Transactions on Replication Research

Conceptual Replication DOI: 10.17705/1atrr.00077 ISSN 2473-3458

Decreasing the Problematic Use of an Information System: A Conceptual Replication in the Context of Digital Streaming Services

Yazhu Maggie Wang

UQ Business School, The University of Queensland

y.wang@business.uq.edu.au

Abstract:

This study is a conceptual replication of Chen, Zhang, Gong, Lee, and Wang's (2020) study that examines factors influencing the intention to decrease problematic Information Systems (IS) use. In contrast with Chen et al.'s smartphone gaming context, we apply their theoretical model to the context of digital streaming services. Aligned with the original study, we tested the model using a scenario-based survey. Results are largely consistent with the original study, albeit with several exceptions. Our findings support that protection motivation theory (PMT) is useful in explaining decreasing problematic use in situations of threats. Threats are the negative consequences caused by problematic streaming service use. Users experience fear when they believe the negative consequences are likely to occur, and the consequential harm will be serious if they occur. When threatened, users are more motivated to decrease use if they believe decreasing use is effective in mitigating the threat and they have confidence in executing it. However, such motivation is not influenced by costs incurred by decreasing use. Further, we validate that invoking fear can break users' viewing habits, which promotes their intention to decrease use. Yet, such an effect is limited. Future research might explore other factors that are effective in breaking users' viewing habits.

Keywords: Digital Streaming Services, Decreasing Problematic IS Use, Protection Motivation Theory, Conceptual Replication.

The manuscript was received 02/07/2022 and was with the authors 3 months for 1 revision.

1 Introduction

Problematic use of digital streaming services has rapidly become prevalent due to the COVID-19 lockdown measures (Rahman & Arif, 2021; Raza et al., 2021). During the pandemic lockdowns, digital streaming services saw a surge in use intensity (Rajan, 2020). With more time spent in solitude, people have become obsessed with consuming multiple episodes of TV shows in rapid succession, known as 'binge-watching', predominantly through digital streaming services (Rahman & Arif, 2021). Recent statistics show that Netflix, one of the most popular streaming services worldwide, had an average of 3.2 hours of daily video consumption in 2020, which increased by 61% from 2019 (Jay, 2022). A survey held in 2020 shows 69.5% of US Netflix users frequently 'binge-watched' Netflix shows back-to-back during the pandemic (Statista, 2020).

Problematic use of digital streaming services is characterized as an addictive behavior involving excessive and uncontrolled consumption of streaming content (Ort, Wirz, & Fahr, 2021; Shim & Kim, 2018). Research suggests that problematic streaming service use, particularly excessive binge-watching, has negative consequences for users' physical, psychological, and social wellbeing (Rahman & Arif, 2021). Excessive binge-watching threatens users' physical health by causing strain on their eyes and body (Flayelle et al., 2020a), sleep deprivation (Starosta & Izydorczyk, 2020), and increased risk of obesity (Groshek, Krongard, & Zhang, 2018). It is also found to harm users psychologically (Raza et al., 2021; Rubin & Wessely, 2020). During the pandemic, streaming service users reportedly experienced symptoms of stress (Huang & Zhao, 2020), depression (Servidio, Bartolo, Palermiti, & Costabile, 2021), and lower self-esteem (Starosta & Izydorczyk, 2020). Furthermore, users who devote an excessive amount of time-consuming streaming content tend to live a solitary lifestyle (Steins-Loeber, Reiter, Averbeck, Harbarth, & Brand, 2020), leading to relationship deterioration (Rahman & Arif, 2021) or social loneliness (Raza et al., 2021).

The negative consequences caused by problematic IS use can be regarded as 'threats' to users (Chen Zhang, Gong, Lee, & Wang, 2020). To avoid the 'threats', research submits decreasing problematic IS use as an effective protective measure (Ning, Dhelim, Bouras, Khelloufi, & Ullah, 2018). However, practical failure in the usage control is prevalent (Chen, Zhang, Gong, & Lee, 2019). Studies repeatedly show that users are often too obsessed with the video content to control their viewing time (De Feijter, Khan, & van Gisbergen, 2016; Flayelle, Maurage, & Billieux, 2017). Similarly, industry reports reveal that users still engage in problematic streaming service use post-pandemic, rather than returning to their pre-pandemic 'normal' use levels (Iqbal, 2022). To help users recover healthy levels of streaming service use, it is imperative to understand what factors impact on users' intention to decrease problematic use.

This study aims to conceptually replicate Chen et al.'s (2020) study to examine factors that influence decreasing problematic use of digital streaming services, particularly binge-watching Netflix. Drawing on protection motivation theory (PMT), Chen et al. (2020) examine factors leading to decreasing problematic use in the smartphone gaming context, where problematic use causes negative consequences. