebook ads can target insecurities like low self-esteem and a need to belong in a group. This can be done so by the strategic placement of ads of social events near friends' posts that depict large groups of people, capitalizing on "FOMO" or the fear of missing out. In the impulsive-antisocial pathway, advertisements that fit into these categories, such as video games and gambling sites or casinos can play to their target consumers. Finally, the extraversion pathway, which works with people who constantly use their phones to stay connected, may have advertisement methods that bombard users with information or are personalized to the user, keeping the user entertained with constant social communication. Of course, the ethicality of these practices is to be debated, but these methods are potentially impactful for advertisers to gain traction and profit.

Moving onto the computational models, an area for future research is to take one compulsive action on Facebook, such as scrolling or clicking, and model that action in a TDRL model such as that from Redish (2004). Each action can be assumed to produce a dopaminergic release, and through collected data that shows the frequency of the specific action over a course of different browsing periods, we can see if we also arise with a computational model that overselects actions that lead towards more "addictive" Facebook browsing.

Behind the scenes, Facebook developers definitely use many of the techniques as described in the "Personalized Advertising Computational Techniques" section. Facebook even clearly admits that they use machine learning to deliver personalized ads. Please see https://www.facebook.com/business/news/good-questions-real-answers-how-does-facebook-use-machine-learning-to-deliver-ads for Facebook's strategy.