Technology Agency on Usage: Grounded Theory and Measurement of Technology Induced Usage Behavior

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Abstract

Most of today's software applications involve a dyadic interplay between human and technology agency. The use of algorithms driven by user can alter users' interaction patterns by affording them novel and relevant technology action possibilities. I argue that algorithmic activities and features embedded in apps can keep users on IT applications (apps) for longer periods of time. I refer to the behavior of interacting with the apps for longer time than planned as technology-induced excessive use. While practitioners are beginning to recognize characteristics of technology-induced excessive use, research on this topic is very limited. I used a multimethod approach to study this phenomenon in three essays. In the first essay, 107 technology users were interviewed, and a (qualitative) grounded theory technique was used to comprehend technology-induced excessive use behavior. The analysis of interview data revealed participants spent longer time with a technology are "hooked" on the technology. The qualitative data also allowed us to develop a variance model identifying the causes and consequences of "hooked" state, as well as a process model describing the progression of hooked from the initial use of technology. In the second essay, I conducted two surveys to validate the model of hooked. The results support various hypotheses how users become "hooked" due to the dynamic interaction between human and technology agencies. Following the ten-step method proposed by MacKenzie et al.(2011), in the third essay, I conceptualized and developed a measurement instrument for technology-induced use, a new usage construct that incorporates the agency of technology in usage and its predictive validity. Taken together, this dissertation presents a theoretical foundation for an emerging phenomenon, introduces a new usage construct, and guides future research on the role of technology in inducing usage.

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I. Introduction and Chapter Overview

Since the introduction of the iPhone in 2007, the widespread use of apps has increased exponentially (Molla, 2017). From communication to task management, learning, gaming, even monitoring one's own physical and relationship health, apps have revolutionized the daily routine (Yang, 2013; Lee, 2018; Ohk, Park, & Hong, 2015). Enhancing the agency of apps even further is the recent incorporation of artificial intelligence, machine learning, and application programming interfaces (APIs) in their development (Spohrer, Fallon, Hoehle, & Heinzl, 2021).

As a result of the increasing pervasiveness and autonomy of apps, young people are now spending a significant amount of time on them (Hart, 2022). A recent survey by Buildfire in 2022 shows that 21 percent of millennials open an app more than 50 times a day (Buildfire 2022). In addition, a recent survey on app usage indicates that, on average, American adolescents spend at least nine hours and forty-nine minutes daily on an app (Jacob 2019).

The phenomenon of significant "dwell time" on apps has garnered considerable attention from academics and technology practitioners as they seek to define and trace its origin. Some academics refer to this phenomenon as *excessive technology use* and assert that users' distorted cognition and addictive tendencies are the root causes of excessive use of technology (Cao, Masood, Luqman, & Ali, 2018). Technology practitioners present a different approach, arguing that t*echnology agency* is primarily responsible for users' excessive dwell time (Eyal, 2014).

Given the lack of consensus in the academic literature on what is excessive technology use, what constitutes excessive technology, and what is the influence of technology agency upon these matters, we require a firmer theorization to better comprehend the phenomenon. This dissertation conducts three essays to do so, both for academics and practitioners. Figure 1 illustrates the overall structure of the dissertation.

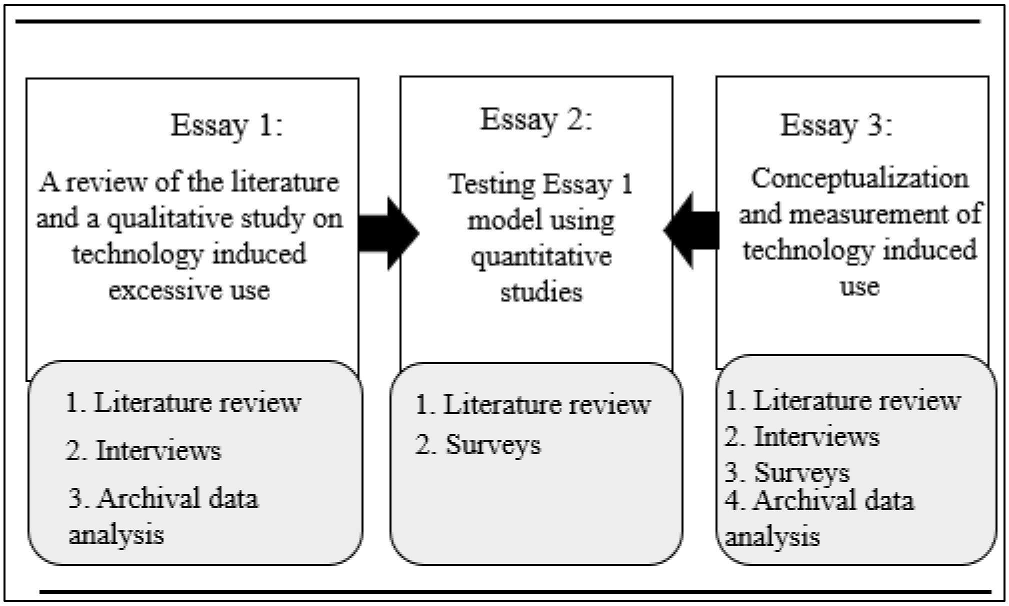


Figure I.1: Overall structure of three essays

The first essay describes the nature and causes of excessive technology use from the practitioner's perspective. Emphasizing the role of technology features in inducing excessive use, I define the term "technology-induced excessive use" to interrogate the role of technology in driving excessive dwell time. A review of literature reveals that technology-induced excessive use differs from existing usage constructs in three chief respects: the agency of technology, the dynamics of usage, and the user experience. As academic literature lacks a concept that may explain technology-induced excessive use, the first essay utilizes a grounded theory method (GTM) to investigate this phenomenon in depth. GTM uncovered that some users perceive that they are constantly induced by technology and reach a point when they use more than they plan. I refer to this state as "hooked" and define it as a technology usage state characterized by users' use of technology longer than they plan. Investigation reveals that users become "stuck" not only due to the agency of technology but by the dynamic interplay between app agency and the agency of the user, as the app induces a positive emotional-cognitive appeal and the fear of missing out (FOMO). Broadening the practitioner's view of excessive use, then, I propose a model of hooked state that incorporates the role of technological agency, human agency, and "stickiness." A process model derived from GTM indicates that technology constantly learns through usage data and reinforces user agency. The process model also demonstrates that users go through the exploration and adoption state before reaching to "hooked" state. Essay 1 contributes a new theorization of excessive technology use and proposes a new construct, "hooked," to represent this phenomenon.

The second essay of this dissertation quantifies the new theorization. Through two surveys testing the validity of the model, I find that, indeed, technology agency and human agency reinforce one another. Results show that positive emotional appeal, cognitive appeal, and the fear of missing out significantly mediate the relationship between technology agency, human agency, and the hooked state. I conclude that the research model proposed in essay 1 has substantial validity.

The third essay focuses on developing measurement instruments for dynamic interaction between technology agency and human agency. Scholars and practitioners both emphasize the need for a new usage construct that can depict the entanglement between technological agency and use. This new construct not only fills the gap in past literature but also challenges the assumption that user intentions, attitudes, and beliefs are the sole drivers for usage. A new conceptualization, "technology-induced use," captures the dynamic interaction between human agency and technology agency. I define technology-induced use as an individual's use of technology to fulfill her situational and innate needs, primarily stimulated by technology triggers. By adopting Mackenzie et al.'s (2011) method of *construct measurement development*, I propose two measurement instruments for technology-induced use and validate the instruments through four surveys.

The findings of the three chapters highlight two important points. First, research on excessive technology use has mainly considered the user's personality traits and addictive tendencies. I argue that these findings provide an incomplete picture of the nature and causes of excessive technology use. Instead, I propose that excessive technology use occurs due to the dynamic interplay between technological and human agencies. My research lends a new perspective of agency to the study of excessive technology use. Second, previous research considers excessive use to be driven by the user's own intentions, beliefs, and attitudes. In a world with increasingly autonomous apps, I highlight the enmeshment of usage with technology agency in proposing a new construct: "technology-induced use," that underscores the increasing role of technological features in triggering overuse.

Together, this research offers a unique theorization which is robust enough to direct future inquiry into the vital dialogue between technological and human agency as the boundaries between the real and virtual worlds increasingly dissolve.

Overview References

Blair, I. (2022). Mobile App Download Statistics & Usage Statistics. Buildfire, 2022. Available at https://buildfire.com/app-statistics/#:~:text=21%25%20of%20Millennials%20open%20an,and%2030%20apps%20each%20month

Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. *Computers in human behavior, 85*, 163-174.

Eyal, N. (2014). *Hooked: How to build habit-forming products*: Penguin.

Hart, R. (2022). Record 3.8 Trillion Hours Spent On Mobile Apps During 2021 In Another Blockbuster Year For Digital Economy. Forbes, Jan 12, 2022. Available at https://www.forbes.com/sites/roberthart/2022/01/12/record-38-trillion-hours-spent-on-mobile-apps-during-2021-in-another-blockbuster-year-for-digital-economy/?sh=51a807ea2a42

Jacobo, J. (2019). Teens spend more than 7 hours on screens for entertainment a day: Report, ABC News, October 29, 2019. Available at https://abcnews.go.com/US/teens-spend-hours-screens-entertainment-day-report/story?id=66607555

Lee, S. A. (2018). Enhancing customers' continued mobile app use in the service industry. *Journal of Services Marketing*.

Molla, R. (2017). How Apple's iPhone changed the world: 10 years in 10 charts. Vox, June 26, 2017. Available at https://www.vox.com/2017/6/26/15821652/iphone-apple-10-year-anniversary-launch-mobile-stats-smart-phone-steve-jobs

Ohk, K., Park, S.-B., & Hong, J.-W. (2015). The influence of perceived usefulness, perceived ease of use, interactivity, and ease of navigation on satisfaction in mobile application. *Advanced Science and Technology Letters, 84*(2015), 88-92.

Spohrer, K., Fallon, M., Hoehle, H., & Heinzl, A. (2021). Designing effective mobile health apps: does combining behavior change techniques really create synergies? *Journal of Management Information Systems, 38*(2), 517-545.

Yang, H. C. (2013). Bon Appétit for apps: young American consumers' acceptance of mobile applications. *Journal of Computer Information Systems, 53*(3), 85-96.

II. Essay 1:The Grounded Theory of Technology-induced Excessive Use

Introduction

Arguably, we are witnessing a new technology usage phenomenon in our society: Many individuals are so engrossed in using apps that they spend a significant amount of time on those apps (Molla, 2020). A recent survey from RescueTime revealed that nine out of ten people do not feel in control of their time spent on apps and use apps mindlessly (MacKay, 2018).

Such a usage phenomenon has gained the attention of IS scholars. IS Scholars refer to this uncontrolled use of apps as excessive use of technology. Primarily, the excessive use phenomenon is described as pathological behavior due to its association with various negative symptoms, such as burnout, exhaustion, and conflict (Turel & Ferguson, 2021). Turel and Ferguson (2021) defined excessive use as “a use pattern that is excessive in that it infringes on the normal functioning of users” (Turel & Ferguson, 2021). Some scholars define excessive use as a “neutral” phenomenon by emphasizing that it is rational behavior (Kwon, So, Han, & Oh, 2016). According to them, excessive use of technology does not manifest negative symptoms, except that excessive technology users cannot monitor usage time (Lee, Cheung, & Chan, 2014; Zheng & Lee, 2016). In my research, I choose the latter viewpoint, which views excessive use as a neutral phenomenon and defines it as the degree to which a user's usage duration exceeds her anticipated usage time.

Reflecting on “excessive use,” some technology practitioners and bloggers say that many apps are deliberately designed to encourage app use for extended durations and repeat use (Eyal, 2014). According to them, these apps are intended to act independently and autonomously with users (Alter, 2017). By lowering user’s self-regulation, these apps can exploit decision-making capacity and can manipulate attention (Alter, 2017). For example, in the social media app context, Nir Eyal compares social media apps with slot machines and mentions, *"Just like pulling on a slot machine, scrolling through social media sites uses the exact psychology that keeps use checking"* (Eyal, 2014).

I illustrate the agency of apps in influencing use in a vignette, which I have adapted from Nir Eryl (2014):

"One day, Brooklyn, an infrequent TikTok app user, came across a video of cooking in TikTok's feed. The videos were posted by a friend of hers. She was enthralled by the video and then discovered a number of other videos that TikTok recommended based on her interest. While examining these videos, numerous additional TikTok features caught her attention, such as live cooking streaming, music related to cooking, celebrity cooking shows, duet option, and so on. She began regularly returning to the TikTok app with no clear plan for what she would do. Different features kept her in the TikTok app, looking for new cooking ideas. At some point, before figuring out what she would do in the app, she found that she may have spent an hour on TikTok."

The anecdote highlights that Brooklyn abruptly begins to spend more time on TikTok, primarily due to TikTok's algorithm and feature sets. Many apps, such as TikTok, offer constantly varied experiences that immerse users in the contents (Siebert, Gopaldas, Lindridge, & Simões, 2020). Because technology recommendations primarily influence Brooklyn's usage behavior, I call this interaction behavior "technology-induced excessive use."

The vignette depicts some distinctive characteristics of technology-induced excessive use. First, such usage is characterized by spending more time than intended. For example, the vignette mentions that, initially, Brooklyn was an occasional TikTok user. Later, she began using TikTok more frequently than she had previously. Second, the vignette reveals that the unplanned usage is primarily induced and maintained by the features and algorithms of TikTok. For instance, Brooklyn received recommendations for videos she would appreciate regularly. Third, the vignette indicates that the interaction pattern is dynamic. Over time, the content recommended by the TikTok app evolved. The app's contents are frequently updated to preserve Brooklyn's presence. For instance, to entice Brooklyn to use the app, TikTok initially presented her with her friend's video that she would find appealing. Later, TikTok provided Brooklyn with a range of recommended content based on its estimation of Brooklyn's interest. Fourth, the vignette suggests that a user seeks variety in response to the variety of recommended contents. For example, the recommendation, algorithm, and new features of TikTok impel Brooklyn to search for live streaming, celebrity cooking, and duet option.

Based on those characteristics mentioned above, I argue that technology-induced excessive use is a distinct type of usage behavior. In the domain of IT use, behaviors discussed are addiction (grounded in human physio-psychology), post-adoption (grounded in reasoned action), and habit (grounded in automaticity). Technology addiction is defined by compulsive technology use behaviors with various adverse outcomes (Turel & Serenko, 2012). It is grounded in the human physio-psychology paradigm, which posits that an individual's negative traits, such as maladaptive cognition, negative personality traits, and negative emotion, are typically the causes of excessive use (Turel, 2015). Next, in the domain of IT use, habit is one of the core constructs to study usage. According to duel systems theory, habit is an automatic or reflective behavior (Soror, Hammer, Steelman, Davis, & Limayem, 2015). In other words, habit is an automatic response to a consistent trigger (De Guinea & Markus, 2009). As habit is an automatic response to a cue, habitual behavior is characterized by the lack of control over the responses to cues (Hou, Kim, Kim, & Ma, 2019). Many IS researchers argue that lack of impulse control can result in excessive use behavior (Lee & Kim, 2018). Finally, grounded in the reason action paradigm, post-adoptive usage is the intention to continue using a technology based on rational factors, such as perceived usefulness and perceived ease of use (Kim, 2009). Although post-adoptive use literature does not explicitly focus on excessive use behavior, the construct "intention to continue use" might result in excessive use. In the literature, I find that excessive use has been studied in those three domains of IS use in different contexts (e, g, social media, gaming, online gambling) and by adopting different perspectives, such as behavioral addiction (Hussain & Griffiths, 2009), personality (Castille & Sheets, 2012), stress (Kardefelt-Winther, 2014), and socio-psychological perspectives (S. Lee, Kim, Mendoza, & McDonough, 2018).

I compare technology-induced excessive use to these three domains of IS use. Technology-induced excessive use is distinct from technology addiction in at least two ways. First, according to addiction literature, deficient self-regulation and maladaptive cognitions trigger excessive use (Hawi & Samaha, 2017). For example, a person with deficient brain reward circuitry could be addicted to technology as the person requires continuous dopamine stimulation to maintain brain homeostasis (West, Brown, & ProQuest, 2013). But rather than a weak brain reward system, technological features and algorithms are the main causes of technology-induced excessive use. For instance, a person could excessively use a dating app since it can match them with profiles they may like. Second, one of the consequences of technology addiction is the manifestation of negative outcomes (Turel, Serenko, & Giles, 2011a). For instance, according to technology addiction literature, addicted individuals develop obsessive-compulsive disorders and personality disorders (Berthon, Pitt, & Campbell, 2019). In contrast, technology-induced excessive use indicates the stimulation from technology to use technology, and the stimulation from technology may not affect users' perception and cognition negatively. Rather, technology-induced excessive use indicates that technology reinforces users' expectations, and users could experience ongoing excitement (as depicted in the vignette). While many may argue that technology-induced excessive use could result in withdrawal symptoms, I contend that technology-induced withdrawal symptoms cannot be compared to the physical withdrawal symptoms caused by technology addiction.

Technology-induced excessive use is distinct from habit in at least two respects. First, this research contrasts the automaticity of habit with the curiosity aspect of technology-induced excessive use observed in the vignette. Second, at the technology feature level, I compare the role of stable context in habit formation. According to dual systems theory, habit is a rapid behavioral response to a cue (Soror et al., 2015). Once the habit is formed, an individual responds naturally to the cue (Limayem, Hirt, & Cheung, 2007). When influenced by technology, however, people typically stay in a dynamic context. The dynamic context may hinder the establishment of automaticity since it may inspire curiosity. For instance, the recommended contents of TikTok constantly change depending on historical and hyper-temporal usage data. The updated recommendations, based on data, could stimulate enduring curiosity because they offer the opportunity to experience new thrills. As recommendations and features can continually pique curiosity, it is unlikely that technology inducement can always be automated. Thus, technology-induced excessive use is distinct from excessive use induced by habit at the feature level. Second, according to the literature, habit requires a specific context (Verplanken, Verplanken, & Ryan, 2018). A specific context repeatedly elicits a particular response. In the absence of the cue, the habit can be broken (Verplanken, 2006). For example, a student may develop the habit of checking a social media app by linking the study break with the app use. The presence of a study break may automatically pull the student to check the app. However, if the student does not get the study break, the habit of checking the app may not form. Thus, a habit requires a consistent context, such as a study break. A characteristic of technology-induced excessive use is that a user seeks variety because of new recommendations. At the feature level, such variety-seeking is distinct from habit. Overall, technology-induced phenomena disrupt a context's "habit" or "expectation" by altering or varying the affordances of technology.

In numerous respects, technology-induced excessive use differs from post-adoptive usage. First, post-adoptive usage has been explained primarily through the expectation-confirmation model and technology acceptance model, in which usage behavior is influenced by rational factors such as perceived satisfaction, perceived usefulness, perceived ease of use, and so on (Bhattacherjee & Lin, 2015). The fundamental assumption of post-adoptive usage is that humans have complete control over technology and use it to achieve their specified or predetermined objectives (Burton-Jones & Gallivan, 2007). The vignette suggests, however, that a major aspect of technology-induced excessive use is that technology has an agency over usage because the usage is constantly guided and maintained by technology features and algorithms. Second, the research on post-adoptive usage regards technology interaction as one-way interaction. For example, according to this literature, performing a task in technology is contingent on users' beliefs and satisfaction. Nevertheless, technology-induced excessive use views technology usage as a two-way exchange between technology and users.

As technology-induced excessive use differs in multiple dimensions from technology addiction, habit, and post-adoptive usage, we need a theory-driven approach to understand this usage behavior. All physio-psychological, automaticity, and reason-action induced excessive use focus exclusively on human psychology and rationality but discount IT artifacts' role in inducing excessive usage. The vignette demonstrates that Brooklyn's usage has evolved under the influence of different features of TikTok. Over time Brooklyn experienced a persistent desire to return to the app. Here, the IT artifacts' agency cannot be separated from IT interaction as Brooklyn's use is guided and maintained by features and recommendations. As I will discuss below, the existing literature lacks a theoretical explanation and an appropriate construct for excessive use induced by technology artifacts. The absence of such a construct also constrains us from comprehending the factors that maintain technology-induced excessive use behavior. Further, the lack of a theoretical explanation restrains our ability to understand the formation and development of technology-induced excessive use. Against this backdrop, this essay asks the following research questions:

How can I explain technology-induced excessive use behavior? What makes users be induced by technology? What is the process underlying the emergence and development of technology-induced excessive use?

As I lack sufficient theoretical understanding of technology-induced excessive use, I studied those research questions using a qualitative approach. Specifically, I conducted a grounded theory methodology (GTM) to inquire about those research questions and used interviews to develop a theory underlying this behavior. Among three distinct paradigms of the grounded theory approach, I follow Strauss and Corbin's (1998) interpretive method of analyzing qualitative data. Following their recommendation, I obtained interview data from 107 individuals using theoretical sampling and then systematically coded the data using micro (open and axial coding) and macro (selective coding) coding procedures. The analysis revealed that although many participants said their technology interaction is prompted by habit, rational factors, and maladaptive cognitions, some participants reported that technology features, algorithms, and recommendations influence excessive usage. Because of technology features, algorithms, and recommendations, those participants frequently return to technology and spend unplanned time with it. As indicated in practice literature, I labeled this usage state as "hooked" (Eyal, 2014). Using analytical tools suggested by the GTM, such as constant comparison, asking questions, and theoretical sampling, I define hooked as a technology usage state characterized by users' use of technology longer than planned. I observed three properties of this new usage state 1) experiential involvement- users' deep involvement with technology features, 2) swaying- feeling of being nudged to explore, and 3) adaptation- users' adjustment to usage. The micro and macro analysis also identified the conditions and consequences of the *hooked* state. I found that technology agency is one of the core causes of the hooked state. I represented technology agency as "perceived agency of technology" in our study. The analysis revealed perceived agency of technology constantly interacts with users' need fulfillment ability, which contributes to the development of the hooked state. Altogether, I answer the first two of our research questions by developing a grounded theory of hooked, a theory that explains excessive usage, its conditions, and consequences. Further, by following Strauss and Corbin's (1998) recommendations of process analysis using qualitative data, I developed a process model that illustrates different usage states through time based on the interviewees' discussions. The process model demonstrates that a user goes through the exploration and adoption state before reaching to hooked state; over time, this hooked state can lead to addiction. Taken together, our theoretical models challenge the predominant view of human agency in technology usage and provide a deeper understanding of stimulus-organism-response and reinforcement theory by demonstrating that technology is a dynamic agent that can constantly induce rewarding interaction.

The remainder of this essay is organized as follows. First, I provide background literature on technology-induced excessive use. Next, I review some competing theoretical perspectives of technology-induced excessive use. Then, I present the research method and our grounded theory study findings. Finally, I conclude with theoretical contributions and practical implications of the essay.

Background Literature

This section aims to review the literature on technology-induced excessive use. After reviewing existing literature on technology-induced excessive use, I compare it to opposing theoretical viewpoints, such as physio-psychologically induced excessive use, automatically induced excessive use, and post-adoptive usage. During the comparison procedure, I also note their similarities. Finally, I present a comparison summary in a table and illustrate a scenario for each of these usage constructs. The steps I followed in the literature review are demonstrated in figure 1.1.

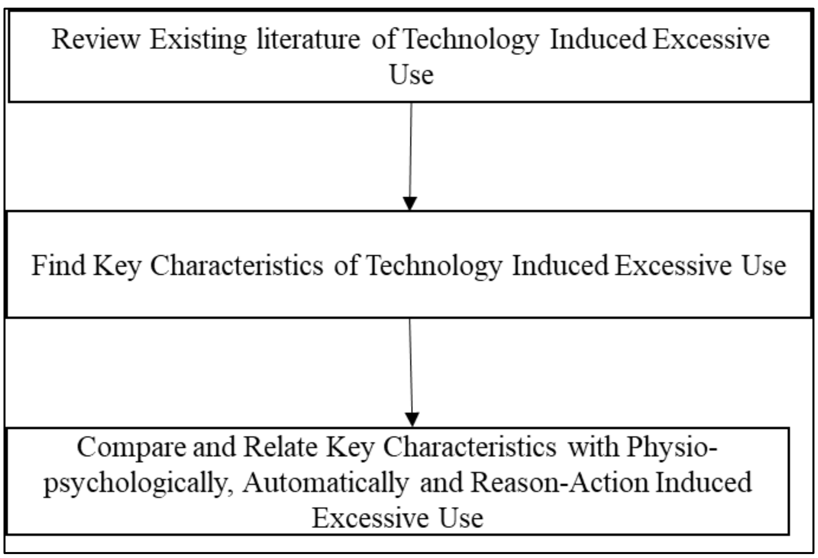


Figure 1.1: Literature review process

Technology-induced Excessive Use

Many technology practitioners argue that we are transitioning from tool-based to manipulation-based technology (Augustine & Xavier, 2021). Tool-based technology functions as a passive agent (Augustine & Xavier, 2021). Users can exploit tool-based technology effectively by providing explicit instructions (Du, 2021). An example of tool-based technology is the personal computer, which processes user-assigned commands only. However, with the advancement of artificial intelligence, machine learning, deep learning, application programming interfaces, and platform-based technologies, manipulation-based technology is emerging in today's technological landscape (Augustine & Xavier, 2021). The manipulation-based technology operates as an active agent capable of selecting the optimal user action based on historical and real-time usage data (Susser, Roessler, & Nissenbaum, 2019). Most apps can function as manipulation-based technology because they can predict optimal action options based on user preferences and past usage data. Users' engagement is the core of manipulation-based technology, as manipulation-based technology can learn more about users through interaction (Susser et al., 2019). As both users and manipulation-based technology can influence one another, the interaction between those is bidirectional as opposed to tool-based technology's unidirectional interaction (Jongepier & Klenk, 2022). According to Susser et al. (2019), the primary criteria for manipulation-based technology is the presence of hidden influence, exemplified by the capacity to exploit users' decision-making weaknesses, such as cognitive biases. For manipulation-based technology to manifest its influence, it must be able to obtain, evaluate data and determine the optimal alternative for users (Susser et al., 2019). In the context of mobile apps, specific categories of apps, including social networking apps, news apps, entertainment apps, health apps, exercise apps, dating apps, and gaming apps, are capable of accessing data, analyzing it, and selecting the optimal option for users. This study focuses on those apps that meet the criteria for manipulation-based technologies, and I refer to those apps as "super apps" (Steinberg, 2020). I define a super app as one that can access and analyze data and that can automatically determine the optimal solution for users. Given the capabilities of super apps to provide users with optimal content, many practitioners and bloggers suggest that super apps can entice users to return frequently and persuade to stay for longer durations. As users' usage is driven by features of super apps, it can be defined as technology-induced excessive use.

In other words, I define technology-induced excessive use as an unplanned usage behavior that emerges from technology artifacts. From here, I will use super apps and technology interchangeably.

I systematically reviewed practice literature to understand how super apps induce excessive use. First, using the embedded case study method[1], I began coding the articles, blogs, and books in which practitioners discuss different features and techniques employed by super apps to induce excessive use (Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015). Next, I cluster those features and techniques into six different groups. Finally, I present the results of clustering in Table 1.1. Those clusters lack natural stops, progression, matching, social comparison, immersion, and self-enhancement.

[1] We followed two step method of embedded case study (Eaton et al. 2015)

Table 1.1: Clusters of app features

Sources	Type of App and Platform	Features/Techniques	Description	A cluster of techniques
Articles, blogs, and books	Messaging app (iMessage/ Messenger)	The wavy dots	It can generate enthusiasm among users to receive something new.	Immersion
	Social Media app (Facebook)	Thumps up button	It can generate a desire for others' approval.	Social comparison
	Social Media app (FaceApp)	AI-driven tools to alternation of photos and videos	It can transform existing images and videos into captivating images and videos.	Self-expression
	Social media app (Snapchat)	Steaks	Steaks offer a gamified social interaction	Social comparison
	Most apps and platforms	Push notifications	It can prompt action and generates the fear of missing out	Lack of Natural Stops
	Dating app (Tinder)	Collection of matches	It creates a group of like-minded users.	Matching
	Dating app (Tinder)	Pings	It can generate a fear of missing out	Progression
	Gaming Platform	Competitive leaderboard	It can generate a sense of mastery, can invoke social comparison	Progression
	Gaming Platform	Escalation of difficulty / Leave tasks unfinished	It can gradually increase in difficulty	Progression
	Entertainment app	Enforced time limit	It can engage users	Progression
	Gaming app	Ranking with in-app checkpoints	It can help set goals and push users to continue playing	Progression
	Health and Fitness app (Fitocracy)	Badges/ Unlocking achievement	It creates a sense of mastery	Social comparison

Table 1.1 (Cont.)

Sources	Type of App and Platform	Features/Techniques	Description	A cluster of techniques
Articles, blogs, and books	Most apps and platform	Latency to load	As the delay of the content display can reduce enthusiasm, most apps and platforms reduce latency	Lack of natural stops
	Entertainment, gaming, and e-commerce platform	Virtual reality	It can generate deep involvement	Immersion
	Social media and dating	Infinity scrolls	It can push a user to check contents continuously	Lack of natural stops
	Most apps and platform	Deep linking (transferring users directly to a specific place in an app)	It can save time by taking users to the desired place	Progression
	Knowledge exchange apps	Upvote	It can increase the cravings for social validation	Social comparison
	Social media apps	Recommended video	It can increase the desire to check more videos	Marching contents and people
	News apps	Infinity New feeds	It can generate enthusiasm to read more news	Lack of natural stops
	Social media and entertainment apps	Recommendations based on what's others like	It can increase the desire to check more videos	Marching contents and people

Table 1.2: Descriptions of clusters

Clusters	Description	Examples of Super apps	Features of Super apps
Lack of Natural Stops	Afford the uninterrupted supply of content without any breaks	Instagram	Infinity scrolling, Dynamic stickers
Progression	Afford the sequence of actions required to obtain a reward (e.g., points, badges)	Pokemon Go	Hatching, Building Army
Matching	Afford content to users according to their preferences	TikTok	For You
Social comparison	Compare and assess user's social networks	Facebook	Following, Like
Immersive environment	Distort reality	Oculus	VR library
Self-expression	Offer the opportunity to convey identity, emotion, and feelings with an app or another person.	Replika	AI-based Voice recognition

I provided a brief description and examples of these clusters in Table 1.2. The first cluster is the lack of natural stops. The lack of natural stops is exemplified by limitless scrolling (Montag, Lachmann, Herrlich, & Zweig, 2019), a feature supported by numerous social media and entertainment apps. Those apps can endlessly supply content based on what users may enjoy based on algorithms. As users continually obtain content they prefer, the lack of natural stops can cause spending more time on these apps. Technological practitioners assert that the "lack of natural stops" technique is based on the psychological principle of intermittent training (Berthon et al., 2019). The second cluster is progression. Obtaining something through gamification is an example of progression (Bitrián, Buil, & Catalán, 2021). According to research on gamification, a user might be highly engaged with a task if the task is split down into numerous parts or pieces (Butler, 2014). Like infinite scrolling, progression is widely used in numerous super apps. The progression requires users to devote time, attention, and money (Bitrián et al., 2021). The algorithms of super apps are designed in a way that users obtain new goals after completing an old one. Thus, the progression technique induces users to stay longer in super apps (Montag et al., 2019). The third cluster is matching, a widely used technique in super apps. Matching offers users relevant content based on the users' historical and current preferences (Jung, Bapna, Ramaprasad, & Umyarov, 2019). Users interact with matched content because it is meaningfully related to their preferences (Huang, Jasin, & Manchanda, 2019). Super applications make recommendations based on usage data tailored to users' preferences. For example, a dating app, OkCupid, matches one partner with another based on demographic information. According to practitioners, super apps use approaches, such as model and data-driven suggestions, to match similar users and to match users' interests with an action possibility. The fourth cluster is social comparison. Super apps use social comparison techniques to prolong use, using the principle that humans want to compare with others to evaluate their position or status (Montag et al., 2019). The features such as like, share, tag, and so on are used as social comparison. Those features support the psychological mechanism of upward and downward comparisons, facilitating gluing users with technology (Kranova, Widjaja, Buxmann, Wenninger, & Benbasat, 2015). The fifth cluster I have identified is immersion. Some super apps can build an immersive atmosphere and obfuscate reality. An immersive environment enables multisensory feedback like touch, hearing, and smell (Barnett & Coulson, 2010). Such multisensory feedback can generate a flow state during interaction (Steed, Roberts, Schroeder, & Heldal, 2005). The flow state can prolong usage, even though users may not be aware of it (Alter, 2017). The sixth cluster is self-expression. Self-expression is a form of self-enhancement, defined as expressing one's identity, emotions, and thoughts (Karahanna, Xu, Xu, & Zhang, 2018). Super apps offer the freedom to express feelings and sensations with other humans or virtual avatars. Those AI-powered technology enhances two-way interaction and can drive users to spend extra time. I argue that those six clusters can function as interaction initiators and facilitators. Some techniques may function as both initiators and facilitators. For example, matching, lack of natural stops, self-expression, and immersive environment can function both as initiator and facilitator, while progression can function as a facilitator.

While academic research on this topic is sparse, some researchers have used systematic methods and demonstrated how features could facilitate usage in some specific contexts. For example, Siebert et al. (2020) used the ethnography method to investigate customers' alternative journey models. They found that innovative technology features and practices have given rise to an alternative customer journey model: the *sticky journey model*. According to them, many products and technologies offer unpredictability, variation, and boundary-spanning advantages, encouraging customers to use their services (Siebert et al., 2020). In another research note, Berthon et al. (2019) argue that technology interaction is engineered through services that can entice consumers to spend time, attention, and money.

Many practitioners use a variety of terms to describe "technology-induced." For example, Eyal (2014) and Alter (2017) use the term "hook" to illustrate the technology-induced phenomenon. The term "hooked" has repeatedly been used to describe users' return to technology. According to Nir Eyal (2014), "hooks" refers to tangible and intangible objects or practices that associate a subject with a positive memory. Eyal (2014) developed the hook model based on his professional expertise in designing persuasive products. According to his hook model, there are four phrases of the hook: trigger, action, variable reward, and investment. Triggers and variable rewards function as hooks in the hook model (Eyal, 2014). Triggers can invite users to perform a specific behavior, while variable rewards encourage users to stay and invest in technology (Eyal, 2014). Explicit triggers, such as notifications, direct a user to act

(Eyal, 2014). Implicit triggers such as the need for a connection can continually bring users back to technology. Even though the word "hook" seems to be a decent way to explain "technology-induced," academic literature lacks a precise definition of hooked.

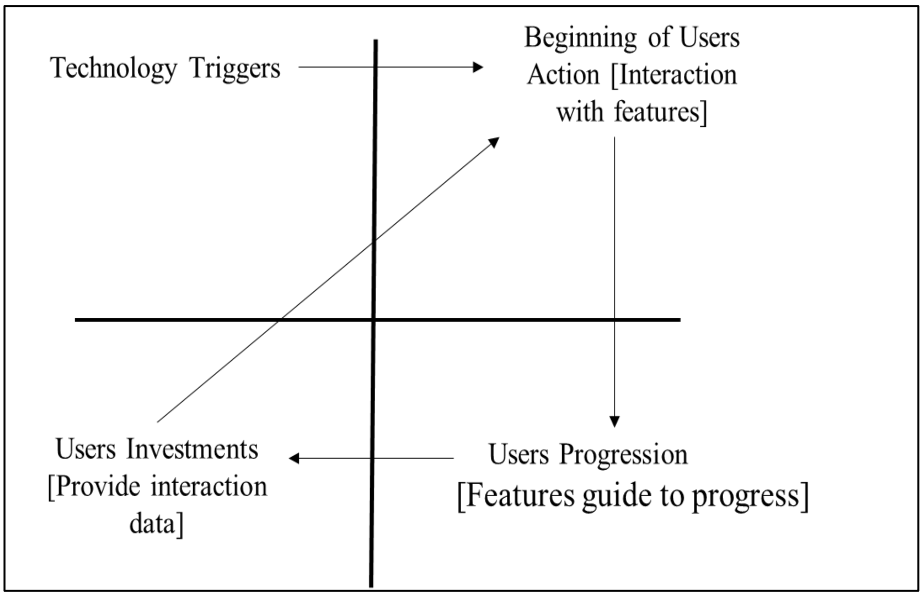


Figure 1.2: Hook model proposed by Nir Eyal

Figure 2 indicates the role of features identified in the embedded case study in encouraging users to return, remain, and spend time on technology. I tie these clusters to the hook model proposed by Eyal (2014). According to the hook model, there are three phases of technology interaction: initiating action in technology, guiding action by technology, and user's investment in technology (Eyal, 2014). The upper right corner shows that a user is initiating an action. The bottom right corner indicates that an action is being guided by technology. Finally, the bottom left suggests that users invest in technology in the form of data and unfinished tasks. Let's link clusters with the model. A notification feature can be regarded as the initiator of action. Super apps can push notifications toward users to initiate action; other initiators match contents, alert, call for action, and so on. Next, the lack of natural stops, immersion, and self-expression can be regarded as initiator and facilitator as they guide users' actions. Next, matching, lack of natural stops, immersion, and progression in pings, steaks, badges, and points can also guide users to stay longer in technology. Finally, users invest in super apps by providing personal data while interacting or leaving interactions unfinished. Super apps can exploit usage data to pull users to the next interaction through the features such as progression and matching. It is a cyclical process as one phrase influences the next.

Based on the six clusters and the hook model, I identify some characteristics of technology-induced excessive use. First, technology-induced excessive use suggests a high level of engagement with technology. Clusters of techniques such as lack of natural stops, virtual reality, progression, and comparison can cause users to focus on the interface continually. Thus, users may demonstrate a high level of engagement. Second, technology-induced excessive use indicates a desire for variety seeking. Clusters of techniques such as matching, progressions, and lack of natural stops could display diverse content and recommendations, encouraging users to search and engage with various activities. For example, Facebook's recommendation offers the option for content sharing, content creation, game playing, and purchasing from the marketplace. Those features of Facebook could cause users to seek various activities. Third, technology-induced excessive use suggests the presence of unpredictable experiences. Clusters of techniques such as matching, progressions, and the lack of natural stops do not generate a regular pattern of rewards. Most of the time, users cannot anticipate the types of content or rewards they may receive during an interaction. Thus, those techniques can render unpredictable experiences. Finally, technology-induced excessive use suggests the presence of having dynamic environment. The usage environment is dynamic because technology constantly learns from user behavior and enhances recommendations. Moreover, technology features continually evolve to improve the user experience. These examples illustrate the presence of dynamic context. Based on those characteristics, I compare and contrast technology-induced excessive use with competing theoretical perspectives and identify similarities and differences among these.

Technology Induced Excessive Use Is Not Physio-psychologically Induced Excessive Use

I use physio-psychologically induced excessive use to refer to excessive use resulting from biological or psychological conditions. In general, physio-psychologically induced use has been extensively studied in the drug use literature, using the addiction perspective to examine its numerous components (West et al., 2013). Drug use literature contents that excessive drug use has negative physical effects in the form of sleep disturbances, headaches, high blood pressure, and abnormal heart rate (Goldman, 1999). According to the literature on drug use, addiction is characterized by recurrent drug use and negative repercussions (Abou-Saleh, 2006). Generally, drug use literature employs two orientations to examine drug use: exposure and adaptive orientation (Alexander & Hadaway, 1982). Exposure orientation contents that different drug properties can cause brain malfunction, leading to addiction (West et al., 2013). Adaptive orientation argues that individuals with maladaptive psychology use drugs to alleviate negative emotions (Alexander & Hadaway, 1982). Although behavioral addiction literature attempts to distinguish behavior-related addiction from drug addiction, current research on addictions suggests no meaningful distinction between the two (Berthon et al., 2019). IS researchers borrowed the addiction perspective, specifically, the adaptive orientation, to study IS phenomena such as excessive technology use and labeled it technology addiction (Serenko & Turel, 2020). Similarities between the symptoms of excessive drug users and excessive technology users motivate this practice. In IS literature, technology addiction has different tags, such as problematic use, dependence, internet addiction, and gaming addiction (Gerlach & Cenfetelli, 2020). All of these categories, however, share the notion that addiction is a chronic condition with adverse outcomes (Andreassen, 2015). In IS literature, the technology addiction perspective has evolved into a potent theoretical perspective to explain negative usage outcomes (Kwon et al., 2016). IS literature defines technology addiction as "a user's psychological state of maladaptive dependency on technology use that is manifested through the obsessive pattern of IT seeking, and IT use behaviors that take place at the expense of other activities, and that has negative consequences" (Turel, Serenko, & Giles, 2011). The six symptoms of technology addiction are conflict, salience, mood modulation, relapse, reinstatement, and withdrawal (Turel et al., 2011). Those six symptoms are used to measure technology addiction. However, the use of symptoms to quantify technology addiction has been questioned by numerous researchers due to the inconsistency of these symptoms across contexts.

Given the nature, definition, and symptoms of technology addiction, one could argue that it focuses on the dysfunctional or negative aspects of use (Turel et al., 2011). For instance, an addicted individual faces withdrawal effects without technology, which can have serious health, psychological, and social implications (Turel & Serenko, 2012). From a neurobiological standpoint, some addiction researchers explained why addicted individuals feel adverse outcomes. According to them, the addicted individual's brain cannot maintain regular dopamine transmission, resulting in a dysfunctional reward structure of the brain (West et al., 2013). Because of the dysfunctional reward structure of the brain, technology addicts are unable to concentrate on activities (Kwon et al., 2013). However, according to our preliminary understanding of technology-induced excessive use, this form of use could less likely generate negative consequences because users become engaged with the technology. To be involved with technology, users do not require a dysfunctional reward structure of the brain. The concept of engagement with technology is mainly associated with positive outcomes, such as high performance (Agarwal & Karahanna, 2000). Thus, while technology addiction focuses on a negative view of excessive technology use behavior, technology-induced excessive use focuses on an engagement aspect of technology use behavior.

Another focus of the technology addiction perspective is maladaptive cognition. The concept of maladaptive cognition comes from cognitive-behavioral theory (Scott E. Caplan, 2006). Maladaptive cognition is a distorted perception that prevails when an individual loses rationality (Turel et al., 2011). Let's make a distinction between adaption and maladaptation. In the case of adaption, if a user finds that a particular technology generates negative consequences, such as stress or anxiety, the person will cope with it by avoiding it or reducing its use (Tarafdar, Maier, Laumer, & Weitzel, 2020). However, a person with maladaptive cognition will still use the technology aggressively, even though it may generate more stress or anxiety. Clinical psychology literature states that maladaptive cognition arises due to dysfunctional dopamine release in the brain (Vaghefi, Lapointe, & Boudreau-Pinsonneault, 2017). In the technology context, maladaptive cognition can induce an overwhelming drive to use technology despite its association with negative consequences (Lee, Cheung, & Chan). Consequently, if we take the agency perspective, I can argue that maladaptive cognition has the main agency over excessive usage in addiction. Nevertheless, the preliminary understanding of technology-induced excessive use indicates that technology features, algorithms, and recommendations are central to excessive use. Thus, both perspectives are distinct in terms of their causal mechanisms.

Technology addiction researchers state that, in most cases, technology-addicted people compulsively seek technology due to negative reinforcement, such as negative affect and emotional relief (Wang & Lee, 2020). The operant conditioning model supports this notion

(Wang & Lee, 2020). In contrast, most practitioners argue that technology may induce constant curiosity in case of technology-induced excessive use. For example, super apps' progression and matching technique induce continued interest to return and stay for longer.

In discussing different conditions of technology addiction, many addictions researchers contend that personality plays a significant role in causing technology addiction (Andreassen, 2015). For example, according to various addiction theories, personality traits such as impulsivity, risk-taking, need for cognition, and sensation-seeking traits are more likely to generate technology addiction (Castille & Sheets, 2012). However, I argue that technology-induced use is a more general phenomenon that can be formed through any personality trait.

Given the similarity of technology addiction with other addiction types, such as substance addiction, and behavior addiction, many researchers interpret the addiction state as having no control over technology interaction (Xu & Tan, 2012). Although there might be various causes for loss of control, one reason could be an obsessive-compulsive disorder or an irresistible desire to use the object (Wang & Lee, 2020). However, users can control technology-induced excessive use by stopping notifications or using different technology cues.

Given that technology addiction literature argues that use is associated with negative consequences, I can predict two implications from this literature. First, technology addiction requires external intervention, such as clinical therapy (Gerlach & Cenfetelli, 2020). Second, people should stop using technology to control the arousal of negative consequences, such as negative emotions (James, Lowry, Wallace, & Warkentin, 2017; Turel et al., 2011). While these remedies might be appropriate for addicts, I argue that they are unnecessary for technology-induced excessive use. Even if an excessive use behavior is not induced by technology, we should not claim that users should stop using technology because excessive use might be motivated to gain knowledge, get entertainment, maintain connections, etc. A recent study by Gerlach and Cenfetelli (2020) provides a starting point to recognize that excessive checking does not necessarily constitute technology addiction because many people can intentionally incorporate excessive checking to understand the world. In fact, such draconian measures may be inappropriate as technology becomes an integral part of our lives. Users need to be mindful about using technology rather than being banned from using technology.

Although technology-induced excessive use is distinct from technology addiction in several dimensions, they have some commonalities. First, one common property between these is excessive use despite the difference in causal mechanisms. Second, another common property between these is the reflexive reaction during technology interaction despite the difference in causative processes. For example, due to technology's features, contents, and recommendations, many individuals, who are influenced by those, may begin interacting with those automatically. In the case of technology addiction, many people can reflexively start interacting due to maladaptive cognitive or maladaptive coping. Third, each behavior possesses reward-seeking. In the case of technology-induced excessive use, reward-seeking behavior might motivate users to engage with technology repeatedly. Such reward-seeking can be attributed to the fact that individuals are aware that technology continuously gives rewards. In the case of technology addiction, research indicates that reward-seeking traits can foster addiction. Forth, both of this behavior can influence normal brain functioning. For example, using different features, technology can blur reality and impact normal brain functioning, such as reducing time sensitivity if users do not deploy sufficient control mechanisms. Thus, although technology-induced excessive use and technology addiction are phenomenologically different, there are some commonalities between these two behaviors.

Technology Induced Excessive Use Is Not Automatically Induced Excessive Use

I define automatically induced excessive use as unplanned and automatic use in the presence of a specific context. Thus, automatically induced excessive use can be considered habit as automaticity is primarily represented by habitual use. Additionally, habit has two other characteristics: lack of awareness and efficiency (Chiu & Huang, 2015). In the light of those characteristics, I argue that habit is the opposite of intention (Soror et al., 2015).

The habit literature argues that habit requires a consistent and stable context (Polites & Karahanna, 2012). According to the habit discontinuity hypothesis (Aldrich et al., 2011), changing a stable context can attenuate habitual responses and eventually disrupt habits. During habit formation, a consistent or stable context links one's mental representation with a specific outcome (Polites & Karahanna, 2013). Given sufficient repetition, the stable context activates a behavior automatically. Thus, habit is a stable context-dependence behavior (Verplanken & Roy, 2016). For example, a technology feature could help form a habit of engaging with an activity. Such as, receiving a specific type of notification repeatedly from a social media app can help develop a habit of reading others' posts if a user makes a connection between notification and reading others' posts. In contrast, technology-induced excessive use operates in a dynamic context. By dynamic context, I refer to the evolution of features and recommendations. The technology learns from past usage updates, offers various features, and crates the dynamic context. As the features and recommendations can change over time, there is a lack of stable context that users can connect to form a habit of performing a specific action. For example, apps such as TikTok constantly monitor what users like and predict their future preferences. Based on those insights, TikTok could induce users to use various features, such as watching videos, listening to music, creating videos, networking, and reading the news. As a result, many users could use multiple features rather than being limited to a specific feature. Thus, technology-induced use is not the same as a habit at the feature level because users may not engage in single behavior linked with features.

As previously mentioned, the properties of habit are automaticity, efficiency, and cue-behavior relationship (Verplanken et al., 2018). Thus, by definition, habit ignores the role of goal during technology interaction in the context of technology. However, technology-induced excessive use does not overlook the role of goal during technology interaction. Technology can induce a series of goals in a hierarchical manner during the interaction. Let's say that an individual habitually reaches for technology. The habitual reach to technology does not explain how the interaction will go further. For example, an individual may habitually go to the Instagram app. After reaching Instagram, a series of goals could be triggered by technology, such as looking for new posts, following somebody, etc. Technology triggers such as matching and infinity scrolling can generate new goals and keep users in the technology. So, activation of interaction can diffuse a variety of goal-oriented activities. The diffusion of various goal-oriented activities can be explained by technology-induced excessive use rather than habit.

According to habit literature, past action is a prerequisite for habit (Hou et al., 2019). However, past behavior might not be a necessary condition for technology-induced excessive use. For example, technology can persuade users to use a feature even if they haven't previously used it. Instead, the situational motivation that is triggered by features, contents, and recommendations is an important prerequisite for technology-induced excessive use.

Although habit and technology-induced excessive use are distinct in many ways, there are some commonalities between these. First, each of these behaviors requires outside input at some point in time. However, it might be a stable external cue for habit, but it might be a dynamic cue for technology-induced excessive use. Second, the hook model reveals two tendencies for technology-induced excessive use: repeatedly returning to technology and staying in the technology. The "repeatedly returning to technology" part of technology-induced excessive use can be explained by habit. Habit can also explain "repeatedly returning to technology" by memory-based propensity or argument, but technology-induced excessive use can explain the part without using a memory-based propensity argument. Third, both habit and technology-induced use are context-dependent behaviors. This behavior supports the idea that intention cannot always predict technology interaction.

Technology Induced Excessive Use Is Not Post Adoptive Usage

Adoption has been defined as the acceptance of technology to fulfill a purpose (Hall and Khan 2002). According to IS literature, technology adoption is defined as intentional or purposeful behavior. IS literature investigates technology adoption in two streams: pre-adoption or adoption and post-adoption (Karahanna et al., 1999). Among those two streams, post-adoptive usage literature studies the intention to continue use of technology (Limayem et al., 2007). While adoption refers to the acceptance of technology, post-adoption has been defined as the "sustained use of IT by an individual over a period of time to accomplish a task" (Bhattacherjee, 2001). According to IS literature, post-adoption is influenced by the following factors: reasoned action, perceived satisfaction, and habitual response (Bhattacherjee & Lin, 2015). I identified that post-adoptive usage literature mainly views technology as a tool for achieving a purpose (Benlian, 2015). This body of work explains individuals' technology continuance using models that consider behavior beliefs, intentions, satisfaction, and confirmations (Kim, 2009). I contend that since manipulation-based technology is distinct from tool-based technology in terms of functionalities and capabilities, the models based on beliefs, intentions, satisfaction, and confirmations may not accurately predict technology continuance in the context of manipulation-based technology.

Using Rogers's (1995) categorization of early and late adoption, Parthasarathy and Bhattacherjee (1998) argued that post-adoption behavior is mainly influenced by interpersonal factors, such as usefulness and satisfaction, then by external factors, such as technology features. According to them, external factors, such as technology features, are particularly relevant in the early adoption stage (Parthasarathy & Bhattacherjee, 1998). This is because, during post-adoption, late adopters set their expectations based on cost-benefit analysis and seek confirmation of the benefits. Late adopters abandon a technology if the benefit does not match the expectation (Bhattacherjee, 2001). Late adopters' usage is primarily driven by interpersonal factors (Parthasarathy & Bhattacherjee, 1998). In contrast, our preliminary understanding indicates that technology-induced excessive use is mainly guided and maintained by technology features and functions. Technology triggers generate persistent curiosity and pull users to the technology. Thus, I argue the nature and underlying assumptions of post-adoption behavior differ from those of technology-induced excessive use.

One fundamental assumption of post-adoptive usage is that human beings have full agency over technology usage. Even though certain users may constantly use technology excessively to receive hedonic benefits, the underlying assumption remains the same for all types of usage; technology is useful, and people using them are rational. The source of this assumption is the theory of planned behavior. The theory of the planned behavior paradigm suggests that human behavior is purposeful and goal oriented (Bhattacherjee & Lin, 2015). According to this paradigm, humans behave rationally, following a rational cognitive process to carry out a behavior (Bhattacharjee, 2001). This assumption is the opposite of technology-induced excessive use. For example, when people continuously use TikTok, the TikTok app learns from the user. Based on learning, the TikTok app offers personalized content and induces users to use other features. In this scenario, the agency of use shifts from human to technology.

Many IS researchers use the expectation-confirmation model to explain post-adoption behavior. According to this model, there are two stages of usage (Bhattacherjee, 2001). Users form an initial expectation in the first stage before using technology (Bhattacherjee, 2001). Then, after using the technology, users will develop a judgment about the performance of the technology (Bhattacherjee, 2001). In the later stage, users compare expectation with performance. If the expectation is confirmed, users will be satisfied and continue using the technology (Bhattacherjee, 2001); otherwise, they will abandon it. I highlight two limitations of this model when applied in manipulation-based technology. First, the expectation-confirmation model argues that initial expectation is based on how technology performs (Bhattacherjee & Lin, 2015). However, some recent research suggests that even if the performance of the technology is superior, many users may not adopt the technology because of environmental, social, and individual factors. Second, even though expectations may be disconfirmed, some users could continue to use technology because “expectation-disconfirmation” could function as a trigger in the form of unpredictability. Thus, the expectation-confirmation model, a grand theory in post-adoption literature, does not explain technology-induced excessive use.

In the post-adoption paradigm, some theories view "technology" as static artifacts or a tool (Benlian, 2015). However, manipulation-based technology indicates that technology can be dynamic and function as a self-evolving agent. Super apps can gather data and recommend novel actions based on user's preferences. The dynamic nature of super apps can accelerate the usage or stimulate more use. Technology-induced excessive usage accepts that technology can be dynamic and self-evolving.

Because of the assumption that users are entirely rational in choosing an action, some IS adoption literature argues that users could use a small range of technology features that only match their purpose. However, this argument ignores that the more likely a user gains usage experience, the more likely she could use a wide range of features that do not match her purpose (Benlian, 2015). In contrast, I observe that technology-induced excessive use considers users' variety-seeking behavior.

. I identify some similarities between technology-induced excessive use and post-adoptive usage. First, although technology-induced excessive use highlights the agency of technology in inducing interaction, I argue that human also poses some extent of the agency. For example, in both cases, users may believe in the degree of benefits that they receive from technology. According to the literature on post-adoptive usage, some factors contributing to forming beliefs are based on socio-psychological, individual, and environmental factors (de Guinea & Markus, 2009). But, in the case of technology-induced use, the beliefs are shaped and reshaped by the agentic role of technology. Thus, as belief is present in both behaviors, each behavior has a human agency component. Second, each behavior indicates the role of perceived satisfaction. Expectation-conformation theory in post-adoptive use argues that satisfaction drives technology continuance (Venkatesh, Brown, Maruping, & Bala, 2008). I argue that it is true for technology-induced excessive use as well. Some individuals could be open to being induced by technology as they gain satisfaction when interacting. Third, each behavior indicates the presence of perceived control over behavior. Perceived control over behavior is one’s ability to perform a certain behavior (Liu, Wang, Min, & Li, 2019). Post-adoption literature argues that an individual perceives control over technology because of self-efficacy in using technology. But perceived control endures in technology-induced excessive use because actions are delegated by technology. Thus, each behavior consists of perceived control over behavior even though conditions of perceived control are different.

Summary of Background Literature

In summary, I find that technology-induced excessive use is distinct from technology addiction, habit, and post-adoption. Table 1.3 summarizes the comparison among technology-induced excessive use, technology addiction, habit, and post-adoption. Besides, to highlight the apparent distinction among those concepts, table 1.4 presents scenarios for each behavior. Although I have identified some characteristics of technology-induced excessive use based on practice literature, the academic literature fails to provide a theoretical account for this distinctive phenomenon. Given this lack of theoretical understanding in academia about technology-induced excessive use, I adopted a qualitative approach to answer our research question. Even though the existing research on technology addiction, habit, and post-adoptive use fails to explain technology-induced excessive use, those research areas initially allow us to understand technology-induced excessive use. However, I still make sure that I do not confine myself to any prior assumptions of addiction, habit, and post-adoptive usage when studying technology-induced excessive use.

Table 1.3: Concept comparisons

Characteristics	Technology-induced excessive use	Physio-psychology-induced excessive use	Automatically Induced Excessive Use	Post Adoptive Usage
Agency	Both technology and human have the primary agency over the usage behavior	Users' physio-psychological maladaptation has the primary agency over usage behavior	Automaticity has the primary agency to induce the behavior	The intention has the primary agency over interaction.
Nature of usage behavior	Usage behavior is characterized by engagement with technology	Usage behavior is characterized by an obsession with technology.	Usage behavior is characterized by the unconscious use of technology	Usage behavior is characterized by the intention to use a technology
Perceived Control	Users may believe that technology features could influence their conduct, but they may also believe that they are in control of their behavior through their use of technology.	Users do not have control over their usage behaviors	Users do not have control of their usage behaviors	Users may feel in control of their usage behaviors.
Dynamism	Technology-induced excessive use considers the fact that technology interfaces change, which could change how people use technology	In the technology addiction conceptualization, technology dynamism has not been considered	Technology dynamism has not been considered in the conceptualization	Technology dynamism has not been considered in the conceptualization
Unpredictability	Technology-induced excessive use considers the unpredictable nature of technology action possibilities, which can keep users returning to technology	In the technology addiction conceptualization, the unpredictability of technological action possibilities has not been considered	The unpredictability of technology action possibilities can influence the early stage of habit formation	In the post-adoptive use conceptualization, the unpredictability of technological action possibilities has not been considered
Curiosity	Technology-induced excessive use considers that users interact with technology with curiosity	In the technology addiction conceptualization, curiosity has not been considered	Users interact with technology automatically rather than out of curiosity	Users intentionally interact with technology
Variety seeking	Users seek varieties because technology offers endless variation	Variety seeking has not been considered in technology addiction conceptualization	Rather than seeking variety, users perform a particular activity in response to a context	Variety seeking has been considered in post-adoptive use literature

Table 1.4: Scenarios of different use behaviors

	Technology-induced Excessive Use	**Technology Addiction**	**Habit**	**Post-Adoption**
Scenario	Brooklyn, an irregular TikTok app user, noticed a cooking video in the app's feeds. It was uploaded by one of her friends. She found the video to be very interesting and then discovered more related videos recommended by the app [**Induced by technology**]. During her exploration of these videos, many additional TikTok elements, such as live cooking streaming, music connected to cooking, celebrity cooking shows, duet options, etc., caught her attention [**Variety seeking**]. The mixer of those features kept her in the TikTok app for discovering new cooking ideas [**Dynamisms**]. Now, before deciding what to do next, she might have spent an hour on TikTok [**Induced excessive use**]	Barbara downloaded the Clash of clans to play games and to remove her looniness. She began playing aggressively from the very beginning. She spent the majority of her awake time playing the game. She attempted to reduce playing, but after doing so, she felt depressed and irritated. [**Withdrawal effects**]. She sometimes played while she was driving. Once, she was involved in an accident and vowed to refrain from playing the game. However, she again started playing for the majority of the day [**Relapse**]	Since 2015, Max has started using a gaming app. Initially, he used it during his study breaks to read his friends' status updates. A few months later, whenever he received a study break, he instantly opened Instagram to view his friends' posts. [**Automaticity**]. Even if he does not read the posts, he found himself in the Instagram postings during study break time [**Stable context**].	Since beginning his job, Anthony has been using the outlook app. He used it five times weekly since he needed to communicate with his coworkers. [**Usefulness**]. After completing his workday around 5 p.m., he rarely returns to outlook [**Human agency**].

Research Methodology

To understand technology-induced excessive use better, I argue that the qualitative method is appropriate since the qualitative approach can provide a detailed explanation of an unclear phenomenon (Miles & Huberman, 1994). I chose the grounded theory approach for data analysis among various qualitative methodologies. Grounded theory is a qualitative approach to generating theory from data (Glaser, Strauss, & Strutzel, 1968). I chose the grounded theory approach for various reasons. First, as I have presented above, although practice literature mentioned different characteristics of technology-induced excessive use, I lack the conceptual understanding and a theoretical explanation of this phenomenon. Grounded theory is a suitable approach to generating theoretical explanation since it allows an analyst to bring insights without being constrained by existing theories, assumptions, and hypotheses (Glaser et al., 1968). Second, technology-induced excessive use is a relatively complicated phenomenon because of its multiple characteristics. Multiple characteristics can create different interpretations. The grounded theory helps accurately interpret a phenomenon by considering its context, process, actions, consequences, and interrelationships (Cram, D'arcy, & Proudfoot, 2019). Third, grounded theory is a flexible approach to generating theory as it allows ongoing iteration between data analysis and data collection (Urquhart, Lehmann, & Myers, 2010). Such flexibility allows us to understand the phenomenon until I reach theoretical saturation.

As a data collection method, I use interviews as recommended in the grounded theory study (Strauss & Corbin, 1998). The interview provides rich information about an emerging phenomenon, such as subjects' opinions, experiences, and behaviors, which are vital to understanding emerging phenomena (Miles & Huberman, 1994).

There are three major paradigms of grounded theory, and each has distinct assumptions and analysis approaches (such as coding) to build theory from data. The first paradigm is the objectivist paradigm. Glaser (1978), who advocates this paradigm, focuses on theoretical coding, and he suggested using a variety of coding families that could serve as a framework for developing a theory (Glaser, 1978). The second paradigm is known as the interpretive paradigm. Strauss and Corbin (1998), who advocate this paradigm, recommended using axial coding, selective coding, and a coding paradigm in data analysis. The third paradigm is known as the constructivist paradigm. Charmaz (2017), who introduced the constructivist perspective, suggests focusing more on the researcher's experience developing theoretical concepts than on coding families and coding paradigms (Charmaz, 2017). Charmaz (2017) views the researcher as a co-creator of knowledge. I followed Strauss and Corbin's (1997) paradigm because Strauss and Corbin's (1998) procedure can generate rigorous analytical theories about a phenomenon compared to others (Mills, Chapman, Bonner, & Francis, 2007). Strauss and Corbin's (1998) method allows us to take the role of interpretive and use the tool, such as flip-top, waving the red flag, and matrix, which makes us more sensitive to the nuances of the data. Among different paradigms of grounded theory, some common standard procedures are: conceptualizing and reducing data, using open coding, elaborating categories in terms of properties and dimensions, and relating categories through a series of propositional statements.

Urquhart et al. (2010) suggest using constant comparison, iterative conceptualization, theoretical sampling, scaling up, and theoretical integration to apply grounded theory in IS context. Those procedures are covered in the Strauss and Corbin (1998) paradigm, except theoretical integration, which compares new and previously generated theories. Thus, I incorporate the theory comparison in the theory-building process.

Among those paradigms of grounded theory, interpretive and constructive paradigms allow bringing prior theory and sufficient literature review before data collection (Sebastian, 2019). Thus, Strauss and Corbin (1998) permit starting with a preconceived area and suggest using them as a basis for emerging new concepts (Cram, Proudfoot, & D'Arcy, 2021). The reason to bring prior knowledge is to compare emerging findings with prior literature and increase sensitivity toward data (Sebastian, 2019). For example, we have sufficient practice literature on technology-induced excessive use, so I use that prior knowledge to improve our theoretical sensitivity. Many IS researchers used Strauss and Corbin's (1998) paradigm and utilized preconceived ideas before collecting data. For example, Cram et al. (2021) introduced the concept "information security fatigue" from practice literature before using grounded theory to understand the phenomenon.

Data Collection

I discuss the data collection section in three parts below. In the first part, I describe different phrases of data collection steps. In the second part, I discuss the overall sampling procedures. Finally, I explain how I collect data about technology-induced excessive use from each participant in the third part.

Data Collection Steps

Strauss and Corbin (1998) suggest collecting and analyzing data iteratively. Following their guidelines, I collected and analyzed data systematically and iteratively in seven steps. Figure 3 describes the overview of those seven steps. In step 1, I generated some preliminary interview questions to understand technology-induced excessive use. After developing questions, in step 2, I started collecting data using convenience sampling. Convenience sampling is a nonprobability sampling technique in which target populations are selected depending on certain factors, such as ease of access and desire to participate (Etikan, Musa, & Alkassim, 2016). I have selected interviewees based on easy accessibility and considered our professional network in the initial phase of our interviews (Gerlach & Cenfetelli, 2020). Next, I started collecting data based on theoretical sampling. Below, I have discussed how I incorporated theoretical sampling into our study. In step three, I used two data collection methods to enrich emerging categories: written interviews and in-depth interviews using theoretical sampling and convenience sampling

(Urquhart et al., 2010). Next, I analyzed data using open coding procedures (step 4). Open coding procedures generate concepts from interview data (Strauss & Corbin, 1997). Next, I began axial and selective coding to develop categories from concepts and the relationships among categories (step 5). Later, in step 6, I stopped analyzing and collecting further data because I did not find any new concepts and categories (Urquhart et al., 2010). Finally, in step 7, I developed a variance and process model to represent the technology-induced excessive use phenomenon. Figure 1.3 summarizes the steps. Below, I discussed steps 3-6 in detail.

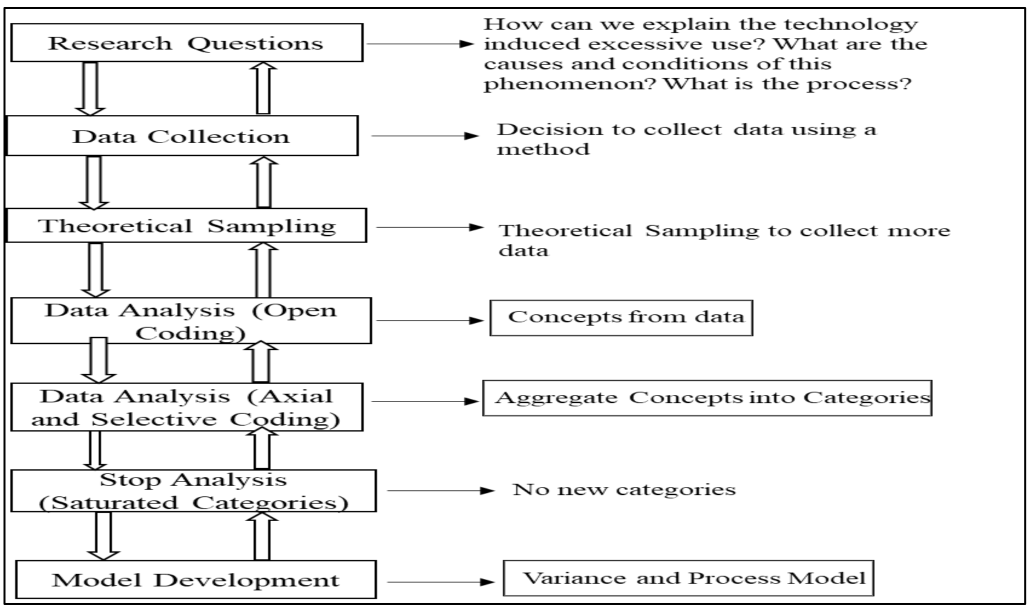


Figure 1.3: Grounded theory process

Sampling Procedures

I used two sampling procedures: convenience sampling and theoretical sampling. I started with convenience sampling. Before I began conducting interviews, I selected two criteria for participation. First, the participant must have experience using apps. Second, the age of the participant should be from 18 to 50[2]. I have selected this age limit because younger people are primarily excessive app users, such as social media (Khoros, 2021). I conducted convenience and theoretical sampling from three sources: personal and professional contacts, behavioral labs, and university classrooms. In the past, I have indicated that I had used two data collection methods to obtain data: in-depth interviews and written interviews. The total number of participants is 107, among which 35 was the in-depth interview, and 72 was the written interview. By following past literature, I conducted written interviews by sending participants a list of questions through email (Mele & Russo-Spena, 2021). I used different sources and data collection methods to increase the generalizability of the study's findings and develop a rigorous theory (Gerlach & Cenfetelli, 2020). Besides, Strauss and Corbin (1998) recommended collecting data using various methods to obtain diverse perspectives. According to them, different data collection methods can also increase the objectivity of a study. Moreover, it helps identify the consensus or dissensus about a phenomenon (Strauss & Corbin, 1998).

I mostly relied on theoretical sampling to collect data. Theoretical sampling ensures the comprehensiveness of a theory (Urquhart et al., 2010). After I had some preliminary data in hand based on convenience sampling, theoretical sampling became our primary device for making decisions, such as what to collect next (Strauss & Corbin, 1998). I used theoretical sampling to collect data on emerging concepts on technology-induced excessive use. Theoretical sampling helped us reduce the size of irrelevant data (Strauss & Corbin, 1998). It also helps us enrich categories by adding variability to each concept. I stopped collecting data when I had reached

[2] We chose this age range to comply with the Institutional Review Board (IRB) instructions

theoretical saturation. Theoretical saturation suggests there is no possibility of obtaining additional information about a phenomenon.

Probing Technique

I used a probing technique during interviews to identify the technology-induced excessive use phenomenon. Figure 1.4 indicates the probing technique. I began with a generic inquiry, such as the name of the app that a participant mostly uses. After learning about the app's name, I focus on her app usage patterns. Participants vary in their apps, such as social media, entertainment, and productivity apps. After asking what technology participants use daily, my next question was: Do they use an app more than they plan to use? This question allowed me to identify whether an individual is an excessive app user. If the participant is not an excessive user, I determined this stage as adoption. Next, I asked questions about how they started to use an app. This question allowed us to choose what factors led them to download an app. Next, if I find that a participant is an excessive user (use more than planned), I ask questions such as what drives them to use those excessively. Based on the participant's response, I asked further questions. For example, whether they use an app automatically and they feel any withdrawal effects if they cannot use it. Those questions allow me to determine whether the participant habitually or addictively uses an app. If a participant mentions that technology features, algorithms, and recommendations primarily cause excessive usage, I immediately recognize this use pattern as technology-induced excessive use. To learn more about technology-induced excessive use, I asked a further question about the phenomenon. For example, what part of the technology induces excessive use? How do you start using technology (app)? How do you react to algorithms? What are the activities they immerse in a technology (app)? How does technology (app) guide them to take further action? How do you evaluate the way technology collects usage data?

The probing procedure allowed me to distinguish between technology-induced excessive use and other relevant concepts. As I continued conducting interviews, I added additional questions to comprehend better the emerging categories linked with excessive technology use and avoid asking questions about concepts I already know. I recorded and transcript all the interviews. Each interview took between 30 to 75 minutes. Besides, the written interviews generate approximately 150 pages of text. I used NVivo software to code all the interview data

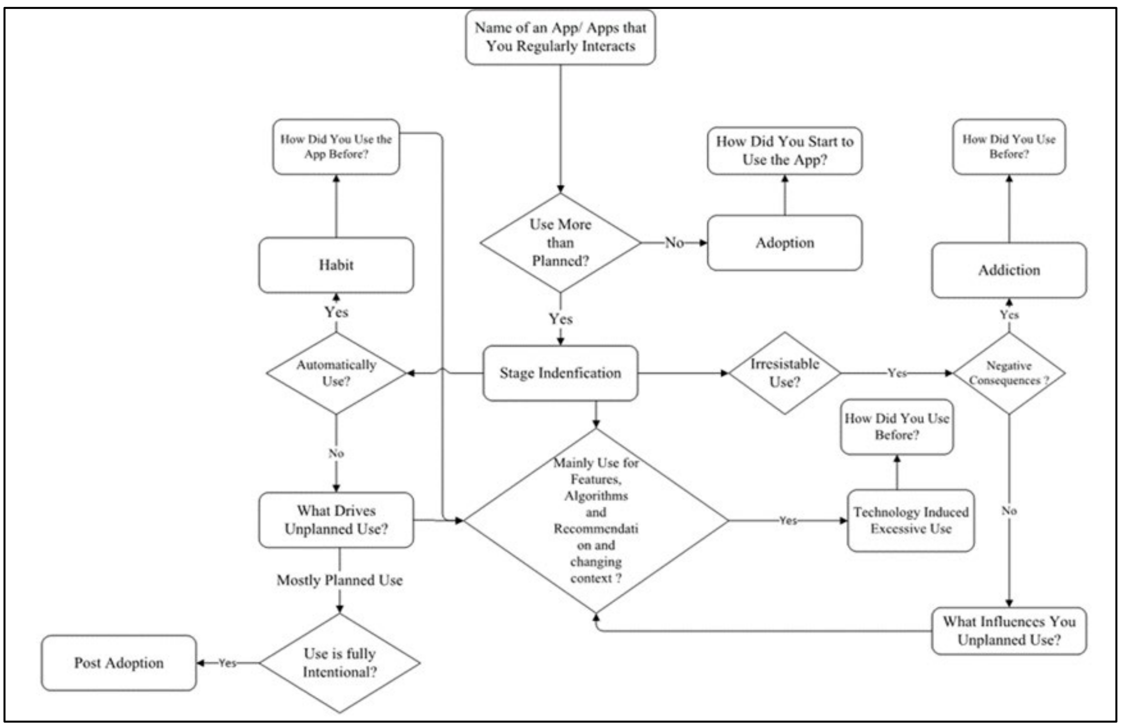


Figure 1.4: Probing technique

Data Analysis

As the nature of grounded theory is iteration between data collection and analysis, I concurrently performed data analysis and data collection. In data analysis, I took several steps to understand the phenomenon systematically and rigorously. As mentioned, I followed Strauss and Corbin's (1998) coding paradigm to develop a theory. I broke down their guidelines into six different steps and used those steps iteratively. The steps are discussed in table 1.5. Note that my substantiative area is “technology-induced excessive use.”

Table 1.5: Data analysis steps

Steps	Purpose	Approach
1. Open Coding	Conceptualizing and discovering categories	▪ Analyzing the interview transcripts line by line ▪ Labeling a concept into a sentence ▪ Developing categories through constant comparison and questioning
2. Memo Writing	Writing notes for codes and directions	▪ Defining the concepts ▪ Summarizing concepts
3. Axial Coding	Linking categories with subcategories	▪ Discovering the central category ▪ Developing other categories around the central category ▪ Relating categories ▪ Discovering conditions of the central category ▪ Discovering the consequences of the central category
4. Selective Coding	Integrating and filtering theory	▪ Writing conceptual memo ▪ Refining the theory
5. Evaluation	Judging the merit of the theory	▪ Evaluating theory based on Strauss and Corbin's (1998) eight criteria
6. Reporting	Presenting the findings	▪ Selecting quotes from interview transcripts ▪ Integrating existing literature with the theory ▪ Finishing Write up

I began the analysis to understand the meaning of the participants' quotes. Open coding is the starting tool to make sense of participants' conversations. According to Strauss and Corbin (1998), open coding helps conceptualize and understand data from participants' points of view. One way to understand the meaning of participants' conversations is to label a concept after reading a line (Strauss & Corbin, 1998). To label a concept, I ask what a participant tries to communicate by responding to our questions. Below, I provide an example of how I use open coding. For example, participant 14 provides the following response:

"*The transition from video to video is very seamless.*" (Interviewee 14)

When I started analyzing what the participant meant by it, I wrote a memo about different meanings that could be anticipated from the line. Next, I agree that this line can be conceptualized as "flexibility." Let us give the example of the memo about the line:

"What does it mean by seamless transition? It might indicate that users may not have to wait to access subsequent content. In the dictionary, "seamless" means smooth, continuous, and lack of gap. Let's compare the seamless transition to an extreme case, such as a troubled transition. I can imagine a scenario to illustrate a troubled transition. For example, a troubled transition can appear when a party wins an election, but the party cannot be guaranteed to take power. It is a troubled transition since even if the winner has the legitimacy to take power, they can't. Such a situation can only arise if an external barrier exists. Thus, the presence of an external barrier is the property of troubled transition. Following the troubled transition example, I could say that seamless transition's properties are the absence of external barriers.

*From the technology perspective, I imagine the seamless meant by the participant is the lack of external barriers or **flexibility**. What does mean by this flexibility? Let's make the opposite comparison, which is steadiness. If something is steady, a person requires effort and others' help to perform a task. So, flexibility is a property of app usage.*" (Analyst)

During open coding, I used constant comparisons and questions as analytical tools to accurately interpret the conversation's meaning (Strauss & Corbin, 1998). Then, I conducted line-by-line coding to ensure I had captured all relevant concepts. After analysis, I found that the total number of open codes is 265.

I engaged in memo writing during and after open coding. Memos offered us two advantages: the ability to record the analysis and choose the direction for theoretical sampling (Strauss & Corbin, 1998). Thus, memo writing became our basis for comparative analysis in theory building. In addition, theoretical sampling notes documented in memos helped us decide what type of concepts require further analysis. Later in the study, I focused on writing conceptual memos. The conceptual memo helped to design the storyline of the theory.

Axial coding is followed by open coding and memo writing. In this step, I connected the categories with subcategories. To relate the categories with subcategories, I use the "coding matrix" proposed by Strauss and Corbin (1998). The coding matrix suggests relating categories based on their role in the data. For example, according to the coding matrix, a phenomenon consists of context, condition, interactions/actions, and consequence (Strauss & Corbin, 1998). Following the coding matrix, I broke down the technology-induced excessive use phenomenon into context, condition, interaction, and consequences. I also use the matrix to generate propositions. Note that I validated each proposition against incoming data. If I had identified any contradiction, I revised the relationship and brought a new theoretical explanation. I continued to use theoretical sampling and constant comparison during axial coding.

During axial and open coding, I maintained objectivity by keeping an open mind about the different interpretations of a concept (Strauss & Corbin, 1998). Besides, I continually compared one case with another. During the comparison, I contrasted each piece of incoming data with existing categories and concepts to determine how it relates to and differs from them (Strauss & Corbin, 1998). It helped me recognize the properties and dimensions of each concept. Sometimes, I look at the literature to find an example of a similar phenomenon.

After conducting open and axial coding, I pursued selective coding. Selective coding focuses on integrating the concepts and categories into a framework. At this point, I ask questions, such as why, how, who, and what, to make categories more abstract (Strauss & Corbin, 1998). I used a conditional/consequential matrix technique to focus on broader conditions related to the phenomenon (Strauss & Corbin, 1998). In this phase, I also wrote a conceptual memo and storyline about the relationship between categories. Urquhart (2010) suggests using “scaling up” when aggregating categories into broader themes in IS context. By scaling up, I mean rising above the details (Urquhart et al., 2010). To scale up, I code around major themes that arise earlier in the interview (Strauss & Corbin, 1998). In addition, I scaled up by comparing theories with existing theories.

Let me explain how I used open, axial, and selective coding iteratively. For example, many participants discussed how technology recommendations generate emotion to return to technology. I conceptualize it as a "positive emotional appeal" in the beginning. Next, I tried to identify the different properties of positive emotional appeal. Using theoretical sampling, I found two properties of emotional appeal: perceived arousal of interest and perceived cheerfulness. Across many interviews, I found evidence of the presence of " positive emotional appeal" in different forms. I combine all those various forms of positive emotional appeal in a single concept. Next, I tried to identify how participants tried to relate positive emotional appeal with other categories. I observed that it functions as a condition for being hooked.

After building the theory, I evaluated the process of building theory using seven criteria proposed by Strauss and Corbin (1998). Those seven criteria are: 1) how was the sample selected? 2) what major categories have emerged 3) what were some events that pointed to the major categories? 4) On what basis has theoretical sampling been conducted? 5) what are some propositions related to the concepts, 6) how the discrepancies are accounted for, and 7) how and why the core category has been selected (Strauss & Corbin, 1998). I identified that I had fulfilled all those seven criteria in building the theory.

After evaluating the theory, I started writing the report. I used quotes from participants and past literature to support our theoretical conjectures in writing the report.

The outcome of the analysis is provided below in table 1.6. The concepts are the outcomes of open coding. The categories are the results of both open and axial coding. Finally, the major themes emerged during the selective coding stages.

Table 1.6: Data structure

Concepts	Categories	Themes
▪ Technology intervened pulling ▪ Curiosity conditioning ▪ Sense of drawn by technology ▪ Stimulated to move forward	Swaying	Hooked
▪ Captivation ▪ Focus ▪ Flow ▪ Perceived disorientation	Experiential Involvement	
▪ Increase time to use ▪ Lack of withdrawal effects ▪ Perceived coping	Adaptation	
▪ Perceived arousal of interest ▪ Perceived cheerfulness	Perceived Emotional Appeal	Proximal Causes of Hooked
▪ Perceived observational learning ▪ Perceived opportunity to engage in challenging ▪ Perceived opportunity to engage in competition	Perceived Cognitive Appeal	
▪ Perceived knowledge gap ▪ Perceived separation anxiety	Fear of Missing	
▪ The unpredictability of action possibilities ▪ Perpetual supply of action possibilities	Perceived agency of technology	Distal causes of Hooked
▪ Ability to seek varieties ▪ Ability to be in control ▪ Ability to express ▪ Ability to modify mood	Need fulfillment ability	
▪ Perceived awareness ▪ Perceived dependence on context	Habit	Consequence of Hooked
▪ Perceived distraction ▪ Perceived sensitivity to time	Perceived work-life balance	

Table 1.6 (Cont.)

Concepts	Categories	Themes
▪ Perceived advantages ▪ Perceived affiliation with value	Intention to Use	Intention to Use
▪ Inquiring about technology	Exploration	Causes of Intention to Use
▪ Connecting with peers	Need to belongingness	
▪ Word of mouth ▪ Peer recommendation	Social Influence	
▪ Influence of technology on usage ▪ Perceived self-regulation ▪ Perceived importance of purpose	Technology Adoption	Technology Adoption
▪ Collecting information	Staying up to Date	Causes of Technology Adoption
▪ Communicating with peers	Maintenance of social connection	
▪ Confronting external pressure	Perceived Coping	
▪ Perceived entertainment	Perceived Hedonic benefits	
▪ Accessibility ▪ Deliverability ▪ Usability	Perceived Advantages	
▪ The intensity of withdrawal effects ▪ Impaired control despite harm ▪ Compulsive thinking ▪ Reduced Productivity	Addiction	Technology Addiction

Findings

I presented the findings of the analysis in two sections. The first section reports a variance model of technology-induced excessive use, which I label as the grounded theory of hooked. The grounded theory of hooked describes and establishes the relationship among action/

interactions, conditions, and consequences associated with technology-induced excessive use behavior (Strauss & Corbin, 1997). The second section reports a process model related to the hooked state. The process model delineates the evolution of technology interaction patterns over time.

In the context of the super app, I mostly prefer to use “interaction” instead of “use” because the interaction is more appropriate to indicate the two-way communication mentioned in human-computer interaction literature.

The Grounded Theory of Hooked

I discovered a pattern in the early phase of the interview. Some participants mentioned that super apps attract them to engage with different action possibilities, such as watching videos, reading news, posting videos, etc. Specifically, those participants commented that "*technology pulls them constantly*" onto the interface. Interestingly, according to them, sometimes, they interact with technology without any specific purpose; instead, they reach out to respond to a technology-generated signal, such as notification, recommendation, and so on. Other times, they interact with technology to fulfill their specific needs. However, regardless of responding to technology signals and their needs, I also found that participants indicated that they feel captivated and stimulated to interact with technology-induced by technology features. Finally, I found that those participants can adjust their interaction patterns based on their needs and technology signals.

I found that this pattern is consistent across many interviews, and the pattern, to some degree, is supported by the description of Nir Eryl in his book *Hooked: How to Build Habit-forming Products* (Eyal, 2014). According to him, the repeated engagement with features could be interpreted as "hooked." I incorporate this term in our study to explain the "action/interaction"

(Strauss & Corbin, 1997) aspects of the technology-induced excessive use phenomenon. Action/interaction is "*a strategic or routine response made by individuals to a happening that arises under those conditions*" (Strauss & Corbin, 1997). Our pattern is an action/interaction because it indicates how participants behave during technology interaction.

The term "hooked," coined by Nir Eryl (2014), has been used in literature in different ways. The dictionary meaning of hooked is "fascinated by or devoted to something". Additionally, according to music literature, the term "hooked" is associated with "hook," which means an object that can persuade people constantly (De Haas & Wiering, 2010). Finally, anthropology researchers used this term to indicate "trapped into something" (Seaver, 2019). As I will explain below, the current understanding of the term "hooked" is well-fitted with the properties of the action/interaction (Strauss & Corbin, 1997) of technology-induced excessive use.

Strauss and Corbin (1998) suggested discovering conditions and consequences after an analyst has identified a primary action/interaction pattern. Following their suggestion, I found different conditions and consequences of hooked using theoretical sampling and constant comparison techniques (Strauss & Corbin, 1998). Together, the construct "hooked," its causes and consequences develop the grounded theory of hooked, a theory that is grounded on actual data.

Hooked State

I observe a pattern by comparing interview cases: a) some participants consistently experience being repeated pulled over to technology interface influenced by their needs and technological signals, such as recommendations; b) they feel engrossed with technology-mediated activities; c) they stay longer time than they plan to stay in the app. The pattern surfaced early in the interview, and I used questionnaires in subsequent interviews to gain a deeper understanding of the pattern. During subsequent interviews, I focus on discovering the causes and consequences of this pattern.

Participants described the pattern from various perspectives and technological contexts (e.g., social media apps, gaming apps, news apps). For example, Interviewee 26, a university student, and social media user, pointed out that the "*mind takes over and ends up extra time on app frequently*." The interviewee feels so enchanted by technology-mediated activities in social media apps that his attention is entirely directed toward those activities. As a result, he ends up spending extra time on those. Interviewee 48, a university student, and Instagram app user, stated, "I think it's easy just to get *caught up in the mindless scrolling. And so, I just get caught up in that and forget what I was originally doing."* Interviewee 48 stressed the same characteristic: channeling full attention and mindlessly using the app more. In addition, he pointed out that he became so involved in the scrolling that he got distracted from his ongoing work.

Further, Interviewee 41, a university student, and social media user, indicated that she often feels like "*downing into a wormhole*." According to her, "*you just kind of find yourself down a wormhole of seeing what everybody's posting instead of just going and responding to somebody what it was initially used for the beginning."* Thus, many participants indicated a pattern, which could be described as steady engagement with technology or staying longer in technology than intended.

To illustrate the steady engagement, we present another case described by interviewee 53. Interviewee 53, a university student and social media user, states that he caught up in activities in apps. He explained that he could not maintain a high degree of self-control over interaction even though he chose to use different tools to curb the degree of interaction.

"I have a 15-minute timer on my Instagram, but I will be scrolling normally and be watching a video, and suddenly I am out of my 15 minutes, but I was watching some video which wasn't finished, so I skip the timer and go back in the app to finish that video and then end up scrolling for another 15 minutes." (Interview 53)

I have found some interesting elements in this pattern. For example, many participants mentioned feeling conditioned when interacting with technology. For instance, interviewee 48, a university student and social media user, states that

"I think it's showing me something that I want. And that's kind of like what pulls me and keeps me in there. Like, every time I scroll, I see something new and something that entertains me. And so, I guess I'm just kind of conditioned to keep scrolling to see more stuff that entertains me." (Interview 48)

Here, interviewee 48 used the word "conditioned" to emphasize the agency of technology. He is conditioned in the sense that recommendations and novel content increase his desire for entertainment content consumption. In addition, he indicated that recommendations constantly reinforce content that he may like. In addition, Interviewee 8, a university student and social media user, states some aspects of this pattern in the following way:

"Even sometimes I am looking for something I am not sure what I am looking for. Like an inspiration quote or something. I want to look at random information until it has been ten minutes. Still, I am scrolling, unsure about what I am looking for. It is crazy; you just started being hooked. Even though I am not a celebrity follower, I see it and want to know more about it. Keep going. There are so many ramifications they present to you. There are no specific reasons besides knowing something more or what is happening." (Interview 8*)*

Interviewee 8 uses the word "*I am not sure what I am looking for*" and "*keep going*" to indicate an essential aspect of the pattern. She mentioned that technology could even pull users without explicit purposes. It indicates that because of the influence of technology, users may act like "present-hedonist," meaning that they might not have any purpose for interaction. Still, they feel the urge to return and engage. Interviewee 46, a professional and social media user, also reinforces this same idea:

"*I use it for no reason for not, not the reason I keep using waiting for something to happen. As if I am not connected to the real world, I don't know what is happening on Facebook. So sometimes I end up wasting a lot of time, not doing anything, just browsing, searching, waiting, something like that*." (Interview 46).

After finding those consistent characteristics of this pattern, such as “engagement” and “conditioned,” I focused on why participants are conditioned and engaged in technology-mediated activities. I incorporated some questions in an interview to find the answer. I identified that most interviewees pointed out that the repeated reinforcement of technology conditioned their behavior. For example, Interviewee 30, a university student and productivity app user, mentioned

"*They create particular stocks that I might be interested in. They are a good match for me. Also, they keep on increasing features. Now, they have savings bank accounts. They offer some kind of customization. The more they add the feature, the more I spend time*." (Interview 30)

According to Interview 30, her behavior was modified over time due to technology reinforcement. We look at the behavior change literature to understand this modification of usage behavior. Many behavioral scientists describe behavioral modification in response to external effects as a swaying (Liu & Karahanna, 2017). I defined swaying as the degree to which individuals are nudged to explore technology-mediated activities. I use the term “nudge” to indicate the process of voluntary engrossing with technology actions influenced by technology reinforcement.

I constantly found evidence of being swayed by technology in the interview. For example, interview 2, who is a university student and social media user, states that

“I usually just keep going to the recommended content to watch the next video. I watch or listen to similar content that is within my interest that the app’s recommendation algorithm.” (Interview 2)

According to Interview 2, “*recommended contents*” swayed him to watch the next set of technology content. He also mentioned that, over time, recommended contents operate within his interest's boundary. As a result, he consciously or unconsciously returns to technology repeatedly.

I wanted to learn more about swaying, and I found that the interviewee’s description of swaying can be explained through Hansen and Jespersen's (2013) framework of nudging. Hansen and Jespersen (2013) developed a framework based on dual-system theory and transparency of externally imposed interventions. The framework is developed in the public policy research context, but I argue that it is important in my research context (Hansen & Jespersen, 2013). Hansen and Jespersen (2013) argued that externally imposed interventions could generate four distinct behaviors: manipulation of choice, behavior, consistent choice, and influenced behavior. According to their framework, manipulation of choice results from non-transparent intervention and reflective thinking. On the other hand, manipulation of behavior is affected by the non-transparent intervention and automatic thinking.

I modified their framework in our study context to better understand the interviewee’s description. Figure 1.5 illustrates the modified framework. Previously, we grouped technologies into two broader categories: manipulation-based and tool-based. Because of its algorithmic capability, manipulation-based technology offers a high degree of reinforcement in the form of highly relevant recommendations, while tool-based technology offers low or no reinforcement. I know from practice literature that manipulation-based technology functions as a self-evolving agent, and tool-based technology functions as a passive agent (Du, 2021). I find that the high reinforcement capacity of manipulation-based technology can sway individuals' interaction patterns.

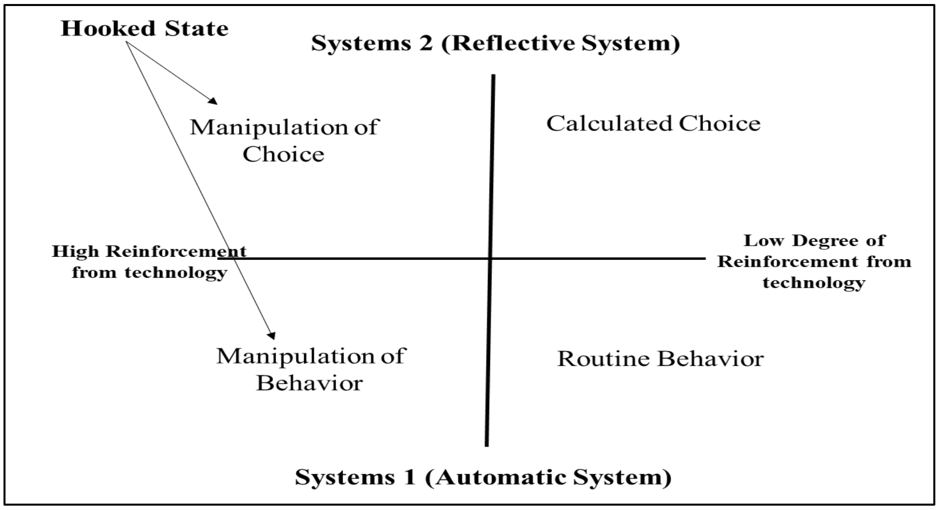


Figure 1.5: Adopted Hansen and Jespersen's (2013) model

I observe that swaying can occur in both reflective (purposeful behavior) and automatic systems (automatic behavior). In a reflective system, swaying occurs when an individual's choice is manipulated. For example, interviewee 37 mentioned that their choice by "made for You page" in TikTok:

"I enjoy scrolling through the "made for me" page. I like watching funny music and TV/ movie clips". (Interviewee 37)

In another example, Interviewee 56, a university student and social media user, states that it makes her aware of her choice, a form of manipulation of choice. According to her:

"They can point me toward different topics or bring my attention to things that I normally wouldn't see/look at" (Interview 56)

Some interviewees also talked about how their behaviors are manipulated. For example, interviewee 42 mentions that

"When I am talking with my friends like "I want chilis today," and an hour later I find chilis add in the Instagram, and it makes me upset that I never type like chilis. It just automatically did that just by listening." (Interview 42)

Interviewee 57, a university student and social media user, also talked about manipulating behavior because of technology reinforcement. According to him:

"I feel that I spend more time on them due to their algorithms and how they continually show me things that I am interested in or want to see." (Interview 57)

Interviewee 57 mentions that the framing of recommendations and the dynamics of algorithms can manipulate his behavior. Overall, I found that technology reinforcement manipulates both users' behavior and choice. Taken together, I call those two technology-reinforced scenarios swaying.

Afterward, I grouped different aspects (swaying, coming back repeatedly in technology) of this pattern into a general "theme" and defined the pattern from the interviewee's perspective and existing literature. As I mentioned before, this category shares some characteristics with the Nir Eryl's (2014) description of "hooked." Thus, I chose the term "hooked" to indicate the pattern. Using a constant comparison among cases and incidents, I preliminary identified that hooked has some characteristics, such as experiential involvement, swaying, and adaptation. Later, I refined our understanding using theoretical sampling. Finally, based on our knowledge of the pattern, I define the hooked state as a **technology usage state that is characterized by users' use of technology longer than planned**. I find that the hooked state can be regarded as a goldilocks zone for technology developers as users optimally engage with the technology features.

I argue that the hooked state is formed through technology's influence. Super apps can utilize users' biases such as attribution and loss aversion biases to influence users. Attribution biases happen as users put greater value on personalized content (Kahneman, Knetsch, & Thaler, 1991). Super apps supply personalized recommendations to allure users to engage more with exciting content. Besides, super apps use loss aversion bias by providing novel content in each session, which can generate the fear of losing novelty.

Besides, I argue that hooked state is a steady engagement state with technology. To explain why I compare hooked state with steady engagement, I use behavioral ecology research. According to optimal foraging theory (a theory in behavioral ecology research), humans are optimal foragers, and humans have a diminishing return when they engage in an activity (Sandstrom, 1994). Because of the possibility of diminishing return, humans switch from an activity to a new type of activity after foraging the old one (Sandstrom, 1994). In the technology interaction context, users have diminishing returns when they engage in a specific activity. For example, the appeal of content novelty may go down, and users may feel bored. However, super apps constantly allure users by providing novel and need-matching action possibilities. It creates a patchy environment that pushes users to move from one technological action possibility to another, reducing the possibilities of diminishing return. This patchy environment can create steady engagement. Thus, hooked is a steady engagement state with technology. In figure 6, I hypothetically illustrate content foraging behavior.

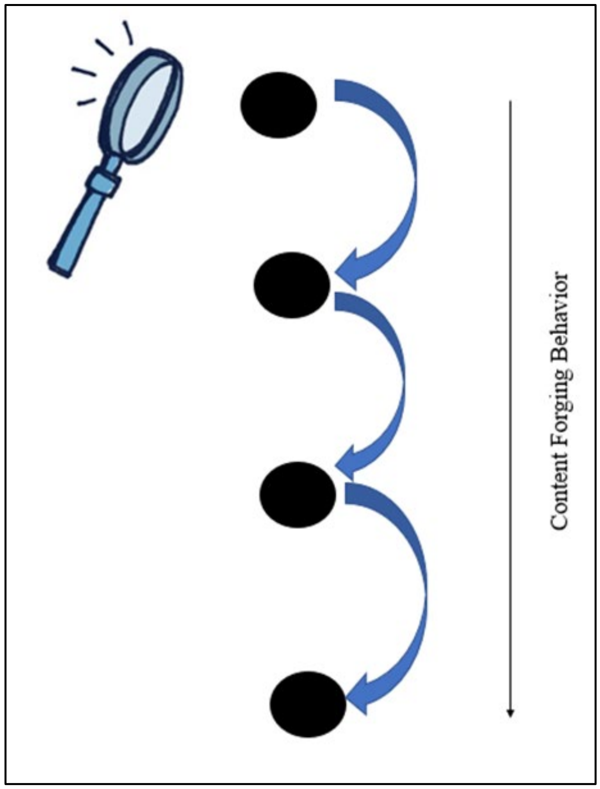


Figure 1.6: Content forging behavior in the app

Properties of Hooked State

I follow Strauss and Corbin's (1998) suggestions to use open and axial coding to identify the properties and dimensions of this construct. I also used questioning, constant comparison, and theoretical sampling. Most interviewees, who were in the hooked state, repeatedly mentioned three properties: experiential involvement, swaying, and adaptation. Below, I will define and describe those properties.

I identify that first property of the hooked state is experiential involvement, which I define as the degree to which individuals are involved in technology action possibilities during the interaction. Many participants reported that they are immersed with technology action possibilities. Sometimes, they mention losing their awareness of the outside world. However, some other participants remarked that technology action possibilities could create a constantly engaging and memorable experience during an interaction. In other words, they remain focused and experience a flow state during an interaction. I observe two features of the concept of experiential involvement in the coding: immersion and stimulation. Our analysis revealed that immersion has three characteristics: a state of focus, flow, and perceived disorientation during the interaction. Below I will show how participants have indicated focus, flow, and perceived disorientation.

Some participants mentioned that they experience a focus state during technology interaction. An important condition for such a focus is the availability of different technology-mediated action possibilities. For example, interviewee 29, a university student and social media user mentioned that the constant availability of new content on WeChat, a social media app, keeps her focused on that app. She was describing an incident in the following ways:

"Sometimes, my son taking to me and asking me to do something. However, I was checking in WeChat and talking to him. I did not even realize what he is taking." (Interview 29)

Interviewee 53, who is a social media user, pointed out the flow states in the following way:

"*I lose my train of thought and lose track of time while using the apps"* (Interview 57)

Some participants describe that they experience flow during the interaction. I define the flow state as the degree to which individuals provide constant attention to the motion of action possibilities. Although the focus is the degree of attention to a particular activity (such as playing only games), flow indicates a degree of attention over a chain of technology-generated activities (playing games, posting, watching videos). For example, Interviewee 43, a university student, and social media user, mentioned about flow state:

"*I would search through Instagram, see someone, and recognize them, then go to their page. And then friends of their friends and so on. So, I spend a lot more time going through then than would be necessary for sure." (*Interview 43*)*

Interview 43 indicates that she navigates to different features and engages with those during technology interaction. As she moves from one feature to another, she does not remain focused on a particular feature but rather on focused on a broad set of features. The flow state makes her spend a lot of time on technology.

I observe that the third characteristic of immersion is perceived disorientation from reality. I define it as the degree to which an individual perceives departure from reality. Some participants mentioned that technology-mediated action possibilities are so engaging that they feel they are into different realities. For example, interviewee 42, a university student and social media, mentions that interaction makes her think that she is in a different world:

"*It makes me feel that I do not have any responsibility or things to do while I am just using the app. It takes me to some different world.*" (Interview 42)

Together, flow, focus, and perceived disorientation from reality constitute the immersion aspects of experiential involvement. I notice that the second feature of experiential involvement is stimulation. I define stimulation as the degree to which individuals perceive enthusiasm in actions generated by the technology triggers. Some participants indicated that they felt a recurrent hunger to stay for a prolonged period interacting with different types of technology action possibilities. According to the optimal stimulation theory, people tend to seek high stimulation (Steenkamp & Baumgartner, 1992). Consistent with optimal stimulation theory, I observe that participants feel recurrent stimulation when interacting with technology action possibilities.

Below, I provide an example of stimulation. Several participants remarked that they are thrilled by the availability of limitless new content in technology at all times. Below, I provide an example of how technology contents make individuals stimulated over time. For example, interviewee 43, a university student and social media user, mentioned that she is stimulated by seeing the content that Instagram provides:

"A lot of people use the exact same apps, and that's how I can see what I was doing like people can post videos on Snapchat, and I'll be like, oh she's at devil's den today, and the same with Instagram they can post pictures on the beach and then I would know that they went to the beach, so it's just kind of pulling me in that everyone else uses it that way" (Interview 43)

The second property of hooked is adaptation. I define adaptation as the degree to which individuals perceive an urge to increase their interaction level to fulfill their situational needs. I view adaptation as the core mechanism to stay longer time in technology. It indicates individuals' revision of their course of interaction.

I use IS literature to understand adaptation. According to IS literature, interaction and adaptation always co-exist in any technology interaction-related construct (Stein, Newell, Wagner, & Galliers, 2015). For example, Stein et al. (2015) argued that users engage in adaptation generated by technology events. In IS context, two common adaptive behaviors are avoidance and revising the interaction (H. Sun, 2012). I argue our concept falls into the second type. I observe that adaptation has been illustrated in various ways in the interview. For example, interviewee 86 pointed out that

"I feel like online interaction helps me stay in an app for a long time because it keeps me informed on what is happening in the world regarding things I care about and am interested in." (Interviewee 86)

Interviewee 86 indicates the motivation to stay longer in the social media app because it keeps updating information that she cares about. In another social media context, interviewee 92 mentions her increased urge to return to technology:

"*I'm in a group chat on Twitter with my friends where we all send the funniest tweets we see, and those notifications are constantly dragging me back in"*(Interviewee 92)

Adaptation indicates a switch from a low to a high degree of usage. However, the shift does not indicate that users' have no control over usage. For example, when individuals feel that their situational needs are fulfilled, they can reduce interaction. This adaptation characteristic sharply contrasts with the addiction perspective, which argues that individuals have no control. I asked some participants how they react if they cannot use the technology (app) whenever they like. Most participants, who use technology excessively and become captivated during the interaction, mentioned that they could replace the activity with others. For example, interviewee 29, a full-time worker and social media user pointed out that although she feels captivation by Facebook, she still can limit the interaction time:

"I enjoy my pastimes by Facebooking after office sometimes. But, you know, almost everything (worldly) is replaceable in this world. So, I'll move on and go back to my old hobbies…. reading books, listening to the song, watching movies, and editing my captured photographs as always, or I will just use the same kind of app" (Interviewee 29)

Additionally, interviewee 43, a university student and social media user, mentioned she could manage stimulations to engage with other activities. According to her,

"I feel a little disconnected from my friends. In TikTok, I would not be too affected. I will be a little upset, but I will be watch movies and go to YouTube. And it just happens temporarily." (Interviewee 43)

The final property of hooked is swaying. I define swaying as the degree to which individuals are nudged to explore technology action possibilities. As I mentioned, the word swaying indicates the manipulation of our hidden psychological biases, such as loss aversion, value attribution, or diagnostic bias. I observe technology reinforces users' needs through recommendations, calls to move further, etc. Those reinforcements, either reflectively or reflexively, pull users to the technology and induce them to stay longer. For many individuals, those reinforcements function as incentives or rewards or support their utility maximization behavior. As a consequence, individuals are swayed.

Many participants described swaying in different reinforcement contexts. For example, Interview 2, a social media user, states that he continues his exploration as he constantly finds need-matching reinforcements.

"I usually just keep going to the recommended content to watch the next video. Once I start using them, it is like I do not want to stop because more content pops up those piques my interest." (Interviewee 2)

Interview 43 indicates that she is constantly nudged to explore more with technology action possibilities. According to her,

"Contents and videos are pulling me to the app. They are just all for entertainment. I find funny videos on TikTok, and then I want to watch more funny videos or see puppy videos on Instagram. I want to see puppies. That is why I want to keep spending more time. Because of those, I wanna return next time." (Interview 43)

Together, according to the interview data and coding, experiential involvement, adaptation, and swaying are constituents of the hooked state. According to the analysis, I conjecture that a participant who is highly involved experientially in technology action possibilities, who experience a high degree of swaying, and who possess a high degree of adaptation is expected to reach to hooked state. However, participants vary with those properties, indicating that hooked states are expected to differ across individuals. Based on our findings from qualitative data, I argue that

Proposition 1: Hooked state is formed by experiential involvement, adaptation, and swaying

The Causes & Consequences of Hooked State

After identifying the major category, Strauss and Corbin (1998) suggested conducting two steps: 1) identify causal conditions and consequences, known as subcategories, of the main category (action/interaction) in the theory-building process, and 2) integrate the main category with the subcategories. I followed these two steps and identified a set of conditions that can drive people to be hooked. I observe that individuals reach a hooked state through a dynamic interaction between human and technology agency. Technology agency is technology's ability to act independently and guide a user to act. Human agency is a user’s perceived autonomy to fulfill their needs. The constant interaction between human agency and technology agency sticks a user into technology by creating appeals, such as positive emotion, cognitive benefits, and fear of missing out. Those appeals constantly motivate users to stay longer time in the technology. Five factors emerge as the leading causes of hooked state: positive emotional appeal, perceived cognitive appeal, fear of missing out, the perceived agency of technology, and perceived need fulfillment ability. Positive emotional appeal, perceived cognitive appeal, and fear of missing out are the proximal causes of getting hooked. Perceived agency of technology and perceived need fulfillment ability are the distal causes of the hooked state. I also observed two consequences of the hooked state: habit and perceived work-life conflicts. Below, I discussed the causes and consequences of the hooked state.

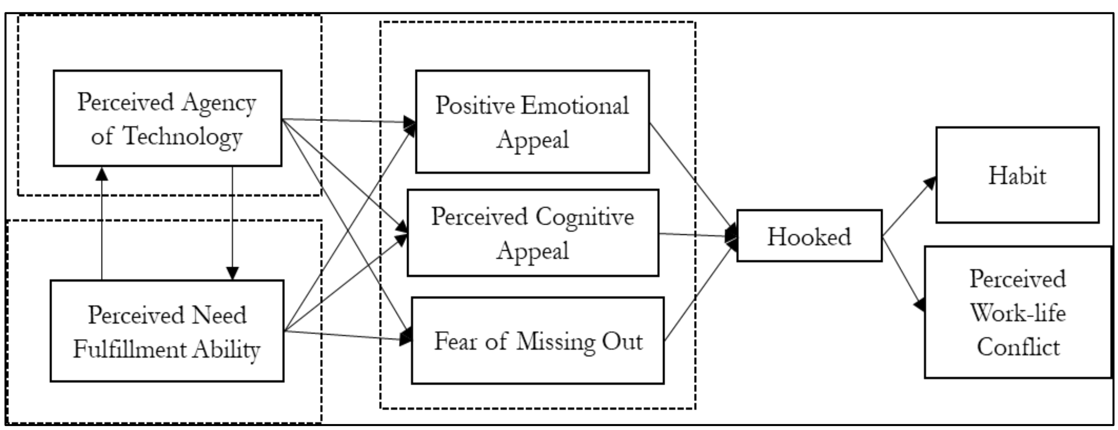


Figure 1.7: Grounded theory of Hooked state

Causes of Hooked State

Positive Emotional Appeal

I observe that positive emotional appeal is one of the proximal conditions of the hooked state. I view emotional appeal as a subjective feeling (Panda, Panda, & Mishra, 2013). In response to technology features, each interviewee, who is in the hooked state, mentioned that they perceive uniform or mixed positive emotions, such as joy, surprise, and happiness. Furthermore, participants said that such aroused positive emotional state sharply contrasts with their normal baseline state. Past literature has shown that IT artifacts can induce emotion in three channels: instrumentality, symbolically, and aesthetically (Stein et al., 2015). The instrumentality channel states that positive emotion can arise as technology support gaining rewards (Stein et al., 2015). The symbolic channel states that positive emotion arises because technology is associated with an individual's identity (Stein et al., 2015). Finally, the aesthetic channel says that positive emotion arises since the representation of technology evokes a sensory pleasure (Stein et al., 2015). I found that super apps elicit positive emotional appeals using all those channels.

Many participants pointed out that positive emotions keep them repeatedly returning to super apps. Emotion has been formally defined as "*an episode of interrelated, synchronized changes in the states of all and most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organisms*" (Scherer, 2005). It is an instinctive response of the human mind (Mulligan & Scherer, 2012). In our study context, I define positive emotional appeal as the degree to which a user perceives positive emotion stimulated by technology features and action possibilities. For example, some participants remarked that technology features evoke joy, happiness, surprise, and pleasure. Those different forms of emotion persuade participants to engage in technology-mediated activities. For example, super apps deliver memories as photos, videos, and so on, as recommendations during an interaction. The representation of memories makes participants feel nostalgic, and the feelings of nostalgia makes them check those content repeatedly.

When participants talked about the positive emotional appeal, I observed that they highlighted two attributes of positive emotional appeal. They are perceived arousal of interest and perceived arousal of cheerfulness. I define perceived arousal of interest as the degree to which an individual perceives technology action possibilities as attractive. Some participants' conversation indicates that they perceive attractiveness because the action possibilities are connected with their identity, society, culture, or even family. For example, Interviewee 6, a social media user, mentioned she found WeChat features are unique as those reinforce her cultural identity. According to her:

"*WeChat is unique because I am from China. So, my friends and families in China and all use WeChat everywhere. We have a family group, I have classmates, and online group, which are unique.*" (Interviewee 6)

Another property of perceived emotional appeal is perceived cheerfulness, which I define individual' feeling of cheerfulness due to technology action possibilities. Cheerfulness is a perception that indicates that action possibilities emerge according to one's desires. I observe that technology action possibilities change a state of mind from boring to cheerful. For example, Interviewee 19, a university student, and gaming app user, describes how technology feature brings cheerfulness from stress:

"It is a way to de-stress. No one I know uses it, and it is more of a niche category app, although it has 1 million users. There are many other similar apps to this one. It has its niche community, and many also like jigsaw games. But this particular one has a feature where when you color in a square, it creates a "stitch," and I find that oddly satisfying." (Interviewee 19)

Although I observe many distinct types of positive emotional appeal, I consistently find three recurring positive emotional appeals: perceived arousal of curiosity, surprises, and vigorousness. I define perceived arousal of curiosity as a type of positive emotion that generates the desire to learn from technology features. For example, interviewee 42, a university student and social media user, described that she feels a desire to know about what her friends are doing through incoming content on Instagram:

*"I stay because the contents suggest like I am curious about what my friends are doing. At the same, I think I try not to spend so much time each time. That is why I open the app 27 seven times a day." (*Interviewee 42).

The second type of positive emotional appeal is perceived arousal of surprise, which I define as a type of positive emotion that make users amused in response to unexpected technology action possibilities. I identify one characteristic of super apps that many participants mentioned: delivery of unexpected action possibilities during the interaction. Many participants mentioned that unexpected action possibilities could rapidly change their mood. They also mentioned that the sudden swing of mood creates surprise. For example, Interviewee 8, a university student and social media user, described that scrolling on Instagram provides new information, which surprises her all the time:

"*When the scrolling of new information is done, it says now here is random information from all over the place, even from the pages that you do not follow. So, it's like always new information now*." (Interview 8)

The third type of positive emotional appeal I identified is perceived vigorousness, which I define as the degree to which the user perceives mental vitality in response to technology action possibilities. I find that technology action possibilities work as a powerful medicament in getting metal vitality for some participants. They perceive that technology interaction makes them feel refreshed. For example, Interview 33, a university student, and social media user, states he constantly goes back to technology because it makes him rechanged.

"Kum app helps me to meditate as well as it helps to sleep faster in the night. It is important for mind and body. It helps me to recharge." (Interview 33)

After discovering properties and typologies of perceived emotional appeal, I found that positive emotional appeal is connected with our core category hooked. Three properties of hooked are swaying, adaptation, and experiential involvement. First, I identify that some participants indicate positive emotional appeal increases experiential involvement (a property of the hooked state). One of the reasons is that emotional appeal functions as "motivation." An activated emotional appeal, such as curiosity, can motivate to engage in action possibilities. Motivation can increase engagement (Sun & Hsieh, 2018) because it increases the sense of "have to." Thus, I argue that positive emotional appeal increases experiential involvement. For example, interviewee 41, a university student and gaming app user, mentions how curiosity, a type of emotion, which is induced by tagged posts, keeps him returning to and engaging to Pokemon Go app:

"*People approach me and on tagged me something if something interesting going on in the community that I am interested in like Pokemon Go. That is what apps come in which I play: Pokemon Go.*" (Interviewee 17)

Further, I know that positive emotional appeal can reinforce behavior or perception (Yuen, Li, Ma, & Wang, 2020). In a technology environment, perceived arousal of interest (a property of positive emotional appeal) can reinforce repeated captivation and stimulation because novel action possibilities could work as a digital reward. For example, participant 43, who is a university student and social media user, states how she is constantly captivated by novel content:

"*Those contents and videos are pulling me to the app. They are just all for entertainment. I find funny videos on TikTok, and then I want to watch more funny videos or see puppy videos on Instagram. I want to see puppies. That's why I want to keep spending more time. Because of those, I wanna return next time.*" (Interviewee 43)

Second, I identify that some participants indicate that positive emotional appeal is associated with swaying. I define swaying as the degree to which individuals are nudged to explore technology-mediated activities. Individuals need to form a positive attitude towards the object to feel nudged to explore. An emotional appeal can generate and reinforce a favorable positive attitude toward the emotional-inducing object (Lee & Hong, 2016). Accordingly, emotional appeal to technology action possibilities generates a positive attitude that technology action possibilities are attention-getting, involving, and memorable. As such an induced positive attitude can nudge to engage with technology action possibilities, I argue that perceived emotional appeal is associated with swaying. For example, Interview 15, who is a university student and social media user, is swayed to return to technology because of perceived emotional appeal:

"*I see a few fun clips, and then it gives me some kind of, you know, relax, relaxing, relaxing mode, so that I can get back.*" (Interviewee 15)

I provided six interview quotations in table 1.7 to illustrate further how positive emotional appeal leads to the hooked state. For example, interviewee 36 indicated that she feels interested when she receives notifications from the Instagram app. Further, she mentioned that such arousal of her interest keeps her in the app for a long time as she reads different types of news besides communicating with her friends. The example indicates that positive emotion, in the form of arousal of interest, can broaden her scope of attention to different things, making her spend a longer time on technology. Past research indicates that positive emotion reduces individuals' decision-making complexity and increases attention span (Japutra & Keni, 2020). Consistent with the past research and the interviewee's description, I argue that positive emotional appeal can lead to the hooked state.

Table 1.7: Illustrative cause quotes

Illustrative casual quotes
1. "*Instagram app is a way to communicate with people, so when I get a notification that someone has responded to me, it makes me interested, and I stay in the app for a longer time. Besides, they have news within the app, so if there's an interesting headline, I will stay in the app to read the article*" (Interviewee 36)
2. "*TikTok constantly finds new videos for me to watch based on what it thinks I like, so I get lots of content that I usually enjoy. In addition, I find cool and unique creators of content or products that I would not have found otherwise. It makes me spend 2-3 hours a day on TikTok* "(Interviewee 49)
3. "*I love the games I play, and I think they are fun and enjoyable; even if I am unaware of how long I play, I still enjoy playing. I play it all the time, without even realizing how many times I play it and for how long they are interesting*" (Interviewee 39)
4. "*Instagram shows me things that interest me, rather than hobbies/ activities that do not pertain to me. I get interested and get lost scrolling on random posts/videos for too long*"(Interviewee 77).
5. "*Those apps know how to put what I am interested in at the top of my page to keep me engaged and give more depth*" (Interviewee 66).
6. "*It seems to know which videos I am not interested in, and I do not have to watch those. For example, I am not watching videos about sports because I never like those. It captivates me to the app, and I never realize how long I am using it*" (Interviewee 31)

Further, interviewee 49 indicated that TikTok constantly finds content based on her interests, and she feels "cool" about it. She also mentioned that she stays a long time daily on TikTok because of the feeling of coolness. This example indicates that positive emotion can help form attachment to technology; consequently, users may stay longer in technology. This is consistent with research on positive emotion and brand (Fredrickson & Branigan, 2005).

In addition, interviewee 39 mentioned that gaming app keeps him interested, making him spend a significant amount of time on the app. According to him, games create the feeling of fun, which increases his temporal focus on the app. As a result, he stays a long time in the app. Furthermore, research on attention indicates that positive emotional appeal can increase temporal focus given a user's increased neural activities (Winterich & Haws, 2011).

Next, interviewees 77 and 66 indicated that Instagram's content interests them, and they get lost in the random posts. According to them, the arousal of interest, a form of positive emotion, keeps them engaged with random posts. Again, this is consistent with interviewee 36's description I presented before. Given that positive emotion can increase attention span, it can influence staying longer in technology.

Further, interviewee 31 mentioned that the TikTok app provides content based on her interest. The constant supply of those content makes her "captivated" by the app. Captivation, a form of positive emotional appeal, indicates feeling trapped in an object (Seaver, 2019). When an individual becomes captivated by a particular object, her scope of attention toward the object increases (Rubenking & Lang, 2014). As a result, the individual may spend a long time interacting with the object (Rubenking & Lang, 2014).

Summing up the conversation, I argue that

Proposition 2: Positive emotional appeal leads to the hooked state

Perceived Cognitive Appeal

Many participants indicated some appeals that could not be classified as positive emotional appeals. For example, some participants perceive benefits, such as learning, competing, receiving points, badges, and others. I identified three common patterns of those benefits: First, participants perceive that they can learn about their surroundings. Second, participants perceive they can engage in competition and cognitively challenging tasks in apps. Third, participants perceive that they can predict a situation or social environment. The constant comparison technique suggests that those perceptions differ from positive emotional appeal because those indicate cognitive benefits rather than emotional arousal. In other words, users can apply their cognitive skills when interacting with technology features. Therefore, I labeled the pattern as perceived cognitive appeal and defined it as the degree to which a user perceives cognitive benefits using technology features. For example, Interviewee 6, who is a university student and social media user, states how the constant updates of news help her learn about her surroundings:

"WeChat provides an update about the top news, and they will tell you, oh my god, how many of your friends read this? Oh, another function is people nearby. So, you can find how many people are nearby immediately. Like, let's say nearby you about three miles or 10 miles who using this." (Interviewee 6)

I find that some participants mentioned different variations of perceived cognitive appeals. I grouped them into five categories: perceived observational learning, perceived ability to predict, perceived opportunity to engage in challenging tasks, and perceived opportunity to engage in competition. Here, I am discussing those properties below. First, I observe that technology action possibilities afford individuals to learn from other people or the environment. I label this phenomenon as perceived observational learning. For example, Interviewee 56, who is a social media user and university student, stated how she could learn from his social surroundings:

*"Some of my friends went somewhere where I want to go. I do not know too many things about that place. I also search on Facebook for what kind of information they are sharing. And also, the places they are going, where parking. That kind of information helped a lot." (*Interviewee 56)

I also observed that technology action possibilities could help some participants to predict the social environment. I label it as the perceived ability to predict. I define the perceived ability to predict as the degree to which an individual can predict a situation or social environment. For example, interviewee 29, a full-time banker and social media user, illustrates how Facebook helps her predict the personality of her virtual friends:

"*I think that Facebook wall is like the mirror of a person. Because it displays what they like, share and post, we can get an idea about a person's personality. Although, we cannot be sure what kind of person they are just by seeing their Facebook wall. But we can get a view about their perspective about life."* (Interviewee 29)

I also observe that technology action possibilities can make some participants realize and predict their needs. For example, many participants mentioned staying engaged in different activities but did not know what activities they might like. Apps can analyze their activities and make them aware of what kind of actions they might like. For instance, Interview 42, a university student and social media user, mentions that

"It definitely made me realize what kind of content I watch. Because I just watched all the content." (Interview 42)

I also observe that technology action possibilities can provide the opportunity to engage in challenging tasks, which I define as the perceived opportunity to engage in challenging tasks. For example, interviewee 83, a university student, who uses Cross Stitch, a gaming app, mentions that

"*In Cross Stitch app, I can color every square field. It takes a lot of effort, but I like the challenge."* (Interview 43)

Finally, I observe that technology action possibilities can provide the opportunity to engage in competition, which I define as the perceived opportunity to engage in competition. For example, interviewee 86, a university student who uses "Snap Games" in the Snapchat app, argues

"To me, the most interesting part of Snapchat is Snap Games. I can play Snake Squad game with my friends and compete with them. It's an interesting way to spend time" (Interviewee 86)

Next, I focused on the relationship between perceived cognitive appeal and hooked. I argue that the relationship between perceived cognitive appeal and the hooked state can be explained through the theory of subjective extension of human boundary (McLuhan & Mcluhan, 1994). The cognitive benefits offer the opportunity to use human mental tools, such as prediction ability, decision-making ability, skill application, and so on. As a result, human boundary expands, and new needs are created constantly. Those new needs work as cognitive appeal, which can facilitate individuals being repeatedly pulled by technology. Consequently, one reaches the hooked state.

Let me give some examples of quotes to support the relationship between perceived cognitive appeal and hooked. First, when participants receive constant cognitive benefits from technology-mediated activities, they experience experiential involvement, a property of hooked. For example, Interviewee 42, a university student and social media user, states how learning, in the form of new recipes, makes her captivated:

"*What I always watch is through the recommendation and how it changes. So it's like, when I'm like, really into cooking, all the recommendations would be like about my like, about the new recipes, and like, all those things, but when I want some of my new clothes, and like, that's the only thing that I'm looking for, it changes to so it's like, it's a way to know what I am really into that time.*" (Interviewee 42).

I provided two illustrative quotes in table 1.8 to illustrate further how perceived cognitive appeal leads to the hooked state. For example, interviewee 69 indicates that the challenging part of the game keeps him staying longer in the app. Challenge in a game is associated with gaining power, wealth, and status (Xu, Turel, & Yuan, 2012). Achieving those objectives requires perseverance; thus, users need to stay longer in a game (Xu et al., 2012). Some anecdotal evidence suggests that taking on challenges in the game is associated with continued game playing (Joe & Chiu, 2009). Using the interviewee’s description and literature, I argue that perceived cognitive appeal leads to the hooked state.

Table 1.8: Illustrative causal quotes

Illustrative casual quotes
1. "*The algorithm tries to match you against opponents of similar skills, so the game does not feel like you're getting destroyed repeatedly and keeps the game challenging. It makes me stay in the game*" (Interviewee 69)
2. "*The Clash Royale app looked good in a commercial, and I downloaded it. I feel a constant urge to check my chests on the game to open and unlock new things. It allows me to take the challenge, which makes me return to the app*" (Interviewee 63).

Further, interviewee 63 indicates that he constantly returns to the Clash Royale app to unlock new things. Unlocking new things in a gaming app requires higher mental processing abilities, making him repeatedly return to the app (Xu et al., 2012). Thus, the ability to use cognitive skills makes some users spend extended time in a gaming app. Some anecdotal evidence from literature supports this notion. For example, the ability to unlock new things can help escape reality, making users spend significant time on technology (Golub, 2010).

So, the perceived cognitive appeal could create a constant urge to return and engage with technology. Taken together those conversations, I argue:

Proposition 3: Perceived cognitive appeal leads to the hooked state

Fear of Missing Out

Many participants mentioned that they constantly return to technology because they fear missing technology experience. I define fear as a negative affection generated by perceiving a real or an imagined threat. In our study context, I identify that some participants mentioned that they anticipate or imagine a threat of missing when they are not engaging with technology action possibilities. They pointed out that technology-generated experience is so attractive that it makes them feel disconnected or unhappy when detached from it. I label this perception as fear of missing out and define it as the degree to which users feel they are missing information, events, or experiences that could be gratifying. For example, Interviewee 8, a university student and social media user, points out that she considers the interaction time very important as she can communicate with her closest friends. She feels fear of missing when she is not interacting. According to her,

"With my closest friend, because I am interacting a lot through the app, maybe I am missing something important that an important person is sending me, not like the overall network. Its missing important time, especially because we are in different time zone." (Interviewee 8)

Further, interviewee 23, a university student and social media user, mention that she fears missing information if she is out of Facebook for an hour. According to her:

"If I stay away from Facebook would be one hour maybe one and a half hours or if it exceeds one more than one or I feel that something's missing." (Interviewee 23)

During the interview, I identified two properties of fears of missing out: perceived knowledge gap and separation anxiety. I define perceived knowledge gap as the degree to which individuals feel worried about the lack of information about entities. For example, Interview 17, a university student and social media user, points out that he feels a sense of urgency to know what is happening around him. According to him,

"If you have your phone on vibrate, or if you have it on loud, you are constantly hearing, you are constantly feeling that something is happening, and I knew that I always felt a sense of urgency to answer what it is because I do not know what it is." (Interview 17)

Some participants also mention their anxiety when they are out of interaction. I define separation anxiety as the degree to which individuals perceive discomfort for not engaging with technology action possibilities. For example, interview 25, a university student and social media user, states that she feels anxiety if she is not able to use the technology at some point

"*If I cannot get on social media at some points of the day, I tend to get anxious*" (Interviewee 25)

Like cognitive and emotional appeals, fear appeal profoundly impacts reaching to the hooked state. Many studies indicate that fear appeal can influence people's attitudes and behavior (Sun et al., 2022). I observe that some participants are likely to engage for a longer time with technology action possibilities to reduce the knowledge gap and separation anxiety. Studies in neuroscience show that removing fear can facilitate attentional engagement (Van Damme et al., 2004). Among many observations related to this relationship, I like to present the comment of Interviewee 3. Interview 3, a university student, and social media user, perceives that fear captivates her to TikTok. According to her,

> *"I do feel very drawn to TikTok, so I can stay on top of trends because if you aren't on there for a week, your entire page is slightly confusing because you have missed so much new stuff."* (Interviewee 3).

I further provided two illustrative quotes in table 1.9 to explain how fear of missing out leads to the hooked state. For example, interviewee 62 mentioned that there is always something new in the TikTok app, and she fears that she will miss those if she is not engaged. Such a fear appeal generates an overwhelming urge for her to stay longer on TikTok. As a result, she becomes drawn to TikTok. According to the past literature, fear of missing out appeal can generate dissatisfaction and anxiety, increasing an individual's tendency to return to technology (Abel, Buff, & Burr, 2016). Consistent with the literature and interviewee's description, I argue that fear of missing out can lead to the hooked state.

Table 1.9: Illustrative casual quotes

Illustrative casual quotes
1. *"I started using the app a few years ago and haven't stopped using it. I am aware of how I started using the app, but gradually, my usage of the app has increased. Tiktok is the one app I go to when I have free time, and it is one of the most used apps on my phone. Because the app has so much content, there is always something new to watch. It makes me miss something if I cannot use it. It causes me to be drawn to this app"* (Interviewee 62).
2. *"I play some games on my phone, and every now and then, when I haven't played in a while, they give me extra free items that convince me to keep playing"* (Interviewee 107).
3. *"The app Snapchat has different friends' stories and famous people, so you can watch them and keep up with them. If I could not follow those, I feel like I was losing information about them. It leads me to spend a lot of time on them"* (Interviewee 93).
4. *"It is a unique way to communicate with friends, allowing them to see what they are doing rather than just texting. If you stay out for a few hours, you need to come back as you may miss something. You end up staying 3 to 4 hours a day"* (Interviewee 59).

Further, interviewee 107 indicated that a gaming app provides him with free items if he does not engage with the app. However, as he does not want to lose those free items, he repeatedly returns to the app and starts playing the game for longer. Thus, the fear of losing extra items keeps him returning to the app. Past literature mentioned that the fear of missing out could lead to forging behavior as users want to forge content to avoid fear of losing content (Roberts & David, 2020). Consistent with the literature and interviewee's description, I argue that fear of missing out leads to the hooked state.

Next, interviewee 93 stated that he follows friends' stories and famous people on Snapchat. He mentioned that if he cannot follow those, it makes him feeling losing vital information. As a result, he repeatedly return to follow those. This is also consistent with past literature and our conjecture that fear of missing out leads to the hooked state.

Furthermore, interviewee 59 mentioned that he used Instagram to connect with his friends and a few hours' gaps could make him feel like missing something, contributing to repeatedly coming to the app. Past literature argues that fear of missing out indicates the existence of unmet needs (Tandon, Dhir, Almugren, AlNemer, & Mäntymäki, 2021). Therefore, users repeatedly return to apps to fulfill their unmet needs and stay longer until their needs are fulfilled. Hence, I propose that

Proposition 4: *Fear of missing out leads to the hooked state*

Perceived Need Fulfillment Ability

Most participants in the interview mention that they keep going back to technology because technology provides them the autonomy to fulfill their needs. I defined this observation as perceived need fulfillment ability. I observe a range of need fulfillment abilities in interviews. I grouped those needs fulfillment ability into five categories: a) ability to seek varieties, b) ability to connect, c) ability to be in control, d) ability to express e) ability to modify the mood. Below I discussed each of those needs and fulfilling abilities.

First, I like to discuss the ability to seek variety. Some participants mentioned that technology keeps them engaged for a long time because they perceive the ability to seek varieties in super apps. For example, Interviewee 12, who is a university student and social media user, mentioned a lack of barrier she feels when she watches videos:

"Because there are millions of videos with no barrier to watching any of them, it's hard to get off of the app." (Interview 12)

I observed that the availability of different action possibilities in the same app provides some advantages to users. It can free up their mental resources to search for action possibilities in different apps. Besides, users can quickly switch between tasks and easily fulfill multiple desires in the same place. Thus, technology provides them the freedom in usage. For example, in interview 32, a university student and social media user explained why she that technology fulfills her needs:

"*All I need to do is click on the video, and I have unlimited access to knowledge from people all over the world.*" (Interviewee 32).

Many participants mentioned that the availability of different action possibilities makes them focused on what they want. For example, Interview 41, a university student and social media app user, states:

"*With the Snapchat feature of allowing me to post shorter as my friends can see it. For example, if I see my friend posted something and I want him to say something about it, it makes it easy to start a conversation with them. And also, like, it keeps you for the longest time right this feature."* (Interviewee 41).

Next, some participants mentioned that they could control tasks when interacting with technology. First, I define perceived being in control as the extent to which an individual perceives that they are in charge of prolonging the interaction time. For example, interviewee 41, a university student and social media user, stated that

"*There are certain ads and stuff like that that will pop up and stuff like that of just recent things I've been looking up and everything. The full control that I believe that I have in the app is just kind of pertaining to I kind of make the initial action. And so that's just kind of what makes me feel like that I do have the control*." (Interviewee 41)

In another case, interviewee 43, a university student and social media user, mentioned that the Instagram app lets her control public conversation since she can see the live picture of her friends. According to him:

"*It allows you to take a picture and send it to that person. And then they're able to open up my picture, and they're able to reply with a picture so it's like I can see them face to face every day without being directly next to them.*" (Interviewee 43).

Another interviewee, 35, pointed out how she feels in control of performing activities in-app. According to her:

"*The app is making life easier or convenient. Right now, I use the app to make life more convenient. I do not take any pleasure in using the app. For example, watching a movie, playing a game, or clicking photos. Over time, as it gets integrated, it makes life easier. Now I pay the bill. I watch Netflix by putting my phone beside me. Everything is geared towards that. It is shifted from that*." (Interviewee 35)

Next, another property of need fulfillment ability is the ability to connect. Some users mentioned that they could connect with others using super apps. For example, Interviewee 7, in the Facebook app context, argues that

"I use it to message family members or friends. I enjoy apps that let me communicate with others, I spend a lot of time on Facebook face timing my family while I'm away at school. I stay on a page that I find funny or entertaining." (Interviewee 7)

Another interviewee, 96, points out in Snapchat app context points out how she gets the ability to connect with others using the Snapchat app:

"My favorite app is Snapchat because it allows me to keep in personal contact with people no matter where they are located around the globe. It also allows me to keep up with them. I am normally on it between one and two hours a day." (Interviewee 96)

Nest, I found that some participants find the ability to express themselves in the app. For example, Interviewee 83, an Instagram user, points out that:

"*I can constantly upload the photos and thoughts in the Instagram app. Instagram has different ways to express my ideas, such as private and public posts*" (Interviewee 83)

Finally, I found that some participants have the ability to change their moods. For example, Interviewee 57, a YouTube app context, points out that:

"*YouTube gives me the seemingly endless opportunity for entertainment. It uplifts my mood*" (Interviewee 57)

I argue that an individual's need fulfillment ability can lead to the hooked state through perceived emotional appeal, perceived cognitive appeal, and fear of missing out. To make the connection among those, let's revisit the difference between tool-based and manipulation-based technology. As tool-based technology has a lower ability to personalize content than manipulation-based technology, I expect that tool-based technology might represent an unnecessary and larger chunk of information to users than users can process. Thus, the availability of excessive and larger chunks of information could lead to information overload, a barrier to processing important information for a required task (Saunders, Wiener, Klett, & Sprenger, 2017). The manipulation-based technology processes past and real-time usage and personalizes information, reducing information overload by providing only relevant information that a user can process. Thus, manipulation-based technology provides a higher ability to fulfill needs quickly. Such an ability allows users to move easily from a patch of technology action possibilities to the next patch of technology action possibilities. As a result, users become engaged and feel the urge to stay for a longer time.

In addition, using a functional perspective, I argue that rational humans want to maximize their subjective utility. As technology constantly provides need-matching content, users want to maximize their utility from those contents. Thus, I argue that perceived need fulfillment ability leads to the hooked state through the mediation of positive emotional appeal, cognitive appeal, and fear of missing out.

I further provided two illustrative quotes in table 1.10 to explain how positive emotional appeal, fear of missing out, and perceived cognitive appeal mediate between need fulfillment ability and the hooked state. For example, interviewee 81 indicates that the Facebook app allows her to fulfill needs like learning about people worldwide. Furthermore, such a need fulfillment ability arouses interest (positive emotional appeal property) in her, given that apps constantly supply contents that address her needs. Finally, according to her, she spends considerable time on Facebook because of the arousal of interest. Interviewees 52, 29, 47, 68, and 20 reinforce the conjecture that arousal of interest, generated through need fulfillment ability in an app, leads to the hooked state. For example, interviewee 47 mentioned the feeling of being captivated on Instagram as it she can connect with her friends and family. Such a feeling of being captivated makes her stay on the Instagram app for a long time. Further, interviewee 20 indicated that she could fulfill her need for entertainment in the TikTok app, and videos related to dogs and sports arouse her interest in engaging with TikTok. As a consequence, she stays a long time on TikTok app. Existing literature argues that the need fulfillment ability in technology can trigger emotional arousal as technology randomly provides need-matching content (Siebert et al., 2020). The random content is generally unanticipated to users, and unpredictable experiences can create positive emotions (Siebert et al., 2020). Further, according to past research, the ability of technology to enhance experience can create positive emotional arousal, immersing users with technology (Orru, Kask, & Nordlund, 2019). Thus, using prior literature and interviewee descriptions, I argue that the need fulfillment ability leads to the hooked state through the mediation of positive emotional appeal.

Table 1. 10: Illustrative casual quotes

Illustrative casual quotes	Link
1. *"I get to see what my friends are doing and what other people around the world are doing. I get to see things I like or am interested in right when I get into the app. It keeps me interested, and I easily spend 2-3 hours daily"(*Interviewee 81)	Need Fulfillment Ability→Positive emotional appeal→ Hooked State
2. *"I always check my Facebook and Instagram every 30 minutes because I want to stay up-to-date with news, chat with friends, or check out the notifications I receive"* (Interviewee 52)	Need Fulfillment Ability→Positive emotional appeal→ Hooked State
3. *"I am motivated to complete the daily lesson for my benefit and partially because I don't want to lose my ongoing several hundred-day completion streaks. It makes me use the app at least 2 hours in a day"* (Interviewee 26)	Need Fulfillment Ability→Fear of missing out→ Hooked State
4. *"I feel like online interaction helps me stay in an app for a long time because it keeps me informed on what is happening in the world regarding things I care about and am interested in"* (Interviewee 29)	Need Fulfillment Ability→Perceived cognitive appeal→ Hooked State
5. *"I like to keep up with friends and family and see what is happening in other people's lives. It captivates me and keeps me on the app longer than I should"* (Interviewee 47)	Need Fulfillment Ability→Positive emotional appeal→Hooked State
6. *"Sometimes, Facebook will make me stay in the app for long periods because of online interactions. I will start reading a post made by someone else that interests me, which causes me to continue to search and scroll other content related to the original post I first found interesting. An example of this is when I read a post about a recent event (Ex: a crime committed in my area). I will then search keywords to find other posts and comments related to the event to learn more information/details about it"* (Interviewee 68)	Need Fulfillment Ability→Perceived emotional appeal→ Hooked State
7. *"TikTok uses an algorithm to mainly show you videos that are going to be of interest to you. So, for example, I love dogs, and I'm a student-athlete, so I get a bunch of videos on my feed about dogs and videos from athletes. It makes me interested, and I grew a tendency to come back and watch more"* (Interviewee 20)	Need Fulfillment Ability→Positive emotional appeal→ Hooked State

Next, interviewee 29 indicated that need to connect with others generates subjective judgment that she can learn and predict about the social and physical world. Such a subjective judgment, a form of cognitive appeal, makes her stay more extended time in the app. Past research indicated that innate and situational needs could generate cognitive appeal as needs fulfillment ability allows users to focus on the positive features of need-fulfilling objects (Septianto & Pratiwi, 2016). Given that cognitive appeal can create the perception of expanding boundaries, users stay in the app for a more extended period to expand their knowledge, skills, and achievements. Thus, I argue that the need fulfillment ability leads to the hooked state through the mediation of cognitive appeal.

Finally, interviewee 26 mentioned that he needs to learn about a particular topic in the app, and the app provides rewards in the form of streaks if he can complete a certain amount of lessons daily. The fear of losing streaks motivates him to return to the app repeatedly. Thus, interviewee 26's description indicates the casual relationship between need fulfillment ability, fear of missing out, and the hooked state. According to social determination theory, the deficit of need fulfillment ability may lead to fear of missing out as apps enable to fulfill needs (Beyens, Frison, & Eggermont, 2016). Thus, I argue that the need fulfillment ability will lead to the hooked state through the mediation of fear of missing out. Summing up the conversation, I argue that:

Proposition 5: Perceived need fulfillment ability leads to the hooked state through the mediation of positive emotional appeal, cognitive appeal, and fear of missing out.

Perceived Agency of Technology

I observe that most participants have acknowledged the agentic role of super apps in initiating and maintaining their interaction. Let's revisit the definition of the hooked state: a technology usage state characterized by users' use of technology longer than they plan. According to the definition, the agency of technology plays a critical role in the hooked state. I observe two technology agencies: the ability to perform autonomous actions and the ability to modify actions to match users' needs. I will first discuss the autonomous activities, and next, I will discuss the modification ability. Before discussing the agentic capabilities of super apps, I first define what I mean by an agent. The agent is "*anything that can be seen as perceiving its environment through sensors and acting on the environment through effectors*" (Russell & Norvig, 2002). According to this definition, an agent can impact an external environment by sensing the external environment. Following this definition, I label agentic capability as technology's ability to achieve a user's goal. Below, I will discuss how the ability to perform autonomous activities and modification abilities can hook users.

Ability to Perform Autonomous Activities

When I turned our attention to interview data, the interviewee discussed various forms of autonomous activities. For example, Interview 42, a university student and Instagram app user, states the recommendation capability of Instagram. According to her,

"*They put recommendation and in a way that they like but all the attractive contents for me to like, they put all the on the recommendation section*." (Interviewee 42)

Similarly, Interview 53, who is a university student and social media user, stated about the recommendation capability of Snapchat. According to him

"I definitely feel that with the app recommendations in an app like Tiktok, which has an amazing algorithm that will curate content according to your likes, followings, time spent on a particular video, and a lot more stuff. It learns over time and gives you content according to you, which pulls me into using that app even more." (Interviewee 53)

Based on interview data, I classify autonomous activities into five themes: need-matching, analyzing, priming, integrating, and delegating. Below, I will discuss each of those properties and explain how perceived agentic capability is associated with being hooked.

Here, I discuss the property associated with autonomous activities. First, I define need-matching as the degree to which individuals perceive that action possibilities match users' demographics and situational needs. Many participants mentioned that the technology representation closely matches their preferences. For example, interviewee 15, a full-time worker and social media user, said how the technological mediated action possibilities relate to his culture:

"Instagram shows those posts those public posts from my country people. So, for example, I don't get any public posts from a person from India, from Canada, where they meet. So, I think Instagram knows, you know my nationality or based on maybe the text. So, I didn't know how the algorithm worked. But the algorithm connects me with, you know, people from my own cultures." (Interviewee 15)

Next, I define "analyzing" as the degree to which technology cognitively processes an individual's information. For example, Interview 6, a university student, and social media user, thinks that technology is analyzing every social information:

"*WeChat gonna share with you will tell you, let's say there's some news, and how many of your friends read this news. So, for example, more than three friends read the news, or more than how many people read the I mean, based on your connections, how your friends were reading these, your friend reading that*." (Interviewee 6)

Next, I define priming as the degree to which users perceive that a specific technology action possibility leads to subsequent action possibilities. For example, Interview 15, a university student and social media user, stated how she gets one action possibility leads to another action possibility. According to her:

"When you click, you can see not only your friends but other Instagram accounts you know posts like videos and pictures, you go to explore section you can see Public Accounts you know videos and maybe this stories this story, and then you feature that you can have a video or photo on your story while you can play music at the same time." (Interviewee 15)

Next, I define integrating as the degree to which individuals perceive the integration of technologies. For example, Interviewee 8, a university student and social media user, states that:

"Facebook, like Instagram, Messenger, WhatsApp, they are trying to sync everything together now. The messenger, you now have new features that you only had in massager but are now a part of the conversation in the Instagram app. So, they are trying to change everything. Even trying to create a marketplace that you had on Facebook in the Instagram now" (Interviewee 8).

Finally, I define delegating as the degree to which individuals perceive their tasks designated to technology. For example, Interview 6, a university student and social media app user, perceived that some action possibilities in WeChat, such as reminding, have been delegated to WeChat. According to her:

"I can subscribe some, you know, how to say that. Add those, I will say. Yes, they can post. So anytime they post something, they're going to remind me. Oh, and one of your subscribers won't miss an update on something. So, I can check up." (Interviewee 6)

Based on my understanding of interview data, I argue that autonomous activities can contribute to the hooked state by arousing emotional appeal, cognitive appeal, and fear of missing out. For example, when super apps recommend content that matches users' needs, users may become emotionally aroused by realizing that super apps grasp their needs automatically. Thus, as the action possibility supported by super apps repeatedly match users' need, users may attach an emotional tag to the action possibility. As a result, autonomous activities can lead to arousal of emotional appeal. As I discussed before that positive emotional appeal can lead to the hooked state, I argue that perceived agentic capability can lead to hooked by inducing emotional appeal.

Additionally, autonomous activities such as analyzing, integrating, and delegating can reduce users' mental effort in providing instructions to technology. Reducing mental efforts can help allocate energy in interacting with diverse technology action possibilities. Therefore, it is cognitively appealing to users as they have incentives to stay longer with technology action possibilities. As cognitive appeal leads to the hooked state (discussed in the past section), I argue that perceived agentic capability can lead to the hooked state by inducing cognitive appeal.

Further, as autonomous activities reinforce users' likeness, they may fear that detachment from technology may lead them to miss important information, events, and so on.

I further provided two illustrative quotes in table 1.11 to explain how positive emotional appeal, fear of missing out, and perceived cognitive appeal mediate between the autonomous ability of technology and the hooked state. First, interviewee 40 mentioned that apps' autonomous activities could reduce his effort to manually search for the content he likes. It creates a subjective judgment that he can quickly gain something without figuring out how to search. Thus, he stays a long time in the app. Existing research supports the notion that reduction of cognitive effort can make people stay longer in technology (Scott E Caplan & High, 2006). Thus, consistent with the literature and interviewee's description, I argue that autonomous activities of technology can lead to the hooked state through perceived cognitive appeal.

Table 1.11: Illustrative casual quotes

Illustrative quote	Explanation
1. *"I have not manually searched for anything to watch on its own besides some specific channels, and most of the content I find is from my recommended page or below other videos. It makes me spend hours in it"* (Interviewee 40)	Perceived agency of technology→Perceived cognitive appeal→hooked state
2. *"The app has ways of configuring things I've liked and showing similar topics to keep my interest in staying on the app for longer periods"* (Interviewee 50)	Perceived agency of technology→Perceived emotional appeal→hooked state
3. *"The notifications that Duolingo sends out push me to return so that I can keep my consecutive daily streak alive"* (Interviewee 63)	Perceived agency of technology →Fear of missing out→hooked state

Further, interviewee 50 indicated that the autonomous activities of the app trigger interest, a form of positive emotional appeal, to engage with the topics. As a result, interviewee 50 stayed in the app for an extended period. According to recent research on artificial intelligence, autonomous activities supported by artificial intelligence can create an enjoyable and pleasing user experience (Gomes & Preto, 2018). Need-matching objects supported by technology can excite users and keep them returning to technology. Consistent with the literature and interviewee's description, I argue that autonomous technology activities can lead to the hooked state by triggering positive emotional appeal.

Next, interviewee 63 mentioned that the Duolingo app provides him streak using a progression mechanism. However, he feels that he may not achieve the streaks daily if he does not interact with the app. Such a feeling keeps him repeatedly coming back to the app. Existing literature indicated that technology's autonomous activities, such as gamification, can generate fear of missing out as those activities constantly provide rewards based on users' performance (Alutaybi, Al-Thani, McAlaney, & Ali, 2020). Such a feeling of fear of missing out can generate the hooked state. Summing up the discussion, I argue that

Proposition 6a: *Autonomous activity of technology leads to the hooked state through the mediation of perceived emotional appeal, perceived cognitive appeal, and fear of missing out*.

Modification Ability of Technology

I define modification ability as the degree to which technology can constantly modify content based on external requirements. Modification ability is a run-time behavior of technology that incorporates users' input and preferences. The heart of modification ability is constantly matching situational needs with outputs.

From interview data, I learned about the modification ability of super apps. Although novel action possibilities can attract and keep users returning to the technology, the novelty effect could wear off after some time, generating disengagement with technology action possibilities. Optimal stimulation and flow theory support the notion that the effect of novelty exits over time (D. Liu, Santhanam, & Webster, 2017). Given the diminishing return of novel action possibilities, constant matching of users' situational needs with action possibilities plays a vital role in reaching to the hooked state. Modification ability captures the dynamic of matching users' situational needs with technology action possibilities.

Many interviewees mention different facets of modification ability. For example, Interview 8, a university student, and social media user, mentions how she constantly perceives the change of content in the technology interface:

"*Now what they are doing is- when the scrolling of new information is done, here is random information from all over the place, even from the pages that you do not follow. So, it's like always new information now*" (Interviewee 8)

The properties of modification ability are the consistent need-matching and the perpetual supply of action possibilities. I define consistent need-matching as the degree to which an individual's cognitive and emotional needs are constantly matched with output. For example, interviewee 17, a university student and social media user, stated

"*It was always an incentive to me to go back because I could end up seeing some new video that went viral, that was fun to watch for something crazy that happened, or to some extent, maybe news a little bit*." (Interviewee 17)

Next, I define the perpetual supply of action possibilities as the degree to which individuals perceive a constant supply of new action possibilities in the form of features and contents. For example, Interviewee 8, a university student and social media user, mentions about constant availability of new action possibilities:

"*Fact that you go to the app, and you are finished with new information, and they show well this is the rest of the world you are not following and bump you with all that information.*" (Interviewee 8)

I argue that modification ability can influence being hooked through positive emotional appeal, cognitive appeal, and fear of missing out. I content the relationships among them using the general evaluability theory (Hsee & Zhang, 2010). According to this theory, attribute evaluability impacts an individual’s evaluation and choice (Hsee & Zhang, 2010). I argue that the evolution of technology action possibilities impacts individuals’ choices as they constantly match users’ needs. Thus, the evaluation of technology action possibilities can generate positive emotional appeal, which can nudge users to stay in technology longer. Additionally, as action possibilities are matched with users’ needs, the disengagement with those action possibilities could generate negative emotions, such as fear of missing. For example, Interview 8, a university student and social media user, states

"And you can never get enough because it is like yea this is new; this is new, and you just keep being there. Everyone knows that the world is huge and there is so much out there." (Interviewee 8)

Modification ability can lead to the hooked state by inducing cognitive appeal. For instance, many participants find they can constantly predict the social environment because of the constant supply of action possibilities. For example, Interview 32, a university student and social media user, thinks that technologies dynamics are changing her behavior by pulling her toward technology action possibilities:

"*I think the app’s continuous upgradation is changing my behavior because it is using more advanced artificial intelligence and machine learning to learn better what videos can pull me deeper into the software.*" (Interviewee 32)

I further provided three illustrative quotes in table 1.12 to explain how positive emotional appeal, fear of missing out, and perceived cognitive appeal mediate between the modification ability of technology and the hooked state. For example, interviewee 76 mentioned that the recommendation system of Instagram ignites his interest, a form of positive emotion, and he stays longer on Instagram to explore the recommendations. This is consistent with our conjecture that the modification ability of technology can lead to the hooked state through the mediation of positive emotional appeal.

Table 1.12: Illustrative casual quotes

Illustrative quote	Link
"Instagram is great at recommending posts that spark my interest, and I always find myself exploring new pages that Instagram recommends" (Interviewee 76)	Perceived agency of technology→Positive emotional appeal→hooked state
"The algorithm is typically good for linking me with the players I like to compete with. I feel so interested that I spend at least an hour a day" (Interviewee 83)	Perceived agency of technology→Perceived cognitive appeal→hooked state
"The easy scrolling feature is a great contributor to staying in the app. The ability to see content for hours and hours in all different forms can create fear of losing them, which is a way to keep users in the app" (Interviewee 89)	Perceived agency of technology→Fear of missing out→hooked state

Next, interviewee 83 indicated that algorithms embedded in the Facebook app could link him with the players interested in playing the game with him. It creates an appeal to him that he can compete with them. Such an appeal keeps him in the app and spends a lot of time. Again, this example indicates that the agency of technology can lead to the hooked state through the mediation of cognitive appeal.

Finally, interviewee 89 indicated that the endless scrolling feature creates a fear that she might lose important content in the app. Such a fear keeps her repeatedly returning to the app and spending a significant amount of time in the app. This is also consistent with the existing literature that mentioned that technology action possibilities could create compensatory appeal to individuals as they may feel like losing important information (Beyens et al., 2016). Summing up the conversation, I propose that:

Proposition 6b: Modification ability of technology leads to the hooked state through the mediation of perceived emotional appeal, perceived cognitive appeal, and fear of missing out.

Dynamic Interplay Between Perceived Agency of Technology and Need Fulfillment Ability

I observe that perceived agency of technology and need fulfillment ability dynamically are related to others. Agency of technology is reflected through technology's autonomous selection of algorithms, learning from data, filtering data according to the user's need, and guiding users to use a feature by creating awareness. On the other hand, the need fulfillment ability is reflected through users' belief that they have the autonomy to fulfill their needs. Through autonomous activities and modification ability, technology constantly reinforces users' needs. Besides, users fulfill their needs by engaging with technology. In return, users provide data to the technology. Users reshape the technology's autonomous and modification abilities by giving data to technology. For example, Interviewee 99, in the Reddit app context, argues that

"Reddit's algorithm is scary good; it can suck you in with the amount of diverse content that can become tailored to what you enjoy viewing." (Interviewee 99)

Interviewee 99 mentioned the role of the agency of technology in shaping his needs. The interviewee also mentions how he perceives control over content because of Reddit's algorithms:

"Personally, I believe content is much more important to me. Reddit is a community-driven social media platform where content is designed in a subreddit for any group, topic, or interest. The constant flow of topically organized user posts and the opportunity to interact with others keeps me coming back" (Interviewee 99)

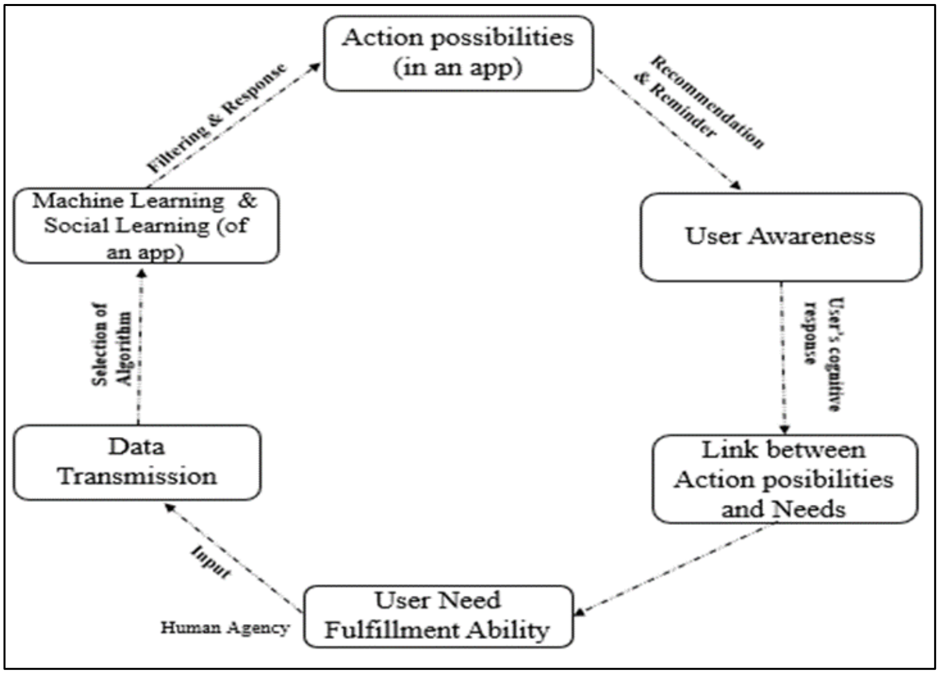


Figure 1.8: Dynamic interaction between the agency of technology and need fulfillment ability

Here, the interviewee mentions that his need to be in control over content is fulfilled through Reddit's algorithm. Further, another interviewee suggests that

" I think that the scrolling feature creates the feeling of needing to see what is next. Also, the reels feature also creates an endless array of content and also utilizes the scrolling idea ." (Interviewee 69)

Summing up the conversation, I argue that

Proposition 7: Perceived agency of technology and need fulfillment ability dynamically relate to each other.

Consequences of Hooked

As a part of the "*coding paradigm*," an important step is identifying relevant consequences of the main category (Strauss & Corbin, 1998). To identify the consequences of hooked state (our main category), I asked a variety of questions, such as how you are impacted by steady engagement and constant return to technology. After analyzing interview data, I found two consequences of the hooked state: habit and perceived work-life balance. Below, I discussed those consequences with their properties

Habit

Some participants mentioned they automatically use technology after reaching a hooked state. I level this pattern as habit. I define habitual interaction as the degree to which a user initiates an action without her conscious intention. For example, Interview 8, a university student, and social media user, mentions that habit makes her return and engage with technology action possibilities:

"Sometimes someone has sent me, I need to check. But sometimes it unconsciously. You just go there. You do not know how happens. My phone is already in my hand. It is automatically." (Interviewee 8)

I identify three properties of habitual interaction from interview: lack of awareness, dependence on context, and lack of excitement. Some participants who formed habit stated that they use technology without any intention. I capture the unintentionality aspect with the property- “lack of awareness”. I define awareness as the degree to which an individual has a goal to use technology. For example, interviewee 31, a university and social media user, mentioned:

"*It has gone beyond utility because sometimes without any reason I check to see what the price is. So, this is happening with me that without even knowing, I am checking the app.*" (Interviewee 31)

Another participant, 53, who is a university student, stated how he usually uses Snapchat:

“*I have a habit of checking my phone without any reason and found myself subconsciously trying to open Snapchat but soon realized that I do not have it on my phone.*” (Interviewee 53)

Interview 29, a social media user and full-time worker, also expresses the nature of awareness. According to her,

"Using Facebook has become regular activity now. It's like eating, drinking, and many other regular parts of life. So, there is no need of any kind of special trigger. If I want to knock

someone, I just use Facebook Messenger. If I want to know the update on any event or news, I just check on Facebook. So, it's the first thing that comes into my mind automatically." (Interviewee 29)

I define the dependence on context property as the degree to which a user depends on automated technology systems or an external context in initiating her action. For example, Interview 10, who is a university student and full-time worker, states:

"For iMessage, I get a notification when a message comes, and I start using the app. For iMessage, you send a lot of pictures, text, and emoji messages. You can send animated emoji messages or voice messages. All those features looked attractive to me." (Interviewee 10)

Next, I define lack of excitement as the absence of users' enthusiasm during the interaction. I observe that those who habitually interact do not feel the excitement during the interaction. For example, Interview 52 mentioned that

"I would not say I feel excited when I enter an app. Especially one that I routinely use. Unless there is something new that everyone is talking about, and I want to see it for myself." (Interviewee 52)

According to our interview, the hooked state represents active interaction with technology. I argue that automatic interaction suppresses the active interaction over time when users stay longer in technology. Due to the constant connectivity of apps, which enables need matching, users frequently interact with the app and link their interaction with their regular activities (cues). The constant association between routine activities (cues) and duration of stay will help the automatic interaction suppress the active or reflexive interaction. So, the habit will form.

I further provided three illustrative quotes in table 1.13 to explain how the hooked state leads to habit. For example, interviewee 43 indicated that because of constant reinforcement of the Instagram app, she repeatedly came back to the Instagram app and stayed longer time there. At some point in time, she used the Instagram app in a way that she did not wait for the notification to reach the Instagram app. Rather, she automatically reached the Instagram app. This description indicates that the hooked state can eventually lead to habit.

Table 1.13: Illustrative casual quotes

Illustrative quote	Link
"I feel as though I use Instagram too much at around the same parts of the day, every day. It has become a habit for me to wake up, check Instagram, and do the same before I go to sleep." (Interviewee 43)	Hooked state-→ Habit
"Over time, Tiktok has become the app I always use to relax at the end of the day. It has become a habit for me to lay in bed at the end of a long day and relax by watching Tiktoks. I would call my usage of Tiktok a habit because it is just what I have gotten used to over the years" (Interviewee 46)	Hooked state→ Habit
"It becomes habit for me to get on the app and scroll as the algorithm helps keep me on the app for longer than I intend to be" (Interviewee 53)	Hooked state→ Habit

Next, interviewee 46 indicated that over time, the TikTok app had become an instrument for relaxing, and she automatically used them. However, before forming the habit, she repeatedly felt drawn to TikTok, indicating the hooked state.

Finally, interviewee 53 mentioned that repeatedly staying longer in the app contributes to forming habit. She also mentioned the algorithm's role in keeping her returning to the app. Eventually, habit controls how she interacts with the app. Summing up those conversations, I argue that

Proposition 8: Hooked state leads to habit

Perceived work-life conflict

I define perceived work-life conflict as the degree to which technology use interferes with the performance of personal duties. I find two properties of perceived work-life conflict: perceived intrusion and perceived lack of control over time.

Let us explain perceived intrusion with an example. For example, interviewee 56, who is a social media user and university student, stated that although he enjoys interacting with technology throughout the day, it prevents him from attaining his goal. According to him,

"Recommendations would end up being something I would enjoy, but for the most part, it just detracts my attention and time from things that I want to see." (Interviewee 56)

I define perceived lack of control over time as the degree to which a user perceives that she can regulate time. I observe that one property of perceived control over time is sensitivity towards time management, which I define as the degree to which individuals pay attention to time management. Some participants, who were in the hooked state, indicated a low degree of sensitivity toward time management. For example, Interviewee 8, a university student and social media user, explains how hooked led to less control over time:

"*So, they do all those well-studied ways of making us hooked to the application. It has a good side, like connecting with people when you cannot physically meet them. But sometimes, it really takes so much time over life."* (Interviewee 8)

In another case, Interviewee 2, a university student, and social media user, indicated her experience with time management:

"*I do not like the app sometimes because I spend too much time watching videos without realizing it."* (Interviewee 2)

According to the hooked state, individuals who are in the hooked state are expected to be highly involved with technology action possibilities. The high involvement with technology action possibilities could create a longer flow state. Past research indicates that when individuals put their total concentration on work, it can result in a loss of time sensitivity (Nonis, Hudson, Logan, & Ford, 1998). Thus, high involvement with technology action possibilities can reduce cognitive capacity to engage in other "hard" activities that require sufficient attention. As a result, individuals may perceive conflict with work because of being hooked.

Besides, prolonged exposure to technology has a spillover effect by diverting time from work. Thus, individuals have less time to engage in other pursuits. I argue that the hooked state can lead to perceived work-life conflicts because of such a negative spillover effect.

I further provided three illustrative quotes in table 1.15 to explain how the hooked state leads to habit. For example, interviewee 8 indicated that repeatedly returning to the Instagram app makes her unproductive as her attention is constantly drawn to the content. Further, interviewee 98 indicated that she found it difficult to get off Twitter, making it difficult to complete a small task.

Table 1.14: Illustrative casual quotes

Illustrative quote	Link
1. *"It can make me unproductive, as it draws my attention to my phone and things, I might be interested in instead of using my time to do more productive tasks."* (Interviewee 8)	Hooked state→ Perceived work-life balance
2. *"It is clearly designed to suck me in and addict me, and I only like to consume in small amounts. Sometimes I need to go somewhere or complete a task but find it tough to get off of Twitter"* (Interviewee 98)	Hooked state→ Perceived work-life balance

Summing up those conversations, I argue that

Proposition 9: Hooked state leads to perceived work-life conflict.

Table 1.15: Construct definition

Constructs	Definitions
Hooked state	A technology usage state that is is characterized by users' use of technology longer than they plan to use it
Perceived agency of technology	User's perception of technology's ability to act independently and guide users to perform specific actions
Perceived need fulfillment ability	User's ability to fulfill her needs using an app's features
Positive emotional appeal	The degree to which a user perceives that interaction with technology elicits positive emotion
Fear of missing out	The degree to which a user feels that she is missing information, events, or experiences in technology could be gratifying
Perceived cognitive appeal	The degree to which a user perceives cognitive benefits using an app's features
Perceived work-life conflict	The degree to which a user perceives that technology interaction interferes with the performance of personal duties
Habit	The degree to which a user tends to perform a behavior automatically

Process Model

Strauss and Corbin (1998) mention that one key component of grounded theory is identifying the underlying process of action and interaction. Thus, I delved into the data to identify the underlying process through which individuals reach to hooked state. I used constant comparison, diagraming, and asking questions to identify the patterns (Strauss & Corbin, 1998). I have identified four usage states by continuously comparing patterns and undertaking theoretical sampling, including hooked.

Analytical Approach

To develop the process model, I followed an analytical approach provided by Langley (1999) and Hengst et al. (2020). Langly (1999) provided guidelines for developing process models using qualitative data. According to Langly (1999), there are seven sense-making strategies to develop a process model from qualitative data: narrative strategy, quantification strategy, alternative templates strategy, grounded theory strategy, visual mapping strategy, temporal bracketing strategy, and synthetic strategy. Among various strategies, I follow the grounded theory strategy to develop a process model (Langley, 1999). Hengst et al. (2020) provided three steps to develop a process model using a grounded approach. I followed their steps to generate our process model. According to their analytical approach, first, researchers should keep records of all the data in qualitative software. I used NVivo software to keep records of all the interview data. Next, the researcher engages in coding to identify common themes in the interview data (Hengst, Jarzabkowski, Hoegl, & Muethel, 2020). The final step is cross-checking the themes with appropriate stakeholders who can evaluate the results. After I had completed the analysis, two app users assessed the generalizability of the results.

Hengst et al. (2020) mentioned that developing a process model is an iterative effort between data collection and data analysis. Therefore, I constantly iterated between data collection and analysis when developing the process model. Finally, Langly (1999) suggested using some sensemaking strategy to analyze the process data. I chose two criteria to make sense of some initial process data: first is the frequency of interaction with technology. Second is the degree of goal orientation. The frequency of interaction indicates the extent to which a user interacts with technology. The degree of goal orientation indicates the extent to which users' interaction with technology is associated with the prior goal. Those two criteria initially helped me identifying a pattern in the process data. I found that almost all participants have a high degree of goal orientation before using technology. This is consistent with existing IS theories, such as technology adoption, diffusion theory, etc. I labeled this state as "intention to use." I identified some properties of this state, such as perceived relative advantage and perceived affiliation with value. In such a state, users compare the relative advantage of an app over other apps. Further, they evaluate how a particular app is aligned with their values. Such a state is an explorative usage state as users remain uncertain whether a particular app will help achieve a purpose. Next, I identified a pattern when individuals have a high degree of goal orientation and a low/high frequency of interaction. The observation is consistent with existing theories, such as the expectation confirmation model and utility theories, in which the focus is "utility" from technology. I labeled it as an "adoption and post-adoption” state. I identified some properties of this state, such as perceived importance of purpose, the influence of technology on usage, and perceived self-regulation. In such a state, users emphasize how apps feature align with their prior goal. Further, in such a state, users exercise self-regulation. For example, even though apps are pervasive and provide the ability to connect constantly, users are not interested in engaging with apps. Next, I identified a state characterized by a high frequency of usage but a low degree of goal orientation. I define this state as the hooked state. In such a state, users spend longer time in apps to fulfill their needs and get immersed in app-mediated activities. Finally, data indicated an extreme interaction pattern: some individuals perceive impaired self-control and a high degree of negative consequences at some point of usage. As shown above, existing IS literature describes this state as "technology addiction." Following that literature, I also label this pattern as technology addiction and identify this state's properties. After analyzing all the interview data, I found all participants were in intention to use and adoption state (107). However, 54 participants were in the hooked state, and 17 were in the addiction state. Figure 9 illustrates the distribution of the states. Figure 6 and 7 indicates the distribution of four states.

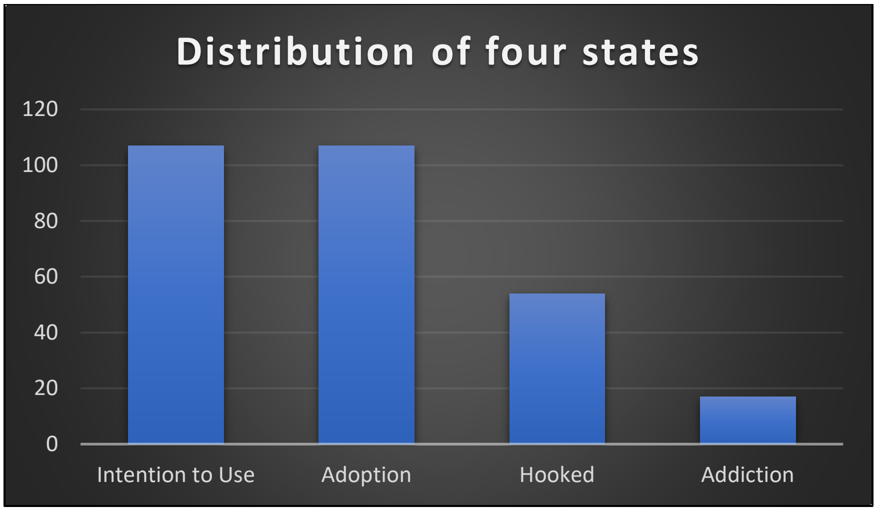


Figure 1.9: Distribution of four states

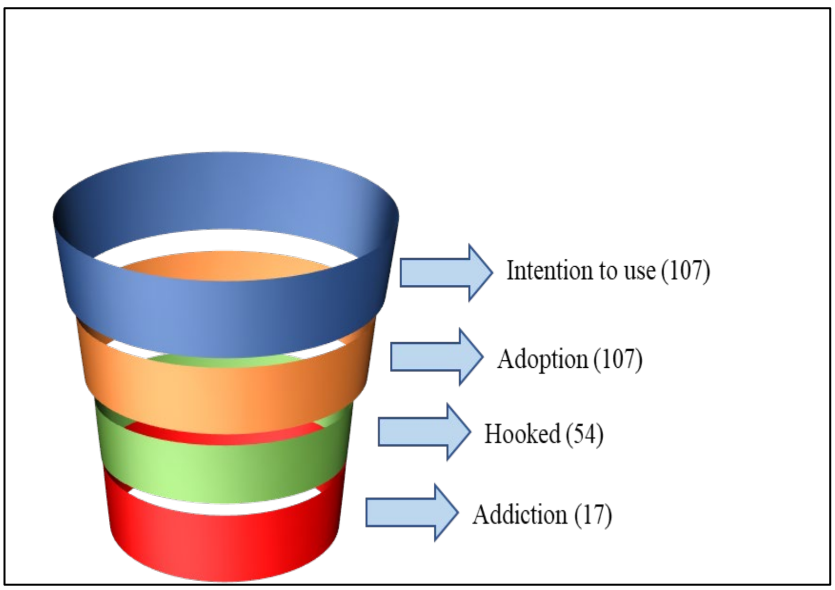


Figure 1.10: Distribution in a funnel model

While I compared different states, I observed that some individuals expressed high self-control over technology use. According to them, their interaction with technology is motivated only by extrinsic benefits gained from technology. Most of them use technology based on perceived utility or cost-benefit analysis. If the perceived return falls short of expectations, they stop using and eventually abandon technology. Notably, even though technology may provide recommendations, they stated that recommendations do not attract them. As I have mentioned before, I call this state adoption. Table 1.16 provides some illustrative quotes related to the adoption state.

Table 1.16: Illustrative quotes related to adoption state

Illustrative quote	State
1. *"Sometimes, the algorithm will recommend posts that I am not interested in. I'm interested in the topic because I visited a page once"* (Interviewee 49)	Adoption
2. *"I only want to come back if I get comment reply to notifications but not to watch videos most of the time"* (Interview 99)	Adoption
3. *It doesn't encourage me to stay in the app because there is always a definite "moment" when I no longer need it* (Interviewee 48)	Adoption
4. *"Sometimes it feels like there is truly just a cesspool of content online. So YouTube can recommend videos from many different users, all posting content of a very similar nature. A good chunk of the time, I am not watching recommended videos. However, I spend my time browsing channels I like"* (Interviewee 56)	Adoption
5. *"I will not ever use an app unless I have a specific purpose. I use apps for entertainment, education, and communication. I do not use them for the above reasons"* (Interviewee 63)	Adoption
6. *"I do not feel like the app constantly pulls me into the interface. I am fully aware of how often I use Facebook and why. I started using Facebook so that I could be updated with events, pictures, and accomplishments of my family and friends"* (Interviewee 59)	Adoption

For example, interviewee 49 states that recommendations provide him with content based on his interest, but he is not interested in the recommended content. He further mentioned that he is interested in a topic aligned with his initial goal. In such a state, he does not feel any appeal to return to technology.

Next, interviewee 99 mentioned that he only comes back to the app to interact with a feature but does not spend time interacting with other features. Further, interviewee 48 mentioned that he does not stay a long time in the app. Additionally, he indicated that the app features do not encourage him to return to the app. Interviewee 56 said that although YouTube recommended a range of content based on his interest, he does not spend time watching those. He only spends some time browsing channels aligned with her prior goal. Interviewee 63 indicated that only a specific purpose drives him to look at the contents in the Instagram app. He does not use the app without any prior goal. Finally, interviewee 59 mentioned that she does not feel any appeal toward the app. She only uses the app whenever she needs to check an event, picture, and accomplishment of her friends and family. Overall, all those examples indicate that some interviewees stay in a state in which prior goal drives them to use the app and do not spend significant amounts of time in it.

Some individuals who stay in the adoption cycle start using the app more than they plan to use it. For example, Interviewee 36 mentioned that:

"I check the app daily for certain things after downloading it a few years ago. I find myself on the app when I wish I were doing something more productive with my time. I feel like I am compelled to check it if I haven't had a notification in a long time." (Interviewee 22)

Interviewee 22 indicated he downloaded the app to check certain things, for example, reading news, interacting with others, etc. However, at some point, he felt compelled to return to the app in response to the notification. As a result, he also started spending significant time on the app. Thus, interviewee 22 indicated that he has moved from the adoption state to a state where the prior goal does not play a significant role in using the app. I call this state the hooked state.

I observe that the adoption state sharply contrasts with the next state, which is the hooked state. During the hooked state, individuals have no or less prior expectations, and they do not always compare the benefits of an app's recommendation against their expectations. Instead, they engage with the app's recommendation. Furthermore, as the course of an app's recommendation shifts over time, they frequently adjust their usage pattern by spending more time on the app. Table 1.17 provides some illustrative quotes associated with the hooked state

Table 1.17: Illustrative quotes related to hooked state

Illustrative quote	State
"I always go to YouTube first thing if I'm bored, and if the algorithm is able to keep me there successfully, then it is algorithm influenced but not always intentional" (Interviewee 59)	Hooked state
"I say that because I don't think I have an important thing to do in the Facebook app, but I am always there" (Interviewee 11)	Hooked state
"The algorithm will give me news updates on any sort of topic, which keeps me in the loop" (Interviewee 100)	Hooked state
"The algorithm heavily influences what I watch. The recommended videos from the algorithm are the far majority of the videos I watch on the app" (Interviewee 46)	Hooked state

For example, interviewee 59 indicated that his app usage is not always intentional; instead, algorithms keep him returning to the app. Next, interviewee 11 indicated that no prior goal drives her in the Facebook app. Further, interviewee 100 indicated that the algorithm in the app constantly brings him in the loop of staying a long time in the app. Finally, interviewee 46 mentioned that the algorithm significantly influenced him to watch most of the videos in the app. As a result, he stays a long time in the app.

Finally, I found that some users who stay in the hooked cycle could not control their usage patterns and become addicted to the app. For example, interviewee 55, who was in the hooked cycle, mentioned that:

"It's pretty much gotten to the point where I just like a video playing in the background (like a podcast or something) while I do schoolwork, etc." (Interviewee 55)

According to him, he reached a point where he could not control his game playing. In addition, such game-playing significantly impacted his schoolwork. Further, interview 106 mentioned that he could not control using the TikTok app even though TikTok discourages long-term use. He claimed himself as addicted to TikTok. According to him:

"On Tik Tok, they even discourage long-term use. I am addicted to apps as one may be addicted to food; it isn't the food's fault or intention. It is just nice to consume." (Interviewee 106)

Below, I discuss the different patterns of use and the relationship between those patterns. Based on our process data, I developed Figures 1.11, 1.12, and 1.13. Figure 8 compares three states based on the dimensions of technology influence and consequences of use. Figure 9 compares three states based on the level of interaction and degree of control. Finally, figure 10 proposes the full process model derived from our data.

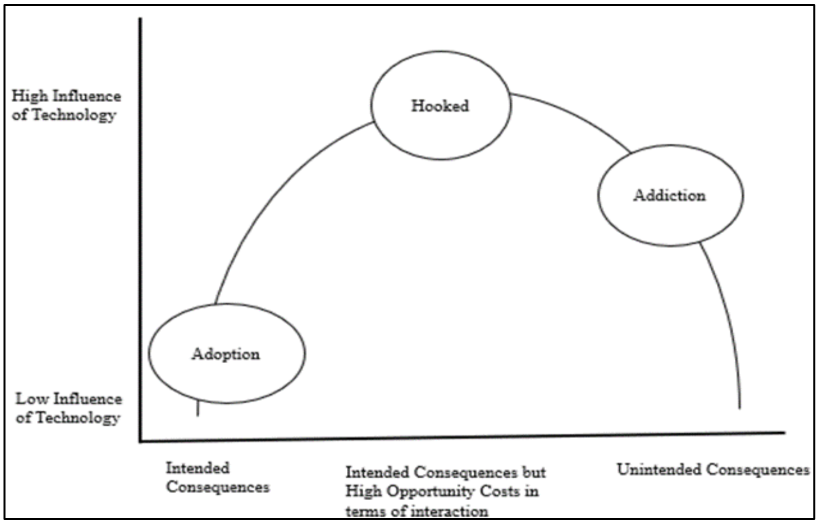


Figure 1.11: Comparison of different stages

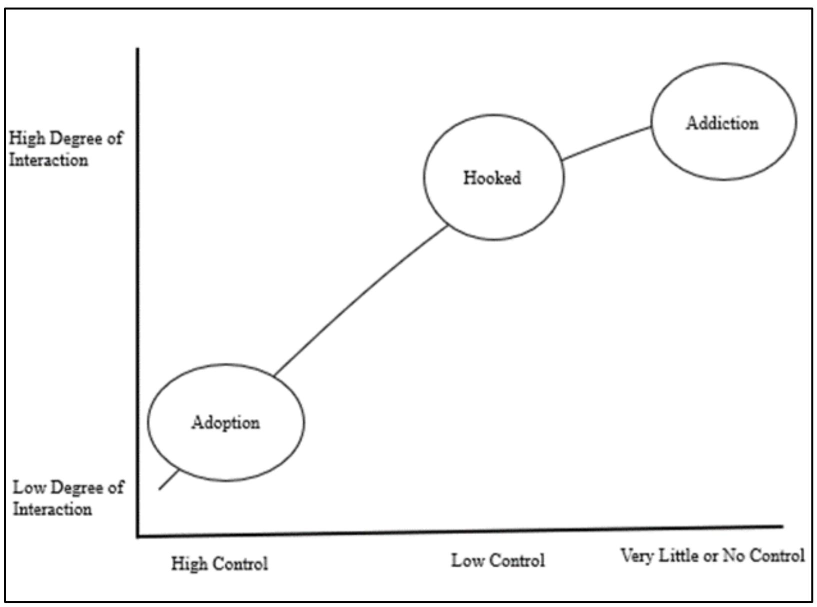


Figure 1.12: Comparison of different stages

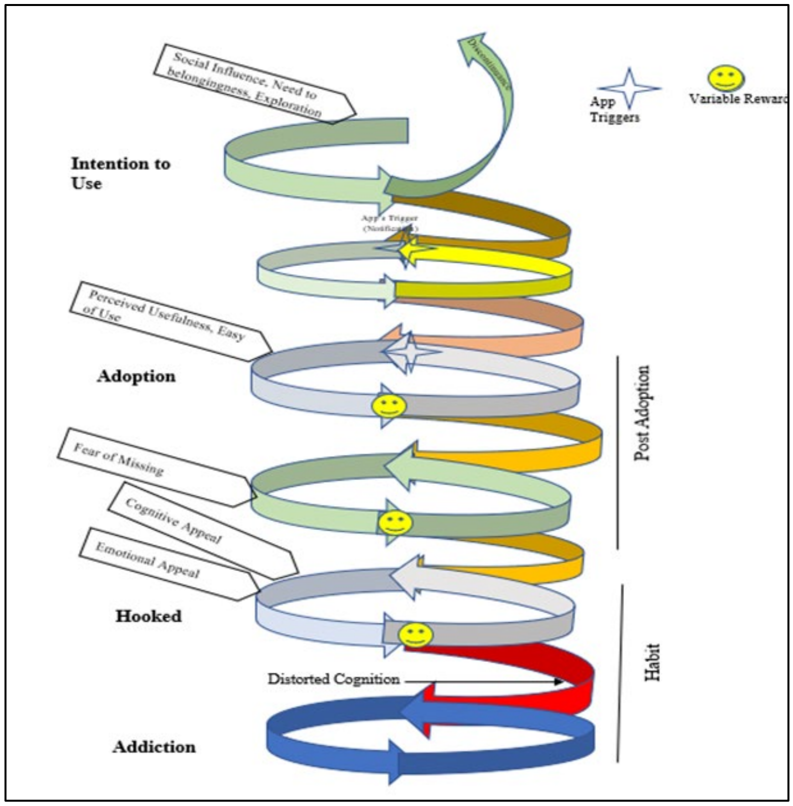


Figure 1.13: The process model

Intention to Use

I define intention to use as the degree to which a person engages with technology with a certain object. Two attributes of intention to use are: perceived advantage and perceived relationship with the agent's value. I define perceived advantage as the degree to which individuals perceive the relative advantage of using a particular technology over other technology. For example, interviewee 17, a university student and social media user, stated that

"*I was interested in content creation and following different content creators that I watch on YouTube. So, for me, that was the initial reason why is because they were tweeting out discussions about whatever I was interested in, whether it be a game or whatever is going on with the content."* (Interviewee 17)

Another property of intention to use is the perceived relationship with the agent's value, which I define as the degree to which individuals perceive that technology-mediated action matches what individual value. For example, Interview 3, who is a university student and social media user, states that

"I value communicating with my friends, sending them things quickly, and getting responses from them so we can connect over the things we see. That is why I download."(Interviewee 3)

I observe three core conditions motivating users to download and use technology: exploration, need for belongingness, and social influence. Note that our technology context is super apps. Below, I will discuss those conditions.

Exploration

I define exploration as an individual's purposeful inquiry about an entity. Most participants indicated they were intentional about what technology features they like to use. I argue that exploration serves as an antidote for the uncertain experience. For example, Interview 43, a university student, and social media user, indicated that her main reason for intention to download technology is exploration:

"*Definitely for exploration. Before downloading, they kind of tell you what it will be. So, I'll look at it and be like everyone else has it that way, we can stay connected share photos, so I download it knowing I'm going to share photos."* (Interviewee 43)

Need for Belongingness

I define the need for belongingness as the degree to which individuals desire social relationships. Many participants' need for belongingness drives them to seek a technology that meets this need. For example, Interviewee 36, who is a university student and social media user, points out that

"*When I was in medical school, I saw many friends using the app. At that time, Facebook is becoming popular. That time my friend suggested to me that you can use the app for a lot of reasons. You can share your picture, make friends from other countries, and attend other medical schools that can help you study. And also, some other activities."* (Interviewee 36)

I argue that the need for belonging can lead to the intention to use through two processes:) Feeling the pressure of losing psychological affordances b) and a new way of getting social support. When individuals discover that their friends are using technology but are not, it generates social pressure. Additionally, social support is one of the critical requirements for maintaining an intrinsically satisfying life (Wang, Lee, & Hua, 2015). In our interview, I found that most participants are more inclined to use social media apps daily because of the social connection feature.

Social Influence

I define social influence as the degree to which individuals incorporate others' opinions into their use of technology. Many respondents indicated that they intend to use technology because of peer influence. For example, interview 33, who is a university student and social media user, points out that

"*I'll only download a new app if my friends tell me to. If a lot of people are talking about a new app and using it, then I usually get it too.*" (Interviewee 33)

Since users are almost always connected to a group and society, others will influence their behavior (Liang & Xue, 2009). According to innovation diffusion theory, we know interpersonal network influences trialing of an innovation (Rogers). Similarly, I argue the trial of super apps depends on social influence. There are two reasons for this. First, the social environment provides easy access to technology-related information. It makes people aware of the value of super apps. Second, the social environment exerts normative influence through three processes: compliance, internalization, and identification (James et al., 2017). Individuals will try to use a socially desirable technology through compliance, internalization, and identification.

In sum, exploration, the need for belongingness, and social influence lead to the intention to use. As I mentioned, the intention to use is the first step in interacting with technology. Thus, I propose

Proposition 1: Intention to use is a necessary condition for using a technology

Adoption

I define adoption as a state of technology acceptance and use in which people use technology voluntarily and purposefully. In such a state, the influence of technology features on initiating and maintaining usage is minimal. For example, interview 30, who is a student and investment app user, states

"*I am using the app to invest in, study, or check the market. So, whenever I know the market is down and time to invest, and the market is up, and time to take out money that time, I am using the app that time."* (Interviewee 30)

According to our findings, after having the intention to use technology, individuals adopt the technology. For example, Interviewee 34 states after forming the intention to use, how he evaluated and adopted an app in his daily life:

"*Even when you go for apps that are all, for example, free, you download a couple of them, you check which one of them is easier to use, which one is more intuitive, which one is more user friendly. So, these are all elements that you may, you know, think about when you want to work with different applications."* (Interviewee 34)

This observation is consistent with the technology adoption research paradigm. Using the argument of this paradigm, I propose:

Proposition 2: Intention to use technology is a necessary condition for the adoption of the technology

Three properties of adoption are the influence of technology in usage, perceived self-regulation, and perceived importance of purpose. I define the influence of technology on usage as the degree to which an individual perceives technology's influence in initiating and maintaining usage. I identify that the influence of technology on usage is low for almost all users in this state. For example, Interview 4, who uses a productivity app and is a full-time worker, points out that rather than technology, the business defines her technology usage:

"I pick up, but it also depends on if I'm busy. So, if, for example, I'm in the middle of a research project farming and teaching, then, of course, be busy doing that, and they don't check the app, or it is of any better put my phone on silent and put it away when I'm at work." (Interviewee 4)

Another property of adoption is perceived self-regulation, which I define as the degree to which individuals perceive self-regulation during usage. I identify that many participants have high self-regulation over technology usage. For example, Interview 46, who is a university student and social media user, points out that

"*Instagram has an 'endless scroll' feature designed to keep users on the screen, I try to avoid all recommendations from the app."* (Interviewee 46)

Another property of adoption is the perceived importance of purpose, which I define as the degree to which individuals emphasize a goal in initiating and maintaining technology usage. For example, interview 17 indicates that purpose is more important for him than technology features.

"*It is one of those things where once I sort of became aware of the time I was spending in an application, I felt like I was no longer affected by new features. So, it is like, I would realize that they're there. And I would know what the purpose is."* (Interviewee 17)

The final property of adoption is a lack of excitement. People who adopt technology indicate a lack of excitement while interacting with technology. Perhaps, the reason for the lack of excitement is that outcome is highly predictable. I know that one criterion of being excited is getting something unexpected. According to the duel process model, the unexpected experience can contribute to using system 1, which is a highly active state. However, an expected outcome requires no active involvement. Thus, people in the adoption state do not feel the excitement. For example, Interviewee 59, who is a university student and social media user, indicates that

"*Sometimes yes sometimes no most of the time if I am using social media apps it's out of boredom, so I don't really feel that excited."* (Interview 59)

I observe four conditions of adoption in the context of super apps. Those are staying up to date, maintaining social connection, perceived coping, perceived hedonic benefits, and perceived ease of use. Below, I will discuss those conditions.

Staying up to date

I define staying up to date as the degree to which an individual uses technology to gain knowledge about the world. For example, Interview 13, who is a university student and social media user, states

"*I use, for example, to look at the news. I'd like to Stay tuned with some news around the world. I use it also for work if I need to look for specific information*." (Interviewee 13)

Additionally, Interview 3, who is a university student and social media user, states why she adopted technology:

"*I like to stay up to date on trends and what people are into*" (Interviewee 3)

Maintenance of social connection

I define maintenance of social connection as the degree to which individuals use technology to maintain a social connection. For example, Interviewee 8, who is a university student and social media user, states why he adopts technology:

"*So, I can connect to people what people are doing. There is no other way to connect. Especially those relationships where you are friends but are not connected as much. The only way to keep it is if I join this social media network*." (Interviewee 8)

Additionally, Interview 5, who is a social media user and university student, states how she can maintain the social connection through the usage of technology:

"The reason I use messenger because I know most of my friends are connected to Facebook, so I can reach out to them using messenger." (Interviewee 5)

Perceived Coping

I define perceived coping as the extent to which individuals view technology as a means of coping with external pressure. For example, interview 7, who is a university student and social media user, states why she adopts a particular technology:

"When I am doing very stressful work, I immediately open up that app., And I will be annoyed if I cannot use that time." (Interviewee 7)

Additionally, interview 24, who is a university student and social media user, states

“Usually, I just use apps if I have free time and am bored. I more likely to use my apps after I'm done with schoolwork and on the weekends.” (Interviewee 24)

Perceived Hedonic Benefits

I define perceived hedonic benefits as the degree to which users adopt technology for pleasure or entertainment. For example, Interview 25, who is a full-time worker and social media user, states

"I usually consider if I'll actually use the app/if it will be fun" (Interviewee 25)

Additionally, Interview 32, who is a university student and social media user, states

“*On Spotify, I spend time listening to music while it plays in the background while I am walking to class.”* (Interviewee 32)

Perceived Advantages

I define perceived advantages as an individual's belief that usage of a particular technology provides functional benefits. I identify three properties of perceived advantages:

accessibility, deliverability, and usability. I define accessibility as the degree of effort required to get content. For example, Interview 34, who is a university student and social media user, stated that:

"I can easily just pull up an application and see what is breaking you, for example, right now on CNN. So, the convenience, speed, and ease of using applications. I think it's something that is very, and it's always important." (Interviewee 34)

Additionally, participant 17, who is university student states

"*To be honest, the main point is that it is very accessible, just because I have it on my phone."* (Interviewee 17)

The second property of perceived advantage is deliverability, which I define as the degree of smoothness a user perceives while interacting with technology. For example, Interview 34, who is a university student and social media user, stated that

"*And then sometimes there the speed of working with apps sometimes take some time, for example, I know, it's not that much these days, what is still on, you know, until the app comes up, for example, or the main page of the app comes of something, sometimes you have to wait a couple of seconds."* (Interviewee 34)

The third property of perceived advantages is usability, which I define as the degree to which users perceive that they can achieve a goal effectively. For example, Interview 27, who is a university student and social media user, stated that

"Even though we have low bandwidth, it is easy to use YouTube. If you watch something on another channel, it takes quite a bit of data. But on YouTube, it is called an auto adjustment, so if your connection is low, it will automatically be like 320 or 140. So, this kind of features giving us easy access, convenience, and that is why I actually prefer those apps." (Interviewee 27)

Summing up those conversations, I propose that

Proposition 3: Staying up to date, perceived advantages, perceived hedonic benefits, perceived coping, and maintenance of social connection are necessary conditions for the adoption of technology

Additionally, I observe that many people who adopted technology eventually continue to use the technology, a stage I define as the post-adoptive state. For example, interview 36, who adopted a social media app, mentioned how she continued to use social media after adoption:

"2011, when I first used it, we had the manual phone. In a manual phone, you cannot see a lot of options for using Facebook. But when I started using the Android phone at the end of 2013, I saw a lot of options in Facebook; for example, you can tag people, add a place, and update your status with several numbers of pictures. Then you can communicate with a lot of people. And that time, I got more interest in Facebook. I felt that Facebook is a very good app. We can chat with more than 4 or 5 of my friends. Also, I can upload videos." (Interviewee 36)

One reason for moving from adoption to post-adoption state is familiarity with features. The familiarity with features reduces users' learning effort. Thus, it becomes easy for a person to continue using the technology. For example, Interview 7 stated that

"I have a built-up familiarity with the app and its features and the communities on it." (Interviewee 7)

Thus, I argue:

Proposition 4: Adoption of technology is a necessary condition for post-adoption state

Hooked State

After repeated interactions with technology, I observed that some participants reached the hooked state. I define hooked as a technology usage state characterized by users' use of technology longer than she plans to use it. Note that in the state of hooked, individuals' needs are constantly being generated and reinforced by technology. This attribute of the hooked state contrasts with the adoption and post-adoption state. In the adoption state, individuals are purposeful and search for technology features. During adoption and post-adoption state, participants do not interact with technology as frequently as in the state of hooked. Further, in the adoption state, the frequency of use is based on purpose, while in the hooked state, in most cases, the frequency of use is based on technology-stimulated need. The three properties of hooked are experiential involvement, adaptation, and swaying.

I identify that after a user reaches post-adoption state, the technology learns users' preferences and stimulates their needs based on usage data. As it may take some time for technology (super apps) to learn about user preferences and build cognitive and emotional appeal, the hooked state occurs after people have adopted or post-adopted a technology. Summing up this observation, I argue that:

Proposition 5: Post-adoption state is a necessary condition for the hooked state

However, I also found that many users in the adoption/post-adoption stage do not get influenced by technology reinforcement. Many of them intentionally avoid interacting with technology. For example, Interview 55, a university student and social media user, states that he stops the recommendation feature of the social media app. According to him

" *I don't like seeing things that I don't support, so I select "Not interested"* (Interviewee 55)

As a result, those individuals reach to hooked state. Those individuals evaluate spending time with technology as uninteresting and expensive. Such avoidance in the post-adoption stage can be regarded as proactive avoidance. I observe that proactive avoidance is a barrier to the hooked state. For example, Interview 62, who is a university student and social media user, indicates that

"*Instagram has an 'endless scroll' feature designed to keep users on the screen, I try to avoid all recommendations from the app."* (Interviewee 62)

Technology Addiction

I find that some individuals can surpass the hooked state. Those individuals indicated considerable adverse effects from spending more time with technology. I recognized that such a state is similar to "technology addiction" discussed in current literature. Following this stream of literature, I labeled the state as technology addiction and defined it as the extent to which technology use is associated with undesirable outcomes (Turel et al., 2011a). I observed that this state has five properties or symptoms: intensity of withdrawal affects impaired control despite perceived harm, compulsive thinking, and reduced productivity. Below, I discuss those properties:

I define the intensity of withdrawal effects as the degree to which technology use is related to users' feelings of withdrawal. I observed withdrawal effects in various forms. One form is that the feeling of depression occurs when a user is not in contact with technology. For example, Interview 31, who is a university student and social media user, states

"*I sometimes feel empty. I feel some negative impacts. It happens frequently. It is very difficult to me to not check the app regularly*." (Interviewee 31)

Next, I defined impaired control as the extent to which individuals constantly use technology, despite the fact that they may experience negative impacts. Numerous studies classify impaired control as a "disorder" since it deviates considerably from normal functioning. For example, Interview 10, who is a university student and social media user, states:

"I practice but can't control it. I use it for like one and two hours or something like that. So it's, it's getting beyond my control. So, I found that if I don't do something or don't act on it I probably it will be even worse, I guess, in future." (Interviewee 10)

Next, I define compulsive thinking as the degree to which individuals obsessively think about technology-mediated activities. As compulsive thinking impairs the normal functioning of action, it can generate significant negative consequences. For example, Interviewee26, a university student and social media user, mentioned how she compulsively thinks about social media posts.

"*I always put a good amount of thought into making a post. Will people enjoy the post? Will they give it a like? Do I want the picture on my feed? Does it paint me in a good light to my viewers?*" (Interviewee 26)

I find that some participants reported their productivity reduction because of technology usage. I label this property as reduction of productivity and define it as the degree to which individuals perceive technology use is associated with loss of productivity. For example, Interview 10, a university student, and social media user, indicated that she was forced to abandon a technology because it was hampering her productivity:

"*The reason I uninstalled it is because I felt that it's taking a lot of my time. It's making me unproductive.*" (Interview 10)

After finding different symptoms of technology addiction, I focus on how some users get addicted to technology. I observed that some participants, who were in the hooked state, indicated that constant engagement with technology action possibilities could generate adverse consequences at some point. These participants reported failing to control their urges, resulting in a total or significant loss of control over technology usage. A complete or considerable loss of control over technology use can lead to compulsiveness and generate adverse effects (Chick, 1988). Thus, I find that some participants in the hooked state became addicted. For example, Interviewee 10, a university student, and social media user, points out that

"*It changed. It's an addiction now. It helps you get out of load on sometimes is good, and you get your willing form of today's world, but at the same time when it goes beyond your control. It becomes an addiction.*" (Interviewee 10)

Summing up those conversations, I propose

Proposition 5: Hooked state is a necessary condition for the addiction state

Validation of the GMT Findings Using Existing Theories

The grounded theory of this study has emerged from data and functions as a mid-range theory that can explain technology-induced excessive use in the context of super apps. However, I argue that using grand theoretical perspectives can validate our findings and broaden our theory's scope. For example, I think the reinforcement and stimulus-organism-response theories could be a valuable lens to explain our results.

According to reinforcement theory, a reinforcing object can be a) a cue that generates the drive to interact and b) a representation that consolidates memory. Given the definition of reinforcing object, I argue that it can create needs and consolidate memory. Many interviewees mentioned that technology features constantly create needs to engage with technology, and those needs can increase their propensity to return to technology by creating positive interaction memories. So, they are reinforced by their needs and technology features to use technology longer than they plan to use. Given the properties of reinforcing objects, I contend that reinforcement theory can validate our findings. Below, I will relate the theoretical statements of reinforcement theory with our results.

Reinforcement theory suggests that if an individual is rewarded for conducting a behavior, the likelihood of performing the behavior could increase (Redish, Jensen, Johnson, & Kurth-Nelson, 2009). This statement is known as positive reinforcement. Second, if a reinforcing object removes an individual's painful situation, the individual increases his propensity to perform the behavior (Gordan & Amutan, 2014). Third, if behavior is repeatedly reinforced, the possibility of repeating the behavior increases over time (Gordan & Amutan, 2014).

Here, I explain how those theoretical statements correspond with the hooked state. First, our grounded theory states that technology's autonomous and modification abilities can reward users by providing novel and need-matching content. In the super app context, I observe that individuals receive two types of rewards during interaction: personal and social rewards. Personal rewards are self-gratifying activities, such as reading others' content, watching funny videos, learning, etc. Social rewards are connecting with a network and communicating with others. Other examples of social rewards are improving status in the network and support from the network, etc. Thus, both rewards can constantly create a need to engage with technology. As such, rewards from super apps can increase the likelihood that users will return to the technology. Those rewards can be regarded as positive reinforcement. So, the positive reinforcement argument explains why technology agencies and humans' ability to fulfill needs by getting rewards can contribute to reaching to hooked state.

Next, I identify that super apps can remove painful situations in many cases. For example, many individuals stated that they perceived removal of negative moods and fear of missing out when they engage with technology. Thus, removing those situations makes the likelihood that individuals will return and engage with the technology.

Finally, I also observe that super apps can reinforce a behavior by constantly providing rewards at the right time and in the proper context. For example, super apps hierarchically recommend (e.g., YouTube) content so users can check content one after another. Thus, staying longer time in technology is repeatedly reinforced by recommendations. Overall, reinforcement theory validates our findings.

I also find that the theory of stimulus-organism-response (SOR) validates our findings. According to SOR theory, stimuli can influence individuals' cognitive and emotional processing. Cognitive and emotional processing can lead to a particular response. According to our grounded theory model, the agentic ability of technology and human's perception of need fulfillment ability may function as stimuli, leading to the arousal of positive emotion, fear of missing out, and cognitive appeal processing. That cognitive and emotional processing finally leads to the hooked state. Thus, SOR theory also validates our findings.

Discussion

This study aims to understand technology-induced excessive use. To do so, I conducted a grounded theory methodology (GTM) and observed a pattern that both technology features and the user's ability to fulfill needs stimulate users to overstay their limits within technology. I also observed what I characterize as a hooked state, a term adopted from practice literature that addresses and explains this pattern. I discovered the causes and consequences of the hooked state and proposed a grounded theory model by linking them to ten propositions. I also proposed a process model that explains the evolution of technology usage along two dimensions: the frequency of use and the degree of goal orientation.

Contributions to the Field

Many IS researchers who study technology-use behavior assume that users have an independent agency when interacting with technology. However, this assumption does not address the agency of technology itself in inducing and guiding user behavior. Other approaches assume that excessive-use behavior is a manifestation of addictive tendency, discounting the role of human agency entirely. The field lacks an alternative perspective that synoptically considers both human and technological agencies. By integrating human and technological agency, our study furthers the "imbrication" approach within the field of Sociomateriality, an area that studies the overlapping of human and technology agency (Leonardi, 2011). The grounded theory I developed indicates that excessive technology-use behavior forms through the many quotidian interactions between the user and technology. Human agency reinforces technological agency by providing data, while technological agency reinforces human agency by providing novel and need-matching content. The overlapping, or imbrication, of human and technological agency in inducing use is thus a new perspective in excessive-use literature.

This study also contributes to the IS-use literature that studies the underlying mechanisms of dwell time. I introduce concepts associated with stickiness, such as positive emotional appeal, fear of missing out, and cognitive appeal, and argue that these factors induce users to dwell longer within the technological ecosystem. Given the increasing agency of technology, stickiness factors are beginning to assume new relevance as a possible explanation for the power of technology on human compulsion. This provides a basis for valuable future research.

The grounded theory of this chapter proposes that the hooked state represents technology-induced excessive use. Based on our understanding of IS literature, I argue that the hooked state is a useful construct that accurately represents the excessive use of technology. It captures the role of technology as an agent acting in concert with human agency. As such, "hooked-ness" is a unique, more holistic construct in contrast with habit, post-adoption, and technology addiction. I provide the comparison in Table 1.18. In this way, I contribute to the theorization of habit, post-adoption, and technology addiction.

Table 1.18: Construct comparisons

	Habit	**Post Adoption State**	**Hooked State**	**Technology Addiction State**
Agency	Automatic reward-response cue	Rational evaluation	Technology features and humans' ability to fulfill needs	Maladaptive cognition
Presence of adaptation	Lack of adaptation	Presence of adaptation	Presence of adaptation, but dynamic in nature	Lack of adaptation
Withdrawal effect	No withdrawal effect associated with usage	No withdrawal effect associated with usage	No withdrawal effect associated with usage	The withdrawal effect is associated with usage
Perceived need matching	May or may not be relevant	May or may not be relevant	Highly relevant to hooked state	May or may not be relevant
Dynamic context	A stable context requires habit	Context is not relevant for adoption	The dynamic context is a necessary condition for the hooked state	The dynamic context is not relevant for addiction
Experiential Involvement	May or may not be relevant	May or may not be relevant	Highly relevant to the hooked state	May or may not be relevant
Swaying	May or may not be relevant	Swaying is not relevant as individuals use full rationality during usage	Swaying is relevant to the hooked state because technology encourages exploration	May or may not be relevant

This paper also advances reinforcement and SOR theory. According to reinforcement theory, positive reinforcement, negative reinforcement, and repeated reinforcement all increase the likelihood of responses. To reinforce user dwell time, habit-forming technology must fulfill some needs of the user. Although the applications of reinforcement theory are limited to psychology and neurobiology, in extending reinforcement theory to the technology field, I extend the application of reinforcement concepts such as SOR theory. Under SOR theory, stimuli elicit cognitive and emotional processing, causing a specific response. Our study advances SOR theory into new realms, showing that the interaction of technology and human need elicits cognitive and emotional attraction, leading to a longer dwell time in response.

I also contribute to the literature regarding negative technology use. Our grounded theory model indicates that the hooked state can lead to perceived work-life conflicts. Our findings are consistent with existing literature within the field of negative technology use. However, from the interview, I find that perceived work-life conflicts emerge not from individuals' negative traits but from the hooked state as users dwell longer within technology than they intend. Our findings contrast sharply with a broader body of literature that blames individual personality traits for perceived work-life conflicts.

This chapter contributes to the *process perspective* of technology use. IS scholars have given scant attention to process research within the context of consumer technology usage. Generally, research on consumer technology use considers the IS usage process dualistically: pre-adoption and post-adoption. This process perspective is simplistic and does not capture the complex phenomenon of frequent high use nor the peculiar quality of human decision-making. I fill this gap by proposing a process model of technology use patterns. Our process perspective deconstructs users' technology interaction into four distinct states, useful for developers who may now choose different strategies for each stage. For example, creating awareness is paramount at the beginning. Developers could choose to supply superior content and facilitate ease of use to make users more aware of the benefits of adopting the particular technology. If developers try to "hook" users at the beginning with predictive algorithms, users may become frustrated by the barrage of recommended content and abandon the technology. The theorization of process states will therefore help developers implement solid, human-centered design strategies.

Finally, this research contributes to the emerging literature on design science. Research on how to design immersive and captivating technology is still limited. One cannot simply guarantee technology use by enhancing technology capabilities; rather, enhancing human agency within the technology platform ensures it genuinely has immersion and replay-ability. Likewise, design science should reckon with how to maximize human agency so that users feel empowered to govern the amount of technology they use.

Table 1.19: Key contributions and implications

Contributions and Implications	For Research	1. Illustrates the role of human and technology agencies in explaining excessive use of technology 2. Describes the underlying mechanism of how an individual excessively uses technology 3. Proposes a state of technology use: hooked state 4. Extends the application of reinforcement and SOR theory 5. Illustrates the negative implication of hooked state 6. Describes the underlying process of technology use (from initial use to negative use)
	For Practice	1. Proposes that only design intervention does not make people reach the hooked state; instead, both design interaction and human agency play an essential role in bringing back users repeated in an app.

Limitations

There are several limitations of this study. First, demographic diversity did not factor into our theory-building process because the aim was to develop a generalizable theory. Where one works and where one lives might explain why one uses technology excessively. The participant universe was only in the U.S. Future research is needed to factor in demographic variables.

Second, I focus on "super apps" in building the theory. Although I think the technology context is appropriate in our grounded theory, one must interpret the results judiciously.

Therefore, future research should investigate how this grounded theory could be applicable in another technology context.

Third, our qualitative study is affected by interview bias. Perhaps some interviewees may be less than forthright in describing their usage patterns. I try to address this concern by using probing techniques mentioned in the method section. Providing cross-validation to our study, both in-depth interviews and written interviews produce concurring results. As the pattern is identical across interviews, self-report bias may be discounted within our study. The second concern is objectivity during data analysis. To maintain objectivity, I follow Strauss and Corbin (1998) in first using different methods (written and in-depth interviews) to check the consensus and dissensus of participants and, secondly, utilizing the comparative analysis to contrast one incident with another. Thirdly, I obtain multiple participant viewpoints regarding a specific phenomenon. Fourth, I checkpoint with the participant often, asking, "what is going on." Following Strauss and Corbin's methods help maintain data objectivity within the analysis.

A fifth limitation may be that the theory ignores situational factors such as global crises. A person can be temporarily hooked on social media for reasons such as the rapid rise in Covid-19 cases within their area. In keeping with the ethic of a generalized model, I excluded situational factors from consideration.

Sixth, in using Strauss and Corbin's 1998 method for maintaining objectivity, I inherit their interpretivist paradigm in interview analysis. Interpretivism competes with two other paradigms of grounded theory, objectivism, and constructivism. Different approaches to the research could yield valuable results.

Future Research Directions

Future research might focus on specific human and technological agency factors leading to a hooked state. Given the scope and nature of our study, I conceptualize different agency factors into two broader themes: human and technological agency. Future research can investigate the specific factors of human and technological agency contributing to the hooked state.

My study's focus was on how an individual reaches a hooked state within the context of a single particular app. However, future research may study how a constellation of apps acts in concert. For example, an individual can simultaneously be hooked on Instagram and Snapchat. Future research should study the role of multiple technologies in acting upon the hooked state.

Several moderation/mediation factors could be used to extend the current models. Both cultural concerns and privacy sensitivity may be two critical factors dampening the effect of technological agency upon the hooked state. Individuals sensitive to data privacy might avoid responding to technology recommendations, letting individuals "off the hook," so to speak. Culturally, two individuals may experience a difference in hooked states because of different cultural perceptions regarding the usefulness of the app's features. Further studies might investigate cultural nuances, further authenticating the current grounded model.

I analyzed the process model using two dimensions. Although the degree of goal orientation and the frequency of usage are two key dimensions I interpret from the data, future studies may use other dimensions to extend the study's findings, for example, identity association.

I also observed an interesting interaction paradox: although technology users identify that some apps violate their privacy by constantly manipulating data and sharing data with other platforms, they still feel an urge to return to these apps repeatedly. Future research should investigate this "privacy paradox."

Finally, although I studied technology-induced excessive use using a qualitative paradigm, future studies could examine the phenomenon using different quantitative paradigms such as longitudinal study, experiment, and design science. Design science, for example, can delve into the creation of dynamic IT artifacts to efficiently and rapidly “hook” users.

Conclusion

The grounded theory illustrates that technology-induced excessive use behavior can be represented by the hooked state. According to my observation, participants in a hooked state mentioned that technology and their ability to fulfill needs stimulate them to return by arousing emotion, cognition, and fear of missing out (FOMO). As the algorithm, features, and many other IT artifacts modify the usage environment, one could ask the question, *will technology, at last, assume complete agency from humans*? To answer such an existential question, we need to understand more about how individuals reach a hooked state. I believe that the grounded theory of hooked provides an initial step to interrogating the future world constructed by technology agency.

There is a debate about the role of technology companies in developing addiction. Some conclude that if technology is responsible for developing addiction, it is important to stop companies from deploying engaging features. In fact, technology must be held accountable for driving sustained engagement in our modern world, but technology agency is not a threat to human agency. The only threat to the human agency is humankind itself, surrendering its will to the planet of the apps.

References of Essay 1

Abel, J. P., Buff, C. L., & Burr, S. A. (2016). Social media and the fear of missing out: Scale development and assessment. *Journal of Business & Economics Research, 14*(1), 33-44.

Abou-Saleh, M. T. (2006). Substance use disorders: recent advances in treatment and models of care. *Journal of psychosomatic research, 61*(3), 305-310.

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, 665-694.

Alexander, B. K., & Hadaway, P. F. (1982). Opiate addiction: the case for an adaptive orientation. *Psychological bulletin, 92*(2), 367.

Alter, A. (2017). *Irresistible: The rise of addictive technology and the business of keeping us hooked*: Penguin.

Alutaybi, A., Al-Thani, D., McAlaney, J., & Ali, R. (2020). Combating fear of missing out (FoMO) on social media: The fomo-r method. *International Journal of Environmental Research and Public Health, 17*(17), 6128.

Andreassen, C. (2015). Online Social Network Site Addiction: A Comprehensive Review. *Current Addiction Reports, 2*(2), 175-184.

Augustine, R., & Xavier, M. S. (2021). A Critical Study on Netflix Docudrama-'The Social Dilemma'. *Media, Culture and Society, 22*, 24.

Barnett, J., & Coulson, M. (2010). Virtually Real: A Psychological Perspective on Massively Multiplayer Online Games. *Review of General Psychology, 14*(2), 167-179.

Benlian, A. (2015). IT feature use over time and its impact on individual task performance. *Journal of the Association for Information Systems, 16*(3), 2.

Berthon, P., Pitt, L., & Campbell, C. (2019). Addictive de-vices: A public policy analysis of sources and solutions to digital addiction. *Journal of Public Policy & Marketing, 38*(4), 451-468.

Beyens, I., Frison, E., & Eggermont, S. (2016). "I don't want to miss a thing": Adolescents' fear of missing out and its relationship to adolescents' social needs, Facebook use, and Facebook related stress. *Computers in Human Behavior, 64*, 1-8.

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly, 25*(3), 351-370.

Bhattacherjee, A., & Lin, C.-P. (2015). A unified model of IT continuance: three complementary perspectives and crossover effects. *European Journal of Information Systems, 24*(4), 364-373.

Bitrián, P., Buil, I., & Catalán, S. (2021). Enhancing user engagement: The role of gamification in mobile apps. *Journal of Business Research, 132*, 170-185.

Burton-Jones, A., & Gallivan, M. J. (2007). Toward a deeper understanding of system usage in organizations: a multilevel perspective. *MIS Quarterly*, 657-679.

Butler, C. (2014). *A framework for evaluating the effectiveness of gamification techniques by personality type.* Paper presented at the International Conference on HCI in Business.

Caplan, S. E. (2006). Relations among loneliness, social anxiety, and problematic Internet use. *Cyberpsychology & Behavior, 10*(2), 234-242.

Caplan, S. E., & High, A. C. (2006). Beyond excessive use: The interaction between cognitive and behavioral symptoms of problematic Internet use. *Communication Research Reports, 23*(4), 265-271.

Castille, C. M., & Sheets, T. L. (2012). The Five Factor Model of personality and employees' excessive use of technology. *Computers in Human Behavior, 28*(5), 1947-1953.

Charmaz, K. (2017). The power of constructivist grounded theory for critical inquiry. *Qualitative Inquiry, 23*(1), 34-45.

Chick, J. (1988). Stress and Addiction - Gottheil,e, Druley,ka, Pashkos,s, Weinstein,sp. *Journal of Psychosomatic Research, 32*(3), 340-341.

Cram, W. A., D'arcy, J., & Proudfoot, J. G. (2019). Seeing the forest and the trees: a meta-analysis of the antecedents to information security policy compliance. *MIS Quarterly, 43*(2), 525-554.

Cram, W. A., Proudfoot, J. G., & D'Arcy, J. (2021). When enough is enough: Investigating the antecedents and consequences of information security fatigue. *Information Systems Journal, 31*(4), 521-549.

de Guinea, A. O., & Markus, M. L. (2009). Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology use. *MIS Quarterly, 33*(3), 433-444.

De Guinea, A. O., & Markus, M. L. (2009). Why break the habit of a lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. *MIS Quarterly*, 433-444.

De Haas, W. B., & Wiering, F. (2010). Hooked on music information retrieval. *Empirical Musicology Review*, *5*(4), 176-185.

Du, S. (2021). Reimagining the Future of Technology:“The Social Dilemma” Review. *Journal of Business Ethics*, 1-3.

Eaton, B., Elaluf-Calderwood, S., Sørensen, C., & Yoo, Y. (2015). Distributed tuning of boundary resources. *MIS Quarterly, 39*(1), 217-244.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical And Applied Statistics, 5*(1), 1-4.

Eyal, N. (2014). *Hooked: How to build habit-forming products*: Penguin.

Fredrickson, B. L., & Branigan, C. (2005). Positive emotions broaden the scope of attention and thought-action repertoires. *Cognition & Emotion, 19*(3), 313-332.

Gerlach, J. P., & Cenfetelli, R. T. (2020). Constant Checking Is Not Addiction: A Grounded Theory of IT-Mediated State-Tracking. *MIS Quarterly, 44*(4), 1705. doi:10.25300/MISQ/2020/15685

Glaser, B. G. (1978). *Theoretical sensitivity*: University of California.

Glaser, B. G., Strauss, A. L., & Strutzel, E. (1968). The discovery of grounded theory; strategies for qualitative research. *Nursing research, 17*(4), 364.

Goldman, M. S. (1999). Risk for substance abuse: Memory as a common etiological pathway. *Psychological Science, 10*(3), 196-198. doi:10.1111/1467-9280.00133

Golub, A. (2010). Being in the World (of Warcraft): Raiding, realism, and knowledge production in a massively multiplayer online game. *Anthropological Quarterly*, 17-45.

Gomes, C. C., & Preto, S. (2018). *Artificial intelligence and interaction design for a positive emotional user experience.* Paper presented at the International Conference on Intelligent Human Systems Integration.

Gordan, M., & Amutan, K. (2014). A Review of BF Skinners Reinforcement Theory of Motivation. *International Journal of Research in Education Methodology, 5*(3), 680-688.

Hansen, P. G., & Jespersen, A. M. (2013). Nudge and the manipulation of choice: A framework for the responsible use of the nudge approach to behaviour change in public policy. *European Journal of Risk Regulation, 4*(1), 3-28.

Hawi, N. S., & Samaha, M. (2017). Relationships among smartphone addiction, anxiety, and family relations. *Behaviour & Information Technology, 36*(10), 1046-1052.

Hengst, I.-A., Jarzabkowski, P., Hoegl, M., & Muethel, M. (2020). Toward a process theory of making sustainability strategies legitimate in action. *Academy of Management Journal, 63*(1), 246-271.

Hou, J., Kim, K., Kim, S. S., & Ma, X. (2019). Disrupting Unwanted Habits in Online Gambling Through Information Technology. *Journal of Management Information Systems, 36*(4), 1213-1247.

Hsee, C. K., & Zhang, J. (2010). General evaluability theory. *Perspectives on Psychological Science, 5*(4), 343-355.

Huang, Y., Jasin, S., & Manchanda, P. (2019). "Level Up": Leveraging skill and engagement to maximize player game-play in online video games. *Information Systems Research, 30*(3), 927-947.

Hussain, Z., & Griffiths, M. D. (2009). Excessive use of massively multi-player online role-playing games: A pilot study. *International journal of mental health and addiction, 7*(4), 563-571.

James, T. L., Lowry, P. B., Wallace, L., & Warkentin, M. (2017). The Effect of Belongingness on Obsessive-Compulsive Disorder in the Use of Online Social Networks. *Journal of Management Information Systems, 34*(2), 560-596.

Japutra, A., & Keni, K. (2020). Signal, need fulfilment and tourists' intention to revisit. *Anatolia, 31*(4), 605-619.

Joe, S.-W., & Chiu, C.-K. (2009). Proposing online game loyalty and its antecedents considering gender as a moderator: a qualitative study. *Quality & Quantity, 43*(5), 731-741.

Jongepier, F., & Klenk, M. (2022). The Philosophy of Online Manipulation. In: Taylor & Francis.

Jung, J., Bapna, R., Ramaprasad, J., & Umyarov, A. (2019). Love unshackled: Identifying the effect of mobile app adoption in online dating. *MIS Quarterly, 43*, 47-72.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives, 5*(1), 193-206.

Karahanna, E., Xu, S. X., Xu, Y., & Zhang, N. A. (2018). The needs–affordances–features perspective for the use of social media. *MIS Quarterly, 42*(3), 737-756.

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior, 31*, 351-354.

Kim, S. S. (2009). The Integrative Framework of Technology Use: an Extension and Test. *MIS Quarterly, 33*(3), 513-537.

Kranova, H., Widjaja, T., Buxmann, P., Wenninger, H., & Benbasat, I. (2015). Why following friends can hurt you: an exploratory investigation of the effects of envy on social networking sites among college-age users. *Information Systems Research, 26*(3), 585-605.

Kwon, H. E., So, H., Han, S. P., & Oh, W. (2016). Excessive Dependence on Mobile Social Apps: A Rational Addiction Perspective. *Information Systems Research, 27*(4), 919-939.

Langley, A. (1999). Strategies for theorizing from process data. *Academy of Management Review, 24*(4), 691-710.

Lee, J., & Hong, I. B. (2016). Predicting positive user responses to social media advertising: The roles of emotional appeal, informativeness, and creativity. *International Journal of Information Management, 36*(3), 360-373.

Lee, S., Kim, M., Mendoza, J. S., & McDonough, I. M. (2018). Addicted to cellphones: Exploring the psychometric properties between the nomophobia questionnaire and obsessiveness in college students. *Heliyon, 4*(11), e00895.

Lee, Z. W., Cheung, C. M., & Chan, T. K. (2014). *Explaining the development of the excessive use of massively multiplayer online games: a positive-negative reinforcement perspective.* Paper presented at the 2014 47th Hawaii International Conference on System Sciences.

Lee, Z. W. Y., Cheung, C. M. K., & Chan, T. K. H. Understanding massively multiplayer online role-playing game addiction: A hedonic management perspective. *Information Systems Journal*, *31*(1), 33-61.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, *35* (1), 147-167.

Liang, H., & Xue, Y. (2009). Avoidance of information technology threats: A theoretical perspective. *MIS Quarterly*, *33*(1),71-90.

Limayem, Hirt, & Cheung. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly, 31*(4), 705-737.

Liu, D., Santhanam, R., & Webster, J. (2017). Toward Meaningful Engagement: a framework for design and research of Gamified information systems. *MIS Quarterly , 41*(4).

Liu, Q. B., & Karahanna, E. (2017). The dark side of reviews: The swaying effects of online product reviews on attribute preference construction. *MIS Quarterly, 41*(2), 427-448.

Liu, Z., Wang, X., Min, Q., & Li, W. (2019). The effect of role conflict on self-disclosure in social network sites: An integrated perspective of boundary regulation and dual process model. *Information Systems Journal, 29*(2), 279-316.

McLuhan, M., & MCLUHAN, M. A. (1994). *Understanding media: The extensions of man*: MIT press.

Mele, C., & Russo-Spena, T. (2021). The architecture of the phygital customer journey: a dynamic interplay between systems of insights and systems of engagement. *European Journal of Marketing*, *56*(1), 72-91.

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*: sage.

Mills, J., Chapman, Y., Bonner, A., & Francis, K. (2007). Grounded theory: A methodological spiral from positivism to postmodernism. *Journal of Advanced Nursing, 58*(1), 72-79.

Montag, C., Lachmann, B., Herrlich, M., & Zweig, K. (2019). Addictive Features of Social Media/Messenger Platforms and Freemium Games against the Background of Psychological and Economic Theories. *International journal of environmental research and public health, 16*(14), 2612.

Mulligan, K., & Scherer, K. R. (2012). Toward a working definition of emotion. *Emotion Review, 4*(4), 345-357.

Nonis, S. A., Hudson, G. I., Logan, L. B., & Ford, C. W. (1998). Influence of Perceived Control over Time on College Students'stress and Stress-Related Outcomes. *Research in Higher Education, 39*(5), 587-605.

Orru, K., Kask, S., & Nordlund, A. (2019). Satisfaction with virtual nature tour: The roles of the need for emotional arousal and pro-ecological motivations. *Journal of Ecotourism, 18*(3), 221-242.

Panda, T. K., Panda, T. K., & Mishra, K. (2013). Does emotional appeal work in advertising? The rationality behind using emotional appeal to create favorable brand attitude. *IUP Journal of Brand Management, 10*(2), 7.

Parthasarathy, M., & Bhattacherjee, A. (1998). Understanding post-adoption behavior in the context of online services. *Information Systems Research, 9*(4), 362-379.

Polites, G. L., & Karahanna, E. (2012). Shackled to the Status Quo: the Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance. *MIS Quarterly, 36*(1), 21-42.

Polites, G. L., & Karahanna, E. (2013). The Embeddedness of Information Systems Habits in Organizational and Individual Level Routines: Development and Disruption. *MIS Quarterly, 37*(1), 221.

Redish, A. D., Jensen, S., Johnson, A., & Kurth-Nelson, Z. (2009). Reconciling Reinforcement Learning Models With Behavioral Extinction and Renewal: Implications for Addiction, Relapse, and Problem Gambling. *Psychological Review, 116*(3), 784.

Roberts, J. A., & David, M. E. (2020). The social media party: Fear of missing out (FoMO), social media intensity, connection, and well-being. *International Journal of Human–Computer Interaction, 36*(4), 386-392.

Rogers, E. Diffusion of innovations 5th Edition. New York 2003. In: Free Press.

Rubenking, B., & Lang, A. (2014). Captivated and grossed out: An examination of processing core and sociomoral disgusts in entertainment media. *Journal of Communication, 64*(3), 543-565.

Russell, S., & Norvig, P. (2002). Artificial intelligence: a modern approach.

Sandstrom, P. E. (1994). An optimal foraging approach to information seeking and use. *The Library Quarterly, 64*(4), 414-449.

Saunders, C., Wiener, M., Klett, S., & Sprenger, S. (2017). The impact of mental representations on ICT-related overload in the use of mobile phones. *Journal of Management Information Systems, 34*(3), 803-825.

Scherer, K. R. (2005). Unconscious Processes in Emotion: The Bulk of the Iceberg.

Seaver, N. (2019). Captivating algorithms: Recommender systems as traps. *Journal of Material Culture, 24*(4), 421-436.

Sebastian, K. (2019). Distinguishing between the types of grounded theory: Classical, interpretive and constructivist. *Journal for Social Thought, 3*(1), 1-9.

Septianto, F., & Pratiwi, L. (2016). The moderating role of construal level on the evaluation of emotional appeal vs. cognitive appeal advertisements. *Marketing Letters, 27*(1), 171-181.

Serenko, A., & Turel, O. (2020). Directing technology addiction research in information systems: Part I. Understanding behavioral addictions. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 51*(3), 81-96.

Siebert, A., Gopaldas, A., Lindridge, A., & Simões, C. (2020). Customer experience journeys: Loyalty loops versus involvement spirals. *Journal of Marketing, 84*(4), 45-66.

Soror, A. A., Hammer, B. I., Steelman, Z. R., Davis, F. D., & Limayem, M. M. (2015). Good habits gone bad: Explaining negative consequences associated with the use of mobile phones from a dual-systems perspective. *Information Systems Journal, 25*(4), 403-427.

Steed, A., Roberts, D., Schroeder, R., & Heldal, I. (2005). *Interaction between users of immersion projection technology systems.* Paper presented at the HCI International 2005, the 11th International Conference on Human Computer Interaction.

Steenkamp, J.-B. E., & Baumgartner, H. (1992). The role of optimum stimulation level in exploratory consumer behavior. *Journal of Consumer Research, 19*(3), 434-448.

Stein, M.-K., Newell, S., Wagner, E. L., & Galliers, R. D. (2015). Coping with information technology. *MIS Quarterly, 39*(2), 367-392.

Steinberg, M. (2020). LINE as super app: Platformization in East Asia. *Social Media+ Society, 6*(2).

Strauss, A., & Corbin, J. (1998). *Basics of qualitative research techniques*: Citeseer.

Strauss, A., & Corbin, J. M. (1997). *Grounded theory in practice*: Sage.

Sun, H. (2012). Understanding user revisions when using information system features: Adaptive system use and triggers. *MIS Quarterly*, 453-478.

Sun, J. C.-Y., & Hsieh, P.-H. (2018). Application of a gamified interactive response system to enhance the intrinsic and extrinsic motivation, student engagement, and attention of English learners. *Journal of Educational Technology & Society, 21*(3), 104-116.

Susser, D., Roessler, B., & Nissenbaum, H. (2019). Technology, autonomy, and manipulation. *Internet Policy Review, 8*(2).

Tandon, A., Dhir, A., Almugren, I., AlNemer, G. N., & Mäntymäki, M. (2021). Fear of missing out (FoMO) among social media users: a systematic literature review, synthesis and framework for future research. *Internet Research*, *31*(3), 782-821.

Tarafdar, M., Maier, C., Laumer, S., & Weitzel, T. (2020). Explaining the link between technostress and technology addiction for social networking sites: A study of distraction as a coping behavior. *Information Systems Journal, 30*(1), 96-124.

Turel, O. (2015). Quitting the use of a habituated hedonic information system: a theoretical model and empirical examination of Facebook users. *European Journal of Information Systems, 24*(4), 431-446.

Turel, O., & Ferguson, C. (2021). Excessive Use of Technology: Can Tech Providers be the Culprits? Seeking to assess the possible responsibility of tech providers for excessive use patterns. *Communications of the ACM, 64*(1), 42-44.

Turel, O., & Serenko, A. (2012). The benefits and dangers of enjoyment with social networking websites. *European Journal of Information Systems, 21*(5), 512-528.

Turel, O., Serenko, A., & Giles, P. (2011a). Integrating technology addiction and use. *Management information systems, 35*(4), 1043-1061.

Turel, O., Serenko, A., & Giles, P. (2011b). Integrating Technology Addiction and Use: an Empirical Investigation of Online Auction Users. *MIS Quarterly, 35*(4), 1043-1061.

Urquhart, C., Lehmann, H., & Myers, M. D. (2010). Putting the 'theory'back into grounded theory: guidelines for grounded theory studies in information systems. *Information Systems Journal, 20*(4), 357-381.

Vaghefi, I., Lapointe, L., & Boudreau-Pinsonneault, C. (2017). A typology of user liability to IT addiction. *Information Systems Journal, 27*(2), 125-169.

Van Damme, S., Lorenz, J., Eccleston, C., Koster, E. H., De Clercq, A., & Crombez, G. (2004). Fear-conditioned cues of impending pain facilitate attentional engagement. *Neurophysiologie clinique/Clinical neurophysiology, 34*(1), 33-39.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS quarterly*, *32*(3), 483-502.

Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology, 45*(3), 639-656.

Verplanken, B., Verplanken, B., & Ryan. (2018). *Psychology of habit*: Springer.

Wang, C., & Lee, M. K. O. (2020). Why We Cannot Resist Our Smartphones: Investigating Compulsive Use of Mobile SNS from a Stimulus-Response-Reinforcement Perspective. *Journal of the Association for Information Systems, 21*(1), 175-200.

Wang, C., Lee, M. K. O., & Hua, Z. (2015). A theory of social media dependence: Evidence from microblog users. *Decision Support Systems, 69*, 40-49.

West, R., Brown, J., & ProQuest. (2013). *Theory of addiction* (2nd ed.). Chichester, West Sussex, U.K: John Wiley & Sons Inc.

Winterich, K. P., & Haws, K. L. (2011). Helpful hopefulness: The effect of future positive emotions on consumption. *Journal of Consumer Research, 38*(3), 505-524.

Xu, H., & Tan, B. C. Y. (2012). Why do I keep checking Facebook: Effects of message characteristics on the formation of social network services addiction. . Paper presented at International Conference on Information Systems, ICIS 2012.

Xu, Z., Turel, O., & Yuan, Y. (2012). Online game addiction among adolescents: motivation and prevention factors. *European Journal of Information Systems, 21*(3), 321-340.

Yuen, K. F., Li, K. X., Ma, F., & Wang, X. (2020). The effect of emotional appeal on seafarers' safety behaviour: An extended health belief model. *Journal of Transport & Health, 16*, 100810.

Zheng, X., & Lee, M. K. (2016). Excessive use of mobile social networking sites: Negative consequences on individuals. *Computers in Human Behavior, 65*, 65-76.

Appendix of Essay

Table 1.20: Interview protocol

How can we get hooked to an app? A study on app use

The purpose of this interview is to determine how and why excessive app usage occurs. The interview will consist of a range of questions to determine how and why you use an app excessively.

1. Which app do you use the most? How frequently per day? How long do you use?
2. What keeps you using the app? How does the app become your favorite?
3. What factors or causes led you to download an app in the past? What do you think now? How do you compare the rationales?
4. How do you feel when disconnected from the application? Do you believe you will be affected if the app ceases to provide the service?
5. Do you feel that you frequently use the app more than you would have intended?
6. If so, why do you return to the app and spend a longer time than intended?
7. If you cannot use the app whenever you desire, do you have any emotional, thought, or behavioral disturbances? Does this seriously impact your work?
8. Do you feel you spend more time due to app recommendations and new content? What effect do these recommendations and the novel contents have on you?
9. What do you like about the app? Why is the app so alluring?
10. How do app recommendations affect your actions?
11. Do you frequently experience excitement when using an app? If yes, why do you feel so?
12. Do you believe that algorithm influences your app usage?
13. How do you evaluate your app usage? Can you briefly explain?

Table 1.21: Interview participants (synchronous)

No.	Gender	Age	Mode	Length in minutes
1	M	22-30	Online (Skype)	33
2	M	24-32	Online (Zoom)	34
3	M	24-35	Online (Skype)	26
4	F	24-32	Online (Skype)	25
5	M	22-30	Online (Skype)	24
6	M	22-30	Online (Skype)	23
7	F	22-33	Online (Skype)	25
8	M	24-35	Online (Skype)	21
9	M	24-35	Online (Skype)	20
10	F	24-35	Online (Team)	40
11	F	22-30	Online (Team)	35
12	M	22-30	Online (Team)	44
13	F	22-30	Online (Team)	44
14	M	24-35	Online (Skype)	45
15	M	24-35	Online (Skype)	58
16	M	22-30	Online (Skype)	20
17	F	24-35	Online (Zoom)	39
18	M	30-45	Online (Zoom)	42
19	F	22-30	Online (Team)	23
20	M	22-30	Online (Team)	25
21	M	24-35	Online (Team)	30
22	M	24-35	Online (Team)	49
23	M	20-25	Online (Zoom)	27
24	M	20-25	Online (Zoom)	32
25	F	20-25	Online (Zoom)	27
26	M	35-50	Online (Zoom)	40
27	F	20-25	Online (Zoom)	38
28	M	24-35	Online (Zoom)	75
29	F	20-25	Online (Zoom)	37
30	M	20-25	Online (Zoom)	28
31	F	24-35	Online (Zoom)	40
32	M	24-32	Online (Zoom)	40
33	M	20-25	Online (Zoom)	60
34	M	20-25	Online (Zoom)	45
34	M	20-25	Online (Zoom)	45

Table 1.22: Interview participants (asynchronous)

No.	Gender	Age	Mode	Page Length
1	M	20-40	Email	2
2	F	20-40	Email	3
3	M	20-40	Email	2
4	F	20-40	Email	3
5	F	20-40	Email	2
6	F	20-40	Email	3
7	M	20-40	Email	3
8	M	20-40	Email	2
9	M	20-40	Email	2
10	F	20-40	Email	3
11	F	20-40	Email	3
12	F	20-40	Email	2
13	M	20-40	Email	3
14	M	20-40	Email	2
15	F	20-40	Email	2
16	M	20-40	Email	3
17	F	20-40	Email	2
18	M	20-40	Email	2
19	M	20-40	Email	2
20	M	20-40	Email	2
21	M	20-40	Email	2
22	M	20-40	Email	2
23	M	20-40	Email	2
24	M	20-40	Email	2
25	F	20-40	Email	2
26	M	20-40	Email	2
27	F	20-40	Email	3
28	M	20-40	Email	2
29	F	20-40	Email	2
30	M	20-40	Email	3
31	F	20-40	Email	2
32	F	20-40	Email	3
33	F	20-40	Email	3
34	F	20-40	Email	2
35	F	20-40	Email	3
36	F	20-40	Email	3

Table 1.22 (Cont.)

No.	Gender	Age	Mode	Page Length
36	F	20-40	Email	3
37	F	20-40	Email	2
38	F	20-40	Email	3
39	F	20-40	Email	2
40	F	20-40	Email	3
41	F	20-40	Email	2
42	F	20-40	Email	3
43	F	20-40	Email	2
44	F	20-40	Email	3
45	F	20-40	Email	3
46	F	20-40	Email	2
47	F	20-40	Email	3
48	M	20-40	Email	2
49	M	20-40	Email	3
50	M	20-40	Email	3
51	F	20-40	Email	2
52	F	20-40	Email	3
53	M	20-40	Email	4
54	M	20-40	Email	3
55	F	20-40	Email	2
56	M	20-40	Email	3
57	F	20-40	Email	2
58	M	20-40	Email	3
59	M	20-40	Email	2
60	M	20-40	Email	2
61	M	20-40	Email	2
62	M	20-40	Email	3
63	M	20-40	Email	2
64	M	20-40	Email	3

Table 1.22 (Cont.)

No.	Gender	Age	Mode	Page Length
65	M	20-40	Email	2
66	M	20-40	Email	3
67	M	20-40	Email	2
68	F	20-40	Email	3
69	F	20-40	Email	3
70	M	20-40	Email	2
71	M	20-40	Email	3
72	M	20-40	Email	2

Figure 1.14: Example of coding

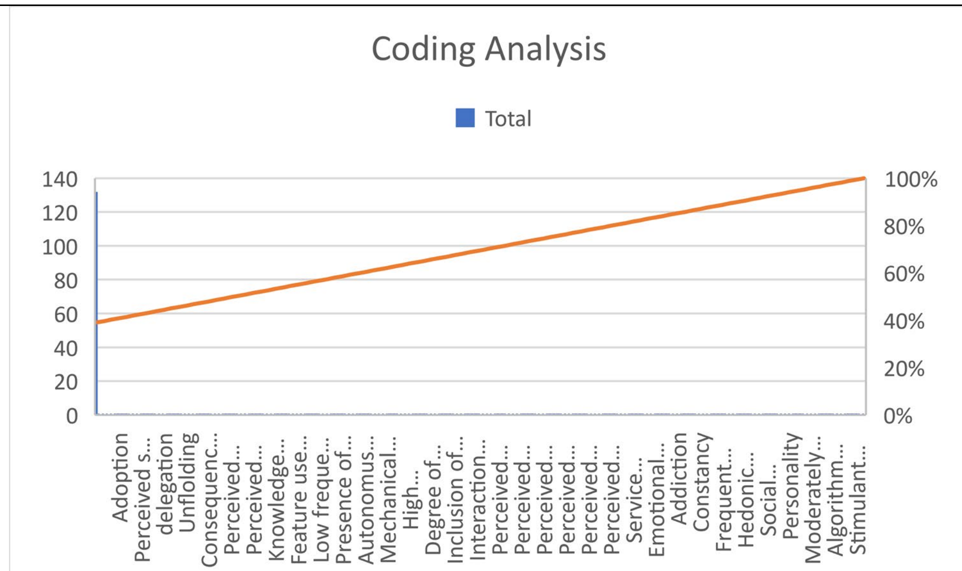


Figure 1: Open Coding

Figure 1.15: Example of coding

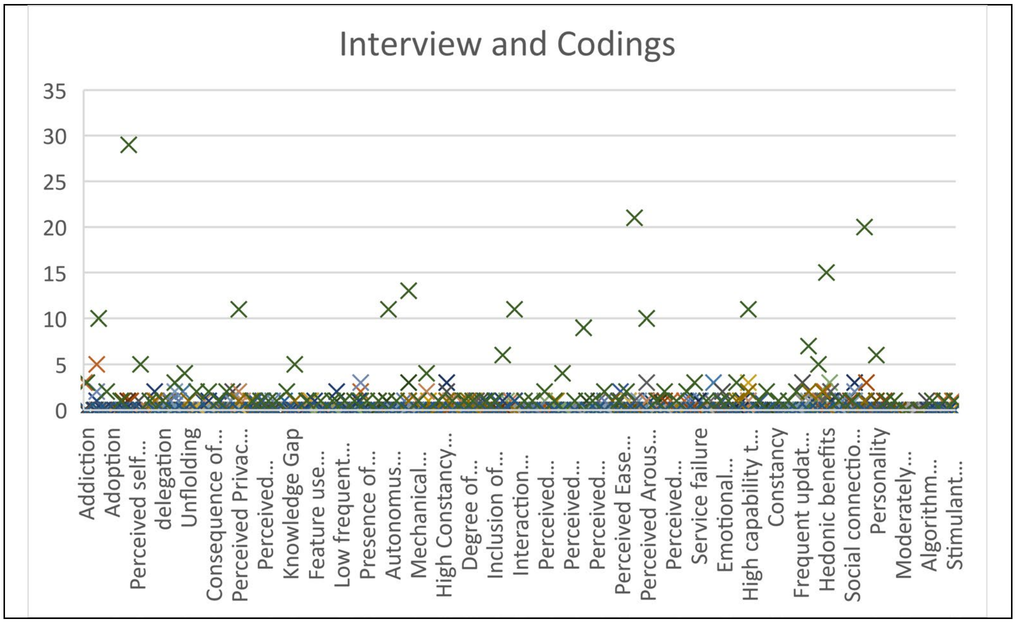
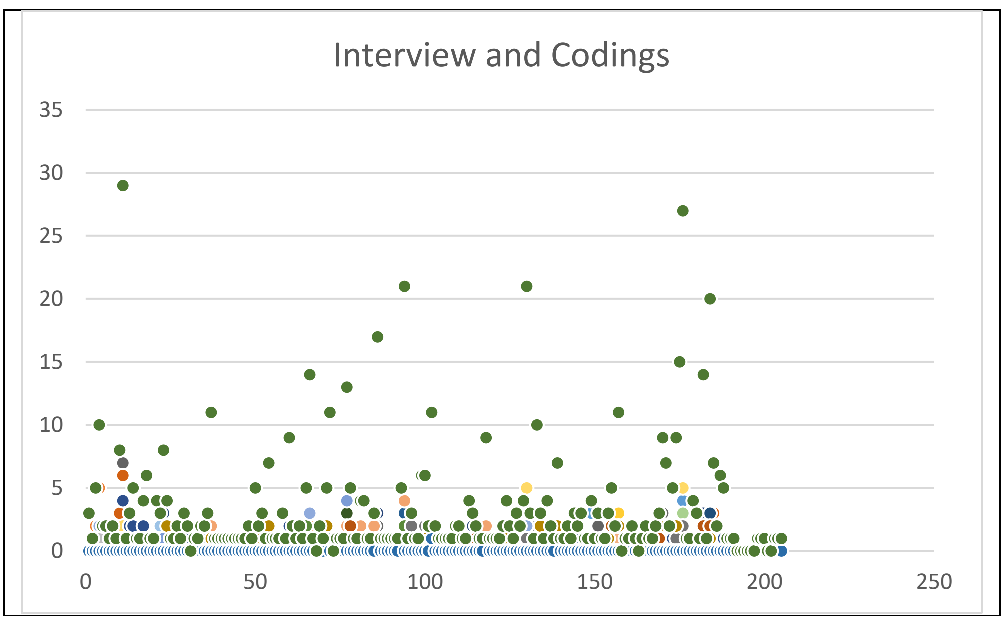


Figure 1.16: Example of coding



III. Essay 2: Investigating the Validity of the Model of Hooked State

Introduction

End-user engagement is one of the most important success indicators for app developers (Hartwig, von Saldern, & Jacob, 2021). Recently, App developers have begun implementing highly effective end-user engagement technologies such as artificial intelligence and machine learning, which, although they enhance the user experience, often engage users so fully that they spend considerable time within them (Kumar, Kaur, & Singh, 2020). For example, it has been estimated that millennials open their mobile apps more than 50 times in a single day (MindSea, 2022). I refer to such a phenomenon as "excessive use of technology."

The prevalence of excessive app usage in our society is an important topic due to its adverse effects society wide. Excessive use of technology has been found to cause conflict, overload, diminished well-being, and reduced work productivity (Zheng & Lee, 2016).

Despite the prevalence of excessive use in society, our current understanding of excessive use is limited. IS literature examines excessive use from three usage perspectives: addiction, habit, and post adoptive use. The addiction perspective views excessive use as a compulsive usage of technology with negative consequences (Turel, Mouttapa, & Donato, 2015). According to the addiction perspective, compulsive use results from an individual's negative traits, such as maladaptive cognition and neuroticism (Turel, Serenko, & Giles, 2011). The habit perspective views excessive use as automatic (Soror, Hammer, Steelman, Davis, & Limayem, 2015). According to the habit perspective, individuals have no control over their excessive use. Finally, the post-adoption perspective views excessive use as intention driven. According to the post-adoption usage perspective, individuals purposefully use technology using rational factors such as perceived usefulness and perceived ease of use (de Guinea & Markus, 2009).

Although these three perspectives have some efficacy in explaining the excessive use of technology, we lack a construct that captures the causal interaction of both technological and human agencies. To fill this gap, I provide a model in chapter one in which excessive use is represented by the construct "hooked state," a state of technology use characterized by prolonged dwell time beyond that which the user intended. Essay 1 argues that the hooked state is an outcome of an interaction between technology and human agency. Furthermore, individuals reach a hooked state driven by the constant fear of missing out and the positive cognitive and emotional appeal generated in the feedback interplay between technological and human agency.

The purpose of this essay is to validate the hooked state model. I use stimulus-organism-response (SOR) theory and the concept of a dynamic interplay between technological and human agency to frame the model. Next, I empirically test the model using two surveys. The results reinforce the model that heavy user engagement is driven by the dynamic interaction between technological and human agency in the forms of cognitive appeal, positive emotional appeal, and the fear of missing out (FOMO). Validation of the model improves our understanding of how excessive use of technology emerges.

The remainder of the paper is structured as follows. First, we review the theoretical background of the hooked state model. Next, we posit the hypotheses. Finally, we illustrate the theoretical and practical contributions of the study.

Background

Excessive use of technology

Within IS literature, excessive use of technology has been defined as "use patterns that are excessive in that they infringe on the normal functioning of users" (Turel & Ferguson, 2021). It is a deviation from an individual's normal usage (Caplan & High, 2006). Within the field, there are two paths of thought about excessive use. The first argues that excessive use is not a new phenomenon but rather is a manifestation of addiction. Accordingly, excessive use of technology is associated with increased loneliness and depression. (Cao, Masood, Luqman, & Ali, 2018).

The second school of thought contends, however, that excessive use is a rational choice (Kwon, So, Han, & Oh, 2016). It contends that the excessive use of technology has many positive implications, such as increasing user productivity (Gong, Zhang, Chen, Cheung, & Lee, 2019). Accordingly, excessive use of technology does not always manifest with salience, withdrawal, conflict, tolerance, and other stages associated with addictive states (Kwon et al., 2016). It often does not meet the criteria of clinical addiction symptoms. Moreover, users who engage in excessive usage often report they do so for fun or to gain knowledge; these are not consequences usually associated with addiction (Zheng & Lee, 2016). It may not be most accurate to characterize excessive use as addiction, therefore.

The argument over what constitutes excessive use of technology generates disagreement regarding the causes of such use. Current literature on excessive use of technology centers the causes of excessive use on individual traits such as a negative emotional and cognitive state or a maladaptive personality. However, current excessive use literature ignores the agentic aspects of technology in inducing usage. Given the increasingly agentic capabilities of technology, I argue that excessive use of technology should be investigated in the light of technology agency.

The Hooked State

To represent excessive use of technology, essay 1 characterizes the term “hooked” as a prolonged dwell time within technology beyond that which the user intended. The term of art "hooked state” was borrowed from practice literature that discusses the role of technology features in inducing usage, hooks being tangible or intangible stimuli that have the ability to captivate the attention of human beings, which are, in the app context, features (Eyal, 2014).

The hooked state has three properties: 1) experiential involvement, 2) adaptation and 3) swaying. Experiential involvement is the degree to which individuals are involved in technology action possibilities. Experiential involvement depicts a user flow state in which the user remains stimulated and focused on technology. This hooked property sharply contrasts with the addiction and habit perspectives which delineate compulsion or automatic technology-seeking behavior.

Another property of the hooked state is adaptation. Adaptation is the degree to which users perceive an urge to increase interaction level to fulfill their situational needs. This property of the hooked state indicates that an increasing user interaction level depends on successful need-fulfillment by the app. Arguably, this property contrasts with addiction and habit constructs discounting user self-control (Soror et al., 2015).

The final property of the hooked state is "swaying." Swaying is the degree to which users feel nudged to delve deeper. Swaying indicates the influence or conditioning of technology upon use. This characteristic also contrasts with the habit and addiction approach, which does not ascribe a swaying influence on technology.

In sum, I argue that the hooked state is a unique usage state that more completely encompasses the causes of excessive use of technology.

Stickiness

In this study, the concept of "stickiness" describes why a user reaches to the hooked state. In marketing literature, stickiness signifies a high degree of loyalty to products (Lin, Hu, Sheng, & Lee, 2010). Marketing literature defines it as a "lock-in" strategy that connects consumers with a product while eliciting desirable behaviors (Lin et al., 2010). Although existing literature discusses various forms of stickiness constructs that can drive loyalty to a product, chapter one outlined three stickiness variables that contribute to getting hooked on technology. Those are positive emotional appeal, perceived cognitive appeal, and fear of missing out (FOMO).

Positive emotional appeal is defined as the degree to which users perceive positive emotion while using technology features. Positive emotional appeal indicates the bond between users and a specific object (Grigaliunaite & Pileliene, 2016). Positive emotional appeal emerges in many different contexts within marketing and communication research, and positive emotional appeal has been found to create a favorable attitude towards advertising (Panda, Panda, & Mishra, 2013), as well as higher click-through rates in online advertising context (Xie, Donthu, Lohtia, & Osmonbekov, 2004).

In the "super app" context, essay 1 found two properties of positive emotional appeal: arousal of interest and arousal of cheerfulness. Arousal of interest indicates users' attractiveness toward the possibilities created by technology interaction. Attractiveness highlights users' association between technology and the expression of their self and group identities. The arousal of cheerfulness delineates the quality from which users derive feelings of positive energy and dynamism within the app. Both dimensions of positive emotional appeal are consistent with the current literature's conceptualization of emotional attachment. As positive emotion adheres individuals to technology through the expression of self and group identities, it is an important stickiness construct in the technology context.

Perceived cognitive appeal is defined as the degree to which users perceive cognitive benefits to using technology features. In technology and communication literature, perceived cognitive appeal has been studied in various contexts. For example, in the context of the website, cognitive appeal has been found to be a significant predictor of website loyalty (Bonnardel, Piolat, & Le Bigot, 2011). Elsewhere, cognitive appeal has been found to be a significant predictor of smoking reduction (Leshner, Vultee, Bolls, & Moore, 2010).

In the context of super apps, cognitive appeal refers to users' ability to exercise decision-making skills, predictive ability, and learning. There are five main types of cognitive appeal: observational learning, perceived prediction ability, perceived opportunity to engage in challenging tasks, and perceived opportunity to engage in competition. As cognitive appeal allows users to apply their thinking abilities, it is an important stickiness construct in the technology context.

Fear of missing out (FOMO) is defined as the degree to which users feel they are missing information, events, or experiences that could be gratifying. Fear of missing out indicates that individuals may feel anxious when they miss out on features they otherwise regularly interact with. Past literature has investigated FOMO in various technology contexts. For example, FOMO can significantly predict the magnitude of social media use (Hetz, Dawson, & Cullen, 2015). In the academic context, FOMO has been linked to poor academic performance (Alt, 2015).

Essay 1 described two properties of FOMO: knowledge gap and perceived separation anxiety. Knowledge gap highlights an individual's unease with missing information. Perceived separation anxiety highlights the feeling of discomfort generated by disengaging with technology. As FOMO creates the urge to return to technology repeatedly, it is an important stickiness construct in the technology context.

Human Agency

Human agency is a user's ability to fulfill their needs using technology features. Humans have innate and situational needs, which motivate humans to act to satisfy them. In the technology context, having the autonomy to satisfy one's needs indicates human agency. Chapter one identified five need-fulfillment abilities in super app contexts: a) ability to seek varieties, b) ability to connect, c) ability to be in control, d) ability to express, and e) ability to modify the mood.

Technology Agency

I define technology agency as technology's ability to act independently and guide users to perform specific actions. In the super app context, chapter one specifies two properties of technological agency: a) the ability to perform autonomous activities and b) modification ability. Both of these abilities indicate agentic activities which fulfill human needs.

Research Model

Figure 2.1 presents the research model. In this model, the hooked state is an outcome of positive emotional appeal, perceived cognitive appeal, fear of missing out (FOMO), and the dynamic interaction between technological and human agency. Let us now distinguish between the hooked state and technological agency. In the first chapter, the hooked state is a technology usage state characterized by users' use of technology longer than intended. Technology has the ability to act independently and guide users to perform specific actions. A user may feel a recurring urge to engage with technology as technology guides them to execute different tasks. Such a drive may keep the user engaged with technology for increasing lengths of time. A user is considered hooked when he or she spends more time than intended in an app and remains engaged with technology. Thus, the hooked state indicates excessive use of technology, while technological agency describes the ability of technology to stimulate user engagement. In the process of becoming hooked, users may feel compelled to return through several appeals, such as positive emotional appeal, perceived cognitive appeal, and the fear of missing out. I propose theoretical arguments for this process in the framework below.

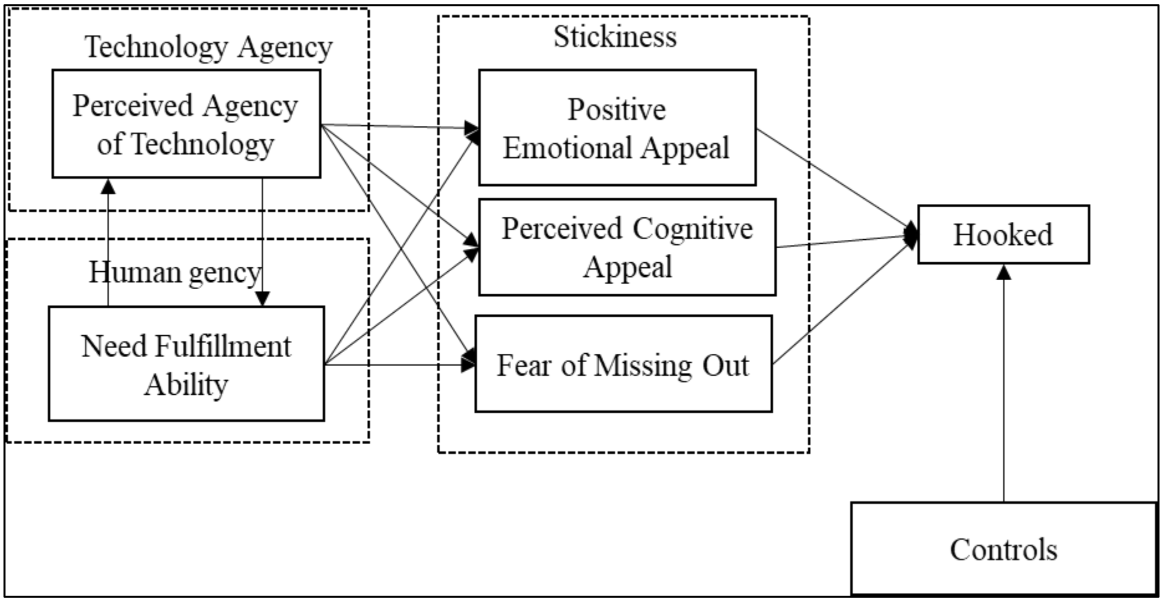


Figure 2.1: The research framework

Dynamic Interplay Between Technology Agency and Human Agency

I claim that technology agency and human agency are dynamically interrelated. The agency of technology expresses itself through autonomous actions performed by algorithms, learning from data, filtering data according to the user's need, and guidance prompting users to use features. Human agency expresses itself through the user's ability to fulfill self needs using technology features. In this cycle, technology constantly reinforces users' needs through autonomous activities and modification ability, while in return, users provide feedback to the technology. By providing data to technology, users reshape the technology's autonomous and modifying abilities.

Here, I use an example to illustrate the dynamic human-technological relationship: TikTok. TikTok attempts to raise user awareness through various features, including notifications, recommendations, and pop-ups. These features encourage users to act. As users become aware, they attempt to cognitively link action possibilities with situational and innate needs. Based on this cognitive process, the users perceive that they have the ability to fulfill their needs using TikTok. Meanwhile, TikTok collects user data. As TikTok autonomously chooses an algorithm, it uses machine learning to analyze and filter the data customized for the individual user's consumption. TikTok pushes new content to the user by updating the user's feed, informing them about new content, or suggesting more. Thus, the relationship between the agency of technology and the user's need-fulfillment ability is bi-directional. Figure 2.2 illustrates the dynamic relationship between 'technology agency and human agency.

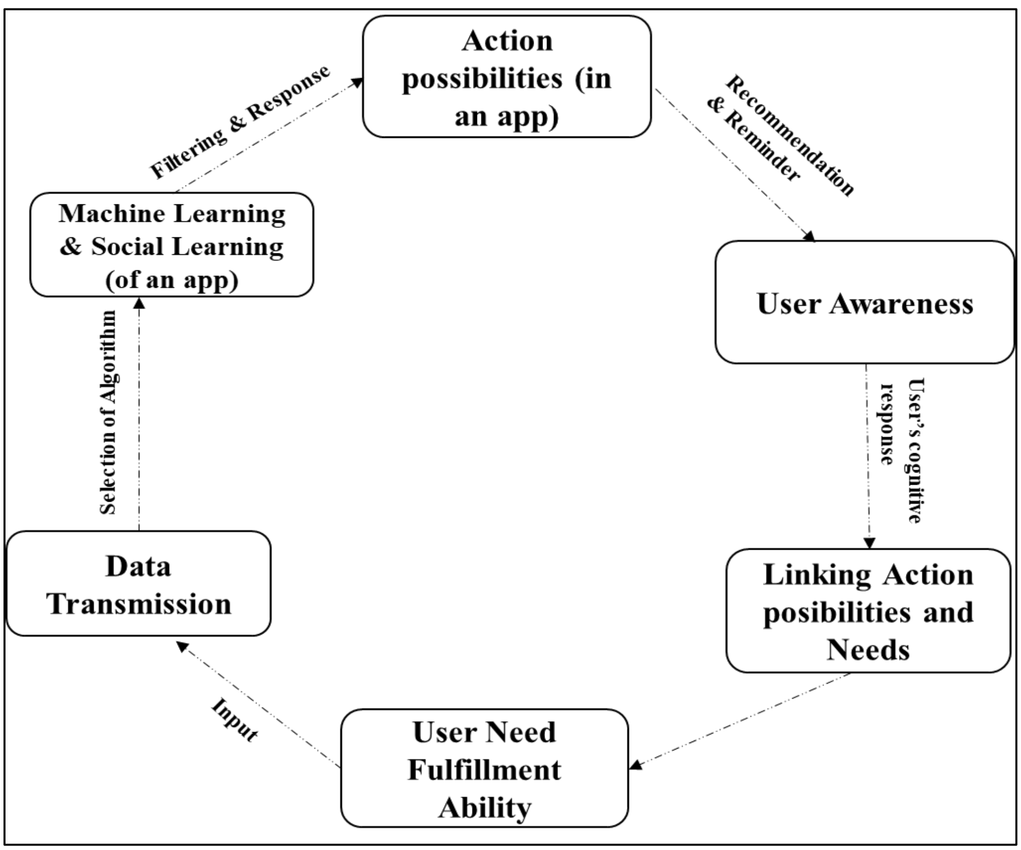


Figure 2.2: Dynamic interaction

Stimulus - Organism- Response (SOR) Theory

Stimulus Organism Response (SOR) perspective is a guiding framework for the research model. According to the SOR perspective, external stimuli trigger cognitive and emotional processing in the human mind, resulting in a specific response (Nagoya et al., 2021). In another sense, an individual's conscious and unconscious interpretations of an object or event can influence how the individual feels and acts in a particular way (J. Kim & Lennon, 2013). According to the SOR perspective, S (stimulus) is a set of signals which cause internal feelings in the organism (O), which then produce a behavioral response (R). In our research model, technological agency (the agentic abilities of a technology) functions as a signal, which stimulates an internal response in the form of the user’s perceived need fulfillment ability, perceived cognitive appeal, positive emotional appeal, and fear of missing out. Individuals then behave in a certain way in response to their internal evaluation. In our study context, the behavior is users’ use of technology longer than planned.

Hypothesis Development

Positive emotional appeal and the hooked state

Positive emotional appeal is a powerful influencer in eliciting particular behavior (Lee & Hong, 2016). Positive emotional appeal has been found to be a strong predictor of technology use (Cohen, 2014). Users with positive emotions exhibit a greater impulse to stay longer within the technology because they feel less restrained and want to reward themselves (Longstreet, Brooks, & Gonzalez, 2019). One reason for this less restrained feeling is that positive emotional arousal can shorten the time it takes to decide, reducing users' decision-making complexity (Septianto & Pratiwi, 2016). Therefore, I argue:

Hypothesis 1: Positive emotional appeal will be positively associated with the hooked state.

Fear of missing out and the hooked state

Fear of missing out is the user's apprehension that detachment from technology will remove access to need matching contents (Roberts & David, 2020). Fear of missing out is an internal evaluation that encourages users to forge content in the app (Hetz et al., 2015). Thus, fear of missing out can be regarded as a compensatory appeal reminding users that their needs are not satisfied (Fang, Wang, Wen, & Zhou, 2020). As fear can negatively affect users' internal state, users will try to avoid it by remaining longer within the technology. Therefore, I argue:

Hypothesis 2: Fear of missing out will be positively associated with the hooked state.

Perceived cognitive appeal and the hooked state

Perceived cognitive appeal is the possibility for the user to gain insights, challenge oneself, and compete with others by using the app. Since gaining insights, facing challenges, and competing all require frequent attempts and perseverance, users are expected to invest more time within the tech ecosystem to do so (Xu, Turel, & Yuan, 2012). Cognitive appeal can be said to operate in a positive feedback loop according to the *subjective extension of human boundary* theory as learning, challenge, and achievement all expand human boundaries by increasing the capability to succeed at a task and having gained something by the pursuit, users perpetuate their investment in task accomplishment within the app (McLuhan & McLuhan, 1994). Therefore, I argue:

Hypothesis 3: Perceived cognitive appeal will be positively associated with the hooked state.

Perceived agency of technology and positive emotional appeal

I define perceived agency of technology as technology's ability to act independently and guide users to perform specific actions. Given that technology delegates users' actions, I argue that users' roles become more of a monitor and engager than a doer (Baird & Maruping, 2021). Overall, the agency of technology provides users flexibility and independence to act (Baird &

Maruping, 2021). Past research on the affect-object paradigm reveals that when users perceive that technology is capable of analyzing, guiding, and delegating tasks based on their behavior, such technology triggers can elicit positive emotion as users derive flexibility and independence (de Guinea & Webster, 2013). In response to those capabilities, users may perceive that technology has the ability to read their mental state (Teubner, Adam, & Riordan, 2015). As a result, positive emotion may elicit. Therefore, I argue:

Hypothesis 4: Perceived agency of technology will be positively associated with positive emotional appeal.

Perceived agency of technology and fear of missing out

Technology can reinforce social comparison by providing people with diverse user-generated content (H.-M. Kim, 2022). Conversely, disengagement from social comparison can fuel fear among users as users may like to evaluate their positions in a network (Montag, Lachmann, Herrlich, & Zweig, 2019). Past research foregrounds the role of system cues that match user preferences within social networks (Moradi & Zihagh, 2022). When users do not have access to cues supported by technology, individuals may experience negative affect, such as fear, as they lack the incentives that are guided by technology (Hetz et al., 2015). Given technology's ability to guide users, detachment from technology can create separation anxiety for the user. Therefore, I argue:

Hypothesis 5: Perceived agency of technology will be positively associated with fear of missing out

Perceived agency of technology and cognitive appeal

Technology such as the “super app” constantly provides the opportunity to engage in social competition, social learning, and challenging tasks. Such action possibilities provide users experiencing the joy of winning, the frustration of losing, or new insights (Teubner et al., 2015). The opportunity of this human-to-human and human-to-app interaction can be very appealing to users as they seek to stimulate and reenact their capabilities (Frith & Frith, 2006). Thus, technological agency can stimulate cognitive appeal among users. Furthermore, technology's ability to act independently and guide users to perform certain tasks reduces the cognitive load involved in the search process, and this reduction of mental effect can allocate more energy to interacting with diverse technology action possibilities (Buchner, Buntins, & Kerres, 2022). Individuals may find different action possibilities cognitively appealing. Therefore, I argue:

Hypothesis 6: Perceived agency of technology will be positively associated with perceived cognitive appeal.

Perceived need fulfillment ability and positive emotional appeal

As I have mentioned before, perceived need-fulfillment ability indicates the user's ability to fulfill her needs using an app's features. Past research on need-fulfillment ability indicates a strong correlation between need-fulfillment ability and positive emotion (Partala & Kujala, 2016). One reason for such a strong correlation is that inducement of positive emotion is an automatic response if individuals place themselves in need-fulfillment situations (Hassenzahl, Wiklund-Engblom, Bengs, Hägglund, & Diefenbach, 2015). Self-determination theory stipulates that need-fulfillment ability increases the feeling of self-esteem, which has also been found to be correlated with the arousal of positive emotion. (Roth, Vansteenkiste, & Ryan, 2019) Therefore, I argue:

Hypothesis 7: A perceived need-matching ability will be positively associated with positive emotional appeal.

Perceived need fulfillment ability and fear of missing out

Perceived need-fulfillment ability measures an individual's ability to fulfill one's needs using an app's features. Given that an individual has the motivation to fulfill one's needs, a rational user will be extrinsically motivated to use technology that can fulfill them (Xu et al., 2012). In the process of need-fulfillment, individuals may often experience fear of missing out by mimicking their peers (Gartner, Fink, & Maresch, 2022). For example, when a user's peer uses technology more, the user may want to use the technology more to match with one's peers (James, Lowry, Wallace, & Warkentin, 2017). This is supported by the upward social comparison perspective, stating that a rational user conducts upward social comparison as others fulfill their own needs for such things as connection and information (H.-M. Kim, 2022). When an individual finds that one has the ability to fulfill one's needs, but she is not maximizing need-fulfillment like one's peers, it can generate strong negative feelings like the fear of missing out. Therefore, I argue

Hypothesis 8: Perceived need-fulfillment ability will be positively associated with the fear of missing out.

Perceived need-fulfillment ability and perceived cognitive appeal

As I have mentioned before, perceived cognitive appeal is an appeal to gain insights, challenge oneself, and compete with others. Some need-fulfillment abilities, such as the ability to control or the ability to predict one's social environment, can be cognitively appealing to users as they can provide users with the ability to use their decision-making ability and related cognitive skills. This conjecture is supported by subjective extension of human boundary theory (McLuhan & Mcluhan, 1994). Utility maximization research shows that rational users want to maximize their subjective utility (Baucells & Sarin, 2010). When users find that using features of the app can provide them the ability to fulfill their situational and innate needs, users may want to maximize the utility of using the features of the app. One way to do so is to engage in tasks that provide intrinsic rewards, such as learning, winning a competition, and self-challenge. Thus, we argue that the ability to maximize utility will generate cognitive appeal as users find the opportunity to learn, complete, or achieve something in a dynamic technological environment. Thus, I argue

Hypothesis 9: Perceived need fulfillment ability is positively associated with perceived cognitive appeal.

Research Methodology

The study's target population is not confined to any one profession, so I use an online crowdsourcing platform—Amazon's Mechanical Turk (Steelman et al., 2014). Prior to the main survey, I conducted a pilot and a pretest to evaluate the questionnaire instructions and items. I invited two Ph.D. students to evaluate my survey items in the pretest. They reviewed each item and suggested a few wording modifications. Accordingly, I adjusted several items in response to feedback. After the refinement, I conducted a pilot study by developing a survey in Qualtrics and sharing the survey link with Amazon Mechanical Turk participants. In the pilot testing, I offered 55¢ to each participant if they completed the entire survey. The average survey completion time was between 13 and 15 minutes. The initial sample size was 180. After the analysis of the attention check, 19 samples are excluded. Thus, our final sample size was 161. Among 161 participants, 100 were females, and 61 were males. On average, participants used mobile applications, the target platform of the survey, for more than three years. Among 161 participants, 142 were White Americans, and 109 participants had at least 4-year bachelor's degrees. After data collection, I ran preliminary analyses for robustness such as reliability, the validity of the measurement model, and the structural relationships among constructs proposed in the research model. I used covariance-based structural equation modeling (SEM) to analyze the results. According to the preliminary analysis, all constructs met the conventional Cronbach alpha, average variance extracted (AVE), and discriminant validity criteria. The preliminary analysis supported the hypotheses. In testing the predictive validity of the hooked state in the pilot study, results show that the hooked state is positively and significantly associated with habit and perceived work-life balance. (The results of the pilot study are provided in the appendix.) After the pilot study, I further refined some problematic items and prepared them for the main study.

Running the main study in Qualtrics, I distributed the link to Amazon Mechanical Turk participants. For the main study, I provided 75-cent incentives for participating and completing the study. The average survey completion time was 10-12 minutes. The total sample size was 468. After analyzing the attention check and time stamp, I retained 347 responses. All the participants are from the U.S. Before participating in the survey, all participants were required to give their consent. After completing the consent form, participants were prompted to identify the app with which they interact most frequently. All the data of the study were collected online and anonymously. Among the 347 participants, 217 identified themselves as of the male gender, with 130 identifying as the female gender. Among 347 participants, 318 participants were white, 10 were African American, and 16 were Native or Pacific Islander. Participant age ranged from 18 to 67. Finally, each participant has an average of 3.3 years of experience using a mobile app.

Operationalization of Variables

The study relies on well-known and reliable measurement instruments from the broader literature to measure the constructs in our model. Whenever I adopt a measure from existing literature, I carefully consider the scale's content validity through pretest. In my study, "perceived agency of technology" is a newly developed construct adopted from essay 3[3].

I follow existing literature to measure perceived need-fulfillment ability (Karahanna, Xu, Xu, & Zhang, 2018). Karahanna et al. (2018) propose 21 items to measure psychological need-fulfillment, a scale that has been validated in numerous studies. For example, in the social media context, Chen (2019) uses it to measure need-satisfaction ability.

To measure perceived emotional appeal, I also follow existing literature (Suh, Kim, & Suh, 2011). Originally developed by Thomson et al. (2005), Suh et al. (2011) use this measure in the IS context. I use all ten items of this contextualized measure.

To measure perceived cognitive appeal, I also follow existing literature (Högberg, Hamari, & Wästlund, 2019). Högberg et al. (2019) propose a measure of cognitive benefits in the gaming app context. I adopt their measure in our app context. Like other measurement scales, I evaluate their content validity before the pilot and full study.

I use well-established measures to measure the fear of missing out (Przybylski, Murayama, DeHaan, & Gladwell, 2013). Przybylski et al. (2013)'s measure has been adopted and validated in numerous studies. As my study context is the app, I refined some items in our study context. After refining the measure, I ran the pretest for content validity.

To measure the hooked state, I also rely on existing literature, which measured the phenomenon of spending a longer time than one plan (Zheng & Lee, 2016). In past studies, Zheng, and Lee's (2016) scale has been found reliable in measuring this phenomenon. I adopt their measure after carefully checking its content validity.

[3] To develop perceived agency of technology construct, essay 3 followed MacKenzie et al. (2011) procedures. We followed 10 steps, which cover conceptualization, development of measures, model specification, scale refinement, validation, and norm development, to develop the scale of perceived agency of technology. Further, this study validated the measure through a pretest and pilot study.

Finally, to measure addictive tendency, I adopt items from an existing study (Deleuze et al., 2015). Deleuze et al. (2015) discuss different facets of addictive tendencies in their study. I adopt this measure by checking its content validity through a pilot study.

Note that I have controlled for addictive tendency, age, and experience in the model. I control addictive tendencies since individuals' repeated use of technology can be influenced by their addictive traits. I statistically control for social desirability bias using the Marlowe–Crowne social desirability scale (Reynolds, 1982). The Appendix includes all scales.

Data Analysis

I used the covariance-based SEM (CB-SEM) tool within STATA (Wang & Lee, 2020). Given the ability of CB-SEM to validate a theory and to calculate the overall fit of a proposed model, CB-SEM is appropriate in this study context (Wang & Lee, 2020). Following existing literature, I model all constructs using reflective indicators. I test assumptions before analyzing the data due to SEM's sensitivity to assumptions such as normality, multicollinearity, heteroskedasticity, and linearity. I test these assumptions by checking plots and using established procedures, for example, residual plots and two-way scatterplots to test normality and linearity. The plots indicate that residuals are normally distributed. In addition, the two-way scatter plot suggests that variables in the model have linear relationships with each other. I use the Breusch-Pagan test to check the heteroskedasticity assumption. A significant p-value in the Breusch-Pagan test indicates that the heteroskedasticity assumption has been met. Results appear in the appendix.

I also check the correlation among variables before conducting the analysis. A significant correlation among variables may indicate a multicollinearity issue in data. However, I did not find a significant correlation among variables. The correlation between perceived agency of technology and need-fulfillment ability is 0.51, which is expected as human agency and technology agency are dynamically related. Table 1 displays the correlation matrix. According to the correlation matrix, the fear of missing out and addictive tendency has the highest correlation of 0.54. This correlation is expected as past research indicates that fear of missing out is strongly associated with an individual's personality traits (Alt & Boniel-Nissim, 2018).

Table 2.1: Correlation matrix

	PAT	NFA	EA	FOMO	COG	HO	AD	AGE	EX	SD
PAT	1									
NFA	0.51	1								
EA	0.52	0.51	1							
FOMO	0.12	0.27	0.49	1						
COG	0.43	0.52	0.52	0.43	1					
HO	0.37	0.45	0.53	0.53	0.49	1				
AD	0.33	0.34	0.54	0.54	0.51	0.53	1			
AGE	0.02	0.01	-0.02	-0.03	0.05	-0.002	-0.03	1		
EX	0.10	0.10	0.01	-0.13	-0.13	-0.005	-0.01	0.25	1	
SD	0.23	0.21	0.32	0.31	0.31	0.33	0.33	-0.14	-0.07	1

Common method bias

I have used various approaches to test the common method bias in my study. First, I use the common method factor within the analysis using Harman's single factor method (Aguirre-Urreta & Hu, 2019). The result of Harman's single factor method does not yield a single dominant factor. The largest variance is explained by a single factor comprising only 30.62% of the total variance, which is below the threshold level of 0.50. Second, I use a marker variable to check the common method bias (Simmering, Fuller, Richardson, Ocal, & Atinc, 2015). The correlation between the marker variable and the perceived agency of technology, need-fulfillment ability, emotional appeal, fear of missing out, cognitive appeal, and hooked state are -0.06, -0.01, -0.08, -0.04, -0.08, -0.05 respectively, indicating that there is no significant correlation between the marker variable and other variables in the model. It reinforces my conclusion that the study does not suffer from common method biases. Further, I have checked the covariance between marker variable and other constructs in the dataset. I found that the covariance between marker variable and perceived agency of technology, need-fulfillment ability, emotional appeal, fear of missing out, cognitive appeal, and hooked state are 0.05, -0.05, -0.05, -0.056, and -0.06, which indicates that the study does not suffer from common method biases.

Third, to reduce common method bias, existing literature recommends keeping respondents anonymous and avoiding ambiguous items (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). I keep the respondents anonymous in the survey. I also avoid ambiguous and vague items flagged previously in the pretest and pilot study. Finally, I apply a procedure specified by Pavlou et al. (2007), who recommend checking the correlation matrix to avoid common method bias. Inter-construct correlations of over 0.9 can raise the issue of common method bias (Pavlou, Liang, & Xue, 2007); however, as the correlation matrix indicates that correlation among variables is below 0.9, we can conclude that the study does not suffer from a common method bias issue.

Social desirability bias

I follow the Marlowe-Crowne Social Desirability scale to control social desirability bias, using a series of scored “Yes” or “No” questions (Reynolds, 1982). I generate a score for each item and sum it up for the final estimation (Soror et al., 2015). The results of the social desirability bias test are provided in table 2. Afterward, I checked the correlation of the social desirability scale with other factors, finding that the social desirability scale is not significantly correlated with any items in the research model.

Table 2.2: Results of social desirability bias test

Test name	Items	yes
Social desirability bias test	1) It is sometimes hard for me to go on with my work if I am not encouraged	157 (45%)
	2) I sometimes feel resentful when I don't get my way	153 (44%)
	3) On a few occasions, I have given up doing something because I thought too little of my ability	138 (39%)
	4) There have been times when I felt like rebelling against people in authority even though I knew they were right	137 (39%)
	5) No matter who I'm talking to, I'm always a good listener	124 (35%)
	6) There have been occasions when I took advantage of someone	136 (39%)
	7) I'm always willing to admit it when I make a mistake	125 (36%)
	8) I sometimes try to get even rather than forgiving and forget	129 (37%)
	9) I am always courteous, even to people who are disagreeable.	156 (44%)
	10) I have never resent being asked to return a favor	131 (37%)
	11) There have been times when I was quite jealous of the good fortune of others	140 (40%)
	12) I am sometimes irritated by people who ask favors of me	139 (40%)
	13) I have never deliberately said something that hurt someone's feelings	125 (36%)

Measurement Model

Prior to evaluating the measurement model, I conducted exploratory factor analysis with varimax rotation to check how items are loaded in each factor, eliminating some items that have lower loadings (< 0.5) and higher cross-loadings (> 0.4). Table 2.3 reports the EFA loadings.

Table 2.3: Loadings and cross-loadings of constructs

	Hooked	**FOMO**	**Cognitive**	**Emotion**	**PAT**	**NFA**	**Addition**
Hooked1	**0.60**	0.23	0.14	0.43	0.34	0.33	0.38
Hooked2	**0.65**	0.36	0.17	0.32	0.21	0.25	0.36
Hooked3	**0.71**	0.26	0.28	0.13	0.15	0.20	0.31
Hooked4	**0.70**	0.33	0.22	0.09	0.10	0.18	0.26
Hooked5	**0.66**	0.31	0.18	0.03	0.06	0.13	0.30
Hooked6	**0.60**	0.31	-0.09	0.08	0.08	0.08	0.15
Emotion1	0.20	0.30	0.37	**0.62**	0.39	0.33	-0.05
Emotion2	0.16	0.31	0.33	**0.61**	0.33	0.32	0.16
Emotion3	0.16	0.16	0.23	**0.53**	0.35	0.17	0.30
Emotion4	0.26	0.13	0.05	**0.53**	0.33	0.31	0.32
Cognitive1	0.27	0.20	**0.61**	0.15	0.08	0.13	0.11
Cognitive2	0.19	0.21	**0.60**	0.21	0.18	0.09	0.04
Cognitive3	0.16	0.18	**0.59**	0.14	0.32	0.23	0.11
FOMO1	0.22	**0.77**	0.05	0.33	0.15	0.15	0.12
FOMO2	0.23	**0.78**	0.23	0.12	0.24	0.06	0.24
FOMO3	0.22	**0.77**	0.17	0.10	0.35	0.08	0.23
FOMO4	0.21	**0.73**	0.16	0.08	0.14	0.12	0.36
FOMO5	0.21	**0.78**	0.06	0.09	0.21	0.10	0.25
PAT1	0.06	0.11	0.12	0.18	**0.85**	0.12	0.13
PAT2	0.19	0.22	0.23	0.24	**0.79**	0.18	0.17
PAT3	0.20	0.31	0.09	0.20	**0.60**	0.38	0.04
PAT4	0.10	0.23	0.12	0.11	**0.75**	0.26	0.13
PAT5	0.14	0.17	0.13	0.36	**0.70**	0.29	0.05
NFA1	0.16	0.15	0.37	0.39	0.25	**0.76**	0.24
NFA2	0.15	0.06	0.39	0.36	0.16	**0.78**	0.21

Table 2.3 (Cont.)

	Hooked	**FOMO**	**Cognitive**	**Emotion**	**PAT**	**NFA**	**Addition**
NFA3	0.21	0.08	0.17	0.34	0.25	**0.63**	0.23
NFA4	0.23	0.10	0.29	0.17	0.20	**0.72**	0.39
Addiction1	0.31	0.13	0.17	0.14	0.24	0.17	**0.67**
Addiction2	0.33	0.25	0.06	0.12	0.17	0.15	**0.71**
Addition3	0.33	0.33	0.04	-0.01	0.02	0.13	**0.73**

After conducting EFA, I check the reliability and validity of each variable in our model. Table 5 reports the reliability and validity of the measurement model. In the beginning, I examined the reliability of the constructs using Cronbach's alpha (CA) to test the construct reliability. I observe that the reliability of all constructs is above 0.76, for example, perceived agency of technology has an alpha of 0.83, need fulfillment ability has an alpha of 0.78, positive emotional appeal has an alpha of 0.82, fear of missing out has an alpha of 0.93, cognitive appeal has an alpha of 0.76, and the hooked state has an alpha of 0.89.

Next, I test the convergent validity of constructs by checking a) the factor loadings and b) the average variance explained (AVE). I find support for convergent validity as all items loaded significantly with the respective construct, and the loadings each exceed 0.60. Additionally, the AVE is above 0.50 for each construct, indicating evidence of convergent validity. I test discriminant validity by checking the cross-loading of the constructs, observing that items load highly on the focal construct with minimum cross-loadings with other constructs, supporting the discriminant validity of the constructs. In addition, I evaluated the confirmatory fit index of each construct. All the fit indexes are above the threshold level, with CFI above 0.91, TLI above 0.90, SRMR below 0.08, and RMSEA below 0.08. I also test the loadings and cross-loadings of constructs and find that each item loads where it should load. The results of reliability and validity are provided in table 4.

Table 2.4: Reliability and validity of constructs

Item	Item Mean	Item Std. Dev	Item-intercorrelation	Item-alpha	CFA Loadings	Cronbach Alpha	AVE
PAT1	5.33	1.23	0.82	0.78	0.83	0.83	0.52
PAT2	5.49	1.15	0.80	0.79	0.71		
PAT3	5.58	1.17	0.70	0.83	0.60		
PAT4	5.38	1.27	0.80	0.79	0.79		
PAT5	5.55	1.20	0.77	0.81	0.67		
NFA1	5.58	1.10	0.80	0.70	0.76	0.78	0.51
NFA2	5.80	1.04	0.77	0.70	0.77		
NFA3	5.58	1.24	0.71	0.74	0.69		
NFA4	5.91	1.06	0.76	0.71	0.68		
EMO1	5.25	1.30	0.83	0.74	0.84	0.82	0.51
EMO2	5.47	1.44	0.80	0.77	0.76		
EMO3	5.62	1.12	0.80	0.77	0.66		
EMO4	5.60	1.24	0.76	0.80	0.61		
FOMO1	4.72	1.64	0.80	0.91	0.84	0.93	0.70
FOMO2	4.82	1.78	0.86	0.92	0.87		
FOMO3	5.02	1.75	0.88	0.92	0.84		
FOMO4	4.95	1.67	0.86	0.92	0.81		
FOMO5	5.06	1.73	0.85	0.93	0.81		
COG1	5.56	1.21	0.83	0.65	0.83	0.76	0.51
COG2	5.56	1.16	0.80	0.64	0.69		
COG3	5.60	1.16	0.77	0.71	0.63		
HOOK1	5.05	1.35	0.78	0.87	0.74	0.89	0.59
HOOK2	5.08	1.44	0.81	0.87	0.78		
HOOK3	5.36	1.36	0.83	0.87	0.81		
HOOK4	5.32	1.34	0.84	0.86	0.81		
HOOK5	5.18	1.39	0.79	0.87	0.75		
HOOK6	5.21	1.49	0.75	0.88	0.68		
AD1	4.86	1.57	0.86	0.81	0.76	0.85	0.65
AD2	5.03	1.56	0.88	0.76	0.83		
AD3	5.18	1.62	0.87	0.77	0.82		

Structural Model

After evaluating the measurement model, I test the paths of the model using the maximum likelihood estimation approach. Figure 2.3 demonstrates the results of the structural model:

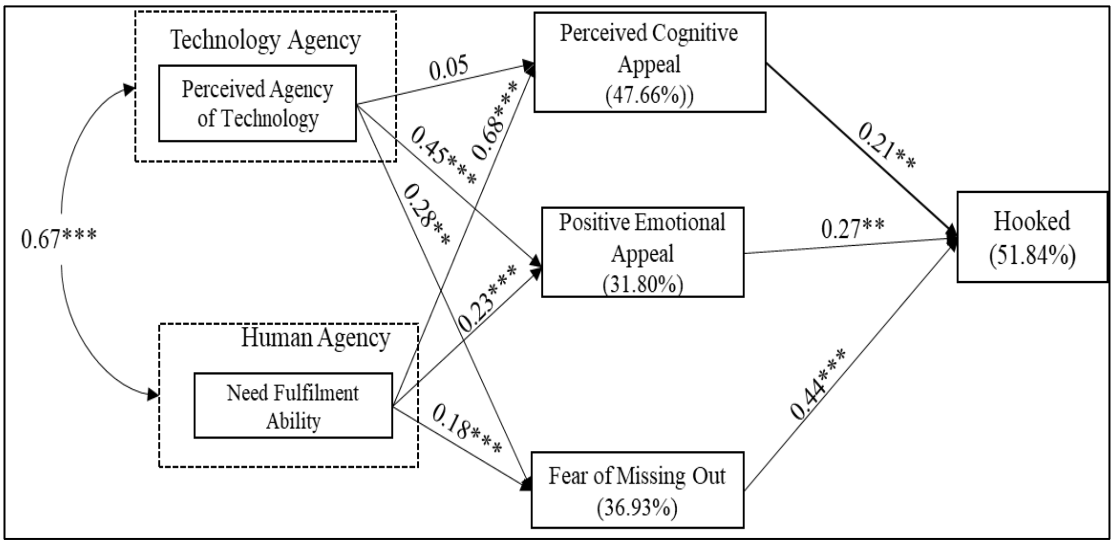


Figure 2.3: Structural model analysis

The structural model meets the threshold of goodness of fit index, which is CFI =0.95; SRMR = 0.05; TLI= 0.91 and RMSEA =0.07. The model controls addictive tendency, age, experience, and social desirability. Table 4 reports the co-efficient of control variables.

Table 2.5: Co-efficient of control variables

Controls	Hooked	Perceived cognitive appeal	Positive emotional appeal	Fear of missing out
Social Desirability	0.07	0.074	0.037	0.03
Addictive tendency	0.70*	0.53*	0.7*	0.8*
Age	0.01	0.08	-0.008	0.04
Experience	0.045	0.03	0.04	-0.12*

The structural model in Figure 2.3 indicates that positive emotional appeal explains 31.80%, perceived cognitive appeal explains 47.66 %, fear of missing out explains 36.93%, and hooked state explains 51.84%. I find that addictive tendency is significantly associated with the hooked state, perceived cognitive appeal, perceived emotional appeal, and fear of missing out. However, age, experience, and social desirability are not significantly associated with any variable in the model.

The summary of hypothesis testing is provided in Table 2.6. Table 5 reports beta coefficient, t-statistics, and significance testing. According to Table 2.6, a total of eight hypotheses are supported by the data. Let me evaluate each hypothesis against the results.

Table 2.6: Results of hypothesis testing

Tested Hypothesis/ Path	B	t-statistic	Support
H1. Positive Emotional Appeal-→ Hooked	0.27	2.09***	Yes
H2. Perceived Cognitive Appeal→ Hooked	0.21	2.14***	Yes
H3. Fear of Missing Out→ Hooked	0.44	4.02***	Yes
H4. Perceived Agency of Technology-→ Positive Emotional Appeal	0.05	6.91***	Yes
H5. Perceived Agency of Technology→ Fear of Missing Out	0.28	4.46***	Yes
H6. Perceived Technology Agency→ Perceived Cognitive Appeal	0.05	0.59	No
H7. Perceived Need Fulfillment Ability→Positive Emotional Appeal	0.23	3.31***	Yes
H8. Perceived Need Fulfillment Ability→Perceived Cognitive Appeal	0.68	7.54***	Yes
H9. Perceived Need Fulfillment Ability→ Fear of Missing Out	0.18	2.85***	Yes

Hypothesis 1: Positive emotional appeal will be positively associated with the hooked state. Positive emotional appeal is positively and significantly associated with being hooked (β = .27, $p < .001$), suggesting that positive emotional appeal is an important factor influencing the hooked state. The finding is consistent with my hypothesis and the interviewee descriptions from chapter one.

Hypothesis 2: Fear of missing out will be positively associated with the hooked state. Fear of missing out is positively and significantly associated with being hooked ($\beta = 0.44$, $p < .001$), suggesting that fear of missing out is a critical factor for the hooked state. The finding is consistent with past research on social media, which indicates that fear of missing out can influence users to use social media (Hetz et al., 2015).

Hypothesis 3: Perceived cognitive appeal will be positively associated with the hooked state. Perceived cognitive appeal also appears positively and significantly associated with the hooked state ($\beta = 0.21$, $p = .06$), suggesting that perceived cognitive appeal is a critical factor for the hooked state. These findings are consistent with interviewee descriptions from essay 1.

Hypothesis 4: Perceived agency of technology will be positively associated with positive emotional appeal. Perceived agency of technology is positively and significantly associated with positive emotional appeal ($\beta = 0.45$, $p = .001$), indicating that technology agency plays a significant role in arousing positive emotion. It further illustrates that technology-mediated activities induce people to be hooked on technology by activating positive emotions.

Hypothesis 5: Perceived agency of technology will be positively associated with fear of missing out. The results further indicate that perceived agency of technology is positively and significantly associated with fear of missing out ($\beta = 0.23$, $p = .001$), suggesting that perceived agency of technology is a basic prerequisite for FOMO.

Hypothesis 6: Perceived agency of technology will be positively associated with perceived cognitive appeal. Interestingly, the results indicate that perceived technology agency is **not** significantly associated with perceived cognitive appeal ($\beta = .05$, $p > .1$). Thus, I did not find support for hypothesis 6.

Hypothesis 7: Perceived need fulfillment ability will be positively associated with positive emotional appeal. The results suggest that need fulfillment ability is positively and significantly associated with positive emotional appeal ($\beta = 0.23$, $p = .001$), indicating that human agency plays a significant role in arousing positive emotion.

Hypothesis 8: Perceived need fulfillment ability will be positively associated with fear of missing out. I observe that need fulfillment ability is positively and significantly associated with fear of missing out ($\beta = 0.18$, $p = .001$).

Hypothesis 9: Perceived need fulfillment ability is positively associated with perceived cognitive appeal. Finally, I find that need fulfillment ability is positively and significantly associated with perceived cognitive appeal ($\beta = 0.68$, $p = .001$).

In sum, each hypothesis except number six (agency of technology correlates with positive cognitive appeal) is solidly and statistically supported.

Robustness Check

What follows is the robustness check I conducted for the model. I introduce the direct effect between a) the perceived agency of technology and the hooked state and b) need fulfillment ability and the hooked state. Figure 2.4 provides the structural model of the robustness check. Similar to the baseline model, the structural model controls for addictive tendency, age, experience, and social desirability. The coefficient of control variables is provided in table 6.

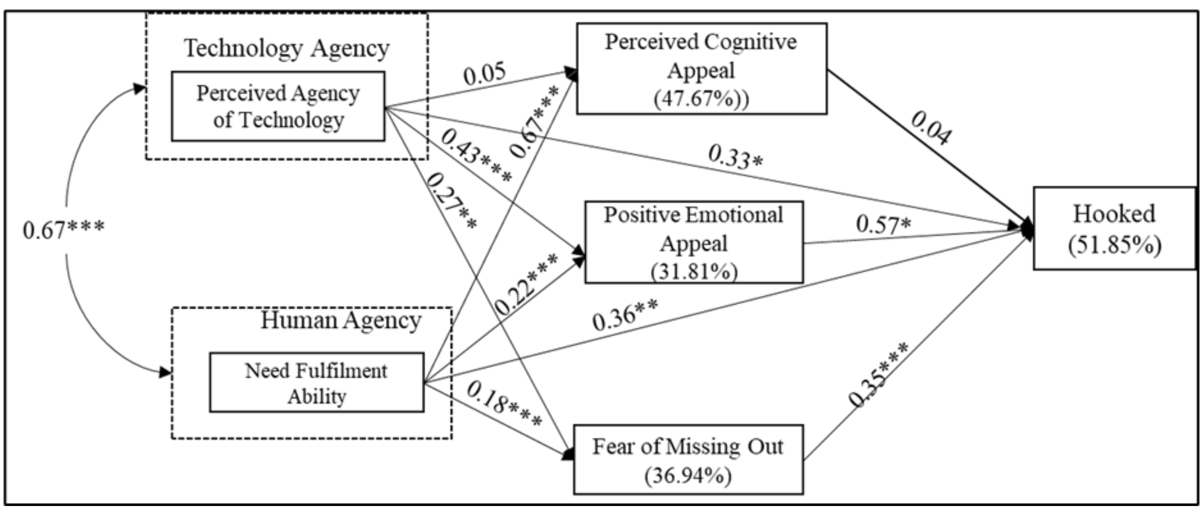


Figure 2.4: Robustness check

Table 2.7: Co-efficient of control variables

Controls	Hooked	Perceived cognitive appeal	Positive emotional appeal	Fear of missing out
Social Desirability	0.11	0.074	0.036	0.07
Addictive tendency	0.71*	0.53*	0.72*	0.81*
Age	0.01	0.084	-0.075	0.04
Experience	0.045	0.036	0.04	-0.12*

The results of hypothesis testing are provided in table 9, according to which perceived technology agency is significantly and positively associated with a hooked state ($\beta = 0.33$, $p = .05$), indicating the partial mediation of perceived agency of technology on the hooked state. The results further indicate that need fulfillment ability is significantly and positively associated with a hooked state ($\beta = 0.36$, $p = .001$), indicating the partial mediation of need fulfillment ability in the hooked state. I observe that all other results still hold the same, except that I do not find support for the direct relationship between perceived cognitive appeal and the hooked state ($\beta = 0.14, p = 0.1$). In addition, I find that some of the goodness of fit indexes improve slightly: CFI = .956, SRMR = .05, TLI = .938, and RMSEA = 0.07. Table 7 describes the results of the robustness check.

Table 2.8: Robustness check

Tested Hypothesis/ Path	B	t-statistic	Support
H1. Positive Emotional Appeal-→ Hooked	0.57	2.66*	Yes
H2. Perceived Cognitive Appeal→ Hooked	0.14	0.73	No
H3. Fear of Missing Out→ Hooked	0.35	2.87*	Yes
H4. Perceived Agency of Technology-→ Positive Emotional Appeal	0.43	6.59***	Yes
H5. Perceived Agency of Technology→ Fear of Missing Out	0.28	4.56***	Yes
H6. Perceived Technology Agency→ Perceived Cognitive Appeal	0.05	0.59	No
H7. Perceived Need Fulfillment Ability→Positive Emotional Appeal	0.23	3.23***	Yes
H8. Perceived Need Fulfillment Ability→Perceived Cognitive Appeal	0.68	7.35***	Yes
H9. Perceived Need Fulfillment Ability→ Fear of Missing Out	0.18	2.84***	Yes

Discussion

Why individuals stay longer time in technology is an emerging topic in the IS field. Early literature on excessive use suggests that maladaptive cognition and personality traits are the primary drivers of excessive dwell time (Cao et al., 2018). Some practitioners contend that the increased agency of technology primarily influences the user's excessive dwell time (Eyal, 2014). This research bridges the gap between early literature on excessive use and the practitioner's perspective by examining the dynamic relationship between technological agency and human agency. In contrast to past IS research that views technology as a passive tool, this study views technology as an agentic artifact that can influence individuals' internal state of emotions and cognition, leading to the hooked state. The preliminary results from two surveys support the hypotheses. Specifically, the results support the positive relationship between technological agency and stickiness aspects such as positive emotional appeal and the fear of missing out (FOMO). Overall, the results validate the theory that the agency of technology plays a vital role in influencing an individual’s bond with technology, leading ultimately to the user’s hooked state. The results also point out that human agency, in the form of need fulfillment ability, plays an important role in the development of stickiness—a role consistent with past studies (Karahanna et al., 2018).

In sum, the study answers the question, "Why do people spend more time using apps?" by offering compelling evidence that the dynamic interplay between technological agency and human agency is primarily responsible for making people stay longer in technology.

Contributions

The study makes several contributions to the existing body of knowledge. To begin with, it contributes to the literature on the excessive use of technology. Previous studies on excessive use of technology assert that an individual’s maladaptive traits, needs, and socio-psychological factors can lead to excessive use. However, the role of technology agency has received limited attention. Given the pervasiveness of technology agency, ignoring the role of technology provides an incomplete picture in explaining excessive use. Illustrating the role of technology agency in inducing excessive use represents an important contribution that the literature lacks.

Second, my study investigates the role of positive emotional appeal in the hooked state, thereby shedding light on the role of positive emotional appeal in excessive use of technology. Past IS literature on emotion limits the investigation to the role of positive emotion in “intention to use” a technology (Suh et al., 2011). Nevertheless, this study is one of the first to explore whether positive emotional appeal plays any role beyond the intention to use technology. I posit that positive emotional appeal is a fundamental process for creating bonds between users and technology and that technological agency constantly reinforces positive emotional appeal, resulting in a hooked state. Consequently, our study offers a more nuanced view of positive emotional appeal in user-technology interaction.

Third, my study aimed to investigate the effects of cognitive appeal on the hooked state. Although the role of cognitive appeal has been studied in the persuasive advertising research context (Septianto & Pratiwi, 2016), the role of cognitive appeal in inciting excessive IS use has received less attention in the field of Information Systems. Given the pervasiveness of gamification elements in super apps, however, we need a deeper and richer examination of the role of cognitive appeal. In the present study, I investigate whether cognitive appeal influences the hooked state. The study opens a new route for future research into the role of cognitive appeal in technology contexts.

Fourth, I contribute to the current body of literature on the fear of missing out. FOMO is an emerging topic grounded in psychology and social media literature (Fang et al., 2020). Primarily, past research investigated FOMO as a predictor of social media use (Hetz et al., 2015). I investigate the role of FOMO in a hooked context and argue that FOMO could initiate foraging behavior, which contributes to excessive dwell time within technology. Consequently, this study advances the predictive validity of the construct for fear of missing out.

Fifth, the study contributes to the current IT artifacts conceptualization literature. Past research on IT artifacts calls for a conceptualization beyond the nominal view of IT (Orlikowski & Iacono, 2001). This study conceptualizes IT artifacts as users' perceptions. Thus, this study extends recent efforts to advance the conceptualization of IT artifacts from the user's perspective (Ayyagari, Grover, & Purvis, 2011).

Sixth, the study contributes to the emerging literature on technology agency. Our conceptualization of how technology agency can influence stickiness is consistent with literature from the practice and IS fields (Baird & Maruping, 2021; Eyal, 2014). The findings of my study demonstrate that the user perception of technological agency significantly impacts users' internal conditions. This suggests that, in order to gain a deeper understanding of human-computer interactions, researchers must look beyond concepts such as perceived usefulness and perceived ease of use.

Seventh, the study adds to the current literature on human agency. Existing literature on human agency indicates that human need-fulfillment ability can motivate users to use technology (Karahanna et al., 2018). I extend this literature by introducing the concept of stickiness, proposing that need-fulfillment ability promotes dwell time through the mediation of positive emotional appeal, perceived cognitive appeal, and FOMO. Thus, I extend the human agency literature by adding a new mechanism through which human agency influences excessive usage.

Finally, I contribute to human-computer interaction literature by validating the measurement instruments of *hooked state* and *perceived agency of technology*. I carefully conducted the surveys to reduce the threat of social desirability and common method bias in order to reduce measurement errors. Operationalization of those variables could be useful for future research studying the excessive use of technology.

Practical Implications

The study provides practical contributions as well. First, consistent with the emerging body of IS literature, the results of this study demonstrate that excessive use of technology should not be neglected as a negative phenomenon (Cao et al., 2018; Gerlach & Cenfetelli, 2020). The emergence of super apps has made the study excessive use current and vital. However, the lack of adequate conceptualization of excessive usage constrains us from understanding the etiology and ontology of excessive use behavior. According to the study, the hooked state represents excessive use of technology, involving the dual roles of human and technological agency. The excessive use of technology is not always a negative behavior, and those who excessively use technology should arguably not be considered addicts. Rather, they are hooked on technology, an important though subtle distinction which shifts responsibility away from the user towards the middle ground.

Second, the study reveals the role that human and technological agencies play in inducing excessive use. These discoveries have important practical implications. Humans still possess primary agency over in-app dwell time. Even if excessive dwell time creates negative spillover effects, users may still exercise their agency to control excessive use. For example, users can disable notifications, nudges, and other features which may otherwise lure them back to their phones. Users can customize app features to blunt the influence of technology agency on their leisure time.

Third, the study has practical implications for app development. The study indicates that intelligent algorithmic and recommendation systems can manipulate human behavior by persuading them to dwell longer within the software ecosystem. One may consider it an ethical dilemma for app developers. Consequently, app developers may engage in reverse engineering algorithms to prevent negative user externalities (Rahwan et al., 2019). Given the capabilities of intelligent algorithmic and recommendation systems, developers should always consider the legal and ethical implications of data manipulation and privacy violation (Rahwan et al., 2019).

Limitations

Although the study provides a number of contributions to the existing body of knowledge, it has several limitations. First, our conceptualization of the hooked state is still at the early stage; therefore, the definition and measurements require further inquiry. Nevertheless, the empirical findings are promising because they display a statistically robust, valid definition and measurements of the hooked state and its associated variables.

Second, I used self-reported app usage data to measure all the constructs. Despite the fact that our research model accounts for the common method and social desirability biases, we believe that participants may have under- or overestimated their app usage experience.

Third, I relied on cross-sectional data. Given the fact that the study investigates some new constructs in the research model, cross-sectional data are acceptable to examine the validity of those constructs. Future research may ground the internal and external validity of the study more deeply in experimental or longitudinal approaches.

Although the stimulus-organism-response theory is my overarching framework, I did not use all of the variables that the SOR theory employs. This is because the study concerns the validity of a specific emerging theory about excessive use of technology, not about validating SOR theory. SOR theory proposes that cognitive dissonance, sadness, and other internally motivating cognitive states could influence responses such as technology use. Due to limitations on scope, these were untested.

Future Research Directions

The study reveals some new avenues for future research. First, future research can extend the hooked concept to other digital technology contexts beyond apps. What factors contribute to a hooked state in the context of wearable technology? Or on IoT? In addition, future research can study contextualized variables (e.g., features of IoT) to investigate the causes of a hooked state.

Second, future studies can investigate more nuanced aspects of human agency. For instance, constructs from the theory of planned behavior, such as subjective norms, attitude, and perceived behavior control, could be utilized to parse human agency quantitatively. Due to the limitations imposed by the qualitative research in chapter 1, I did not explore various aspects of human agency described in the existing literature. Future studies can expand our model by integrating more nuanced aspects of human agency.

Third, another interesting avenue for future research could be investigating different kinds of stickiness variables. Loss aversion, psychological ownership, and self-discovery are all examples of potential factors that may encourage individuals to spend more time with technology. Future research can incorporate those factors in order to gain a more comprehensive understanding of mechanisms that lead to the hooked state.

Conclusion

This essay represents an initial step in understanding the factors and mechanisms that lead to the development of the hooked state. To develop the model of the hooked state, I integrate existing literature on the agency (human and technology), stickiness, and literature on excessive use. Prior research has examined a number of characteristics of excessive use, but the layered role of technology and human agency together has not received sufficient consideration. I filled this gap by demonstrating that the dynamic interaction between technology and human agency can generate stickiness, which contributes to the emergence of a hooked state. Based on empirical results, there is now a theory to describe the pandemic phenomenon of younger populations spending exceedingly greater time on super apps than intended. I anticipate that this research will advance even more comprehensive theories and mechanisms of the hooked state, helping us understand the emerging human/online world crafted by our increasingly autonomous digital ecosystems.

References of Essay 2

Aguirre-Urreta, M. I., & Hu, J. (2019). Detecting common method bias: Performance of the Harman's single-factor test. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 50*(2), 45-70.

Alt, D. (2015). College students' academic motivation, media engagement and fear of missing out. *Computers in Human Behavior, 49*, 111-119.

Alt, D., & Boniel-Nissim, M. (2018). Using multidimensional scaling and PLS-SEM to assess the relationships between personality traits, problematic internet use, and fear of missing out. *Behaviour & Information Technology, 37*(12), 1264-1276.

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly*, 831-858.

Baird, A., & Maruping, L. M. (2021). The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS quarterly, 45*(1).

Baucells, M., & Sarin, R. K. (2010). Predicting Utility Under Satiation and Habit Formation. *Management Science, 56*(2), 286-301.

Bonnardel, N., Piolat, A., & Le Bigot, L. (2011). The impact of colour on Website appeal and users' cognitive processes. *Displays, 32*(2), 69-80.

Buchner, J., Buntins, K., & Kerres, M. (2022). The impact of augmented reality on cognitive load and performance: A systematic review. *Journal of Computer Assisted Learning, 38*(1), 285-303.

Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. *Computers in human behavior, 85*, 163-174.

Caplan, S. E., & High, A. C. (2006). Beyond excessive use: The interaction between cognitive and behavioral symptoms of problematic Internet use. *Communication Research Reports, 23*(4), 265-271.

Cohen, E. L. (2014). What makes good games go viral? The role of technology use, efficacy, emotion and enjoyment in players' decision to share a prosocial digital game. *Computers in Human Behavior, 33*, 321-329.

de Guinea, A. O., & Markus, M. L. (2009). Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology use. *MIS Quarterly, 33*(3), 433-444.

de Guinea, A. O., & Webster, J. (2013). An Investigation of Information Systems use Patterns: Technological Events as Triggers, the Effect of Time, and Consequences for Performance. *MIS Quarterly, 37*(4), 1165.

Deleuze, J., Rochat, L., Romo, L., Van der Linden, M., Achab, S., Thorens, G., . . . Rothen, S. (2015). Prevalence and characteristics of addictive behaviors in a community sample: A latent class analysis. *Addictive Behaviors Reports, 1*, 49-56.

Eyal, N. (2014). *Hooked: How to build habit-forming products*: Penguin.

Fang, J., Wang, X., Wen, Z., & Zhou, J. (2020). Fear of missing out and problematic social media use as mediators between emotional support from social media and phubbing behavior. *Addictive Behaviors, 107*, 106430.

Frith, C. D., & Frith, U. (2006). The neural basis of mentalizing. *Neuron, 50*(4), 531-534.

Gartner, J., Fink, M., & Maresch, D. (2022). The Role of Fear of Missing Out and Experience in the Formation of SME Decision Makers' Intentions to Adopt New Manufacturing Technologies. *Technological Forecasting and Social Change, 180*, 121723.

Gerlach, J. P., & Cenfetelli, R. T. (2020). Constant Checking Is Not Addiction: A Grounded Theory of IT-Mediated State-Tracking. *MIS quarterly, 44*(4), 1705.

Gong, X., Zhang, K. Z., Chen, C., Cheung, C. M., & Lee, M. K. (2019). Antecedents and consequences of excessive online social gaming: a social learning perspective. *Information Technology & People*, *33*(2), 657-688.

Grigaliunaite, V., & Pileliene, L. (2016). Emotional or rational? The determination of the influence of advertising appeal on advertising effectiveness. *Scientific Annals of Economics and Business, 63*(3).

Hartwig, K., von Saldern, L., & Jacob, F. (2021). The journey from goods-dominant logic to service-dominant logic: A case study with a global technology manufacturer. *Industrial Marketing Management, 95*, 85-98.

Hassenzahl, M., Wiklund-Engblom, A., Bengs, A., Hägglund, S., & Diefenbach, S. (2015). Experience-oriented and product-oriented evaluation: psychological need fulfillment, positive affect, and product perception. *International Journal of Human-Computer Interaction, 31*(8), 530-544.

Hetz, P. R., Dawson, C. L., & Cullen, T. A. (2015). Social media use and the fear of missing out (FoMO) while studying abroad. *Journal of Research on Technology in Education, 47*(4), 259-272.

Högberg, J., Hamari, J., & Wästlund, E. (2019). Gameful Experience Questionnaire (GAMEFULQUEST): an instrument for measuring the perceived gamefulness of system use. *User Modeling and User-Adapted Interaction, 29*(3), 619-660.

James, T. L., Lowry, P. B., Wallace, L., & Warkentin, M. (2017). The Effect of Belongingness on Obsessive-Compulsive Disorder in the Use of Online Social Networks. *Journal of Management Information Systems, 34*(2), 560-596.

Karahanna, E., Xu, S. X., Xu, Y., & Zhang, N. A. (2018). The needs–affordances–features perspective for the use of social media. *MIS Quarterly, 42*(3), 737-756.

Kim, H.-M. (2022). Social comparison of fitness social media postings by fitness app users. *Computers in Human Behavior, 131*, 107204.

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk and purchase intention: Based on the stimulus-organism-response model. *Journal of Research in Interactive Marketing*, *7*(1), 33-56.

Kumar, Y., Kaur, K., & Singh, G. (2020). *Machine learning aspects and its applications towards different research areas.* Paper presented at the 2020 International conference on computation, automation and knowledge management (ICCAKM).

Kwon, H. E., So, H., Han, S. P., & Oh, W. (2016). Excessive Dependence on Mobile Social Apps: A Rational Addiction Perspective. *Information Systems Research, 27*(4), 919-939.

Lee, J., & Hong, I. B. (2016). Predicting positive user responses to social media advertising: The roles of emotional appeal, informativeness, and creativity. *International Journal of Information Management, 36*(3), 360-373.

Leshner, G., Vultee, F., Bolls, P. D., & Moore, J. (2010). When a fear appeal isn't just a fear appeal: The effects of graphic anti-tobacco messages. *Journal of Broadcasting & Electronic Media, 54*(3), 485-507.

Limayem, Z. S. B. H. M. (2014). Data collection in the digital age: Innovative alternatives to student samples. *MIS Quarterly38, 355*, 378.

Lin, L., Hu, P. J.-H., Sheng, O. R. L., & Lee, J. (2010). Is stickiness profitable for electronic retailers? *Communications of the ACM, 53*(3), 132-136.

Longstreet, P., Brooks, S., & Gonzalez, E. S. (2019). Internet addiction: When the positive emotions are not so positive. *Technology in society, 57*, 76-85.

Montag, C., Lachmann, B., Herrlich, M., & Zweig, K. (2019). Addictive Features of Social Media/Messenger Platforms and Freemium Games against the Background of Psychological and Economic Theories. *International Journal of Environmental Research and Public Health, 16*(14), 2612.

Moradi, M., & Zihagh, F. (2022). A meta-analysis of the elaboration likelihood model in the electronic word of mouth literature. *International Journal of Consumer Studies*.

Nagoya, R., Bernarto, I., Antonio, F., Pramono, R., Wanasida, A. S., & Purwanto, A. (2021). Exploring Intention to Enroll University Using an Extended Stimulus-organism-response Model. *Academy of Strategic Management Journal, 20*, 1-12.

Orlikowski, W. J., & Iacono, C. S. (2001). Research commentary: Desperately seeking the "IT" in IT research—A call to theorizing the IT artifact. *Information Systems Research, 12*(2), 121-134.

Panda, T. K., Panda, T. K., & Mishra, K. (2013). Does Emotional Appeal Work in Advertising? The Rationality Behind Using Emotional Appeal to Create Favorable Brand Attitude. *IUP Journal of Brand Management, 10*(2).

Partala, T., & Kujala, S. (2016). Exploring the role of ten universal values in using products and services. *Interacting with computers, 28*(3), 311-331.

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly*, 105-136.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior, 29*(4), 1841-1848.

Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., . . . Jackson, M. O. (2019). Machine behaviour. *Nature, 568*(7753), 477-486.

Reynolds, W. M. (1982). Development of reliable and valid short forms of the Marlowe-Crowne Social Desirability Scale. *Journal of Clinical Psychology, 38*(1), 119-125.

Roberts, J. A., & David, M. E. (2020). The social media party: Fear of missing out (FoMO), social media intensity, connection, and well-being. *International Journal of Human–Computer Interaction, 36*(4), 386-392.

Roth, G., Vansteenkiste, M., & Ryan, R. M. (2019). Integrative emotion regulation: Process and development from a self-determination theory perspective. *Development and Psychopathology, 31*(3), 945-956.

Septianto, F., & Pratiwi, L. (2016). The moderating role of construal level on the evaluation of emotional appeal vs. cognitive appeal advertisements. *Marketing Letters, 27*(1), 171-181.

Simmering, M. J., Fuller, C. M., Richardson, H. A., Ocal, Y., & Atinc, G. M. (2015). Marker variable choice, reporting, and interpretation in the detection of common method variance: A review and demonstration. *Organizational Research Methods, 18*(3), 473-511.

Soror, A. A., Hammer, B. I., Steelman, Z. R., Davis, F. D., & Limayem, M. M. (2015). Good habits gone bad: Explaining negative consequences associated with the use of mobile phones from a dual-systems perspective. *Information Systems Journal, 25*(4), 403-427.

Suh, K.-S., Kim, H., & Suh, E. K. (2011). What if your avatar looks like you? Dual-congruity perspectives for avatar use. *MIS Quarterly*, *35*(3), 711-729.

Teubner, T., Adam, M., & Riordan, R. (2015). The impact of computerized agents on immediate emotions, overall arousal and bidding behavior in electronic auctions. *Journal of the Association for Information Systems, 16*(10), 2.

Turel, O., & Ferguson, C. (2021). Excessive Use of Technology: Can Tech Providers be the Culprits? Seeking to assess the possible responsibility of tech providers for excessive use patterns. *Communications of the ACM, 64*(1), 42-44.

Turel, O., Mouttapa, M., & Donato, E. (2015). Preventing problematic Internet use through video-based interventions: a theoretical model and empirical test. *Behaviour & Information Technology, 34*(4), 349-362.

Turel, O., Serenko, A., & Giles, P. (2011). Integrating technology addiction and use. *MIS Quarterly, 35*(4), 1043-1061.

Wang, C., & Lee, M. K. O. (2020). Why We Cannot Resist Our Smartphones: Investigating Compulsive Use of Mobile SNS from a Stimulus-Response-Reinforcement Perspective. *Journal of the Association for Information Systems, 21*(1), 175-200.

Xie, T., Donthu, N., Lohtia, R., & Osmonbekov, T. (2004). Emotional appeal and incentive offering in banner advertisements. *Journal of Interactive Advertising, 4*(2), 30-37.

Xu, Z., Turel, O., & Yuan, Y. (2012). Online game addiction among adolescents: motivation and prevention factors. *European Journal of Information Systems, 21*(3), 321-340. doi:10.1057/ejis.2011.56

Zheng, X., & Lee, M. K. (2016). Excessive use of mobile social networking sites: Negative consequences on individuals. *Computers in Human Behavior, 65*, 65-76.

Appendix of Essay 2

Table 2.9: Correlation table of the pilot study

	PAT	PMM	NFA	PCA	FOMO	HO	TF	HA	IM
PAT	1								
PMM	0.53	1							
NFA	0.53	0.51	1						
PCA	0.52	0.61	0.52	1					
FOMO	0.51	0.21	0.40	0.39	1				
HO	0.30	0.41	0.28	0.45	0.62	1			
TF	0.40	0.22	0.46	0.36	0.72	0.60	1		
HA	0.36	0.35	0.25	0.34	0.51	0.55	0.55	1	
IM	0.15	0.18	0.37	0.24	0.61	0.38	0.63	0.62	1

Table 2.10: Reliability and validity of constructs in the pilot study

Item	Item Mean	Item Std. Dev	Item-intercorrelation	Item-alpha	Loadings	Cronbach Alpha	AVE
PAT1	5.4	1.28	0.80	0.73	0.75	0.81	0.51
PAT2	5.8	1.09	0.79	0.74	0.73		
PAT3	5.5	1.13	0.77	0.76	0.66		
PAT4	5.6	1.17	0.78	0.75	0.70		
PMM1	5.5	1.20	0.80	0.64	0.69	0.72	0.50
PMM2	5.6	1.17	0.82	0.60	0.75		
PMM3	5.6	1.20	0.79	0.67	0.65		
NFA1	5.4	1.16	0.82	0.68	0.73	0.78	0.52
NFA2	5.5	1.09	0.81	0.68	0.72		
NFA3	5.6	1.08	0.82	0.69	0.70		
PEA1	5.5	1.20	0.75	0.78	0.64	0.81	0.51
PEA2	5.5	1.18	0.81	0.74	0.74		
PEA3	5.6	1.32	0.81	0.75	0.75		
PEA4	5.5	1.22	0.81	0.75	0.74		
PCA1	5.5	0.98	0.81	0.64	1	0.70	0.62
PCA2	5.4	1.18	0.79	0.65	0.50		
FOMO1	4.7	1.5	0.80	0.93	0.77	0.94	0.67
FOMO2	4.7	1.74	0.87	0.93	0.85		
FOMO3	4.9	1.68	0.86	0.93	0.84		
FOMO4	4.9	1.60	0.80	0.93	0.76		
FOMO5	4.8	1.63	0.84	0.93	0.81		
FOMO6	4.6	1.63	0.81	0.93	0.78		
FOMO7	4.9	1.61	0.83	0.93	0.80		
FOMO8	5.1	1.67	0.89	0.92	0.87		
HO1	5.2	1.35	0.82	0.89	0.78	0.91	0.62
HO2	5.4	1.35	0.79	0.90	0.73		
HO3	5.2	1.36	0.81	0.89	0.75		
HO4	5.3	1.40	0.85	0.88	0.83		
HO5	5.4	1.35	0.82	0.89	0.80		
HO6	5.4	1.35	0.85	0.88	0.82		
TF1	4.9	1.56	0.87	0.93	0.83	0.93	0.75
TF2	4.8	1.74	0.89	0.92	0.88		
TF3	4.9	1.77	0.89	0.92	0.87		

Table 2.9 (Cont.)

Item	Item Mean	Item Std. Dev	Item-intercorrelation	Item-alpha	Loadings	Cronbach Alpha	AVE
TF4	4.9	1.72	0.89	0.92	0.87		
TF5	5.0	1.78	0.89	0.92	0.87		
HA1	5.3	1.20	0.68	0.91	0.62	0.91	0.54
HA2	5	1.56	0.77	0.90	0.67		
HA3	5	1.43	0.78	0.90	0.76		
HA4	4.9	1.66	0.77	0.90	0.75		
HA5	4.9	1.54	0.80	0.89	0.80		
HA6	5.2	1.37	0.79	0.90	0.75		
HA7	4.9	1.53	0.76	0.90	0.75		
HA8	5.2	1.30	0.78	0.89	0.76		
HA9	5.3	1.22	0.72	0.90	0.66		
IM1	4.2	1.85	0.86	0.95	0.85	0.96	0.74
IM2	3.2	2.12	0.65	0.96	0.58		
IM3	4.1	2.01	0.90	0.95	0.88		
IM4	4.3	1.91	0.9	0.95	0.91		
IM5	4.2	1.90	0.91	0.95	0.91		
IM6	4.4	1.84	0.90	0.95	0.89		
IM7	4.4	1.90	0.88	0.95	0.87		
IM8	4.3	1.91	0.90	0.95	0.90		
IM9	4.5	1.95	0.89	0.96	0.88		

Table 2.11: Results of the pilot study

Tested Hypothesis/ Path	B	t-statistic	Support
H1. Perceived Emotional Appeal-→ Hooked	0.35	3.28***	Yes
H2. Perceived Cognitive Appeal→ Hooked	0.03	0.27	No
H3. Fear of Missing Out→ Hooked	0.71	13.22***	Yes
H4. Perceived Agency of Technology-→ Perceived Emotional Appeal	0.4	3.86***	Yes
H5. Perceived Agency of Technology→ Perceived Cognitive Appeal	0.47	2.04***	Yes
H6. Perceived Agency of Technology→ Fear of Missing Out	0.33	3.28***	Yes
H7.Perceived Ability to Modify Mood→ Perceived Emotional Appeal	0.61	6.05***	Yes
H8. Perceived Mood Modification→ Perceived Cognitive Appeal	0.51	3.99***	Yes
H9. Need Fulfilment Ability→ Fear of Missing out	0.07	0.71	No
H10. Hooked-→ Habit	0.65	12.63***	Yes
H11. Hooked-→ Perceived Work-Life Conflicts	0.79	0.78***	Yes

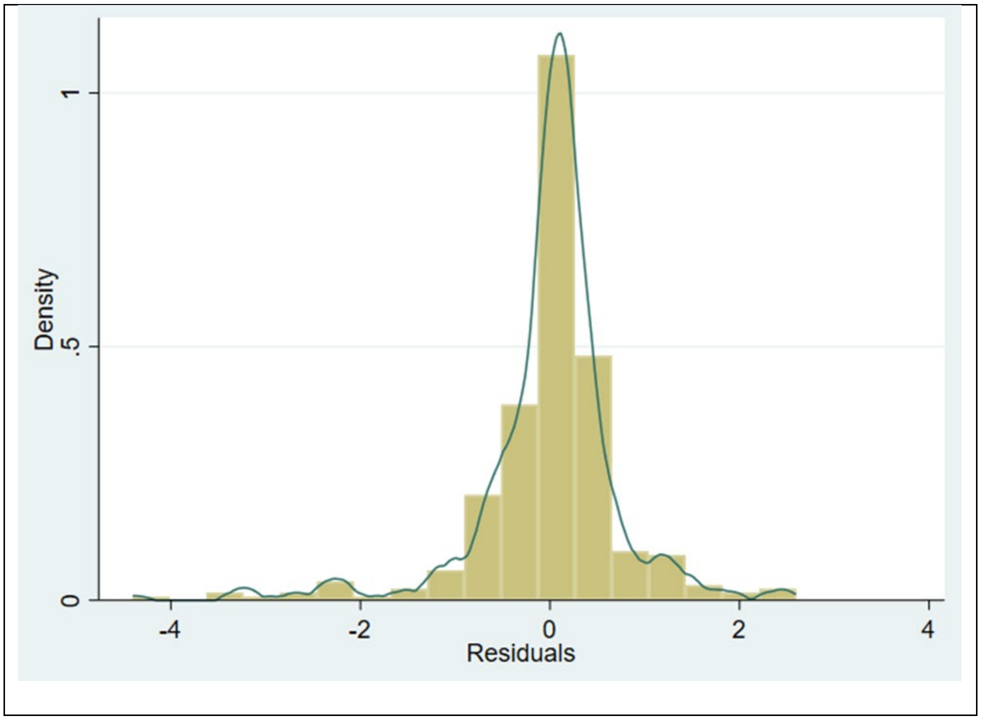


Figure 2.5: Assumption testing for the main study

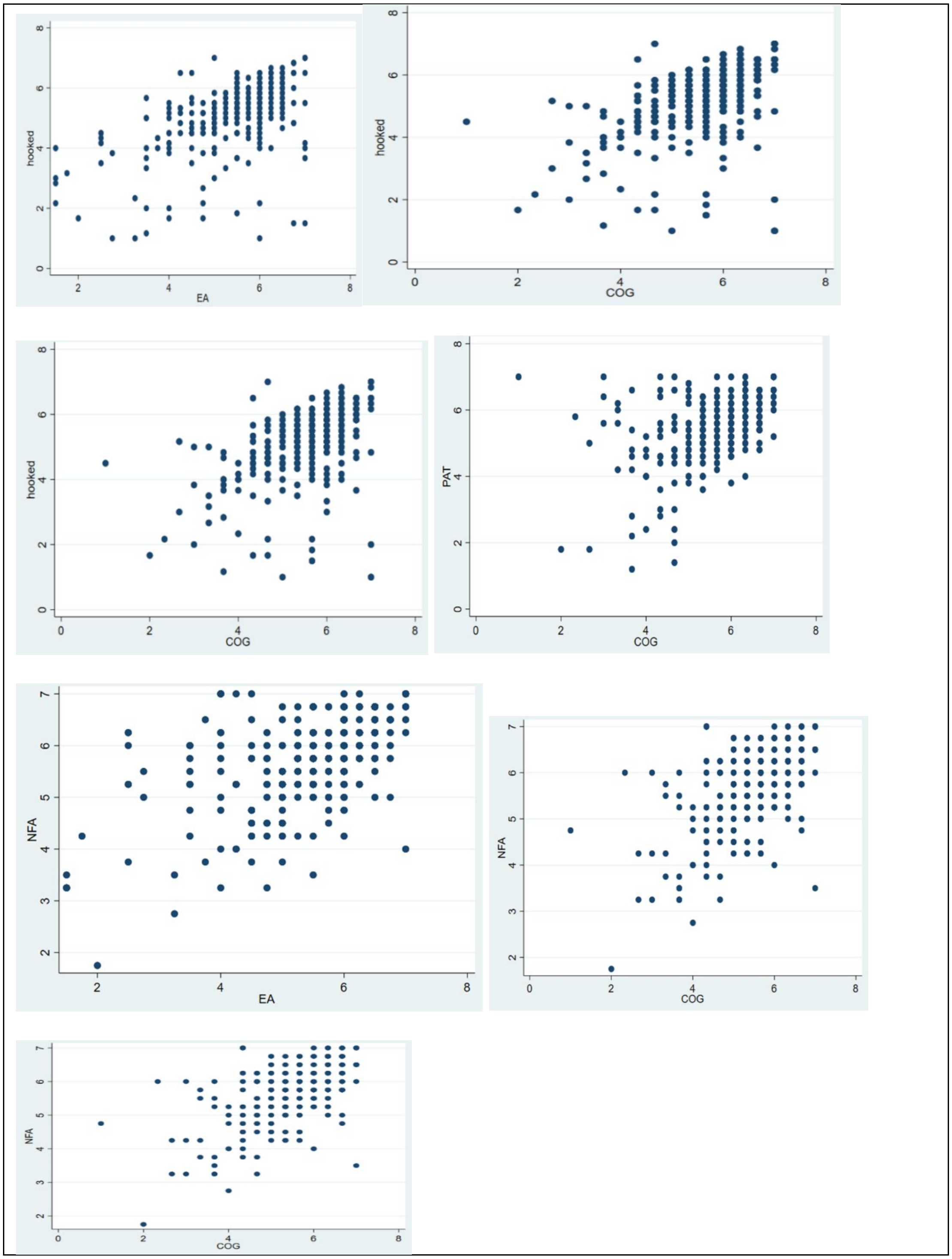


Figure 2.6: Assumption testing for the main study

Table 2.12: Survey instruments of PAT

Constructs	Adapted from TIU measure (Behavior)
Perceived Agency of Technology	Think about the app you most frequently interact with (i.e., the one you identified earlier). The app has features that draw on data. Sometimes, many of you may feel that those features can pull us into the app and guide us to perform behaviors, such as social interaction, reward seeking, information gathering and so on. The following questions will illustrate how the app guides us to carry out different activities. Please answer the following questions based on your experience with the app (i.e., the one you identified earlier) with which you usually interact
	1. The app contains features (e.g., notification, recommendation, infinite scrolling) that allow me to get new content.
	2. The app contains features (e.g., recommendation, infinite scrolling, watch more) that allow me to get new experience
	3. The app contains features (e.g., notification, leaderboard, chatbots) that allow me to perform tasks efficiently
	4. The app contains features (e.g., recommendations) that allow me to get my preferred content
	5. The app contains features (e.g., recommendation, search, complete, compare) that allow me to be involved with pleasant activities.
	6. The app contains features (e.g., level, point, badge) that allow me to receive rewards.
	7. The app contains features (e.g., like) that allow me to appreciate others' content
	8. The app contains features (e.g., share) that allow me to share content with others
	9. The app contains features (e.g., react, like) that allow me to react to others' activities
	10. The app contains features (e.g., recommendations) that allow me to browse others' content
	11. The app contains features (e.g., follow) that allow me to track online communities
	12. The app contains features (e.g., collaborate) that allow me to perform tasks with others
	13. The app has features (e.g., learn more, discover, notification, recommendation) that allow me to learn about events
	14. The app has features (e.g., search, notification, learn more) that allow me to learn about the latest news
	15. The app has features (e.g., notification, recommendation, learn more) that allow me to learn about current trends

Table 2.13: Survey instrument of NFA

			Adopted
Need fulfillment ability		Think about the app you most frequently interact with (i.e., the one you identified earlier). The app has features that draw on data. Sometimes, you may feel that the features of the app guide you to engage in activities and help you fulfill your needs. Please answer the following questions based on your experience with the app that you identified earlier. Using the app's (i.e., the one you identified earlier) features….	Karahanna et al. 2018; Interview
	Autonomy	1) I can freely voice my ideas and opinions	
		2) I can freely decide what I want to do	
	Relatedness	3) I can socially interact with people	
		4) I can develop friendships with people	
		5) I can be close to many people	
	Competence	6) I can feel competent	
		7) I can feel capable in what I do	
		8) I can show how capable I am	
	Expressing self-identity	9) I can express who I am	
		10) I can express my personality	
		11) I can express my self-identity	
	Mood modification	12) I can reduce my boredom	
		13) I can avoid my feeling of emptiness	
		14) I can feel relaxed	

Table 2.14: Survey instrument of positive emotional appeal

	Items	Adopted from
Positive Emotional Appeal	Describe the extent to which the following words describe your typical feeling when you interact with the app (i.e., the one you identified earlier)….	Thomson et al. 20005; Suh et al. 2011
	1) affectionate	
	2) lovely	
	3) peaceful	
	4) friendly	
	5) attached	
	6) bonded	
	7) connected	
	8) passionate	
	9) delighted	
	10) captivated	

Table 2.15: Survey instrument of fear of missing out

Construct	Items	Adopted from
Fear of missing	When I cannot interact with the app (i.e., the one you identified earlier)……	Przybylski et al. 2013; Zhang et al. 2018
	1. I fear others have more rewarding experiences than me	
	2. I fear my friends have more rewarding experiences than me	
	3. I get worried as others are having fun without me in the app	
	4. I get anxious as I don't know what my friends are up to	
	5. It bothers me as I feel missing an opportunity to get new content	
	6. I feel sad as I cannot share my contents	
	7. I get anxious when I do not know what my friends are up to	
	8. It bothers me as I miss an opportunity to interact with friends	
	9. I feel anxious because I know something important, or fun must happen	

Table 2.16: Survey instrument of perceived cognitive appeal

		Items	Adopted from
Perceived cognitive appeal		Think about the app you most frequently interact with (i.e., the one you identified earlier). Sometimes we feel that the features of those apps provide us with a lot of cognitive benefits. For example, we can engage in learning, problem-solving, competing with others, and achieving something. Please answer the following questions based on your experience with the app that you most frequently interact with. When I interact with features of the app(i.e., the one you identified earlier)…….	Hogberg et al. 2018; Interviews
	Learning	When I interact with features of the app……	
		1)I can learn new things	
		2)I can solve new problems	
		3) I can apply my critical thinking ability	
		4) I can examine a phenomenon from different perspectives	
		5) I can create new things	
	Challenge	6) I can try to push myself beyond my limits	
		7) I can push myself to achieve something	
		8)I can test my ability to achieve something	
	Competition	9) I am able to compete with others	
		11) I can strive to be the best	
	Accomplishment	12) I can engage in setting clear goals	
		13) I can progress and get better to achieve goals	
		14) I can engage in taking myself to the next level	

Table 2.17: Survey instrument of hooked

		Adapted from
Hooked	Think about the app you most frequently interact with (i.e., the one you identified earlier). Sometimes, you may feel that the app is constantly guiding you to interact with it. Please answer the following questions based on your experience with the app:	Interview; Wang et al. 2020
	1) The amount of time I spend on the app is usually longer than I plan	
	2) I spend an unusually large amount of time interacting with the app	
	3) I spend more time using the app than I originally intend	
	4) The time I spend using the app exceeds my expectations	
	5) I spend more time in the app than I would like to	
	6) I frequently lose track of time on the app	

Table 2.18: Survey instrument of perceived technology-life conflict

		Adapted from
Perceived technology-life conflict	Think about the app you most frequently interact with (i.e., the one you identified earlier). Sometimes, we feel that usage of the app interferes with our family life. Please answer the following questions based on your experience with the app with which you usually interact. My use of the app (i.e., the one you identified earlier)……	Ahuja et al., 2007
	1) interferes with my home and family life	
	2) makes it difficult to fulfill family my responsibilities	
	3) makes it difficult to get things done at home	
	4) produces strain that makes it difficult to fulfill my family duties	
	5) results in making changes to my plans for family activities	

Table 2.19: Survey instruments of habit

		Adapted from
Habit	Using the app (i.e., the one you identified earlier) is something..…	Verplanken and Orbell 2003
	1) I do frequently	
	2) I do automatically	
	3) I do with having to consciously remember	
	4) I do without thinking	
	5) I start doing it before I realize I'm doing it	
	6) I have no need to think about doing it	
	7) that would require effort not to do it	

Table 2.20: Survey instruments of the addictive personality

		Adapted from
	Please respond to the following regarding your general tendencies:	Deleuze et al., 2015
Compulsive behavior	1) I have a tendency to engage in excessive shopping	
	2) I have a tendency to engage in excessive eating	
	3) I have a tendency to engage in excessive drinking	
	4) I have a tendency to engage in excessive chatting	
	5) I have a tendency to engage in excessive gambling	
	6) I have a tendency to engage in excessive networking	
	7) I have a tendency to engage in online searching	

Table 2.21: Survey instruments of social desirability

		Adapted from
Social desirability bias (Yes/ No answer)	1) It is sometimes hard for me to go on with my work if I am not encouraged	Reynolds 1982
	2) I sometimes feel resentful when I don't get my way	
	3) On a few occasions, I have given up doing something because I thought too little of my ability	
	4) There have been times when I felt like rebelling against people in authority even though I knew they were right	
	5) No matter who I'm talking to, I'm always a good listener	
	6) There have been occasions when I took advantage of someone	
	7) I'm always willing to admit it when I make a mistake	
	8) I sometimes try to get even rather than forgiving and forget	
	9) I am always courteous, even to people who are disagreeable.	
	10) I have never resent being asked to return a favor	
	11) There have been times when I was quite jealous of the good fortune of others	
	12) I am sometimes irritated by people who ask favors of me	
	13) I have never deliberately said something that hurt someone's feelings	

III. Essay 3: Conceptualization and Measurement Instruments of Technology induced use

Introduction

"It's 7 am on a Saturday. Ryan wake up from his sleep when he hears a notification from Instagram. He checks the notification out of curiosity. It is a picture posted by one of his friends from their high school reunion from the year before. A "like" button is next to the photo, driving Ryan to click it. Suddenly, a "share" button shows up, asking Ryan to put it in his feed. Ryan shares the photo. His feed shows him similar photos posted by his other friends. He starts to watch each of them for an hour."

The preceding example illustrates how apps constantly divert users' attention to app-mediated activities, fostering dependency. Many technological features, such as notifications, recommendations, and sharing, are designed to entice users to click on them (Eyal, 2014). These features constantly stimulate users' needs and direct them to fulfill them through the app. In this way, the intertwinement between technology's ability to persuade users and users' ability to fulfill their needs leads to a new feedback mechanism in our society: technology-induced use. Due to constant attention capture, many users like Ryan have become passive users of technology-mediated activities (Alter, 2017).

Technologies such as apps are increasingly capable of executing activities without user intervention (Baird & Maruping, 2021). TikTok may select the best possible recommendations and respond to users' needs without request. Artificial intelligence (AI) and machine learning (ML) innovations have accelerated the trend where machines guide users to fulfill needs through the app, self-evolving to match best actions with user needs in real-time, reducing user search costs (Berente, Gu, Recker, & Santhanam, 2021). As a result of continuous data access and the ability to rapidly process real-time usage data, technologies like apps now have a deeper grasp of user personality profiles, preferences, and opinions, enabling them to fully capture the user's attention (Nambisan, Lyytinen, Majchrzak, & Song, 2017). Because technology's capabilities align with users' needs, users keep returning to it, and their enthusiasm does not seem to diminish (Siebert, Gopaldas, Lindridge, & Simões, 2020).

Some IS researchers and practitioners are beginning to express concerns regarding the growing agentic capabilities of technology (Turel & Ferguson, 2021). According to Eyal (2019), increased technology agency forms a strong relationship between technology and user, accelerating the formation of strong usage habits. A range of usage behaviors emerges because of technological agency: the compulsion to return, to seek recommendations, to immerse oneself in activities, intensifying excessive dwell time within technology (Alter, 2017; Courtwright, 2019; Eyal, 2014, 2019). Such emergent behaviors indicate that technology usage behaviors have assumed a new dimension as technological features and human agency have become inexorably intertwined.

In recent years, the intertwinement between technology agency and human agency has been linked to the formation of echo chambers, especially in the case of social media apps (Kitchens, Johnson, & Gray, 2020). The echo chamber is a metaphor for a prison-like atmosphere in technology in which algorithmic activities reinforce certain types of emotional content and restrict content diversity, allowing confirmation bias to flourish (Kitchens et al., 2020). Increased technological agency in social media diminishes content diversity by offering exclusively user-preferred content, constructing an echo chamber of belief (Cinelli, Morales, Galeazzi, Quattrociocchi, & Starnini, 2021).

The trend of managing user behavior through the algorithm, characterized by algorithmic matching and algorithmic control, exemplifies the growing connection between technology and human agency (Möhlmann, Zalmanson, Henfridsson, & Gregory, 2021; Tarafdar, Page, & Marabelli, 2022). By matching users' needs in real-time and nudging them to use different features, embedded algorithms in apps "stick" users in apps (de Lima Salge, Karahanna, & Thatcher, 2021). Because algorithmic activities can continuously drive usage, technology agency is indistinguishable from human agency. This was demonstrated in the Ryan's case at the essay's open, in which app features repeatedly stimulated Ryan's use of Instagram. A new usage construct is necessary to characterize the intertwining dynamics of technological and human agency.

The intertwining of technology and human agency has gained attention among technology practitioners. Recent works of IS scholars emphasize the significance of agentic technological capabilities like algorithm empowerment, social bots, and artificial intelligence (Baird & Maruping, 2021; Möhlmann et al., 2021; Rai, Constantinides, & Sarker, 2019). However, most of these works have envisioned technology and human agency as separate phenomena(Baird & Maruping, 2021). These works primarily viewed usage behaviors from a functional perspective, presuming that a) users' intentions and goals drive technology use and b) technology is a passive agent that only carries out users' instructions (Baird & Maruping, 2021). Against this backdrop, I propose a new construct—technology-induced usage—which instrumentalizes the combined interaction between technology features and human agency.

Typical studies in IS measure usage as a function of the intention to use or continue using a technology (Bhattacherjee, 2001), a measuring instrument that lacks the dynamic interaction between technology agency and human agency. Thus, a new usage measurement is required to capture the dynamic interaction between technological and human agency. This essay proposes new measurement instruments purposed for technology-induced use able to capture the interdependence between technological and human agencies.

At the beginning of this study, we were limited by the paucity of academic research on the intertwinement between technological and human agency. I began my research by evaluating the narratives and perspectives of technology practitioners regarding how technological agency influences human agency. Next, I conceptualized the construct—technology-induced use—from two perspectives: a) the agency of technology in inducing usage and b) users' attraction to technology. Using both views, I articulated the influence of technology's agency on human agency. During this process, I developed a new construct, technology-induced use, defined as an individual's use of technology to fulfill his/her situational and innate needs. This is a type of new usage construct that can capture the dynamic relationship between technology and human agency. After conceptualizing technology-induced usage, I followed the processes outlined by MacKenzie et al. (2011) to develop technology-induced use measurement items. This paper provides a foundation for theorizing and measuring the dynamic relationship between human and technological agency, inspiring future research to examine the agency from various viewpoints.

Background Literature of Technology-Induced use

Technology agency influences human agency, and its nature, mechanism, and outcomes have received great attention in recent practice and academic literature. First, I will examine both practice and academic literature's conclusions about technology-driven app use. Next, I explore technology-induced use's conceptual significance, mechanisms, and consequences. Finally, I conclude with a discussion in three ways: a) technology features that can influence human agency discussed in practice and academic literature, b) underlying mechanisms that influence human agency discussed in social psychology and psychology literature, and c) consequences of technology-induced use discussed in practice and IS literature.

In the app context, practitioners and academics discuss significant features manipulating human agency. Of the magnetic features of super apps studied in the literature, such as dating, health, social media, entertainment, and gaming, Eyal broadly categorizes two kinds: a) call-to-action features and b) engagement features (Steinberg, 2020). The call-to-action concept, eliciting an urgent response through invitation, traces its origin to marketing technique (Eyal, 2014). These features are visual and auditory prompts that invite immediate use (Berthon, Pitt, & Campbell, 2019). **Call-to-action** prompts can, first, immediately request a user to engage in technology activities (Eyal, 2014), and second, these can remind users to complete unfinished tasks (Alter, 2017). **Call-to-action features** include notifications, invitations, reminders, and alerts. Perhaps these features do not provide an explicit reward, but they can persuade users to initiate an action (Eyal, 2014). The algorithm embedded in a given app calculates the optimal time to push call-to-action features based on individual usage history (Eyal, 2014).

Engagement features are features that can entice users to participate in a variety of activities. Engagement features are based on a schedule of rewards depending on the number of times a user initiates an in-app action (Eyal, 2014). Broadly, engagement features can be classified into two sorts: social reward and self-reward (Eyal, 2014). Social reward features allow users to interact, compare, and exchange with others. For example, Instagram provides "voting" while Facebook provides "liking" (Siebert et al., 2020).

Self-reward features allow users to get self-gratification (Eyal, 2014). For example, Snapchat provides rewards in the form of "Steaks," Instagram provides "Bonuses," and Tinder provides a "Collection of Matches" (Siebert et al., 2020). In sum, a closer review shows that some technology features generate desires for incentives that stimulate the use of technology.

Next, we discuss psychological and socio-psychological mechanisms that influence human agency. Alter (2017), a practitioner and researcher, describes three mechanisms that can influence human agency. The first is loss aversion (Kahneman, Knetsch, & Thaler, 1991). According to the loss aversion principle, people experience loss more severely than gain (Novemsky & Kahneman, 2005). Some apps' features encourage users to participate in technological action possibilities allowing them to enjoy more and avoid losing out on important content (Berthon et al., 2019). For instance, some notifications specify "do not miss the content" so that users may feel the possibility of losing if they do not interact with the app.

The second principle is the sense of creating something new. Humans are intrinsically motivated to create something new (Alter, 2017). Features like "build home for Zens" in the CityZen gaming app allow users to create something new virtually ((Alter, 2017). Those features can generate a flow state, enticing users to return repeatedly.

The final principle is social comparison. The notion of social comparison is that people have an inherent tendency to make upward and download comparisons with others (Turel, 2021). Many features provide an endless way to compare oneself with others, for example, "leaderboard," "like," etc. (Montag, Lachmann, Herrlich, & Zweig, 2019).

Eyal (2014) points out three other mechanisms to explain why some users are captivated by technology features. The first mechanism is the **heuristics effect** (Eyal, 2014). Evolutionary theory shows that many people use shortcuts when making decisions or performing actions to lower cognitive load (Cassotti et al., 2012). Users tend to prefer these *heuristics* to make quicker decisions. Many features enable practicing heuristics, which allow users to act quickly. For example, the recommendation features enable users to select content swiftly and reduce searching time.

The **search for novelty** is the second mechanism mentioned by Eyal (2014). The theory of novelty-seeking suggests that humans prefer novelty over seeking the same thing (Cassotti et al., 2012). Many apps are designed to deliver novel content. For example, the infinite scrolling feature ensures a steady supply of new information in social media and video-sharing apps (Montag et al., 2019).

The last mechanism mentioned by Eyal (2014) is **limitless variability**. The limitless variability theory claims that the appeal of predictable experiences can diminish over time (Siebert et al., 2020). As a result, many features are designed to provide diverse content to maintain attractiveness over time. For example, a gaming app might introduce one new game level after another (Alter, 2017). Overall, many technology features are designed to manipulate psychological biases.

Practitioners predicted many consequences associated with technology-induced use. For example, one consequence of induced use is the development of emotional attachment to apps (Eyal, 2014). The repeated exposure to content that matches needs can create an urge to have unique and renewable experiences, resulting in attachment development (Susser, Roessler, & Nissenbaum, 2019). Another consequence of technology-induced use is the emergence of obsessive-compulsive disorder-like symptoms, such as withdrawal cravings after disuse (James, Lowry, Wallace, & Warkentin, 2017). Finally, habits such as checking apps during driving could be formed due to the constant inducement mechanism of technology (Eyal, 2014).

Our review reveals that practitioners have focused on features and mechanisms that can induce usage. But there is a paucity of conceptualization and theory-based discussion about it.

Conceptualization of Technology-Induced Use

I conceptualize technology-induced use under two themes: a) features' ability to drive use and b) users' inducement to the technology. Below, I elaborate on those two themes. To introduce the first theme, I first introduce my paradigm technology, drawing the boundary of the discussion. Next, I apply general system theory to describe the feedback loop between technology and the user. Further, I advance Eyal's (2014) model of hooked to explain the bidirectional relationship between technology and user. Finally, I elaborate on stimulus-response-reinforcement theory and need-matching theory to discuss the last theme.

Technology perspectives

This section describes three different perspectives of technology. I select the agentic view of technology, highlighting technology agency, contrasting the agentic view of technology with the two which come before in order to justify its use.

First, the functional view of technology is the most common in the IS domain. According to this perspective, technology is a tool for completing a task (Burton-Jones & Gallivan, 2007). For example, IS literature views ERP systems as a tool to support work (Nandhakumar, Rossi, & Talvinen, 2005). Users who employ the ERP system use it to complete specific work-related tasks. This perspective focuses on human agency and argues that humans use technology purposively (Karahanna, Straub, & Chervany, 1999). Many of the most widely espoused IS theories, such as TAM, Innovation Diffusion, and the Effective Use of Technology theory, are based on a functional view of technology.

However, the functional view of technology has several limitations. First, the functional perspective makes no assumption regarding technological capabilities. Artificial intelligence and machine learning have prompted us to reconsider technology's capabilities as we reconsider the degree to which it is a passive tool (Baird & Maruping, 2021). Functional perspectives ignore algorithmic operations embedded in technology. Given the data-driven nature of today's technologies, algorithmic activities are critical in describing how technology encourages people to use it. Lastly, the functional view of technology emphasizes many characteristics of technology adoption that are not useful in explaining usage behaviors in the app context (Alawi, 2021). For example, perceived ease of use and utility are two characteristics that are no longer appropriate constructs to explain the adoption of modern apps (Alawi, 2021). Many technologies, such as super apps, do not require that users have prior knowledge about technology nor a high-level skills base in order to use them (Baird & Maruping, 2021).

Next, I consider the socio-material view of technology that explains the relationship between humans, technology, and organization (Orlikowski, 2000). According to this view, practices that emerge from the interaction with technology can shape humans' perception of technology and organizational culture (Orlikowski, 1992). In turn, human perception of technology and organizational culture can shape the design and use of technology (Orlikowski, 1992). This perspective examines the relationship between technology and human agency by focusing on the idea that practices that emerge from technology can influence human perceptions of technology (Orlikowski, 1992).

The socio-material view of technology has two limitations, however. First, a socio-material view of technology can only be generalized in an organizational setting. Second, rather than seeing technology as an artifact, this view perceives technology as a mental representation (Orlikowski & Iacono, 2001). I argue that technology can impact human agency as an artifact rather than a mere mental representation.

The agentic perspective of technology contends that technologies such as apps, chatbots, and virtual assistants should be perceived as active agents rather than passive instruments since technology can carry out tasks autonomously (Baird & Maruping, 2021; Fügener, Grahl, Gupta, & Ketter, 2021). A technology requires two properties to be considered an active agent. First, an agentic artifact should have some degree of intelligence (Baird and Maruping, 2021). In other words, an agent can interpret data from the outside world on its own and make effective decisions (Baird & Maruping, 2021). Second, an agentic artifact can control how it interacts with the environment on its own (Baird & Maruping, 2021). This suggests that agentic artifacts can sense and respond to the environment on the human agent's behalf (Baird & Maruping, 2021). Third, an agentic artifact can rationally carry out tasks to determine the best outcome for a user. (Baird & Maruping, 2021).

The agentic view of technology focuses mainly on technology agency (Baird & Maruping, 2021). Although the human agency is at the center of previous viewpoints, the agentic view of technology asserts that technology can perform actions without human intervention and thereby reinforce human agency (Berente et al., 2021). Not all technologies can be regarded as agentic artifacts. An agentic artifact should be able to gather, analyze, and manipulate data (Baird & Maruping, 2021). Because super apps like social media, entertainment, health, and sports apps can collect, analyze, and manipulate data from users, the agentic perspective of technology can be used to explain their agency (Steinberg, 2020).

Feedback loop

General system theory (GST) explains the feedback loop between technology and human agency. The feedback loop embedded in technology is the core mechanism of the intertwinement between technology features and human agency. GST explains the feedback loop in a coherent framework (Skyttner, 2001). According to this framework, a) a system has four major components: input, process, output, and feedback loop, b) each component is interrelated in the system, and c) all parts of the system share a common purpose (Skyttner, 2001). Let us consider an app, such as social media. According to the first tenet, social media should have input, process, feedback, and output components. We can define input as data or information entered into a system. The input of a social media app is the log-in ID and password. Next, the output is the processed product. In the social media context, input, such as the entry of a piece of information, can be transformed into an output, such as the display of content. The final component is the process of social media, a series of algorithmic activities required to convert an input into an output. In the context of a social media app, the algorithm responds to a user's inquiry, which can be defined as a process.

Finally, I define a feedback loop as the ability of a system to learn from user input and use what it learns to generate user-matching output. For example, social media apps can learn what users like based on their input. Later, social media can recommend similar content to users as output based on what it learns. A feedback loop connects output with input in a system. The algorithmic mechanism embedded in the app controls the feedback loop. Figure 1 illustrates the mechanism of General System Theory.

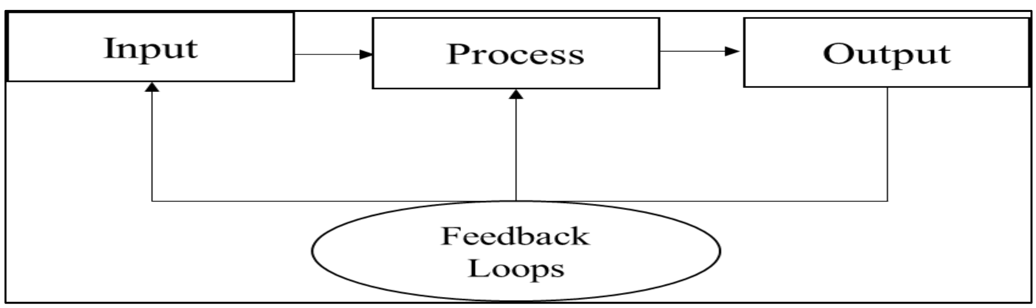


Figure 3.1: Feedback loops

Based on the feedback loop dynamics, technology interaction can be explained in two ways: human agency (input) and technology agency (learning from input). The feedback loop constantly reinforces usage by matching user input with output, i.e., technological agency. Let us examine human agency and technology agency in the context of a specific app, TikTok. Suppose a user searches for a cooking video on TikTok (human agency). Then, TikTok displays the cooking video (technological agency). Next, TikTok uses social and self-learning mechanisms to find similar cooking videos that users may enjoy (technology agency). TikTok can further adjust its learning based on user reactions to the cooking video (technological agency).

The Intertwinement between Technology Features and Use

To illustrate the intertwining of technology features and human use, I use Eyal's (2014) model of the hooked state. According to Nir Eyal, an individual uses a technology (app) through a sequence of experiences designed by technology features. An agentic artifact, such as an app, employs a variety of features to prompt individuals to act on them (Eyal 2014). Hence, instead of a user determining how and what to look for in technology, the technology executes these duties based on the user's behavior. This reflects a high level of technological agency. Here, technology influences human agency by matching the individual's needs and prompting the next step.

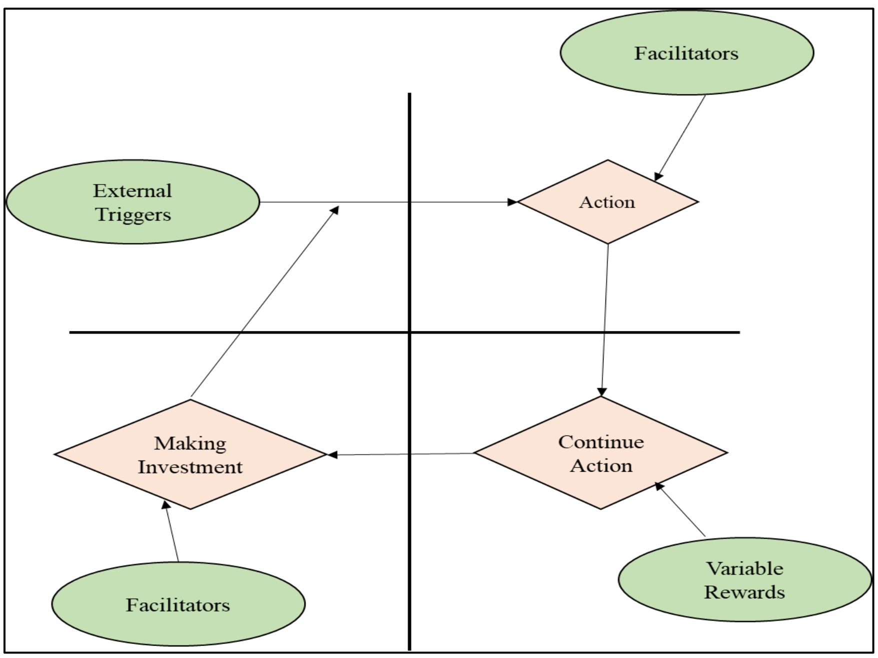


Figure 3.2: Model of hook adopted from Nir Eyal

Figure 3.2 below shows how technology guides people to act and then continues to nudge them forward using technology in an app context. External triggers, such as notifications, encourage users to interact with an app by inviting them to act on certain features. When a user launches the app, certain features act as facilitators by guiding the user to a call to action. In the social media app context, for example, the infinite scrolling feature prompts users to search for content uploaded by friends. To nudge users, the app provides rewards in the form of points, likes, steaks (social media), and so on. Finally, the app collects and manipulates data to create new notifications. The model implies two conjectures. First, agentic artifacts can activate usage behavior. Second, users can get engaged with agentic artifacts. The model explains how an app's activities spur users on to greater levels of engagement.

User Inducement to Technology

The previous discussion focused mainly on intertwining technological features and human use from the agentic artifact perspective. Next, I explain technology inducement from the user's perspective. To explain inducement, I use two theories: stimulus-response-reinforcement theory and need-supply fit theory.

Stimulus-Response-Reinforcement Theory (SRT)

SRT theory points out that human behavior is contingent on external stimuli (Chen, Tan, Liu, & Wang, 2020). The central thesis of this theory is that an encounter with *S* (stimulus) can produce an immediate response *R* (checking, reward-seeking) (Zhu & Chang, 2013). Technology features can be considered a stimulus, and user reaction to the feature can be thought of as a response. According to the theory, behavior can change due to the interaction between stimulus and response (Zhu and Chang 2013). This theory has been used in a variety of studies in past research. In the context of online shopping, for example, this theory has been used to develop an online purchasing model for e-commerce sites (Lim, Lee, & Kim, 2017). Lim et al. (2007) found in this context that stimuli (websites) can increase impulsiveness and intention to act. Figure 3.3 illustrates the relationship between stimulus, reinforcement, and response.

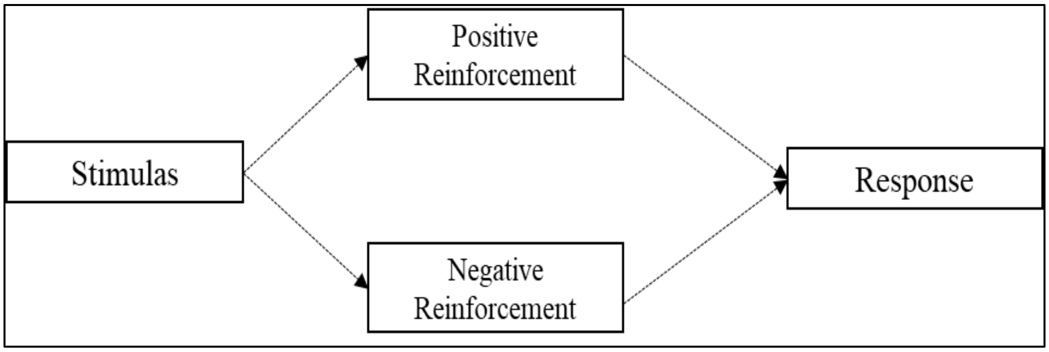


Figure 3.3: SRR theory

Understanding the relationship between stimulus and response is critical for understanding user inducement to technology. The link between stimulus and response strengthens if the stimulus is associated with rewards, positive outcomes, or removing negative outcomes (Verplanken, 2006). The constant linkage between stimulus and response can be defined as reinforcement (Wang & Lee, 2020). Once the connection forms between stimulus and response, reinforcement becomes the main mechanism to maintain the connection between them (Verplanken, Verplanken, & Ryan, 2018). Reinforcement helps form user memory about the stimulus, a process known as operant conditioning (Verplanken et al., 2018). The learning or formation of memory generally occurs outside of conscious awareness (West, Brown, & ProQuest, 2013).

Any tool that facilitates reinforcement can strengthen the link between stimulus and response (Verplanken, 2006). A feedback loop-containing technology can maintain reinforcement because it can learn from data about a specific stimulus that users may like and can constantly supply the stimulus. Technology features such as notifications and alerts can direct the user's attention to a specific stimulus, producing a predictable response. The constant attention of users to a specific stimulus can be interpreted as inducement or captivation.

Need-Supply Fit Perspective

I choose the need-supply fit perspective to explain user motivation because it emphasizes the influence of the external environment in meeting human needs (Krumm, Grube, & Hertel, 2013). This theory is an extension of the person-organization fit paradigm (Gerdenitsch, Korunka, & Hertel, 2018), which explains how technological agency influences human agency by matching user needs. According to this theory, the fit between the external environment and a user's need can elicit desired behavior (Maden, 2014). The theory also indicates that external environments adjust to fit the user's needs (Maden, 2014). The adjustable environment, in turn, plays an important role in fulfilling user needs. Figure 3.4 illustrates the need-supply fit perspective.

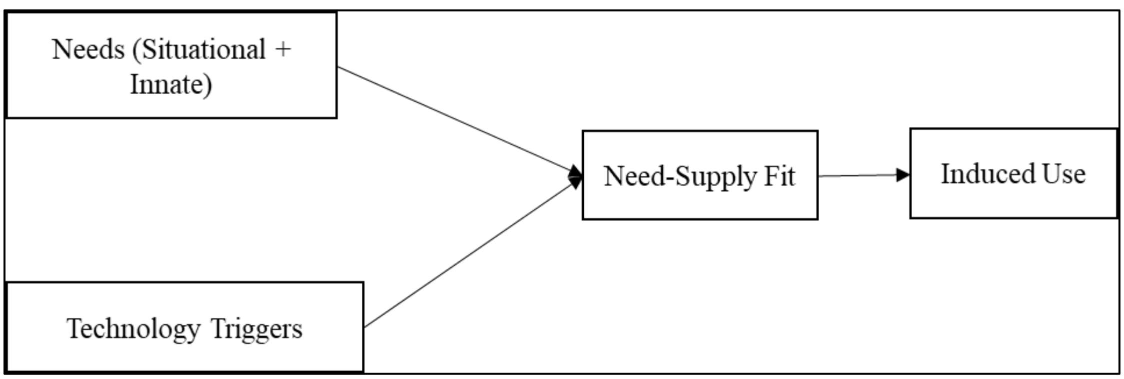


Figure 3.4: Need-supply fit perspective

A feedback loop-containing technology can learn from data about users' preferences and constantly supply content matching them, adapting to the user's needs. Given that continuous fulfillment of needs can transfix a user within the system, a feedback loop-containing technology influences human agency by adjusting content according to the user's needs.

Technology-Induced Use

The previous discussion illustrates that technology, such as apps, can influence human agency because of agentic capabilities and feedback loops. Users may feel drawn to technology because technology-mediated actions are linked to needs.

I now define the construct I use in the rest of the chapter: technology-induced use. To define the construct, we should first consider its conceptual domain and specify the entity to which it applies. Because it indicates interaction with technology, conceptually, technology-induced use is usage behavior. It is distinct from other usage behaviors because technology-induced use indicates the presence of technological agency in usage, which is absent from other types of usage constructs. In this way, technology can learn from user input, match user needs, and provide triggers to bring users back to technology. Users constantly use the technology to fulfill their situational and intrinsic needs. Thus, I define technology-induced use as an *individual's use of technology to fulfill their situational or innate needs, primarily stimulated by technology triggers.*

This definition of technology-induced use assumes two things. First, we assume that technology can drive usage. The algorithms in technology can process and manipulate usage data, which provides content that the user may like. Second, we assume that humans have needs (both situational and innate) that drive them to interact with technology (Leonardi, 2011).

Assessment of Technology-Induced Use

Here, I compare technology-induced use to other usage constructs. A review of the literature identifies three usage constructs similar to technology-induced use: habitual, post-adoptive, and problematic use. Under post-adoption of technology paradigms, several post-adoptive usage constructs have been studied, such as enhanced use, extended use, system use, adaptive system use, and so on. The source, name, and definition of those constructs are provided in Table 3.1.

Table 3.1: Name and definitions of different types of post-adoptive usage constructs

Source	Use Construct	Definition	Context
Bhattacherjee, 2001	IS continuance intention	"Users' intention to continue using a technology."	Internet
Detlor 2003	Internet-based IS use	"Users' intention to use an internet-based system."	Internet
Hsieh and Wang, 2007	Extended use	"Individuals use different feature sets of a technology to perform a work."	Inter-organization systems
Mettler and Wulf, 2019	Wearable technology use	"Individuals' use of wearable technology to perform a task."	Wearables data analytics technology
Kuegler et al., 2015	Enterprise systems and social platforms use	"Individuals' use of enterprise social software platform to improve performance."	Enterprise social software platform
Schwarz and Hirschheim, 2003	Routine use	"The extent to which technology use becomes a normal part of work routine."	Organization information technology
Ahuja and Thatcher, 2005	Trying to innovate with IT	"Users' goal of finding novel uses for IS ."	Consumer technology
Nambisan et al., 1999	Intention to explore	"Users' willingness to and goal for exploring IS and identifying its potential use."	Organizational information technology
Negoita et al., 2018	Collective systems use	"A unit level construct that is rooted in instances of individual-level use with the context of a common work process."	Organizational information technology
Osatuyi and Turel, 2018	Corrective IS use	"A user's attempt to reduce use of a system."	Social networking site
Venkatraman et al. 2018	Deviant use	"Intentional use of technology that is contrary to the implicit and explicit norms of society or organization."	Organizational information technology
Burton-Jones and Straub, 2006	System use	"Individual's use of a system to achieve a goal."	Organizational information technology
Tong et al., 2017	Indirect IS use	"The user's delegation of some parts of IS used to others while retaining the responsibility of IS use task."	Organizational information technology
Bagayogo et al., 2014	Enhanced use	"Individual's novel way of employing technology features."	Organizational information technology
Zhang and Venkatesh, 2017	Knowledge management system use	"Individual use of knowledge management systems to enhance job outcomes."	Knowledge management system
Sun, 2012	Adaptive system use	"A user's revision of which and how system features are used."	Organizational information technology
Saga and Zmud, 1994	Standardized use	"Users' utilization of IS in a way that reduces variations in usage patterns."	Organizational information technology

In table 3.2, we compare technology-induced use to habitual use, post-adoptive use, and problematic use.

Table 3.2: Construct difference

Properties	**Technology induced use**	**Problematic Use**	**Post adoptive use**	**Automatic Use**
Agency of use	A combination of human and technology agency	No human agency and unclear technology agency	Human agency	No human agency and unclear technology agency
Control over behaviors	Low	Low	High	Low
Usage pattern	Adaptive	Maladaptive	Adaptive	Adaptive
Initiation of use	Curiosity	Compulsion	Intention	Automatic
Prior use of technology	Not a necessary condition	A necessary condition	A necessary condition	A necessary condition
Feedback loop mechanism of technology	A necessary condition	Not a necessary condition	Not a necessary condition	Not a necessary condition

Habitual use is users' automatic interaction with technology in the presence of a stable cue (De Guinea & Markus, 2009). Habits rely on consistent external cues. Users automatically form a link between a stable cue and use, a necessary condition for habit formation (Baucells & Sarin, 2010). Changes in cues can potentially disturb habitual use (De Guinea & Markus, 2009).

Let me compare habitual use with technology-induced use. First, technology-induced use emphasizes the role of technology in inducing human agency, whereas habitual usage emphasizes the automatic response to a steady cue. Checking an app during a study break is an example of habitual use, in which the study break functions as a stable cue. Second, habitual use does not consider need fulfillment, whereas technology-induced use does. This is due to the fact that habitual usage is driven by automaticity, while technology-induced usage is driven by the need to use technology. Third, technology-induced use operates in a dynamic, not stable, environment. The environment is continually altering features and recommendations in response to user needs. The formation and maintenance of habitual use, however, do not require a dynamic environment. Habitual use and technology-induced use both require external input. Habitual use necessitates a stable external cue, but technology-induced use necessitates a dynamic environment.

Post-adoptive use is different from technology-induced use. Post adoptive use is the user's intentional use of technology to complete a task (Burton-Jones & Gallivan, 2007). This paradigm focuses on the primacy of human agency in use and argues that purpose or intention drives use (Baird & Maruping, 2021). In contrast, technology-induced use doesn't focus on the intention to use technology. Instead, technology agency focuses on the intertwinement between technology agency and human agency. TikTok, for example, learns from the way people use it. Through learning, the TikTok app matches content to what users like and encourages them to use other features. Thus, technology-induced use intimates how technological and human agency are closely intertwined. Literature on post-adoptive use focuses on social and cognitive factors that influence use (such as perceived behavioral control, perceived usefulness, perceived ease of use, social influence, and attitudes) (Limayem, Hirt, & Cheung, 2007). Technology-induced use, however, focuses on how technological features influence use.

Finally, let me compare technology-induced use with problematic use. Problematic use focuses on the negative effects of being too dependent on technology and the unhealthy ways people use it (Turel, 2016). Examples of negative consequences are conflicts at work, social isolation, and obsessive-compulsive disorder. The focus of technology-induced use, in contrast, is on the need to use technology, not on the negative consequences when people use it.

According to past research on problematic usage, cognitive dysfunction causes problematic use (Turel, 2016). However, technology-induced use is driven by technological features. Problematic use shares one property with technology-induced use: both types of use assume that users seek the fulfillment of needs in the form of rewards (networking, steaks, likes, etc.).

Overall, I suggest that technology-induced use is a distinct construct with several distinct properties not found in other constructs established in the IS research. Table 3.3 on the next page describes contrasting scenarios for each construct.

Table 3.3: Example of scenarios in the app context

	Technology-Induced use	Problematic use	Automatic use	Post adoptive use
Scenario	Jack is 18 years old and uses Snapchat on his phone. He receives at least two notifications from the Snapchat app every hour. He opens those with a curious mindset and checks what is going on.	Zara uses the Clash of Titan app excessively. She interacts with the app during most of her class days. Although Zara tries to reduce the interaction time, she does not succeed, making her feel sad and irritated. She sometimes plays while she is in traffic. Once, she has a minor car accident because of inattention while driving. She promises that she will not interact with the app. However, she starts playing again during most of the class day.	William has started using a gaming app in the last two months. In the beginning, he used the app whenever he finished his homework. However, after one month, his fingers automatically reach for the app whenever he gets any homework.	Max has been using the Workday app on his phone since he started his new job. He routinely uses the workday app five hours daily to communicate with his clients.

Continuum of Technology induced use

Based on its definition, assumptions, and properties, I argue that technology-induced use ranges in the continuum illustrated in table 3.4. This continuum can be divided into three blocks: no technology-induced use, technology-induced use, and high technology-induced use.

The first block indicates goal-directed or purposeful conduct independent of technological features. For example, a person has a prior goal (conducting business) to transfer money from a bank account. After considering multiple options to send money, the person chooses PayPal, a mobile payment app. To send money for business purposes (a prior goal), the person uses PayPal (feature use). The example indicates that a prior goal can influence users to use the app, indicating no technology-induced use.

Table 3.4: Continuum of technology-induced use

Blocks	Description	Locus of control	Features that may drive such use
No Technology induced use(TIU)	Purposeful use	Prior goal	Search, payment, tracking
Technology-induced use (TIU)	Curious to fulfill needs	Somewhat features	Networking, Chatting, Points, badges, progression
High Technology induced use(TIU)	The intense need to fulfill needs	Features	Notifications, Recommendations

The second block is technology-induced use. This is characterized by the influence of technological agency on human agency. Some technological features influence human agency by stimulating users' curiosity to fulfill their needs. For instance, gamification features in the Pokemon Go app can motivate users to walk through their city to meet the challenge of "catching them all." Networking features in the Pokemon Go app can stimulate users' curiosity to make friends with others they might otherwise never have met. In this block, users require initial curiosity to meet their needs. Technological influence on human agency is not as strong as in the third category.

The third block indicates high technology-induced use. In this block, technology features create an intense need to use the technology. Such a block indicates high human agency. For example, notification features can create an intense need to use an app. Another example of high technology-induced use is playing chess with a gaming app. The chess game app constantly monitors users' actions and prompts them to act.

The domain of Technology-Induced Use, Reflected by Feature Categories

A technology feature is a ready-to-use technological artifact (Benlian, 2015). Features afford users the ability to perform a specific activity on a technological platform. I conducted a qualitative coding analysis on 30 apps to identify common feature categories, collecting feature descriptions from them using App Annie, an app analytic platform. These 30 apps were chosen representatively from 5 categories: social media, entertainment, health and fitness, photo and video sharing, games, and dating. Each app belongs in the top 20 charts on the App Annie website. Table 3.5 provides the list of apps.

Table 3.5: List of apps in the study

Category	List of Apps
Social Media	TikTok, Facebook, Instagram, Snapchat, Reddit
Entertainment	Netflix, Amazon Prime Video, Disney, Hulu
Health & Fitness	Fitbit, Google Fit, Nike, Calm, FitCoach & Diet
Photo & Video	YouTube, Google Photos, FaceApp, Amazon Photo, Shutterfly
Game	Pokemon Go, Temple Run, Clash of Clans, Wordle, Airport Security
Dating	OkCupid, Tinder, Hinge, Bumble, Badoo

My goal in conducting qualitative coding analysis was to identify common feature categories that induce users to use apps. To do so, I collected all feature descriptions from App Annie. App Annie highlights the name and function of features for each version of an app. For example, TikTok had 25 versions until June 10, 2022. In each version, TikTok includes new features or modifies old features. I collected all of the discussions related to apps and imported those discussions into a word file. I considered each app as a case in the qualitative study.

Next, after collecting feature descriptions, I followed grounded theory procedures to encode each feature description (Strauss & Corbin, 1998). Specifically, I followed open, axial, and selective coding methods to analyze the app description (Strauss & Corbin, 1998) using NVivo data analysis software. In the beginning, I open coded the description of features. After reading each line of a feature description, I provided a label. For example, the following is a description collected from App Annie: *"Watch an endless amount of videos customized specifically for you"* (Collected from App Annie). I labeled this line during the open coding stage as "customized content." Each separate entry received a memo in deeper detail. This open code highlights that the narrator is describing a content recommendation feature. In the above example, I wrote that TikTok provides customized content recommendations to users.

After coding all the descriptions, I engaged in axial coding. Axial coding helps identify underlying categories based on open codes. For example, based on the two open codes, "customized content" and "content based on one's last visit," I formed a category called "content recommendation." Based on the constant comparison and through inquiry, I identified 14 categories in the axial coding: sharing, following, chatting, record keeping, control, gamification, search, security settings, display settings, social recommendation, product recommendation, place recommendation, notification, and invitation.

Finally, I used selective coding to abstract and generalize these categories. I also used literature to guide me in parsing common themes. In this phase, I tried to find the similarities and differences among the categories. After this, I found four major categories of features: input-dependent features, task control features, recommendation features, and prescriptive features. These feature categories are consistent with the existing literature that develops feature set categories based on the technological agency (Baird & Maruping, 2021). Table 3.6 reports the first order codes, categories, and major categories after conducting open, axial, and selective coding.

Table 3.6: Data structure

First order codes	Categories	Major Categories
▪ Private information share ▪ Emotion share ▪ Fact share	Share	Task control feature
▪ Follow friends ▪ Follow products ▪ Follow celebrity	Follow	
▪ Chat with friends ▪ Exchange message	Chat	
▪ Store on cloud ▪ Store on my lists	Record	
▪ Block ▪ Increase visibility	Control	
▪ Time constraint ▪ Points ▪ Badges	Gamification	
▪ Scroll ▪ Find an object	Search	
▪ Set up security ▪ Control privacy	Security settings	Input dependent feature
▪ Change color ▪ Change brightness	Display settings	
▪ People like you ▪ People you may like	Social recommendation	Recommendation
▪ Product one may like ▪ Product based on one's past purchase	Product recommendation	
▪ Customized content ▪ Content-based on one's last visit	Content recommendation	
▪ Notification from friend ▪ See more ▪ Watch more ▪ Alerts ▪ Discover	Notification	Prescriptive
▪ Invite your friend ▪ Join live now	Invitation	

After identifying the major feature categories, I defined these based on notes, memos, and existing literature. While developing their agentic artifacts archetypes, Baird and Maruping

(2021) used the intelligence of archetypes themselves to define them. Intelligence indicates how a feature can make an autonomous decision based on algorithms and usage data. In addition to intelligence, my notes and memos indicated that another dimension that could be used to define features is interactivity, the degree to which a feature can interact with users. Based on these two dimensions, I defined four major categories. Table 3.7 defines those major categories along with the features related to the major categories identified during open coding.

Table 3.7: Definition and examples of the type of features

Types	Definition	Example
Input dependent feature	A type of feature that is not dynamic and that only performs activities based on input given by a user	Security settings, display setting
Task Control Feature	A type of feature that is dynamic and that helps users to perform a task effectively	Gamification features, social networking
Recommendation Feature	A type of feature that is dynamic and that can proactively advise different options to a user	Content recommendation, social recommendation
Prescriptive Feature	A type of feature that is dynamic and that can prescribe what a user needs to do or act	Notification, invitation

I define an input-dependent feature as a static feature that can only perform activities based on input provided by a user, for example, security settings, color settings, and brightness settings. These features are not highly interactive and intelligent. Input-dependent features have a lower ability to induce users.

Next, I define a task control feature as a dynamic feature that helps a user perform a task effectively, for example, gamification features, sharing, and following. Task control features are very interactive and can involve in inducing users significantly.

Next, we have recommendation features, defined as dynamic features that can proactively advise different options to a user, for example, content and social recommendation. These features are very interactive and have a high degree of intelligence, and thus have a greater ability to induce users.

Finally, I define a prescriptive feature as a dynamic feature that can prescribe what a user needs to do or act. For example, notifications, alerts, invitations, and so on are examples of prescriptive features. These features are very interactive and have a high degree of intelligence; therefore, they have a high degree of user inducement ability.

After defining those major categories, I identified what feature categories could be regarded as dimensions of technology-induced use. To do so, I developed a matrix of features based on two dimensions. Figure 3.5 displays the matrix, indicating two dimensions: intelligence and interactivity, which we have found to be significant in the qualitative coding analysis. The matrix indicates that prescriptive and recommendation features are highly intelligent and interactive. Some task control features are highly interactive but limited in intelligence. Finally, input-dependent features are neither interactive nor intelligent.

	Intelligence of Features		
Interactivity of Features		**Expanded Decision making**	**Limited Decision making**
	Highly interactive	1. Prescriptive Features 2. Recommendation Features	4. Task control feature (Gamification type features)
	Low interactive	3. Task control feature (Social networking type features)	5. Input-dependent feature (low interactive)

Figure 3.5: The matrix of feature clusters

The matrix presented in figure 5 identifies potential dimensions of technology-induced use. According to the matrix, prescriptive, recommendation, and task control features have higher interactivity and intelligence capability than input-dependent features. This means that input-dependent features may not be able to induce users, as users only use them to improve the usability of apps. Given the characteristics of input-dependent features, these are not included as a dimension of technology-induced use. Thus, technology-induced use has three dimensions: prescriptive, recommendation, and task control features.

The Domain of Technology-induced Use, Reflected by Usage Behaviors

After identifying three major feature categories, I also observed that these feature categories elicit a range of app usage behaviors. For example, the sharing feature, a part of the task control feature category, can influence social behavior. Moreover, I found that the content recommendation feature, a part of the recommendation feature category, can influence novel experience-seeking behavior. To understand these feature-induced usages more deeply, I decided to conduct a written interview. I used a range of questions to identify feature-induced usage behaviors, such as, "What part or feature of an app makes you return to it? How do you explain your app usage behavior?" After developing interview question sets, I conducted 28 written interviews via email. After receiving their answers, I followed grounded theory methodology coding procedures to understand the interviewee's responses more deeply. I conducted three types of coding: open coding, axial coding, and selective coding (Strauss & Corbin, 1998).

At the beginning of open coding, I read each line in the interview and provided a code. For example, Interviewee 15, a social media user and university student, mentioned that *"Instagram's recommendation shows me the information I am looking for/ information that I wasn't looking for but am glad to find the knowledge on."* Interviewee 15 pointed out that the recommendation feature induced her toward information acquisition behavior. I used open code "Learning latest information" to label this line.

Elsewhere, Interviewee 11, a social media user and university student, mentioned that *"Snapchat's social networking feature allows me to communicate with friends in multiple ways,* *whether that is via messages, pictures, or videos."* Interview 11 points out that social networking features, which belong to task control features, induce her to communicate with her friends. I used open codes, such as "chatting with friends" and "communicating with others," to label this information.

Additionally, Interviewee 8, a social media user and university student, mentioned that: *"Twitter's notifications notify me to check my friends' interactions with me on the app."* Interviewee 8 points out that notification features, features that belong to prescriptive features, induce her to learn about her friends. I used open code "Learning what friends are up to" to label this line.

I found a total of forty-eight codes in the open-coding stage. After encoding all of the descriptions, I started conducting axial coding. Axial coding helps us identify the underlying categories based on open codes. For example, based on the three open codes "Learning latest information," "Learning global information," and "Learning product information," I formed a category called "News learning." During the process of axial coding, I used constant comparison and asked questions to identify categories. In total, I found nine categories: sharing, following, chatting, commenting, liking, experience-seeking, performance improving, point-seeking, news learning, and trend learning.

After conducting axial coding, I engaged in selective coding to make those categories abstract. Based on the similarities and differences among those categories, I found three major categories of technology-induced usage behavior: induced reward-seeking behavior, social behavior, and learning behavior. I define induced reward-seeking behavior as individuals' engagement in pursuing rewards in the form of content, experience, points, badges, progression, and the like, primarily stimulated by technological triggers. I define induced social behavior as individuals' involvement in connecting with other people, primarily stimulated by technological triggers. Finally, I define learning behavior as individuals' acquisition and consumption of information, concepts, and knowledge about the world, people, and hobbies, primarily stimulated by technology triggers. Table 3.8 reports the results of the coding.

Table 3.8: Data structure

First order codes	Categories	Major Categories
▪ Sharing posts ▪ Sharing	Sharing	Induced Social behavior
▪ Following posts ▪ Following celebrities	Following	
▪ Chatting with friends ▪ Chatting with family	Chatting	
▪ Commenting on other's posts ▪ Commenting on a product ▪ Communicating with others	Commenting	
▪ Liking other's posts ▪ Liking products	Liking	
▪ Seeking novel experience ▪ Seeking pleasurable experience	Experience seeking	Induced Reward seeking behavior
▪ Performing a task effectively ▪ Achieving a goal	Performance improving	
▪ Getting badges ▪ Getting points	Point seeking	
▪ Learning latest information ▪ Learning global information ▪ Learning product information	News learning	Induced Learning behavior
▪ Learning what's friends are up to ▪ Learning current style	Trend learning	

Based on the interviewee descriptions, I identified that some features drive reward-seeking behavior, some drive social behavior, and others drive learning behavior. Figure 6 illustrates the linkage. According to interviews, the features of invitation, notification, content, and product recommendation induce users' reward-seeking behaviors. In response to those features, users seek new experiences, points, and badges. Share, follow, and chat features primarily induce users' social behaviors. In response to those features, users like to communicate and share information with others. Finally, I observed that notification, invitation, and search features primarily induced users' learning behavior. In response to those features, users like to acquire information and gain knowledge about the social and physical world.

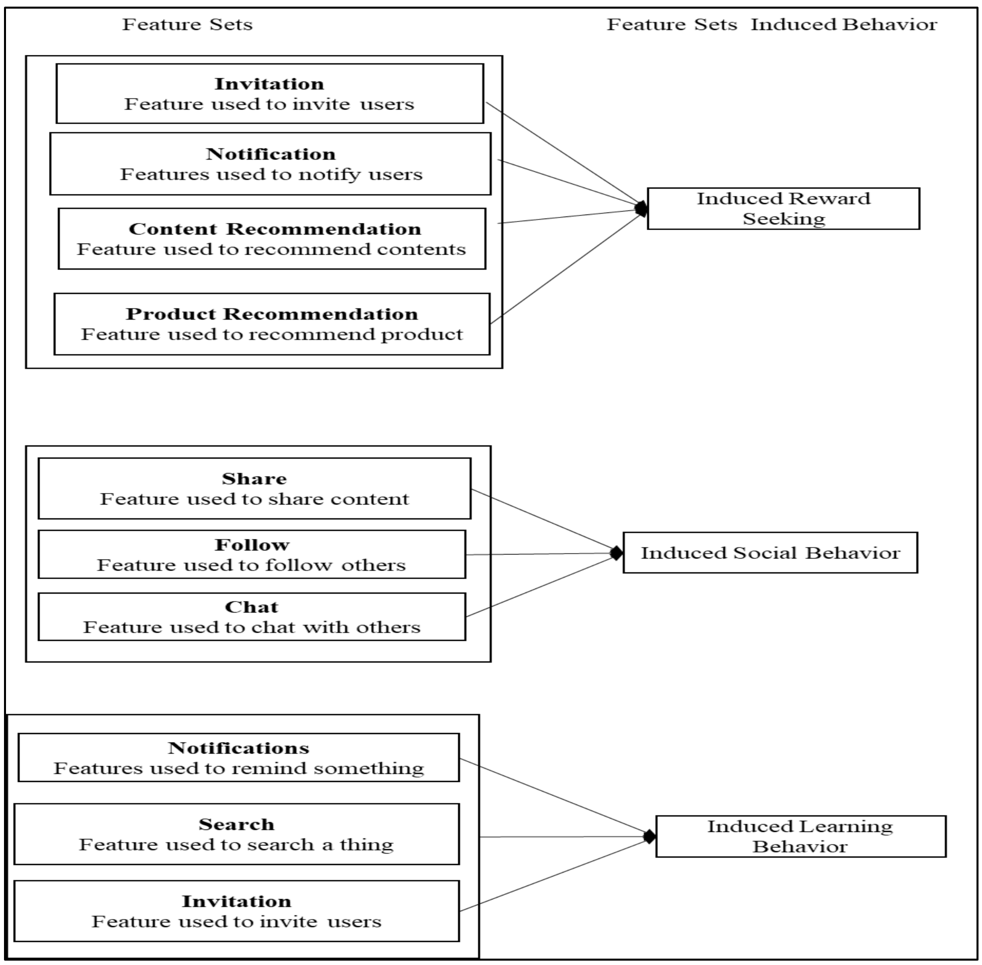


Figure 3.6: Linking feature sets with induced behavior

The three major technology-induced use categories are consistent with different app-related behaviors discussed in the existing literature. I conducted a literature review concerning different types of app usage behaviors. The review indicated several behaviors, such as following, sharing, networking, receiving rewards, and learning trends. I found that those behaviors are consistent with the three major behaviors identified in the interview process. Table 9 indicates the findings of our literature review.

Table 3.9: Different app-induced behaviors in literature

Study	Context	Behaviors
Karahanna et al. (2018)	Social media app	Following, sharing, commenting, monitoring,
Ghose et al. (2022)	mHealth app	Networking, learning, communicating
Jung et al. (2019)	Dating app	Learning, following
Smink et al. (2022)	Augmented Reality App	Receiving points, monitoring progress
Matrix (2014)	Entertainment app	Watching movies, learning trends, sharing
James et al. (2019)	Fitness app	Networking, connecting, information monitoring, information retrieving
Zheng et al. (2018)	Gaming app	Constant progressing, receiving points, achieving levels

The three emerging categories are consistent with existing theories, such as the psychological need theory. Psychological need theory, which is extensively used in IS literature, predicts those three types of behaviors based on an individual's needs (Karahanna, Xu, Xu, & Zhang, 2018). According to this theory, fulfillment of psychological needs is associated with an individual's well-being (Ryan & Deci, 2000). The major types of psychological needs are the need for autonomy, need for connectedness, and need for competence. The **need for autonomy** is an innate desire to be in control (Karahanna et al., 2018). Features like notifications and recommendations induce users to learn about social and physical worlds. Learning information induced by those features can fulfill the need for autonomy since it provides independence and a sense of control over when and what they learn (Octaberlina & Afif, 2021). Next, the **need for**

connectedness is an innate need to relate with others (Karahanna et al., 2018). Features such as share, like, and comment can help connect users with others and fulfill the need for connectedness. Finally, the **need for competence** is an innate need to feel to be effective in an environment (Karahanna et al., 2018). Features, points, and badges can give users a sense of achieving something, such as new experiences, new skills, etc. Overall, the dimensions of technology-induced use are consistent with the psychological need theory.

Development and Validation of Technology-Induced Use Measurements

To develop measuring instruments for technology-induced use, I followed the procedure described by MacKenzie et al. (2011), which provides a rigorous guideline for conceptualization, development of measures, model specification, scale evaluation, validation, and norm development. Figure 3.7 illustrates the 10-step procedure.

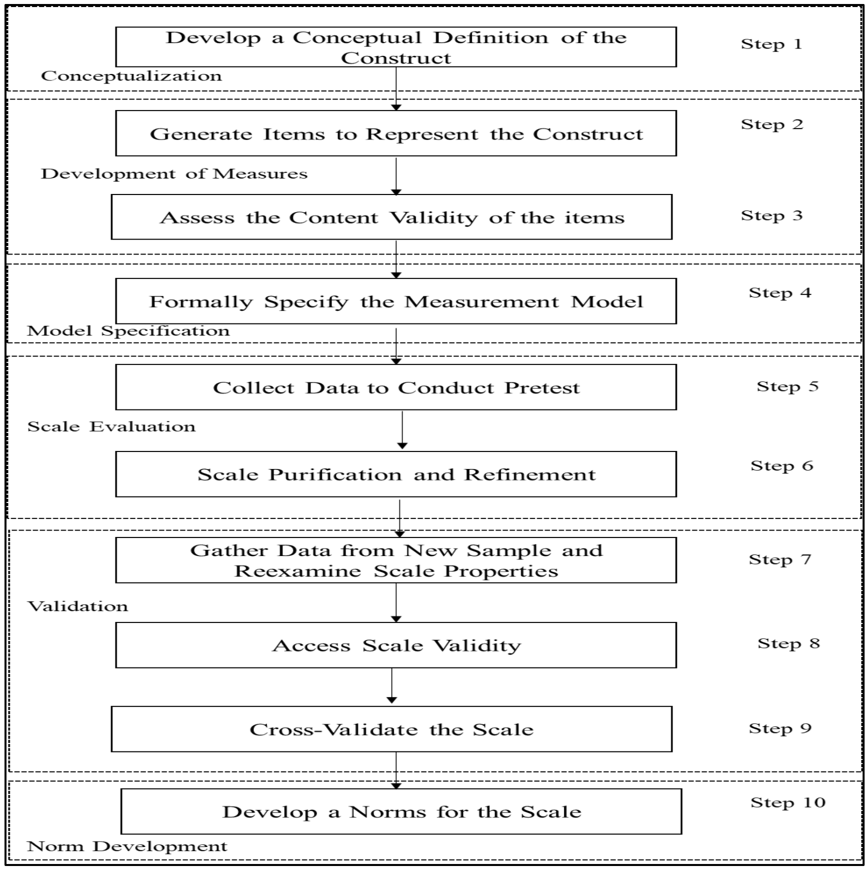


Figure 3.7: Ten-step procedures

Step One: Conceptualization

In the early stages of instrument development, Mackenzie et al. (2011) recommend the following five activities: a) review of literature, b) specify the domain of the construct, c) specify the conceptual theme of the construct, and d) provide a definition based on prior literature, interviews, and other sources of data. Accordingly, I used literature, interviews, and archival data to conceptualize technology-induced use.

I conceptualize technology-induced use in two categories: a) the ability of technology to induce users and b) the inducement of users to technology. Using these two categories, I define technology-induced us as an individual’s use of technology to fulfill situational and innate needs, primarily stimulated by technology triggers. Table 10 summarizes the conceptualization.

Table 3.10: Step 1 of Mackenzie et al. (2011)

Factors considered in step 1	Findings
Focal construct in past research	▪ The focal construct is absent in the academic literature ▪ The focal construct has been discussed in practice literature without any label. ▪ The fundamental meaning of the construct: use
Nature of the construct's conceptual domain	▪ Construct domain: technology use ▪ Entity= person ▪ General property= behavior
Conceptual theme of the construct	▪ Common attributes: 1) technology can induce users to use technology 2) an individual inducement to technology
Definition	▪ An individual's use of technology to fulfill her situational and innate needs, primarily stimulated by technology triggers.

The domain of technology-induced use can be viewed from two perspectives: the influence of features on use and the user behavior perspective. Three subdomains exist within the feature driven use perspective: prescriptive feature-driven use, recommendation feature-driven use, and task control. I find three subdomains within the user behavior perspective: induced reward-seeking behavior, social behavior, and learning behavior. The definitions of these dimensions are given in table 3.11.

Table 3.11: Definition of dimensions

Types	Definition
Task Control Feature Driven Use	Individuals use of technology to fulfill situational and innate needs, primarily triggered by features that are dynamic and that help users perform a task effectively
Recommendation Feature Driven Use	Individuals use of technology to fulfill situational and innate needs, primarily triggered by features that are dynamic and that can proactively advise different options to a user
Prescriptive Feature Driven Use	Individuals use of technology to fulfill situational and innate needs, primarily triggered by features that are dynamic and that can prescribe what a user needs to do or act

I propose that technology-induced use is a unidimensional construct from both perspectives since it focuses solely on the need to use a technology triggered by technology triggers instead of focusing on the use of a specific feature or the performance of a feature. As the number of innate and situational needs changes, the use of different types of features changes accordingly. Technology-induced use focuses on general app-induced behaviors stimulated by technology triggers instead of specific behaviors such as reward seeking. As the number of innate and situational needs change, a user may exhibit different behaviors, not restricted to reward-seeking, social, and learning.

Step Two: Generate Items to Represent Construct

The next phase is to generate items (MacKenzie, Podsakoff, & Podsakoff, 2011). I developed a set of representative items that can tap into the nature of technology-induced use using interviews, definitions, and conceptualizations of technology-induced use from chapter one. I developed representative items of technology-induced from the two domains of technology features and user behavior. Initially, I developed 18 items for feature-based measurement and 19 items for behavior-based measurement. Table 3.12 and Table 3.13 report the initial pool of items.

Table 3.12: Items of feature-based measure

Dimensions	Initial items
Prescriptive Feature	1.The app notification stimulates me to check the app
	2.The alert from an app makes me want to check the app
	3.The invitation message from an app makes me want to check the app
	4.The find out more feature stimulates to check the app
	5.When the app displays my achievement, I feel stimulated to check the app
	6.The never-ending feed feature makes me want to check the app
	7.The watch more message drives me to check the app
	8.The trending now message stimulates me to click on content in the app
Task control feature	9. The rank feature (score, status in a network) of the app makes me check my position in the app constantly
	10.The award (in terms of points, badge) message of the app prompts my desire to spend time in the app
	11. The level up (level 1, 2 - progression) feature of the app gives me a need to interact with the app
	12. The tagging feature of the app makes me want to use the app
	13. The networking feature of the app makes me use the app constantly
	14.The Friend's Feed feature of the app stimulates me to click on content in the app
	15. The social monitoring feature of the app makes me want to use the app
Recommendation feature	16. The matching feature of the app makes me want to click on the content in the app
	17. The personalization feature of the app stimulates me to click on content in the app.
	18. The What Friend's Like feature of the app stimulates me to click content within the app

Table 3.13: Items of behavior-based measure

Dimension	Items
Induced reward seeking	1. I search for rewards (points, badges, pleasure) in the app induced by the notification feature
	2. I search for varied content in the app motivated by the invitation feature
	3. I pursue rewards in the app because of the level-up (progression) feature
	4. I discover rewards in the app because of the "Find out more" feature
	5. I explore new content in the app because of the recommendation feature
Induced social behavior	6. I connect with a community in the app because of social features
	7. I make new friends in the app impelled by social features
	8. I communicate with my friends in the app, motivated by social features
	9. I invite new friends to the app motivated by the invitation feature
	10. I reach out to people in the app induced by the recommendation feature
	11. I seek validation from friends in the app stimulated by the feedback feature
	12 I communicate with people in the app influenced by the matching feature
	13.I convey information to my friends influenced by sharing feature
Induced learning behavior	14. I learn about the world in the app prompted by the never-ending content feature"
	15. I learn about the world in the app because of the notification feature
	16. I acquire information about my acquaintance in the app, enticed by the information updating feature
	17. I inquire about my friends and acquaintances in the app, enticed by the comparison (i, e, follower, following) feature
	18. I gain insight about people in the app influenced by the "Learn More" feature
	19. I gain insight about people in the app influenced by the content recommendation feature

After developing items, we conducted face validity of the items. The goal of face validity is to investigate whether item wording is sufficiently precise. During the face validity check, participants aren't asked to evaluate an item but to identify if an item is difficult to understand. According to MacKenzie et al. (2011) ambiguous items should be clarified in this stage. I conducted a face validity check by surveying students. Twenty undergraduate students participated in the face validity checking. Before conducting the face validity test, I provided participants with a thorough explanation of the study's context and goals to ensure that they understood the items. I asked that all of the items be rated as "Easy to Understand" or "Confusing." Furthermore, I asked participants to write down wording if they thought anything needed to be changed. Following the face validity check, I changed the wording of several items that participants found confusing.

Step Three: Assessment of Content Validity

The third step is to assess the content validity of the construct in order to identify how the item fits, conceptually, to the construct. Mackenzie et al. (2011) defined content validity as "the degree to which items in an instrument reflect the content universe to which the instrument will be generalized." MacKenzie et al. (2011) recommended addressing two questions in step three: 1) *Is the individual item representative of an aspect of the content domain of the construct?* and 2) *Are the items as a set collectively representative of the entire content domain of the construct?*

To address those two questions, it is recommended to use the procedure developed by Hinkin and Tracey (1999). This approach employs a matrix in which items are arranged in rows and constructs definitions are listed at the top of columns ((Hinkin & Tracey, 1999). Then, raters identify the extent to which each item captures the construct domain using a numeric rating scale (1 *very low* to 5 *very high*). Tables 3.14 and 3.15 illustrate the matrix used in the content validity check.

Table 3.14: Content validity check of initial items (feature-based)

	Prescriptive feature-driven use	Task control feature-driven use	Recommendation features-driven use
1. The notification from Instagram app reminds me to check the app	5	1	2
2. The alert from Instagram app makes me check it	5	1	1
3. Receiving an invitation from Instagram app makes me to check the app	4	1	4
4. The find out more request from Instagram app makes me want to check the app	4	2	4
5. The check now message from the Instagram app makes me want to check the app	5	1	1

Table 3.15: **Content validity check of initial items (behavior-based)**

	Induced reward-seeking behavior	Induced social-behavior	Induced learning-behavior
1. I search for rewards (e.g., points, badge, pleasure) in the app stimulated by the notification feature	4	1	2
2. I search for contents in the app stimulated by the invitation message	5	3	1
3. I pursue rewards in the app because of the progression (level 1, 2) feature	4	1	4
4. I discover rewards in the app because of the alert message	4	2	4
5. I explore new content in the app because of the recommendation feature	5	1	1

Following MacKenzie et al. (2011), I created a matrix with the subdomain definitions (e.g., induced reward-seeking, induced social behaviors, and induced learning behavior) in the columns and the items in the rows (Yao et al., 2007).

I conducted a content validity check using an online survey tool called Qualtrics. Twenty-six undergraduate students participated in this stage of content validity checking. Undergraduate students represent an accurate user population in this study since the majority of undergraduate student's report using apps frequently and spending significant amounts of time within them. I used verbal and written protocols to ensure students understood the study purpose. Verbal protocols were provided in the classroom, encompassing the purpose of the study, the construct definition, and the construct's subdomains. In addition, I added open-ended questions in Qualtrics to elicit feedback about any wording issues for each item.

After collecting data from twenty-six students, I used one-way repeated measure ANOVA to assess content validity, as Mackenzie et al. (2011) recommend. In checking the content validity for both feature-based measures, repeated one-way ANOVA revealed that an item's mean rating on a construct's subdomain differs significantly from its mean ratings from another domain (F (34, 408) = 2.2, p < .001). Given that the F test is significant, MacKenzie et al. (2011) suggest determining whether the mean rating for an item on the hypothesized subdomain is greater than the mean rating from another subdomain. I used the overall mean table to examine the distribution of item means across three subdomains; as predicted, I found that the mean for items one through seven (all of them prescriptive dimensions of feature-based measure) are higher in the prescriptive dimension than in other dimensions. The mean for items eight through 15 are highest in the task control dimension. Finally, the mean for items 16 through 18 is highest in the recommended feature dimension. Table 16 illustrates the results.

Table 3.16: Feature-based item's mean on each dimension

	Factor	Mean	Std. Deviation
Item 1	Prescriptive	4.00	1.41
	Task Control	3.89	1.45
	Recommendation	2.33	1.58
	Total	3.41	1.62
Item 2	Prescriptive	3.89	1.36
	Task Control	3.56	1.50
	Recommendation	2.22	1.48
	Total	3.22	1.57
Item 3	Prescriptive	3.78	1.56
	Task Control	2.67	1.22
	Recommendation	2.22	1.20
	Total	2.89	1.45
Item 4	Prescriptive	3.89	1.26
	Task Control	2.56	1.33
	Recommendation	2.00	.86
	Total	2.81	1.38
Item 5	Prescriptive	3.11	1.26
	Task Control	3.22	1.09
	Recommendation	2.78	1.64
	Total	3.04	1.31
Item 6	Prescriptive	3.33	1.50
	Task Control	3.22	1.30
	Recommendation	2.56	1.59
	Total	3.04	1.45
Item 7	Prescriptive	3.56	1.23
	Task Control	2.78	1.64
	Recommendation	3.22	1.48
	Total	3.19	1.44
Item 8	Prescriptive	3.44	1.50
	Task Control	3.24	1.33
	Recommendation	3.22	1.56
	Total	3.37	1.41
Item 9	Prescriptive	2.33	.50
	Task Control	3.22	1.20
	Recommendation	2.33	1.32
	Total	2.63	1.11
Item 10	Prescriptive	2.89	1.76
	Task Control	3.89	1.05
	Recommendation	3.00	1.00
	Total	3.26	1.34

Table 3.16 (Cont.)

Factor	Mean	Std. Deviation	Factor
Item 11	Prescriptive	3.22	1.20
	Task Control	3.89	1.45
	Recommendation	3.33	1.73
	Total	3.48	1.45
Item 12	Prescriptive	3.56	1.01
	Task Control	4.00	1.11
	Recommendation	2.56	1.42
	Total	3.37	1.30
Item 13	Prescriptive	2.44	1.59
	Task Control	3.56	1.23
	Recommendation	2.89	1.36
	Total	2.96	1.42
Item 14	Prescriptive	2.44	1.13
	Task Control	3.56	1.23
	Recommendation	3.11	1.36
	Total	3.04	1.28
Item 15	Prescriptive	2.67	1.22
	Task Control	2.89	1.53
	Recommendation	2.67	1.58
	Total	3.07	1.46
Item 16	Prescriptive	4.00	1.22
	Task Control	3.11	1.69
	Recommendation	4.00	1.22
	Total	3.70	1.40
Item 17	Prescriptive	3.22	1.39
	Task Control	3.22	1.20
	Recommendation	3.56	1.59
	Total	3.33	1.35
Item 18	Prescriptive	2.33	1.22
	Task Control	2.89	1.36
	Recommendation	4.00	1.11
	Total	3.07	1.38

In the case of behavior-based measures, repeated one-way ANOVA revealed that an item's mean rating on a construct's subdomain differs significantly from its mean ratings within another domain (F (36, 432) = 10.356, p < .001). As with feature-based measures, I examined the distribution of item means across three subdomains using the overall mean table. As predicted, I found that the mean for items one through five is highest in the reward-seeking dimension. In addition, the mean for items six through 13 is highest in induced social behavior.

Finally, the mean for items 14 through 19 is highest in induced learning behavior. Table 3.17 illustrates the mean table.

Table 3.17: Behavior-based item's mean on each dimension

	Factor	Mean	Std. Deviation
Item 1	Reward seeking	4.33	1.32
	Social behavior	1.78	1.30
	Learning behavior	2.00	1.11
	Total	2.70	1.68
Item 2	Reward seeking	3.67	1.32
	Social behavior	2.44	1.13
	Learning behavior	3.11	1.69
	Total	3.07	1.43
Item 3	Reward seeking	4.22	1.09
	Social behavior	1.89	1.26
	Learning behavior	2.11	1.53
	Total	2.74	1.65
Item 4	Reward seeking	4.44	1.01
	Social behavior	2.11	1.26
	Learning behavior	1.78	1.09
	Total	2.78	1.62
Item 5	Reward seeking	3.22	1.48
	Social behavior	2.33	1.32
	Learning behavior	3.00	1.73
	Total	2.85	1.51
Item 6	Reward seeking	2.00	1.41
	Social behavior	4.44	.88
	Learning behavior	1.78	.83
	Total	2.74	1.60
Item 7	Reward seeking	2.00	1.22
	Social behavior	4.33	1.11
	Learning behavior	2.11	1.16
	Total	2.81	1.57
Item 8	Reward seeking	2.00	1.58
	Social behavior	4.67	.70
	Learning behavior	2.00	1.41
	Total	2.89	1.78
Item 9	Reward seeking	1.67	1.11
	Social behavior	4.00	1.11
	Learning behavior	1.67	.86
	Total	2.44	1.50
Item 10	Reward seeking	2.00	1.32
	Social behavior	4.00	1.32
	Learning behavior	1.67	1.11
	Total	2.56	1.60

Table 3.17 (Cont.)

	Factor	Mean	Std. Deviation
Item 10	Reward seeking	2.00	1.32
	Social behavior	4.00	1.32
	Learning behavior	1.67	1.11
	Total	2.56	1.60
Item 11	Reward seeking	1.56	.72
	Social behavior	3.78	1.48
	Learning behavior	1.67	1.00
	Total	2.33	1.49
Item 12	Reward seeking	1.67	1.11
	Social behavior	3.89	1.16
	Learning behavior	2.56	1.42
	Total	2.70	1.51
Item 13	Reward seeking	2.11	1.36
	Social behavior	4.22	1.30
	Learning behavior	2.11	1.16
	Total	2.81	1.54
Item 14	Reward seeking	2.11	1.26
	Social behavior	2.56	1.42
	Learning behavior	4.11	1.16
	Total	2.93	1.51
Item 15	Reward seeking	2.33	1.50
	Social behavior	2.44	1.23
	Learning behavior	4.22	.97
	Total	3.00	1.49
Item 16	Reward seeking	2.00	1.32
	Social behavior	2.78	1.64
	Learning behavior	4.00	1.22
	Total	2.93	1.59
Item 17	Reward seeking	2.00	1.32
	Social behavior	2.11	1.26
	Learning behavior	3.89	1.16
	Total	2.67	1.49
Item 18	Reward seeking	2.00	1.32
	Social behavior	2.67	1.50
	Learning behavior	4.22	.83
	Total	2.96	1.53
Item 19	Reward seeking	2.11	1.53
	Social behavior	2.56	1.42
	Learning behavior	4.56	.72
	Total	3.07	1.63

Despite the fact that our first-round data statistically supports the initial item pools' content validity, some participants mentioned that some items had significant wording issues. To address the wording issues, I revised the wording of some items and conducted a pretest (according to Zhang et al., 2022). Three Ph.D. students participated in the pretest. Based on the feedback from this focus group, I refined several ambiguous items. In addition, I dropped items six, 11, and 14 of the feature-based measure due to significant wording issues, in addition to items 11, 17, and 18 of the behavior-based measure. Table 3.18 indicates all the dropped items.

Table 3.18: Dropped items after pretest

Feature-based measure	1. The never-ending feed makes me want to check the app
	2. The level up (level 1, 2 - progression) feature of the app gives me a need to interact with the app
	3. The Friend's Feed feature of the app stimulates me to click on content in the app
Behavior-based measure	1. I seek validation from friends in the app stimulated by the feedback feature
	2. I inquire about my friends and acquaintances in the app enticed by the comparison (i, e, follower, following) feature
	3. I gain insight about people in the app influenced by the "Learn More" feature

Step Four: Formally Specify the Measurement Model

I next formally specify the measurement model of technology-induced use. Mackenzie et al. (2011) state that the measurement model represents the relationship between indicators and focal constructs. In this step, I modeled technology-induced use as a unidimensional reflective construct since I anticipate each technology-induced use item to be strongly correlated with other items. Items should be correlated as all behaviors emerge from a single app and each behavior depends on another. For example, reward-seeking and learning behavior are correlated with each other as gaining knowledge can also be regarded as a reward. At a deeper level, the need to use a technology exists independently from usage behaviors. Any change in the need to use technology is expected to cause a change in usage behaviors.

Although I propose technology-induced use is a unidimensional reflective construct, I considered two alternative models as MacKenzie et al. (2011) recommended. Those are the three correlated three-dimensional models and uncorrelated three-dimensional models. These alternative models indicate that technology-induced use exists as a three-dimensional model in which subdimensions are uncorrelated. Thus, my proposal is a single-factor model in which all items are directly linked with technology-induced use reflectively. The alternative second model is a three-dimensional model in which each dimension is uncorrelated from the others, and the third alternative model is a three-dimensional model in which each dimension in which all three elements (from both viewpoints) are correlated with each other. Figure 8 illustrates the measurement models.

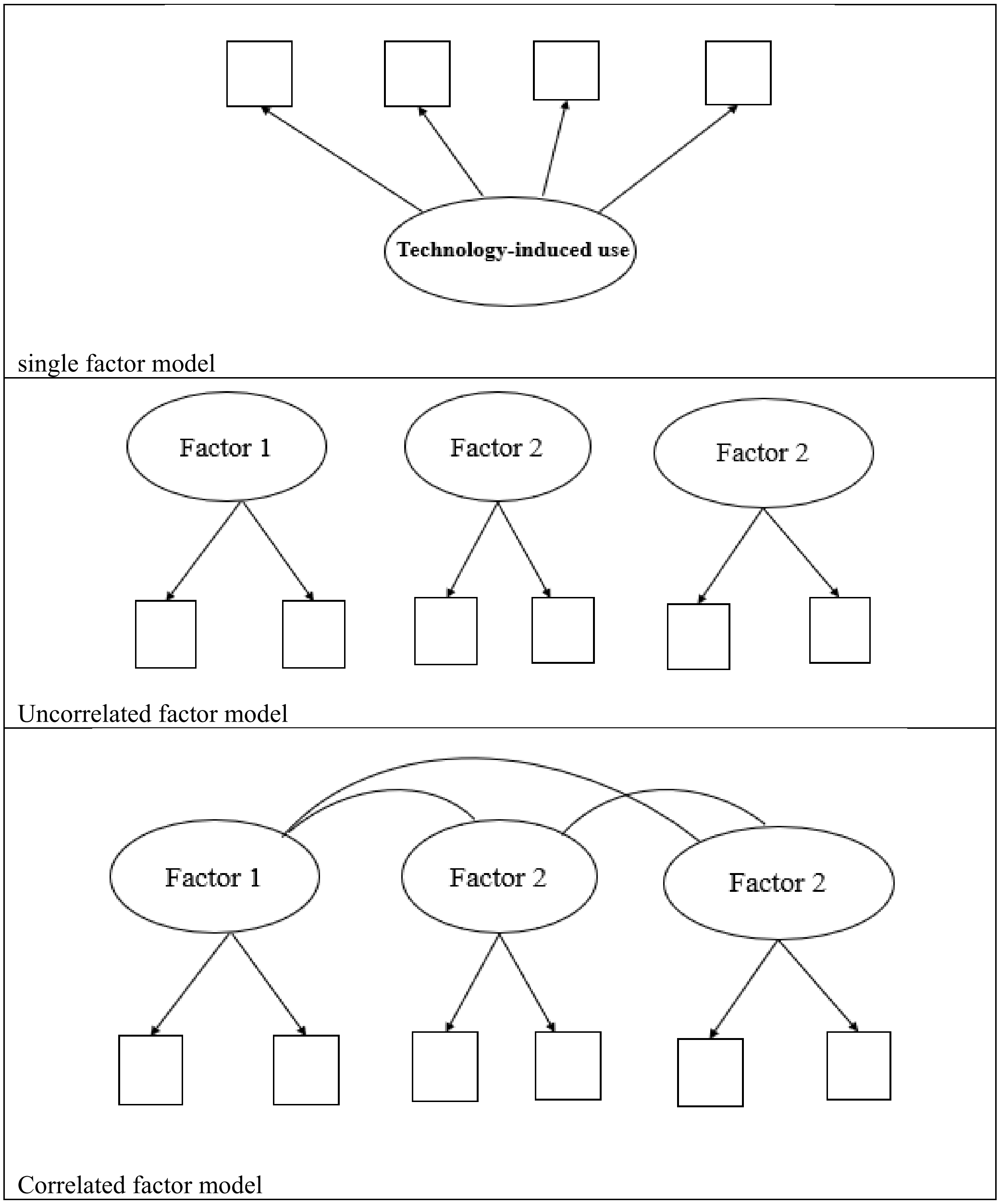


Figure 3.8: Measurement models

Step Five: Collect Data to Conduct Pretest

After revising item wording and after specifying measurement models, I conducted a pretest to refine the items using Qualtrics to gather data. During the pretest survey, I evaluated the psychometric properties of technology-induced use, such as item loadings, convergent validity, discriminant validity, and model fit. I also included several open-ended questions to identify poor items. MacKenzie et al. (2011) recommend using 100-500 participants in the pretest.

I collected the pretest survey data from undergraduate students using Qualtrics. The total number of samples was 320 app users. After collecting the survey data, I filtered the survey data based on attention check, total completion of questions, and total time spent in the survey. The average time spent on the survey was 15-18 minutes. I deleted 20 participants whose completion time was below seven minutes, in addition to 18 participants who did not complete the survey and five participants who failed the attention check (an item directing the respondent to “please select strongly disagree”). Overall, 43 samples were removed from the study. The final sample size was 277. All the items were measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Table 19 provides the demographics of the respondents. The total number of males who participated in the survey was 140 (female = 137), and the age ranged from 18 to 50.

Table 3.19: Respondent demographics of (Pretest)

Demographic	**Category**	**N=277**
Gender	Male	140
	Female	137
Race	White	219
	Hispanic	21
	African American	12
	Asian	10
	Others	15
Education	Undergraduate	277
Age	Minimum	18
	Maximum	50

I conducted an initial quantitative assessment of the reliability and validity of the scale using the pretest data, first using exploratory factor analysis (EFA) to see how each item loads with technology-induced use (both feature-based and behavior-based measures).

Behavior-Based Measure

In the beginning, I conducted EFA on behavior-based items using principal component factor analysis with varimax rotation. Table 20 reports EFA results. In the table, R2 and R3 indicate reward-seeking behavior, S1-S3 indicates social behavior, and L1-L6 indicates learning behavior. I kept the items post-EFA that had loadings above .50.

Table 3.20: Principal component factor analysis loadings of behavior-based measure (Pretest)

	TIU
R1	0.67
R2	0.72
S1	0.60
S2	0.68
S3	0.62
L1	0.64
L2	0.53
L3	0.67
L4	0.71
L6	0.66

Next, I evaluated the psychometric properties of the behavior-based measure, following MacKenzie et al.'s (2011) five-step procedure. Figure 9 summarizes the results of the five-step procedure.

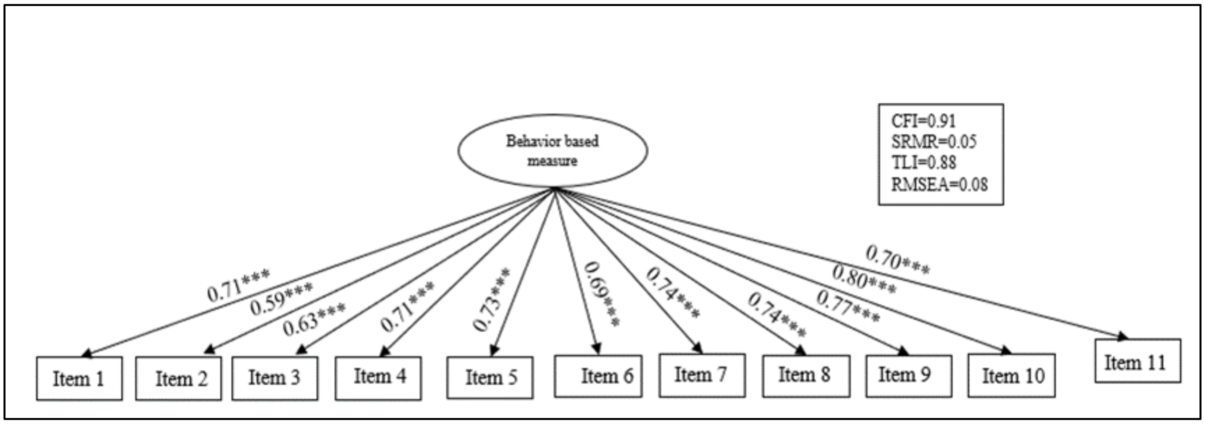


Figure 3.9: Loadings and fit indexes of behavior-based measure

The first step of evaluating psychometric properties is to check the loadings and fit indexes. Figure 10 indicates that all the loadings of behavior-based measures are above .63. The fit indices show that *CFI* > .90, *RMSEA* < .08, and *SRMR* < .08. I also calculated AVE, Cronbach's alpha, and composite reliability. Table 21 summarizes the findings.

Table 3.21: Descriptive and Psychometric properties of behavior-based measure (Pretest)

	Mean	Std.	Loadings	P<0.5	AVE	Composite Reliability	Cronbach Alpha
R1	3.79	1.60	0.71	Yes	0.505	0.68	0.91
R2	3.40	1.71	0.59	Yes			
S1	4.35	1.70	0.63	Yes			
S2	3.86	1.76	0.71	Yes			
S3	3.90	1.68	0.73	Yes			
L1	4.70	1.53	0.69	Yes			
L2	4.14	1.74	0.74	Yes			
L3	4.46	1.52	0.74	Yes			
L4	4.48	1.61	0.77	Yes			
L5	4.46	1.59	0.80	Yes			
L6	4.61	1.51	0.70	Yes			

Table 21 indicates that the model's average variance extracted (AVE) is above .505, and the composite reliability is .68, indicating behavior-based measurement instruments' reliability and convergent validity. In addition, the Cronbach's alpha of the measurement instrument is .91, indicating the reliability of the measurement instruments. All of the items significantly loaded with technology-induced use, and the square root of AVE is larger than the items' intercorrelation, indicating the construct's discriminant validity.

Feature-based measure

After evaluating the psychometric properties of the behavior-based measure, I focus on feature-based measurements, first conducting an exploratory factor analysis to check feature-based measure loadings. Table 3.22 reports the loadings.

Table 3.22: Principal component factor analysis loadings for feature-based measure (Pretest)

Items	TIU
P1	0.78
P2	0.79
P3	0.62
P4	0.61
T1	0.78
T2	0.78
T3	0.80
R1	0.68
R2	0.60

Next, I followed MacKenzie et al.'s (2011) five-step procedure to evaluate the psychometric properties of the feature-based measure. Figure 3.10 summarizes the results of the five-step procedure.

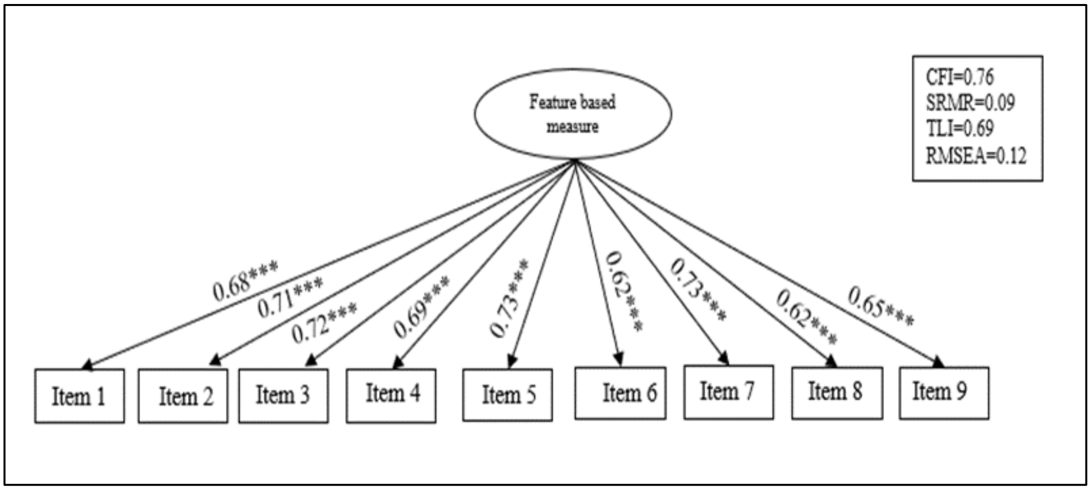


Figure 3.10: Loadings and fit indexes of feature-based measure

The first step of evaluating psychometric property is to check the loadings and fit indices. Figure 10 indicates that the loadings of the feature-based measure are all above .62. However, the fit indices show that *CFI* < .90, *SRMR* > .08, and *RMSEA* > .08. This indicates that the feature-based measures fail to meet the conventional cutoff value. Based on MacKenzie et al.'s (2011) procedure, I also calculated AVE, Cronbach's alpha, and composite reliability. Table 3.23 summarizes the findings.

Table 3.23: Descriptive and Psychometric properties of feature-based measure (Pretest)

	Mean	Std.	Loadings	P<0.5	AVE	Composite Reliability	Cronbach Alpha
P1	4.87	1.5	0.68	Yes	0.461	0.63	0.88
P2	4.34	1.5	0.71	Yes			
P3	4.43	1.66	0.72	Yes			
P4	4.43	1.65	0.69	Yes			
T1	3.55	1.67	0.73	Yes			
T2	3.38	1.66	0.62	Yes			
T3	3.30	1.80	0.73	Yes			
R1	4.90	1.48	0.62	Yes			
R2	4.61	1.56	0.65	Yes			

Table 23 indicates that the model's average variance extracted (AVE) is below .5. Although Cronbach’s alpha is in the acceptable range, the model fails to indicate convergent validity.

The results of the pretest indicated the feature-based measurement instruments require modification. Therefore, to modify feature-based measurement, a pretest (qualitative assessment) was conducted immediately following.

Step Six: Scale Purification and Refinement Through Pilot Study

I conducted a pretest (qualitative assessment) and ran study one to purify the scale and refine measurement items of both behavior-based and feature-based measures. In the beginning, I conducted the pretest (qualitative assessment), whose primary purpose was to assess some modified items’ content validity. Two Ph.D. students participated in the qualitative assessment of the measurement items. Based on their feedback, I refined the wording of several items for features and behavior-based measures.

Next, I conducted study one to refine both scales. To conduct study one, I used Amazon Mechanical Turk as it provides some anonymity of the samples, access to diverse participants, and controls for participation selection (Steelman, Hammer, & Limayem, 2014). However, there are some concerns associated with collecting data in Mechanical Turk, such as non-response bias (Steelman, Hammer, & Limayem, 2014). To reduce the bias, I took precautions, such as setting time stamps and attention checks. The initial number of respondents was 346. However, after cleaning the data based on the attention check and the time spent on the survey (less than 9 minutes), I deleted 61 samples from the dataset. The final sample size was 285. I paid $ 0.55 to each participant. The average time spent on the survey was 18- 20 minutes. The total number of female respondents was 167, while male respondents were 118. Among 285 participants, 252 were employed in the last six months.

Scale Purification of Behavior-Based Measure

In the beginning, I conducted an exploratory factor analysis on behavior-based items, again with principal component factor analysis and varimax rotation. Table 3.24 reports the results of the exploratory factor analysis of the behavior-based measure. The EFA indicates that ten items have loadings above .50.

Table 3.24: Principal component factor analysis loadings of behavior-based measure (Study 1)

Items	Loadings
Item1	0.81
Item2	0.80
Item3	0.68
Item4	0.67
Item5	0.75
Item6	0.69
Item7	0.71
Item8	0.74
Item9	0.75
Item10	0.78

Next, I used Mackenzie et al.'s (2011) five-step process to purify a scale. Those five-step processes are: a) evaluating the goodness of fit of the measurement model, b) assessing the validity of the set of indicators at the construct level, c) assessing the reliability of the set of indicators at the construct level, d) evaluating individual indicator validity and reliability. The summary of the scale purification is provided in figure 3.11.

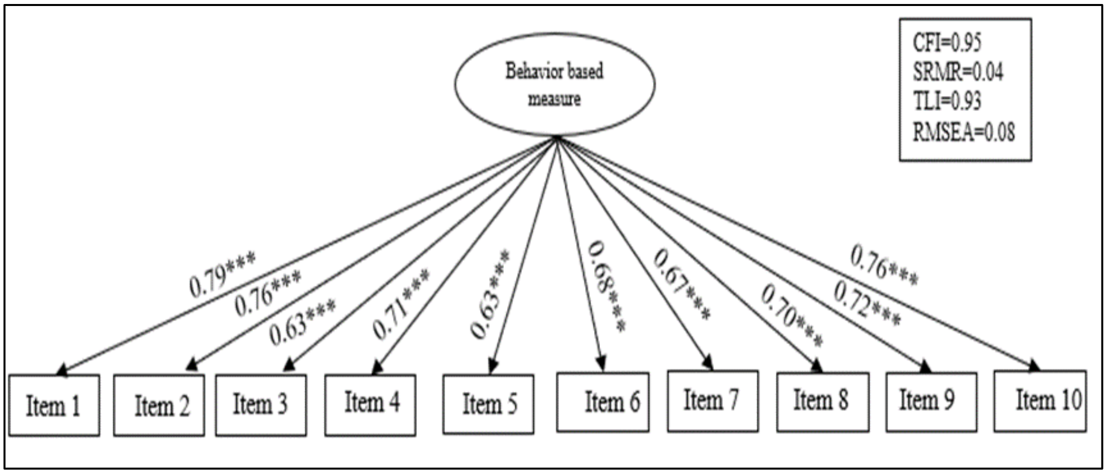


Figure 3.11: Loadings and fit indexes of behavior-based measure

Figure 11 indicates that all of the ten items of behavior-based measure load significantly with technology-induced use. CFA indicates that *CFI* > 0.90, *RMSEA* < 0.08, and *SRMR* < .08, all above conventional cutoff values. Further, the AVE of the behavior-based model is 0.501, which exceeds the limits of cutoff 0.5, indicating the indicators' validity at the construct level (provided in table 24). The square root of the AVE is higher than the correlation of items, suggesting that the model demonstrates discriminant validity. The Cronbach's alpha of the model is 0.91, indicating that the items are reliable at the construct level. Table 24 summarizes the findings.

After finding satisfactory psychometric properties of the behavior-based measure, I compared three different models of behavior-based measure. Note that the proposed model is a single-factor model. I considered two competing models: the uncorrelated three-factor model and the correlated three-factor model. After running each, I compared each model's goodness of fit index to identify which model performed well. Table 3.25 summarizes the findings.

Table 3.25: Descriptive and Psychometric properties of behavior-based measure (Study 1)

Items	Means	Std	Factor loadings	P<0.05	AVE	Composite Reliability	Cronbach Alpha
Item1	5.3	1.2	0.79	Yes	0.501	0.67	0.91
Item2	5.3	1.2	0.76	Yes			
Item3	5.4	1.2	0.63	Yes			
Item4	5.3	1.2	0.71	Yes			
Item5	5.3	1.3	0.63	Yes			
Item6	5.2	1.2	0.68	Yes			
Item7	5.2	1.1	0.67	Yes			
Item8	5.4	1.2	0.70	Yes			
Item9	5.3	1.3	0.72	Yes			
Item10	5.1	1.2	0.76	Yes			

Table 3.26 compares the correlated three-factor and the single-factor models, excluding the uncorrelated factor model since maximum likelihood procedures did not find a convergence of this model. Among the two models analyzed, the proposed model performs better than the correlated three-factor model. The goodness of fit index is more accurate and above the conventional cutoff value in the case of the single factor model.

Table 3.26: Comparison of measurement models of behavioral-based measure (Study 1)

Index	Correlated three-factor model	Single-factor model
CFI (≥.90)	0.94	0.95
SRMR (≤0.08)	0.04	0.04
TLI (≥.90)	0.92	0.93
RMSEA (≤0.08)	0.09	0.08

Overall, study one indicates that behavioral-based measures show strong statistical validity. I provide the refined items of behavior-based measures in Table 3.27.

Table 3.27: Refined items (behavior-based study) after study 1

Constructs	Items
Induced reward-seeking behaviors	1. The app contains features with the ability to provide me with new content
	2. The app includes features with the ability to provide me with exciting content
	3. The app contains features with the ability to reduce my boredom
	4. The app has features that enable me to get immediate pleasure
	5. The app has features with the ability to provide me novel experience
Induced social behaviors	6. The app contains features that enable me to follow people
	7. The app has features that enable me to appreciate others' content
Induced learning behaviors	8. The app has features that enable me to keep track of what other people are up to
	9. The app has features that enable me to gain information about the people I follow
	10. The app contains features that allow me to know more about a task I like

Scale Purification of feature-based measure

After refining behavior-based measurement instruments, I focus on feature-based measurement instruments. Note that I used study one for both behavior-based and feature-based measurements.

In the beginning, we conducted an exploratory factor analysis on feature-based items using principal component factor analysis with varimax rotation. Table3. 28 reports the results of the exploratory factor analysis of the feature-based measure. The EFA indicates that 13 items have loadings above 0.50.

Table 3.28: Principal component factor analysis loadings of feature-based measure (Study 1)

Items	Loadings
Item1	0.62
Item2	0.71
Item3	0.64
Item4	0.59
Item5	0.64
Item6	0.60
Item7	0.67
Item8	0.67
Item9	0.71
Item10	0.63
Item11	0.73
Item12	0.71
Item13	0.71

Next, I used Mackenzie et al.'s (2011) five-step process to purify the scale. The summary of the psychometric scale evaluation is provided in figure 3.12.

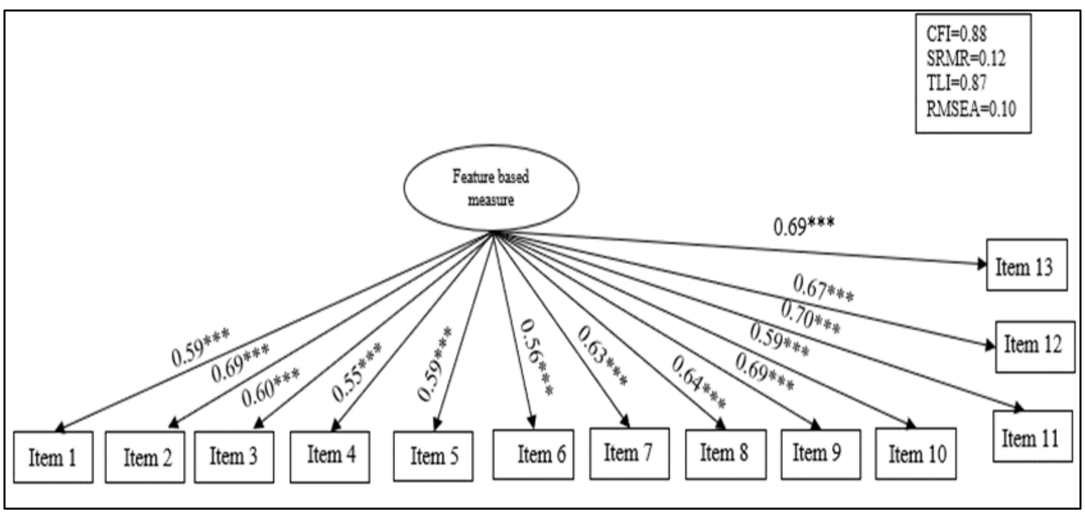


Figure 3.12: Loadings and fit indexes of feature-based measure

I first checked the CFA loadings and goodness of fit indices to evaluate the measurement instruments. Figure 13 indicates that all of the feature-based measure loadings are above 0.55.

However, the fit indices indicate that *CFI* < 0.90, *SRMR* > 0.08, and *RMSEA* > 0.08. This further indicates that the feature-based measures fail to meet the conventional cutoff value. Based on MacKenzie et al.'s (2011) procedure, I also calculated AVE, Cronbach's alpha, and composite reliability. Table 3.29 summarizes the findings.

Table 3.29: Descriptive and Psychometric properties of feature-based measure (Study 1)

Items	Means	Std	Factor loadings	P<0.05	AVE	Composite Reliability	Cronbach alpha
Item1	5.3	1.2	0.59	Yes	0.401	0.52	0.89
Item2	5.3	1.2	0.69	Yes			
Item 3	5.4	1.2	0.60	Yes			
Item4	5.3	1.2	0.55	Yes			
Item5	5.3	1.3	0.59	Yes			
Item6	5.2	1.2	0.56	Yes			
Item7	5.2	1.1	0.63	Yes			
Item8	5.4	1.2	0.64	Yes			
Item9	5.3	1.3	0.69	Yes			
Item10	5.1	1.2	0.59	Yes			
Item11	5.3	1.1	0.70	Yes			
Item12	5.1	1.2	0.67	Yes			
Item13	5.1	1.2	0.69	Yes			

Table 29 indicates that the average variance extracted (AVE) of the model is below 0.5. Although I found the Cronbach's alpha to be in an acceptable range, the feature-based measurement model fails to indicate convergent validity.

Table 30 indicates the 13 items that were used in the psychometric evaluation. Given that the feature-based measurement instrument did not meet statistical validity, I reexamined the items and conducted a qualitative assessment of the feature-based item. I found that usage of the specific context in the survey, such as "Instagram," "YouTube," and "Netflix," was problematic since some participants mentioned that they did not have experience in using those apps. To avoid confusion, I developed six feature-based items that can represent most apps, using features common to most apps in order to develop these six feature-based items, namely: notification, search, share, recommendation, follow, and infinite scrolling features. Finally, I conducted a content validity check to ensure that the items tap into the domain of the construct. To check the content validity of these new items, I asked two Ph.D. students to check the items and provide feedback, refining wordings based on feedback.

Table 3.30: Refined items (feature-based study) after study 1

Constructs	Items
Prescriptive feature-driven use	1. The "app notification" feature in the Instagram app stimulates me to look for new content
	2. The "swipe to watch more" feature in the Instagram app induces me to watch more content
	3. The "upload a photo" feature in the Instagram app induces me to upload photos
Task Control feature-driven use	4. The "share to" feature in the Instagram app stimulates me to share the content
	5. The "comment" feature in the Instagram app induces me to comment on other people's content
	6. The "follow" feature in the Instagram app stimulates me to follow individuals
	7. The "like" feature in the Instagram app induces me to like content
Recommendation features-driven use	8. Instagram's content recommendation based on my previous use stimulates me to look for the content
	9. Instagram's content recommendation based on social groups I follow stimulates me to browse the content
	10. Instagram's content recommendation based on popular topics induces me to look for the content
	11. Instagram's content recommendation based on people I follow stimulates me to browse the content
	12. Instagram's location-based content recommendation induces me to look for the content
	13. Instagram's content recommendation based on friends I communicate with stimulates me to browse the content

Step Seven: Collect Data from New Sample and Purification of Scale Properties

After refining the items from study one, I collected two waves of data (study two and study three) to reexamine and purify the scale properties. Study two is based on the instruments of behavior-based measure, while study three is based on the instruments of feature-based measure. Before conducting the study, I went through a qualitative pretest, asking two Ph.D.

students to comment on the quality of the items. Based on their feedback, I updated the wording of several items.

Behavior-based measure

I conducted study two in Amazon Mechanical Turk to further purify the scale properties of the behavior-based measure. In study two, the total number of respondents was 254. I used attention checks and time stamps to filter responses. The average time spent on the survey was 10-12 minutes. I deleted responses that took less than 5 minutes. After deleting the response based on the attention check and time stamp, the final sample size was 236. I paid each participant $0.55. Among 236 participants, 141 were male, 96 were female, and 206 were employed in the last six months.

In study two, I checked the scale's validity at the sub-domain level (three factors) and at the construct level (single factor). I first conducted an exploratory factor analysis to check the loadings. The principal component factor analysis indicated that all items of induced reward-seeking behaviors had loadings above 0.65 (eigenvalue = 3.49), social behaviors had loadings above 0.75, and learning behavior above 0.79. The cross-loadings were below 0.40. At the construct level, the loadings were above 0.65. Table 3.31 reports the results of the principle component analysis.

Table 3.31: Principal component factor analysis loadings of behavior-based measure (Study 2)

Items	TIU
R1	0.83
R2	0.79
R3	0.73
R4	0.79
R5	0.80
R6	0.69
S1	0.76
S2	0.79
S3	0.76
S4	0.80
S5	0.75
S6	0.76
L1	0.82
L2	0.81
L3	0.79

After checking the factor loadings, I used Mackenzie et al.'s (2011) five-step process of scale purification and refinement. Again, this five-step process is: a) evaluating the goodness of fit of the measurement model, b) assessing the validity of the set of indicators at the construct level, c) assessing the reliability of the set of indicators at the construct level, and d) evaluating individual indicator validity and reliability. Figure 3.13, 3.14, and 3.15 summarizes the findings.

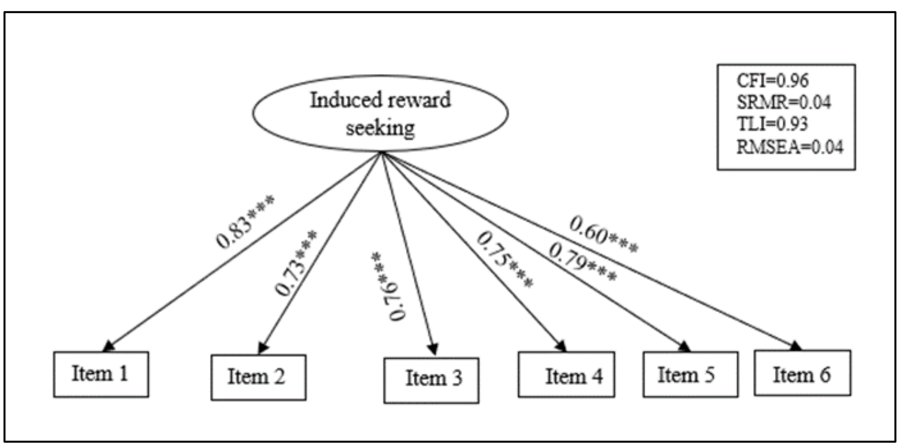


Figure 3.13: Loadings and fit indexes of induced reward-seeking measure

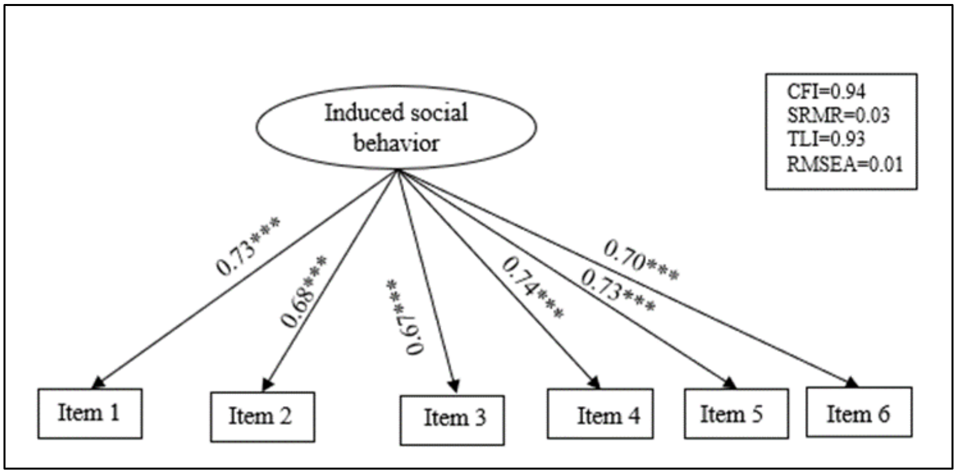


Figure 3.14: Loadings and fit indexes of social behavior measure

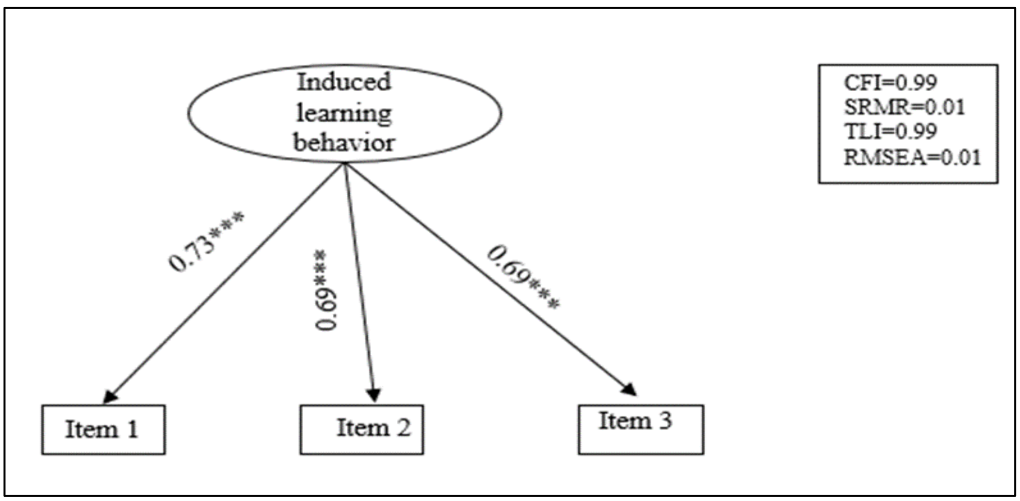


Figure 3.15: Loadings and fit indexes of induced learning behavior measure

CFA indicates that *CFI* > 0.90, *RMSEA* < 0.08, and *SRMR* < .08, indicating a good fit. Furthermore, the AVE of all three dimensions is equal to or above 0.50, indicating the model's validity of the set of indicators at the construct level (provided in table 32). The square root of the AVE is higher than the correlation of items, suggesting that the model demonstrates discriminant validity. The Cronbach's alpha of the model is above 0.77, indicating that items are reliable at the construct level. Table 32 summarizes these findings.

Table 3.32: Psychometric properties of behavior-based measure (Study 2)

Items	Loadings	AVE	Composite Reliability	Cronbach Alpha
Reward seeking				
R1	0.83	0.529	0.75	0.93
R2	0.73			
R3	0.765			
R4	0.75			
R5	0.79			
R6	0.60			
Social behavior				
S1	0.73	0.501	0.67	0.96
S2	0.68			
S3	0.67			
S4	0.74			
S5	0.73			
S6	0.70			
Learning behavior				
L1	0.73	0.501	0.66	0.77
L2	0.69			
L3	0.69			

After purifying the scale properties, I compared the proposed model (single-factor) with two alternative models (correlated three-factor model and uncorrelated three-factor model) for behavior-based measurements. I conducted confirmatory factor analysis (CFA) for each of the models. CFA indicates that the single factor model performs better than the correlated three-factor and uncorrelated three-factor models. The CFI of the single factor model is 0.97, which indicates a high degree of fit compared to the CFI of the co-related three-factor model (0.88) and uncorrelated three-factor model (0.66). SRMR, TLI, and RMSEA indices also indicate that the single factor model performs better than the two alternative models. Overall, the data support our notion that the single factor model represents technology-induced use better in contrast to the alternatives. Table 33 reports the comparison between the three models.

Table 3.33: Measurement model comparison of behavior-based measure (Study 2)

Index	**Uncorrelated three factors model**	**Co-related three factors model**	**Single-factor model**
CFI (≥.90)	0.66	0.88	0.97
SRMR (≤0.08)	.36	.05	.03
TLI (≥.90)	0.56	0.86	0.96
RMSEA (≤0.08)	.19	.09	.06

After purifying and comparing models, I finalized the following items for behavior-based measurements. Table 3.34 reports those items.

Table 3.34: Refined items (behavior-based study) after Study 2

Constructs	Items
Induced reward-seeking behaviors	1. The app contains features (e.g., notification, recommendation, infinite scrolling) that allow me to get new content.
	2. The app contains features (e.g., recommendation, infinite scrolling, watch more) that allow me to get new experience
	3. The app contains features (e.g., notification, leaderboard, chatbots) that allow me to perform tasks efficiently
	4. The app contains features (e.g., recommendations) that allow me to get my preferred content
	5. The app contains features (e.g., recommendation, search) that allow me to be involved with new actions.
	6. The app contains features (e.g., level, point, badge) that allow me to receive rewards.
Induced social behaviors	7. The app contains features (e.g., like) that allow me to appreciate others' content
	8. The app contains features (e.g., share) that allow me to share content with others
	9. The app contains features (e.g., react, like) that allow me to react to others' activities
	10. The app contains features (e.g., recommendations) that allow me to browse others' content
	11. The app contains features (e.g., follow) that allow me to follow online communities
	12. The app contains features (e.g., collaborate) that allow me to perform tasks with others
Induced learning behaviors	13. The app has features (e.g., notification, recommendation) that allow me to learn about events
	14. The app has features (e.g., search, notification) that allow me to learn about the latest news
	15. The app has features (e.g., notification, recommendation) that allow me to learn about current trends

Feature-based Measure

After conducting study two, I conducted study three to purify the scale of feature-based measurements. In study three, I used a modified set of items for feature-based measures based on the feedback form pretest. Rather than considering any context, I identified some general features of apps. I identified six general features of apps based on the feedback from participants in the pretest.

We collected study two data from Amazon Mechanical Turk. The total number of respondents was 209. After deleting the response based on an attention check, the final sample size was 142. Each participant was paid $0.50. The average time spent on the survey was 10-12 minutes. Among 142 participants, 81 were male, with 126 participants employed in the last six months. Table 35 describes the demographics.

I first conducted an exploratory factor analysis to check the loadings. The principal component factor analysis indicates that all items of feature-based measure have loadings above 0.59. Table 35 reports the EFA loadings.

Table 3.35: Principal component factor analysis loadings of general feature-based measure (Study 3)

Items	Loadings
Item1	0.62
Item2	0.71
Item3	0.64
Item4	0.59
Item5	0.64
Item6	0.60

Next, I used Mackenzie et al.'s (2011) criteria to evaluate the goodness of fit of the measurement model. The factor analysis indicates that *CFI* > 0.90, *RMSEA*< 0.08, and *SRMR* < .08, indicating a good fit. Figure 16 reports the loadings and fit index.

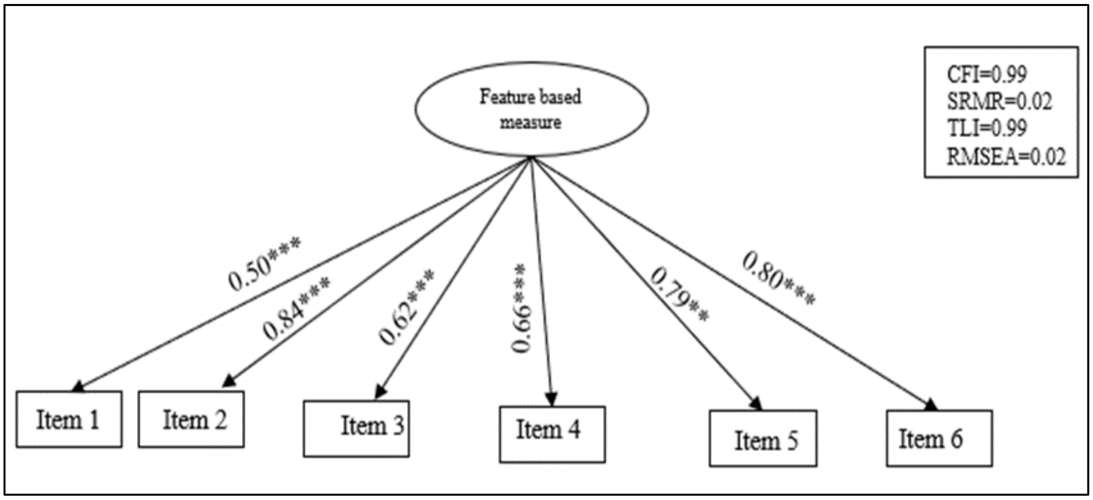


Figure 3.16: Loadings and fit indexes of feature-based measure

Next, I assessed the validity of the set of indicators at the construct level. The AVE of the model is 0.51, which exceeds the limits of cutoff 0.5, indicating the model's validity of the set of indicators at the construct level. In addition, the R-squared was 0.93, further indicating the validity at the construct level. The square root of the AVE was higher than the correlation of items, suggesting that the model demonstrates discriminant validity. The Cronbach's alpha of the model was 0.85, indicating that items are reliable at the construct level. Finally, each factor significantly loads with the constructs, indicating the reliability of each item. Table 3.36 reports the AVE, Cronbach's alpha, and composite reliability. I report the refined list of feature-based items in table 37.

Table 3.36: Descriptive and Psychometric properties of feature-based measure (Study 3)

Items	Means	Std	Factor loadings	P<0.05	AVE	Composite reliability	Cronbach Alpha
F1	5.7	.99	0.50	Yes	0.51	0.67	0.85
F2	6	.97	0.84	Yes			
F3	5.9	1.04	0.62	Yes			
F4	6.1	0.93	0.66	Yes			
F5	6	1.01	0.79	Yes			
F6	6.1	0.92	0.80	Yes			

Table 3.37: Refined items (feature-based study) after Study3

	Items
Feature-based measure	1. The notification feature of an app stimulates me to look for content
	2. The search feature of an app stimulates me to search for content
	3. The share feature of an app stimulates me to share content
	4. The recommendation feature of an app stimulates me to browse content
	5. The following feature of an app stimulates me to follow individuals
	6. The constant information updating feature of an app stimulates me to look for content

Step Eight: Assess Scale Validity

After finding that the technology-induced use scale has satisfactory psychometric properties, my next step was to determine "whether the responses to the scale behave as one would expect if they were valid indicators of the focal construct" (MacKenzie et al., 2011). To test how the newly developed construct performs, I checked its predictive validity.

To select what technology-induced use could predict, I first analyzed interviewee descriptions (28 interviews). Interviewees repeatedly mentioned the formation of habit, satisfaction, and involvement due to the inducement of technology. For example, interviewee nine, a social media user and university student, mentioned that "*The algorithm helps keep me on the app* longer *than I intend to be. It definitely formed* a *habit for me as I get on the app and scroll when I am bored."* Interviewee 9 indicates that she forms habits because of algorithmic activities.

Next, interviewee 17, a social media app user, mentioned that *"I feel a sense of satisfaction as algorithms that Instagram has maintained* on the *featured page show me things I* *would like."* Interviewee 17 indicates that algorithmic activities provide him a sense of satisfaction.

Finally, Interviewee 21, a social media app user, mentioned that "*the explore page on Instagram recommends various videos and images to me that I always get caught up and absorbed* with *looking at for long periods of time."* Interviewee 21 indicates that a feature on Instagram constantly catches her attention and absorbs her in immersive use. In summary, these interviewee descriptions indicate that habit, satisfaction, and absorption are potential outcomes of technology-induced use.

Next, I considered the conceptual domain of technology-induced use. In the domain of usage and usage-related behaviors, past studies have looked at a number of phenomena that are outcomes of usage. Several studies find that use and usage-related behavior can predict satisfaction (Rouibah & Hamdy, 2009; Zhang & Venkatesh, 2017) and habit (Lankton, Wilson, & Mao, 2010). Consistent with the literature, I tested the predictive validity of technology-induced use on satisfaction and habit, given that technology-induced use belongs to the domain.

In the domain of IT-related personality traits, past studies found that personal innovativeness with IT could lead to cognitive absorption (Agarwal & Karahanna, 2000). Consistent with this literature and interviewee description, I also tested the predictive validity of technology-induced use on cognitive absorption.

Although IS literature studies a range of variables to predict habit and satisfaction, the most dominant variable that has been used is technology use. The construct of technology use is one of the core constructs in the literature (Venkatesh, Brown, Maruping, & Bala, 2008). Although IS literature operationalizes technology use in many ways, I use a standard measurement instrument of technology use: frequency, duration, and intensity (Venkatesh et al., 2008). Frequency indicates the number of times a user uses an app (Venkatesh et al., 2008). Duration indicates the number of hours a user uses an app (Venkatesh et al., 2008). Finally, intensity indicates the number of features a user uses (Venkatesh et al., 2008). Given that technology use is the most important predictor of habit and satisfaction, I compare technology-induced use with technology use in predictive validity to test whether technology-induced use predicts over technology use.

IS literature studies many personality trait variables to predict cognitive absorption. Among different predictors of cognitive absorption, personal innovativeness with IT is the most studied predictor. The construct "personal innovativeness" indicates individual traits reflecting a willingness to try out different features (Agarwal & Karahanna, 2000). Given that personal innovativeness is a significant predictor of cognitive absorption, I compared technology-induced use with personal innovativeness in predictive validity to test whether technology-induced use predicts over personal innovativeness.

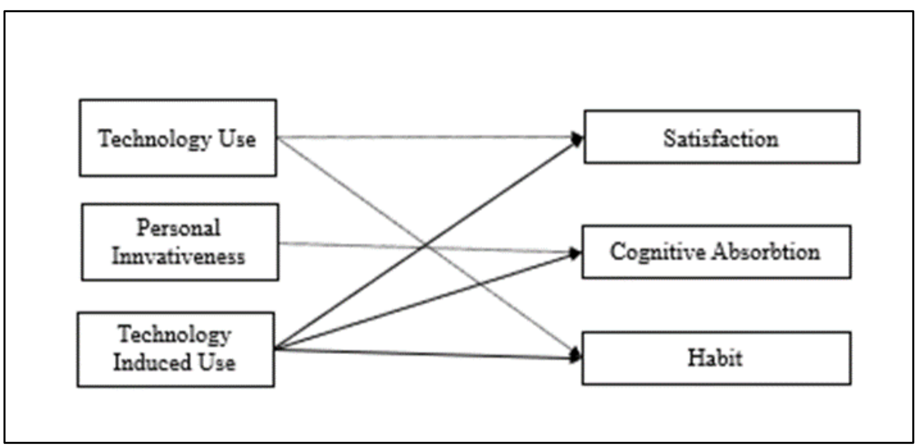


Figure 3.17: Predictive validity testing

Below, I first provide the rationale for the relationship between technology-induced use and habit, satisfaction, and cognitive absorption. Then, I provide the statistical results of predictive validity checks.

Relationship between Technology-Induced Use and Habit

I define habit as the extent to which people tend to use a technology automatically (Soror, Hammer, Steelman, Davis, & Limayem, 2015). Habit formation usually requires constant exposure to a stimulus (Polites & Karahanna, 2013). Habit literature argues that the frequency of exposure to a stimulus is necessary for habit formation (De Guinea & Markus, 2009). I previously discussed the way that apps could constantly reinforce users' choices by matching their needs with technological action possibilities. I contend that the congruence of need and action possibilities can frequently drive usage. The more reinforcement an app provides in matching needs and action possibilities based on usage data, the more likely users will form a habit (Verplanken et al., 2018). This is because repeated exposure to novel content, primarily generated through technology agency, can help to form a link between getting novel content in technology and the user's automatic response.

In predicting habit, I argue that technology-induced use will predict habit over technology use. Technology use captures the subjective usage aspect (frequency, duration, intensity) of an individual's technology use. This subjective aspect of usage does not consider human and technology agency. Moreover, if users do not have prior usage experience, they might not develop a habit of use because they might not develop a stimulus-response relationship with the unfamiliar technology. Technology-induced use captures the dynamic interplay between technological and human agency. Given that technological agency encourages people to use technology, such an inducement is more likely to rapidly establish a habit than measured routine use alone.

Relationship between Technology-Induced Use and Satisfaction

Technology-induced use implies the useful role of technology in carrying out tasks autonomously that users may require effort to complete, such as content search. The autonomous operations of technology can reduce users' cognitive load and facilitate the speedy delivery of a user's need-fulfilling content. Prescriptive and recommendation features rapidly communicate with users based on algorithmic activities, reducing the cognitive efforts of users by eliminating the need to search for content. Reducing cognitive effort can free users to shift their mental energy toward less mundane activities. Thus, technology-induced use should be positively associated with satisfaction by reducing users' cognitive effort.

In predicting satisfaction, I argue that technology-induced use will predict satisfaction over and above technology use. Technology use only captures the subjective aspect of use and does not indicate users' relationship with the task. Many tasks may not be the right fit for autonomous technology use, but they still require using technology in some way. In the tasks that it can be involved in, technology-induced use should reinforce human agency through the reduction of cognitive effort and the provision of need-fulfilling content. As such, technology-induced use should predict satisfaction over technology use.

The Relationship between Technology-Induced Use and Cognitive Absorption

According to the information processing fit perspective, when an external environment fits the information, content, or object with a user's need, such an environment can affect the effective utilization of technology (De Dreu, 2007). As technology agency fits technology features and contents with users' needs, a user is expected to stay in an involved state. Past research also indicates that need-fulfillment ability can predict cognitive absorption (Nah, Telaprolu, Rallapalli, & Venkata, 2013). Anchoring that research, I argue that technology-induced use will predict cognitive absorption.

In predicting cognitive absorption, I argue that technology-induced use will predict over and above personal innovativeness. It is expected that early adopters are expected to experience an involvement state more readily in app ecosystems (Agarwal & Karahanna, 2000). However, as the activity of technological agency provides novel content and experiences, individuals may increase user levels not just due to innate adopter characteristics but because technology stimulates their curiosity. As technological agency provides an endless supply of novel and need-matching content, many individuals who do not have personality innovativeness traits should also be expected to increase technology use. As such, technology-induced use should predict cognitive absorption over and above technology use alone.

Empirical Test of Predictive Validity: Technology-Induced Use and Habit

I conducted two studies to check the predictive validity of technology-induced use on habit. Below are the discussions of studies one and two.

Study One

The data of study one was collected from Amazon Mechanical Turk. Table 3.22 above described the demographics; the total sample size (after excluding 61 based on attention check and time spent) was 285. The results of predictive validity from study one are provided in figure 3.18. The results indicate that technology-induced use significantly predicts habit ($\beta = 0.58$, $p = 0.001$). The results further indicate that technology use is not significantly related to habit ($\beta = 0.02$, $p = .41$). Goodness of fit indices met conventional cutoff values ($CFI > 0.90$, $SRMR < 0.08$, $RMSEA < .08$, $TLI > 0.90$). Habit explained a 77.3% variance of the model, controlling for age and experience. Table 3.38 reports the T-statistics of the model.

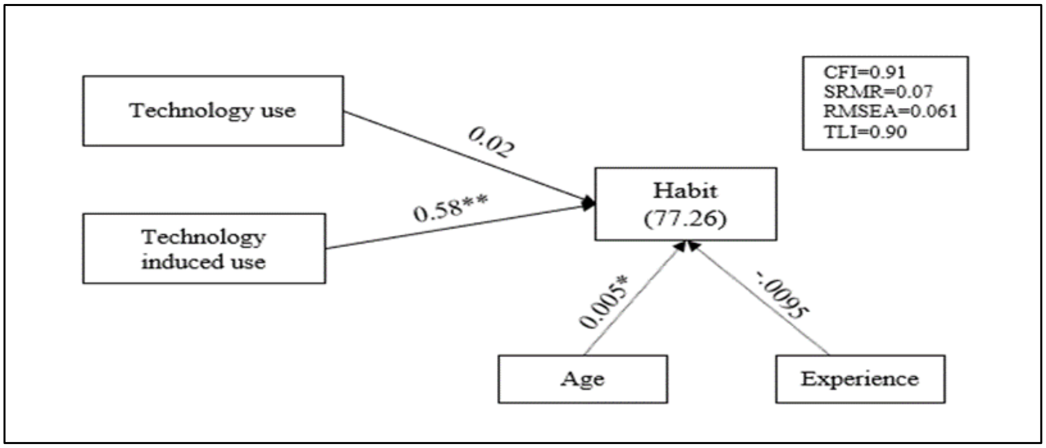


Figure 3.18: TIU→ Habit in Study 1

Table 3.38: T-statistics

Relationship	T-value	Supported
TIU→Habit	27.22***	Yes
TU→Habit	0.12	No

The co-efficient in the model indicates that technology-induced use significantly predicts habit over technology use. I used the data set from study two to test the relationship further.

Study Two

As before, data for study two was collected from Amazon Mechanical Turk. The total number of samples was 236 (after excluding 18 based on attention check and time spent). The results of study two are provided in figure 3.19. Results indicate that technology-induced use significantly predicts habit ($\beta = 0.54$, $p = 0.001$). The results further indicate that technology use is not significantly related to habit ($\beta = 0.03$, $p = 0.49$). Goodness of fit indices met the conventional cutoff values ($CFI > 0.90$, $SRMR < 0.08$, $RMSEA < .08$, $TLI > 0.90$). According to the results, habit explains a 55.87% variance in the model. I controlled for age and experience. Table 3.39 reports the T-statistics of the model.

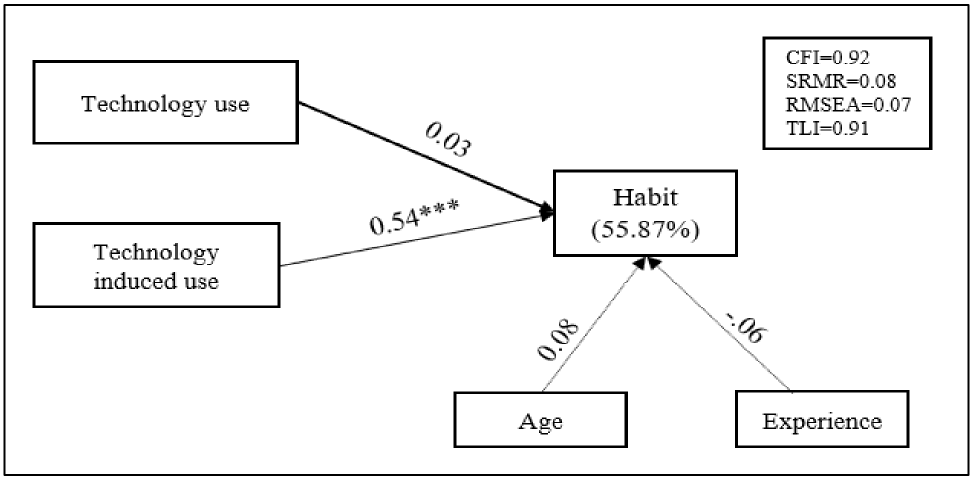


Figure 3.19: TIU→ Habit in Study 2

Table 3.39: T-statistics

Relationship	T-value	Supported
TIU→Habit	9.49***	Yes
TU→Habit	0.50	No

The co-efficient in Figure 3.19 indicates that technology-induced use significantly predicts habit over technology use. This indicates that the dynamic interplay between human agency and technology agency plays a major role in the formation of habit rather than the subjective measure of technology use alone.

Technology-induced use and satisfaction

I conducted two studies to check the predictive validity of technology-induced use on satisfaction.

Study One

The results of predictive validity from study one are provided in figure 3.20. I find that technology-induced use significantly predicts satisfaction (β = 0.60, p = 0.001). The results further indicate that technology use significantly predicts satisfaction (β = 0.006, p = .001).

CFI > 0.90, *SRMR* < 0.08, *RMSEA* < .08, and *TLI* > 0.90, indicating that goodness of fit indices met the conventional cutoff value. Satisfaction explains the 49.3% variance of the model, controlling for age and experience. Table 3.40 reports the T-statistics of the model.

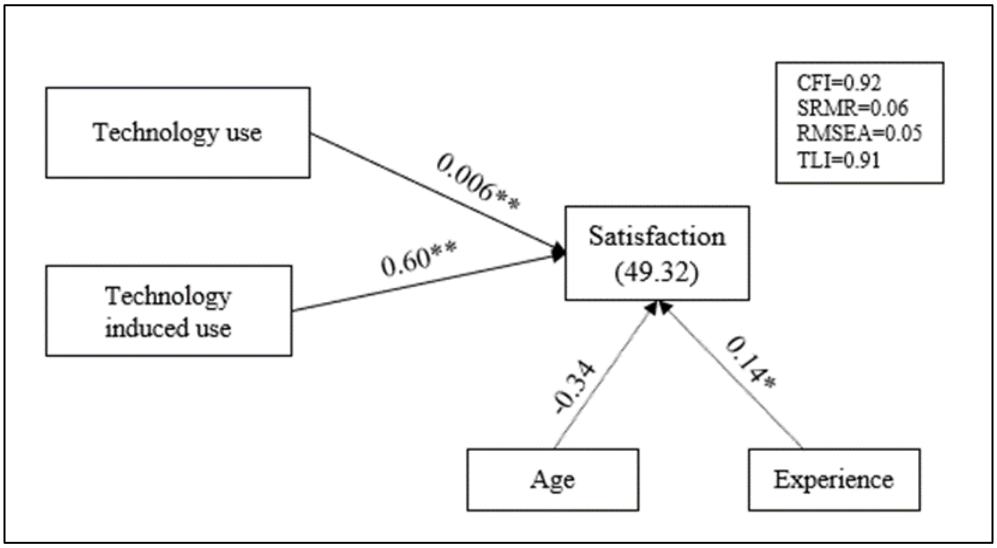


Figure 3.20: TIU→ Satisfaction in Study 1

Table 3.40: T-statistics

Relationship	T-value	Supported
TIU→Satisfaction	15.16***	Yes
TU→Satisfaction	2.58**	Yes

The co-efficient in the model indicates that technology-induced use significantly predicts satisfaction over technology use. To further test the relationship, we used the data set from study two.

Study Two

Figure 3.21 shows the predictive validity result of study two. The results indicate that technology-induced use significantly predicts satisfaction ($\beta = 0.53$, $p = 0.001$). The results indicate that technology use significantly predicts satisfaction ($\beta = 0.2$, $p = .001$). Goodness of fit indices met the conventional cutoff value (*CFI* > 0.90, *SRMR* < 0.08, *RMSEA* < .08, *TLI* > 0.90). Satisfaction explains the 37.3% variance of the model. I controlled for age and experience. Table 3.41 reports the T-statistics of the model.

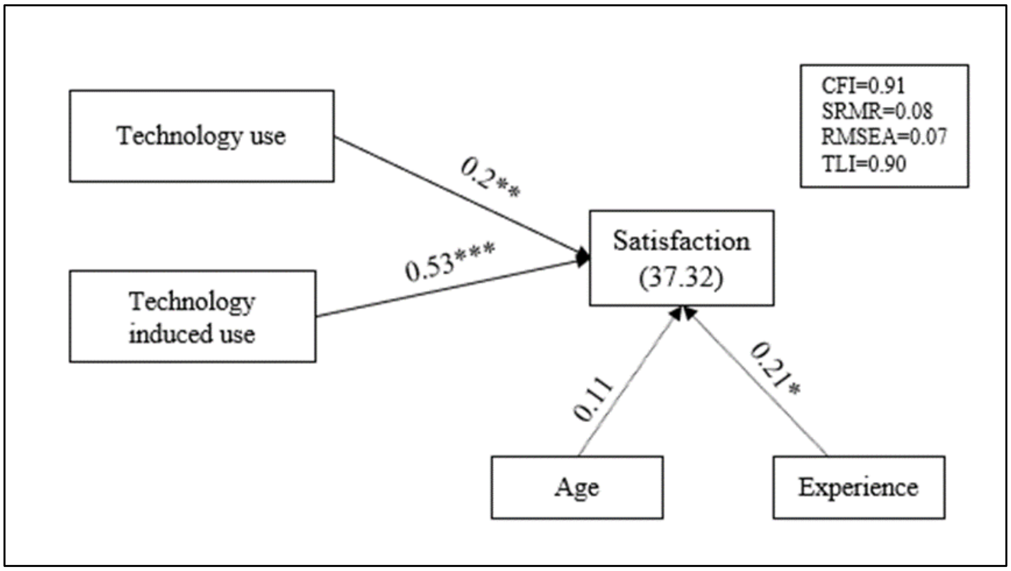


Figure 3.21: TIU→ Satisfaction in Study 2

Table 3.41: T-statistics

Relationship	T-value	Supported
TIU→Satisfaction	9.69***	Yes
TU→Satisfaction	3.06**	Yes

The co-efficient in figure 20 indicates that technology-induced use significantly predicts satisfaction over technology use. This indicates that the dynamic interplay between human agency and technology agency plays a major role in driving satisfaction rather than the subjective measure of technology use alone.

Technology-Induced Use and Cognitive Absorption

I conducted two studies to check the predictive validity of technology-induced use on cognitive absorption.

Study One

The results of predictive validity from study one are provided in figure 3.24. The results indicate that technology-induced use significantly predicts cognitive absorption ($\beta = 0.63$, $p = 0.001$). The results further indicate that personal innovativeness significantly predicts cognitive absorption ($\beta = 0.3$, $p = .001$). Goodness of fit indices met the conventional cutoff value (*CFI* > 0.90, *SRMR* < 0.08, *RMSEA* < .08, *TLI* > 0.90). Cognitive absorption explains the 77.7% variance of the model controlling for age and experience. Table 3.42 reports the T-statistics of the model.

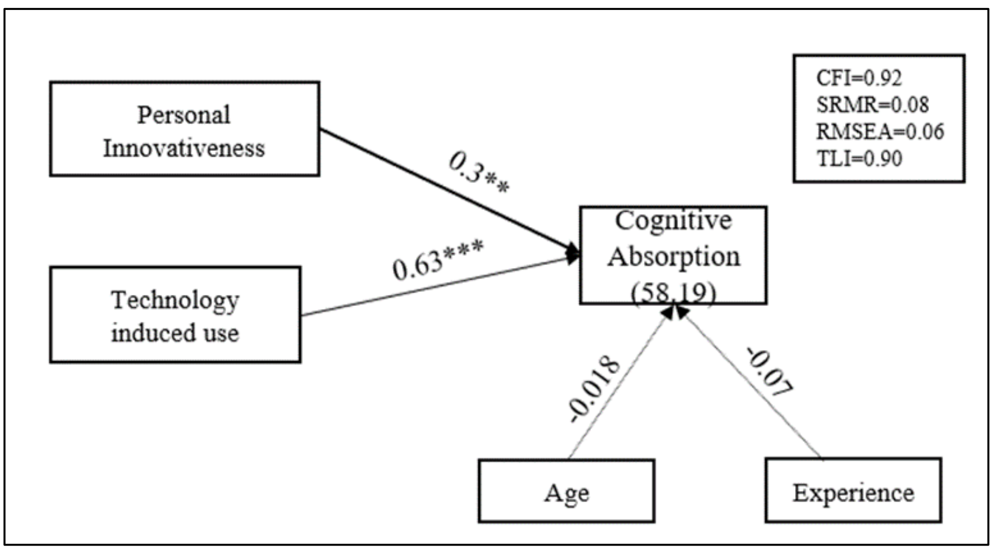


Figure 3.22: TIU→Cognitive Absorption in Study 1

Table 3.42: T-statistics

Relationship	T-value	Supported
TIU→Cognitive absorption	19.05***	Yes
Personal Innovativeness → Cognitive absorption	4.03**	Yes

The co-efficient in the model indicates that technology-induced use significantly predicts cognitive absorption over personal innovativeness. I used the data set from study two to further test the relationship.

Study Two

The results of predictive validity from study two are provided in figure 3.23. The results indicate that technology-induced use significantly predicts cognitive absorption ($\beta = 0.6$, $p = 0.001$). The results further indicate that personal innovativeness significantly predicts cognitive absorption ($\beta = 0.4$, $p = .001$). Goodness of fit indices met the conventional cutoff value ($CFI > 0.90$, $SRMR < 0.08$, $RMSEA < .08$, $TLI > 0.90$). Further, cognitive absorption explains the total 58.19% variance of the model, controlling for age and experience. Table 3.43 reports the T-statistics of the model.

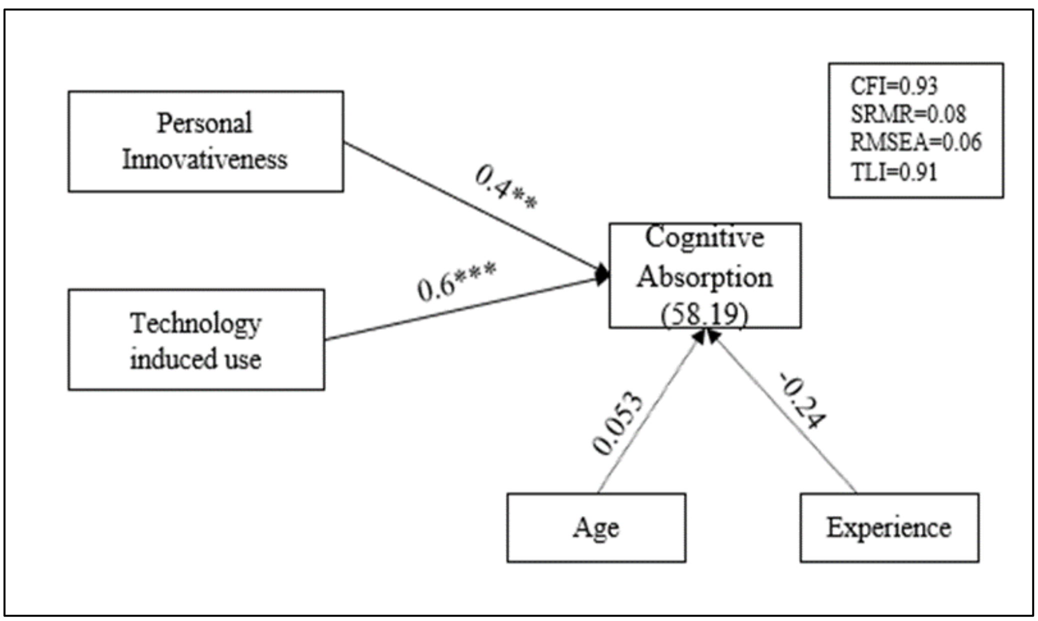


Figure 3.23: TIU→Cognitive Absorption in study 2

Table 3.43: T-statistics

Relationship	T-value	Supported
TIU→Cognitive absorption	6.07***	Yes
Personal innovativeness →Cognitive absorption	3.06**	Yes

The co-efficient in the model indicates that technology-induced use significantly predicts cognitive absorption over personal innovativeness. Overall, we can conclude that technology-induced use establishes predictive validity over cognitive absorption. This indicates that the dynamic interplay between human agency and technology agency plays more of an operative role in driving satisfaction than individuals' personality traits.

Predictive Validity in IS Continuance Model

I also tested the predictive validity of technology-induced use in an IS continuance model (Bhattacherjee 2001). The results indicate that technology-induced use significantly predicts satisfaction (β = 0.6, p = 0.001). The results further indicate that satisfaction significantly predicts IS continuance intention (β =0.43, p = .001). Goodness of fit indices met the conventional cutoff value ($CFI > 0.90$, $SRMR < 0.08$, $RMSEA < .08$, $TLI > 0.90$). Satisfaction explains the total 39% variance of the model. I controlled for age and experience in the model. Table 3.44 reports the T-statistics of the model.

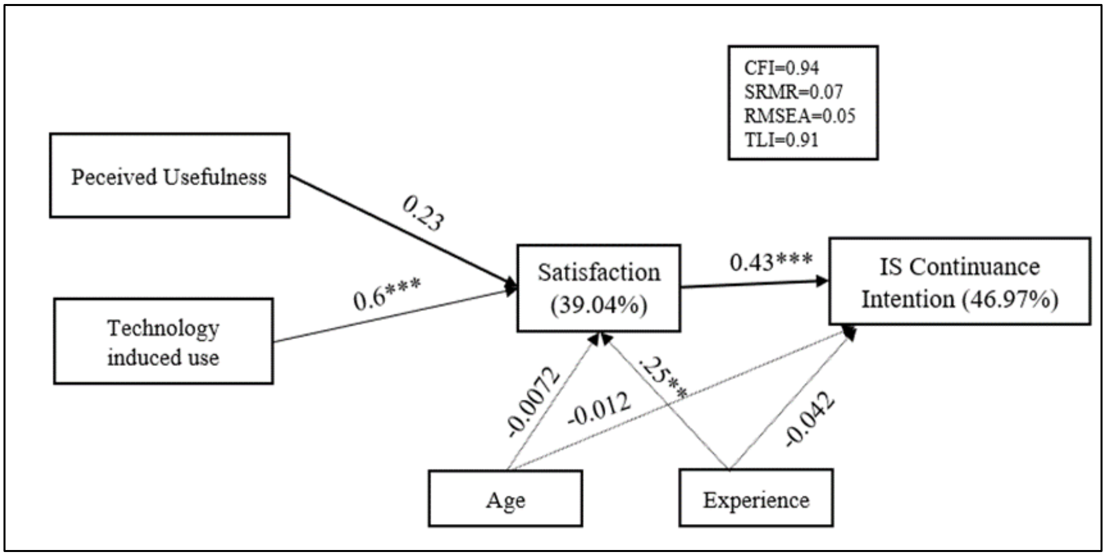


Figure 3.24: Predictive validity in IS continuance model

Table 3.44: T-statistics

Relationship	T-value	Supported
TIU→Satisfaction	4.77***	Yes
Perceived usefulness → Satisfaction	1.3	No
Satisfaction → IS continuance	7.00***	Yes

Step Nine: Cross-Validation of Scale

I cross-validated our scale after study collecting data from Amazon Mechanical Turk in study four. The total sample size was 468. After analyzing the attention check and time stamp, 347 responses were retained. All participants were from the U.S. Before participating in the survey, and all participants gave research consent. The average survey completion time was 10-12 minutes. After completing the content form, participants were prompted to identify the app with which they interact most frequently. Study data were collected online and anonymously. Among the 347 participants, 217 identified themselves as male, 130 as female. Among 347 participants, 318 participants were white, 10 were African American, and 16 were Native or

Pacific Islander. Participant age ranged from 18 to 67. Finally, each participant has an average of 3.3 years of experience using a mobile app.

Behavioral-Based Measurement

To compare loadings with previous studies, I conducted an exploratory factor analysis on behavior-based items using principal component factor analysis with varimax rotation. Table 3.45 reports the results of the exploratory factor analysis of the behavior-based measure. The EFA indicates all item loadings are above 0.50.

Table 3.45: Principal component factor analysis loadings of behavior-based measure (Study 4)

Items	Technology induced use
R1	0.70
R2	0.71
R3	0.66
R4	0.65
R5	0.64
R6	0.38
S1	0.60
S2	0.65
S3	0.71
S4	0.66
S5	0.60
S6	0.60
L1	0.60
L2	0.61
L3	0.66

After conducting exploratory factor analysis, I used confirmatory factor analysis to assess the measurement model of behavior-based measure. Figure 24 illustrates the loadings and goodness of fit indices. $AVE > 0.50$ in each dimension of the behavior-based measure, indicating that the measurement model met the convergent validity criteria. In addition, the Cronbach's alpha of each dimension is above 0.75. Table 3.46 reports the findings.

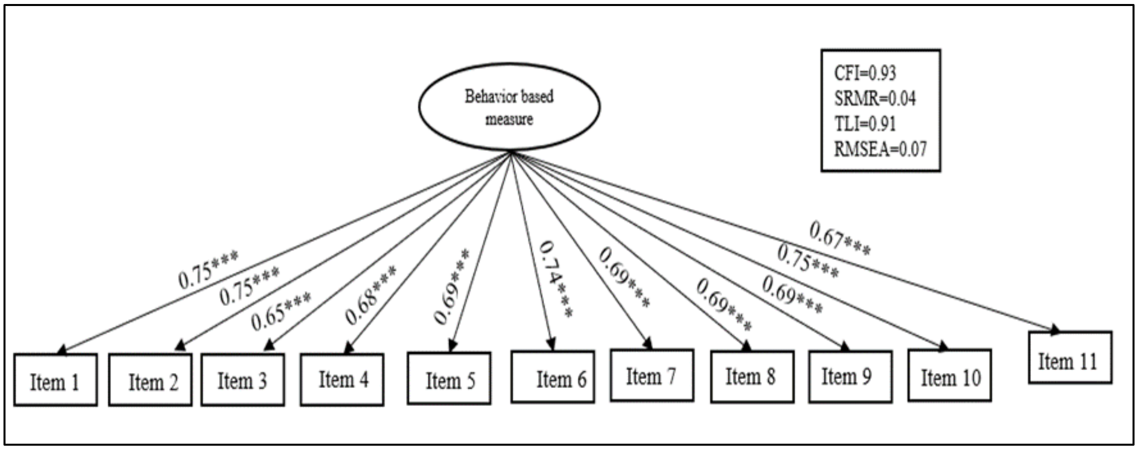


Figure 3.25: Loadings and fit indexes of behavior-based measure

Table 3.46: Psychometric properties of behavior-based measure (study 4)

Items	**Loadings**	P<0.05		**AVE**	**Composite Reliability**	**Cronbach Alpha**
R1	0.75	Yes		0.51	0.80	0.78
R2	0.75	Yes				
R4	0.65	Yes				
R5	0.68	Yes				
S1	0.69	Yes		0.50	0.79	0.75
S2	0.74	Yes				
S3	0.69	Yes				
S4	0.69	Yes				
L1	0.69	Yes		0.50	0.75	0.77
L2	0.75	Yes				
L3	0.67	Yes				

The list of behavior-based measure items is provided in table 3.47.

Table 3.47: Item lists for behavior-based measure

Constructs	Items
Induced reward-seeking behaviors	1. The app contains features (e.g., notification, recommendation, infinite scrolling) that allow me to get new content.
	2. The app contains features (e.g., recommendation, infinite scrolling, watch more) that allow me to get new experience
	3. The app contains features (e.g., recommendations) that allow me to get my preferred content
	4. The app contains features (e.g., level, point, badge) that allow me to receive rewards.
Induced social behaviors	5. The app contains features (e.g., share) that allow me to share content with others
	6. The app contains features (e.g., react, like) that allow me to react to others' activities
	7. The app contains features (e.g., recommendations) that allow me to browse others' content
	11. The app contains features (e.g., follow) that allow me to follow online communities
	8. The app contains features (e.g., collaborate) that allow me to perform tasks with others
Induced learning behaviors	9. The app has features (e.g., notification, recommendation) that allow me to learn about events
	10. The app has features (e.g., search, notification) that allow me to learn about the latest news
	11. The app has features (e.g., notification, recommendation) that allow me to learn about current trends

Feature-Based Measurements

At first, I conducted an exploratory factor analysis on behavior-based items to compare loadings with previous studies, using principal component factor analysis with varimax rotation. Table 48 reports the results of the exploratory factor analysis of the feature-based measure. The EFA indicates all item loadings are above 0.50.

Table 3.48: Principal component factor analysis loadings of feature-based measurements (study 4)

Items	Technology induced use
F1	0.72
F2	0.69
F3	0.70
F4	0.65
F5	0.69
F6	0.68

After conducting exploratory factor analysis, I used confirmatory factor analysis to assess the measurement model of feature-based measures. Figure 3.26 illustrates the loadings and goodness of fit indices. Figure 3.26 indicates that the measurement model met the criteria of goodness of fit indices. In this analysis, AVE is greater than 0.51, and Cronbach's alpha is 0.75, indicating the construct validity and reliability. Table 49 reports the findings. The list of behavior-based measure items is provided in table 3.50.

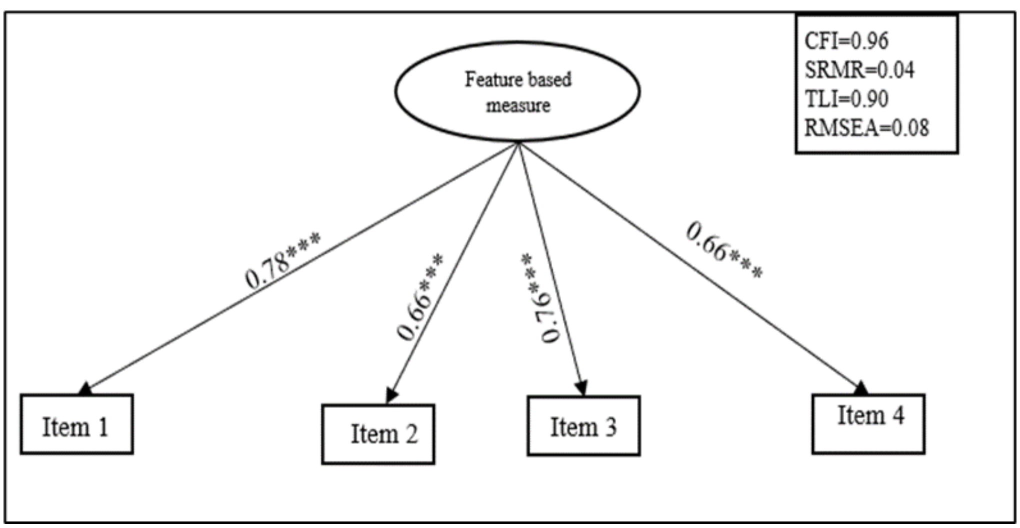


Figure 3.26: Loadings and fit indexes

Table 3.49: Psychometric properties of feature-based measure (study 4)

Items	Factor loadings	P<0.05	AVE	Composite reliability	Cronbach Alpha
F1	0.78	Yes	0.51	0.79	0.75
F2	0.66	Yes			
F3	0.76	Yes			
F4	0.66	Yes			

Table 3.50: Item lists for feature-based measure

Construct	Items
Feature-based measure	1.The notification feature of an app stimulates me to look for content
	2.The search feature of an app stimulates me to search for content
	3. The recommendation feature of an app stimulates me to browse content
	4. The constant information updating feature of an app stimulates me to look for content

Predictive Validity in Cross-Validation (On Habit)

The results of cross-validation (on habit) are provided in figure 3.27. The results indicate that technology-induced use significantly predicts habit (β = 0.51, p = .001). The results further indicate that technology use is not significantly associated with habit (β = 0.05, p = .001). Goodness of fit indices met the conventional cutoff value (*CFI* > 0.90, *SRMR* < 0.08, *RMSEA* < .08, *TLI* > 0.90). Habit explains a total of 34.8% variance from the model, controlling for age, social desirability, and experience. Table 51 reports the T-statistics of the model.

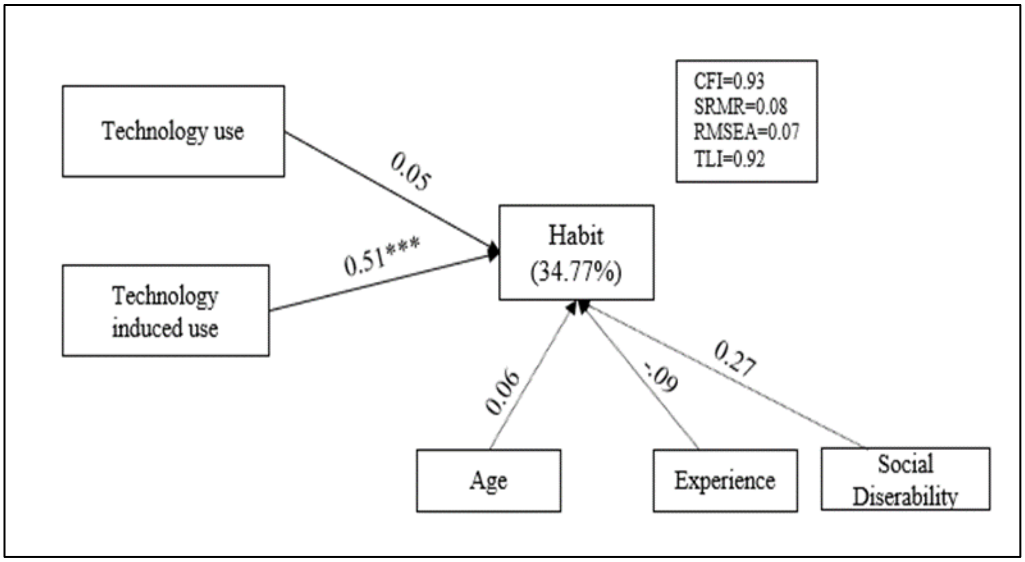


Figure 3.27: Cross-validation (on habit)

Table 3.51: T-statistics

Relationship	T-value	Supported
TIU→habit	9.73***	Yes
TU→Habit	1.01	Yes

The results validate previous findings that technology-induced use significantly predicts habit over and above technology use.

Predictive Validity in Cross-Validation (On Satisfaction)

The results of cross-validation (on satisfaction) are provided in figure 27. The results indicate that technology-induced use significantly predicts satisfaction (β = 0.68, p = .001). The results further indicate that technology use is significantly associated with habit (β = 0.41, p = .001). Goodness of fit indices met the conventional cutoff value (*CFI* > 0.90, *SRMR* < 0.08, *RMSEA* < .08, *TLI* > 0.90). Satisfaction explains 62.9% of the variance of the model, controlling for age, social desirability, and experience. Table 52 reports the T-statistics of the model. Results confirm that technology-induced use significantly predicts satisfaction over and above technology use.

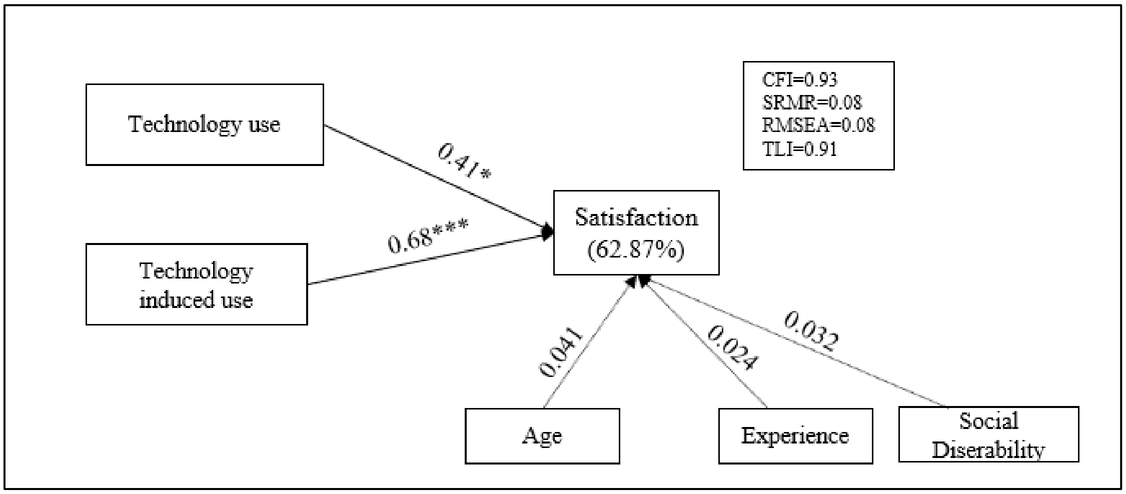


Figure 3.28: Cross validation (on satisfaction)

Table 3.52: T-statistics

Relationship	T-value	Supported
TIU→satisfaction	15.54***	Yes
TU→satisfaction	5.17**	Yes

Step Ten: Develop Norms for the Scale

The final step is the development of norms for the new scale. This step guides future research on how a newly developed measurement instrument could be used in future studies (MacKenzie et al., 2011). MacKenzie et al. (2011) recommend providing guidelines about the target population, sample size, and research context in this step. First, the context of technology-induced use is apps, such as social media, health, video, photo sharing, etc. However, I argue that both measurement instruments (behavior-based and feature-based) can be used in other technology contexts with some modifications. As younger populations use apps most frequently, I recommend that target populations should correspond roughly to our study's average age range, 25 to 39 years old.

Furthermore, an important consideration for future research is the sample size. I argue that the sample size should be large enough to conclude that "the scales are truly stable" (Hoehle & Venkatesh, 2015). In a majority of our studies, the sample size ranges from 150 to 400, large enough to develop the measurement items of a construct based on MacKenzie et al.'s (2011) procedures. Data collection constraints limited us to U.S. samples. Future studies may test the validity of the measurement instruments in other country contexts. I believe the results will hold the same regardless of the country context. Finally, I encourage the researcher to use prompts similar to the following (which we used for the behavior-based measure of technology-induced use). I think that using such a prompt may help participants to better grasp the research context.

"Think about the app you most frequently interact with (e.g., Facebook, Instagram, TikTok). Those apps have features (notification, level, point, badge, explore, earn streaks) that draw on data. Sometimes, many of us feel those features pull us into the app, guiding us to perform learning, reward-seeking, and social behaviors. In other words, we are being nudged to perform different activities (learning, reward-seeking, and social behaviors) because of app features."

Discussion

The aim of this study was to understand the dynamic interplay between technological and human agency. While the technology agency has become pervasive, our understanding of how it reinforces human agency is still limited. I contend that the lack of a proper theory-driven conceptualization of a usage construct impedes the advancement of research in this domain. To capture the dynamic relationship between technology and human agency, I proposed a new construct, technology-induced use, defined as the use of technology to fulfill user's innate and situational needs, in a way that is primarily stimulated by technology triggers.

Based on this conceptualization, I proposed two measures of technology-induced use: behavior-based and feature-based. I developed the behavior-based measure from the perspective of users' usage behaviors, finding that usage behaviors can be broadly placed in three categories: induced reward-seeking behaviors, social behavior, and learning behaviors. Using these three categories, I developed survey items for technology-induced use. Feature-based measures were developed by considering the ability of features to induce use. Feature-based measures can be broadly classified into four categories: input-dependent features, prescriptive features, recommendation features, and task control features. Among those four categories, I determined that the input-dependent feature set does not induce usage as they have little technological agency. I used the remaining three categories of feature sets to develop items surveying technology-induced use. Following MacKenzie et al. (2011), I conducted five studies to validate the measurement scales of behavior and feature-based measures, finding that, compared to feature-based measures, behavior-based measurements are more generalizable and relatively context-independent.

After developing and validating the measurement scale of technology-induced use, I tested its predictive validity on habit, satisfaction, and cognitive absorption. I compared the predictive power of technology-induced use to that of technology use and personal innovativeness. The predictive validity test indicated that technology-induced use predicts habit and satisfaction significantly over and above technology use. This comparison indicates that subjective usage measures have limitations in predicting habit and satisfaction, which could be addressed by technology-induced use. One major limitation of subjective measures of usage is that it ignores the dynamics between technology and human agency. Ignoring the agency in usage unnecessarily circumscribes the explanation for why users repeatedly return to technology or even create emotional bonds with their favorite apps. The predictive validity test revealed that technology-induced use significantly predicts cognitive absorption over and above personal innovativeness. It offers new insight as a substantial explanation for why many people stay absorbed with technology action possibilities. Many people remain engrossed in technology not because they are willing to try new things but because technological features stimulate them to search for new things.

Overall, this work brings novel insights into the usage domain and creates the following new avenues for future research.

Contributions

The study makes three key contributions. First, I advance research on technology use by proposing and validating a new usage construct in the technology use domain. Research on how technological agency stimulates usage is more relevant than ever. Past research on the usage domain primarily focuses on human agency, personality traits, and automaticity (Limayem et al., 2007). Further, past research uses technology usage construct to capture the subjective aspects of usage. In addition, the intention to use construct has been used to capture the human agency aspect of usage. Although technology practitioners have pointed out the role of technology agency in stimulating usage, scant research in the usage domain has incorporated technology agency and human agency. This work builds upon the practitioners' point of view, extending the usage domain by incorporating the dynamic nature of technological and human agency in a new usage construct: technology-induced use. I developed and validated a new measurement that can help future research to capture the dynamic interaction between humans and technology.

Second, I advance research on algorithm perception literature (Burton, Stein, & Jensen, 2020). Some recent work on algorithms indicates that they function as "co-workers" while interacting with humans (Tarafdar et al., 2022). Although most of the work in algorithm perceptions is based on qualitative study, I offer a new construct—technology-induced use—which can objectively measure the algorithm's agency over human interaction. In other words, this new usage construct can capture the level of control algorithms hold over human agency.

Third, I contribute to the emerging literature on the agentic artifact of technology (Baird & Maruping, 2021). This literature domain primarily focuses on technology agencies' role in human-technology interactions (Baird & Maruping, 2021). This literature theorizes that agentic artifacts are an agent of users in conducting tasks. However, one limitation of this literature is the lack of a construct measuring the dyadic interaction between technology agents and humans (Samuel, Kashyap, Samuel, & Pelaez, 2022). My work can be leveraged to address this limitation as technology-induced use directly measures the dyadic interaction between technology and human agency.

Finally, I contribute to the emerging literature on gamification (Liu, Santhanam, & Webster, 2017). Gamification literature argues that game design influences users' interaction with technology (Liu et al., 2017). However, it lacks a measurement that can capture the dynamic interaction between game design and users' use of game elements. I argue that this study can provide new insight into the dynamic interaction between game design and users' use of game elements.

Limitations

Although I have collected multiple waves of data to develop and purify the scale, the study has limitations. First, the study's focus was on super apps, such as social media, entertainment, gaming, health, video, photo sharing, and the like. The measure should be judiciously applied in untested technology contexts, such as organizational systems and BI systems.

Next, it is difficult to rule out social desirability and common method bias concerns. Although I controlled for common method bias by considering marker variables and Harmon's single factor measures, I could not rule out social desirability bias in the first few surveys.

My research has not directly included items related to algorithms in the technology-induced use scale. Including it in the scale could have enriched the present scale. However, because I focused on features and use, I ignored the algorithmic aspect of apps in the scale development process. Future research can explicitly consider the role of algorithms in the technology-induced use measurement scale.

Future Research Directions

This research opens important paths for future research. First, future research may broaden the measurement instrument of technology-induced use by considering the collective agency of multiple apps (Baird & Maruping, 2021). Many users use multiple social media apps on their smartphones (Facebook, Twitter, Instagram, Snapchat). The collective agency from multiple apps may significantly influence human agency compared to the influence from a single app. Research may ask questions like: *How can collective agency influence human agency? What additional factors need to be considered while studying collective agency?*

Second, future research may study technology-induced use's potential causes and consequences. For example, certain personality traits, such as impulsivity and reward sensitivity, could be potential antecedents of technology-induced use. Those traits indicate an individual's tendency to act without thinking. Given that technology guides users to act, individuals with these personality traits could be quickly induced by technology. One notable consequence of technology-induced use could be the formation of an addiction state, moreover. Certain individuals may use technology longer than intended because of constant inducement by technology. They may develop an addiction to technology at some point if they do not exercise self-control. Another consequence of technology-induced use could be work-life conflicts. Individuals repeatedly induced by technology may spend progressively longer times within its ecosystems, generating negative spillover effects upon their work life.

Third, future research could study potential mechanisms and moderators linking technology-induced use with habit, satisfaction, and cognitive absorption. For example, work-related stressors can be moderators between technology-induced use and habit. Work-related stress can amplify the relationship between technology-induced use and habit, and some individuals may follow technology-guided activities more when they perceive stress from work. Over time, those individuals may find engaging with technology is an additional stressor, which can amplify the process of habit formation.

Conclusion

Increasingly, technology and human agency have become intertwined with each other. So far, little research has been done in this domain. This study contributes to this area by developing and validating a new usage construct that captures the intertwining of technology and human agency. In following MacKenzie et al. (2011) to develop and validate technology-induced use measurement items, I believe that my work significantly contributes to HCI and IS literature by helping future research build new theories in important, emerging, little-studied domains such as echo chambers, society-wide usage patterns, and the negative abuses of technology.

References of Essay 3

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, *24*(4), 665-694.

Alawi, N. (2021). *The IS Social Continuance Model: Using Conversational Agents to Support Co-Creation in Teams.* University of South Florida,

Alter, A. (2017). *Irresistible: The rise of addictive technology and the business of keeping us hooked*: Penguin.

Baird, A., & Maruping, L. M. (2021). The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS Quarterly, 45*(1), 315-341.

Baucells, M., & Sarin, R. K. (2010). Predicting Utility Under Satiation and Habit Formation. *Management Science, 56*(2), 286-301.

Benlian, A. (2015). IT feature use over time and its impact on individual task performance. *Journal of the Association for Information Systems, 16*(3), 2.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433-1450.

Berthon, P., Pitt, L., & Campbell, C. (2019). Addictive de-vices: A public policy analysis of sources and solutions to digital addiction. *Journal of Public Policy & Marketing, 38*(4), 451-468.

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS quarterly, 25*(3), 351-370.

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making, 33*(2), 220-239.

Burton-Jones, A., & Gallivan, M. J. (2007). Toward a deeper understanding of system usage in organizations: a multilevel perspective. *MIS Quarterly*, *31*(4) 657-679.

Cassotti, M., Habib, M., Poirel, N., Aïte, A., Houdé, O., & Moutier, S. (2012). Positive emotional context eliminates the framing effect in decision-making. *Emotion, 12*(5), 926.

Chen, J., Tan, L., Liu, L., & Wang, L. (2020). Reinforcement learning of irrelevant stimulus-response associations modulates cognitive control. *Journal of Experimental Psychology: Learning, Memory, and Cognition*.

Cinelli, M., Morales, G. D. F., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences, 118*(9).

Courtwright, D. T. (2019). The Age of Addiction. In *The Age of Addiction*: Harvard University Press.

De Dreu, C. K. (2007). Cooperative outcome interdependence, task reflexivity, and team effectiveness: a motivated information processing perspective. *Journal of Applied Psychology, 92*(3), 628.

De Guinea, A. O., & Markus, M. L. (2009). Why break the habit of a lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. *MIS Quarterly*, *33*(3), 433-444.

de Lima Salge, C. A., Karahanna, E., & Thatcher, J. B. (2021). Algorithmic Processes of Social Alertness and Social Transmission: How Bots Disseminate Information on Twitter. *MIS Quarterly*, *46*(1), 229-259.

Eyal, N. (2014). *Hooked: How to build habit-forming products*: Penguin.

Eyal, N. (2019). *Indistractable: How to control your attention and choose your life*: BenBella Books.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021). Cognitive Challenges in Human–Artificial Intelligence Collaboration: Investigating the Path Toward Productive Delegation. *Information Systems Research*, *33*(2), 678-696.

Gerdenitsch, C., Korunka, C., & Hertel, G. (2018). Need–supply fit in an activity-based flexible office: a longitudinal study during relocation. *Environment and Behavior, 50*(3), 273-297.

Hinkin, T. R., & Tracey, J. B. (1999). An analysis of variance approach to content validation. *Organizational Research Methods, 2*(2), 175-186.

Hoehle, H., & Venkatesh, V. (2015). Mobile application usability. *MIS Quarterly, 39*(2), 435-472.

James, T. L., Lowry, P. B., Wallace, L., & Warkentin, M. (2017). The Effect of Belongingness on Obsessive-Compulsive Disorder in the Use of Online Social Networks. *Journal of Management Information Systems, 34*(2), 560-596.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic perspectives, 5*(1), 193-206.

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information Technology Adoption Across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs. *MIS Quarterly, 23*(2), 183-213.

Karahanna, E., Xu, S. X., Xu, Y., & Zhang, N. A. (2018). The needs–affordances–features perspective for the use of social media. *MIS Quarterly, 42*(3), 737-756.

Kitchens, B., Johnson, S. L., & Gray, P. (2020). Understanding Echo Chambers and Filter Bubbles: The Impact of Social Media on Diversification and Partisan Shifts in News Consumption. *MIS Quarterly, 44*(4), 1619-1649.

Krumm, S., Grube, A., & Hertel, G. (2013). No time for compromises: Age as a moderator of the relation between needs–supply fit and job satisfaction. *European Journal of Work and Organizational Psychology, 22*(5), 547-562.

Lankton, N. K., Wilson, E. V., & Mao, E. (2010). Antecedents and determinants of information technology habit. *Information & management, 47*(5-6), 300-307.

Leonardi, P. M. (2011). When Flexible Routines Meet Flexible Technologies: Affordance, Constraint, and The Imbrication of Human And Material Agencies. *MIS Quarterly, 35*(1), 147-167.

Lim, S. H., Lee, S., & Kim, D. J. (2017). Is online consumers' impulsive buying beneficial for e-commerce companies? An empirical investigation of online consumers' past impulsive buying behaviors. *Information Systems Management, 34*(1), 85-100.

Limayem, Hirt, & Cheung. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly, 31*(4), 705-737.

Liu, D., Santhanam, R., & Webster, J. (2017). Toward Meaningful Engagement: a framework for design and research of Gamified information systems. *MIS Quarterly, 41*(4), 1011-1034.

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, *35*(2), 293-334.

Maden, C. (2014). Impact of fit, involvement, and tenure on job satisfaction and turnover intention. *The Service Industries Journal, 34*(14), 1113-1133.

Montag, C., Lachmann, B., Herrlich, M., & Zweig, K. (2019). Addictive Features of Social Media/Messenger Platforms and Freemium Games against the Background of Psychological and Economic Theories. *International journal of environmental research and public health, 16*(14), 2612. doi:10.3390/ijerph16142612

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). Algorithmic Management Of Work On Online Labor Platforms: When Matching Meets Control. *MIS Quarterly, 45*(4), 1999-2022.

Nah, F. F.-H., Telaprolu, V. R., Rallapalli, S., & Venkata, P. R. (2013). *Gamification of education using computer games.* Paper presented at the International Conference on Human Interface and the Management of Information.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital Innovation Management: Reinventing innovation management research in a digital world. *MIS quarterly, 41*(1), 223-238.

Nandhakumar, J., Rossi, M., & Talvinen, J. (2005). The dynamics of contextual forces of ERP implementation. *Journal of Strategic Information Systems, 14*(2), 221-242.

Novemsky, N., & Kahneman, D. (2005). The boundaries of loss aversion. *Journal of Marketing Research, 42*(2), 119-128.

Octaberlina, L. R., & Afif, I. M. (2021). Online learning: Students' autonomy and attitudes. *International Journal of Higher Education, 14*(1), 49-61.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization science, 3*(3), 398-427.

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization science, 11*(4), 404-428.

Orlikowski, W. J., & Iacono, C. S. (2001). Research commentary: Desperately seeking the "IT" in IT research—A call to theorizing the IT artifact. *Information Systems Research, 12*(2), 121-134.

Polites, G. L., & Karahanna, E. (2013). The Embeddedness of Information Systems Habits in Organizational and Individual Level Routines: Development and Disruption. *Mis Quarterly, 37*(1), 221.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next Generation Digital Platforms:: Toward Human-AI Hybrids. *MIS Quarterly, 43*(1), iii-ix.

Rouibah, K., & Hamdy, H. (2009). Factors affecting information communication technologies usage and satisfaction: Perspective from instant messaging in Kuwait. *Journal of Global Information Management (JGIM), 17*(2), 1-29.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist, 55*(1), 68.

Samuel, J., Kashyap, R., Samuel, Y., & Pelaez, A. (2022). Adaptive cognitive fit: Artificial intelligence augmented management of information facets and representations. *International Journal of Information Management, 65*, 102505.

Siebert, A., Gopaldas, A., Lindridge, A., & Simões, C. (2020). Customer experience journeys: Loyalty loops versus involvement spirals. *Journal of Marketing, 84*(4), 45-66.

Skyttner, L. (2001). *General systems theory: ideas & applications*: World Scientific.

Soror, A. A., Hammer, B. I., Steelman, Z. R., Davis, F. D., & Limayem, M. M. (2015). Good habits gone bad: Explaining negative consequences associated with the use of mobile phones from a dual-systems perspective. *Information Systems Journal, 25*(4), 403-427.

Steelman, Z., Hammar, B., Limayem, M. (2014). Data collection in the digital age: Innovative alternatives to student samples. *MIS Quarterly 38*(2), 355, 378.

Steinberg, M. (2020). LINE as super app: Platformization in East Asia. *Social Media+ Society, 6*(2), 2056305120933285.

Strauss, A., & Corbin, J. (1998). *Basics of qualitative research techniques*: Citeseer.

Susser, D., Roessler, B., & Nissenbaum, H. (2019). Technology, autonomy, and manipulation. *Internet Policy Review, 8*(2).

Tarafdar, M., Page, X., & Marabelli, M. (2022). Algorithms as co-workers: Human algorithm role interactions in algorithmic work. *Information Systems Journal*.

Turel, O. (2016). Problematic use of social networking sites. *Journal of Management Information Systems, 33*(4), 1087-1116.

Turel, O. (2021). Technology-Mediated Dangerous Behaviors as Foraging for Social–Hedonic Rewards: The Role of Implied Inequality. *MIS Quarterly, 45*(3), 1249-1286.

Turel, O., & Ferguson, C. (2021). Excessive Use of Technology: Can Tech Providers be the Culprits? Seeking to assess the possible responsibility of tech providers for excessive use patterns. *Communications of the ACM, 64*(1), 42-44.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly*, *32*(3), 483-502.

Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology, 45*(3), 639-656.

Verplanken, B., Verplanken, B., & Ryan. (2018). *Psychology of habit*: Springer.

Wang, C., & Lee, M. K. O. (2020). Why We Cannot Resist Our Smartphones: Investigating Compulsive Use of Mobile SNS from a Stimulus-Response-Reinforcement Perspective. *Journal of the Association for Information Systems, 21*(1), 175-200.

West, R., Brown, J., & ProQuest. (2013). *Theory of addiction* (2nd ed.). Chichester, West Sussex, U.K: John Wiley & Sons Inc.

Zhang, X., & Venkatesh, V. (2017). A nomological network of knowledge management system use: Antecedents and consequences. *MIS Quarterly, 41*(4), 1275-1306.

Zhu, D.-H., & Chang, Y.-P. (2013). Negative publicity effect of the business founder's unethical behavior on corporate image: Evidence from China. *Journal of Business Ethics, 117*(1), 111-121.

Appendix of Essay 3

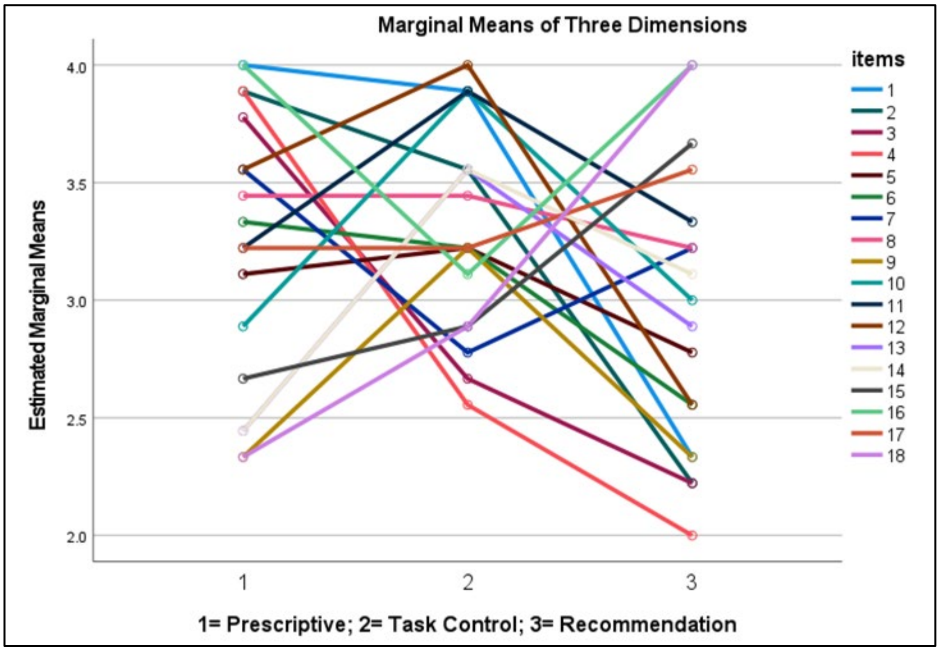


Figure 3.29: Marginal mean plot

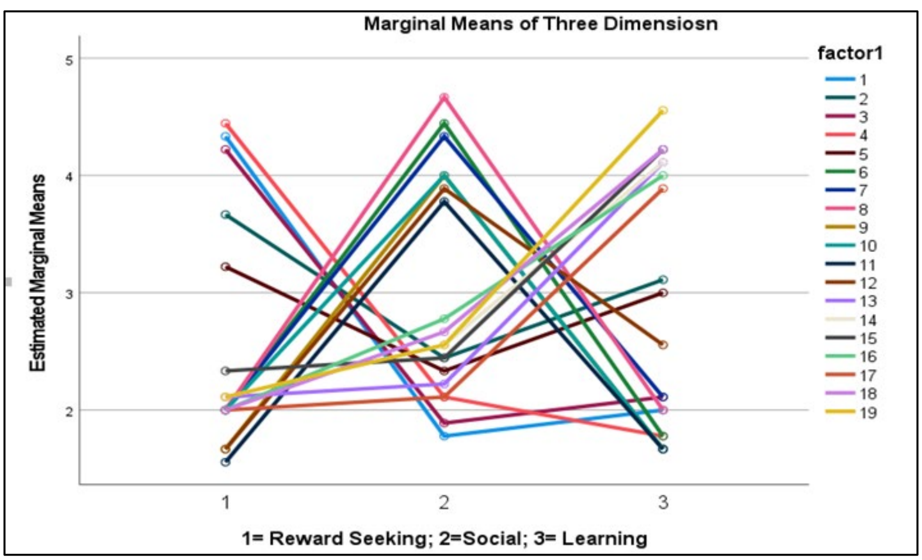


Figure 3.30: Marginal mean distribution of behavior-based measure

Table 3.53: Sample interview questions

Understanding App Use
The purpose of this interview is to determine your app usage behavior. Please answer the following questions based on your app usage experience 1. Which app do you use the most? How frequently per day? How long do you use it? 2. What features of the app keep you coming back? 3. What do you like about the app? Why is the app so alluring? 4. What are the different behaviors you engage in while interacting with apps? 5. Do you frequently experience excitement when using an app? If yes, why do you feel so? 6. How do you evaluate your app usage? Can you briefly explain?

Appendix: Research Compliance Protocol

UNIVERSITY OF ARKANSAS

To:	Sandip Kumar Sarkar BELL 4188
From:	Douglas J Adams, Chair IRB Expedited Review
Date:	07/23/2020
Action:	**Exemption Granted**
Action Date:	07/23/2020
Protocol #:	2006269500
Study Title:	How do we get hooked to an App? A Grounded Theory of App-induced Hooked

The above-referenced protocol has been determined to be exempt.

If you wish to make any modifications in the approved protocol that may affect the level of risk to your participants, you must seek approval prior to implementing those changes. All modifications must provide sufficient detail to assess the impact of the change.

If you have any questions or need any assistance from the IRB, please contact the IRB Coordinator at 109 MLKG Building, 5-2208, or irb@uark.edu.

cc: Zach Steelman, Investigator
Varun Grover, Investigator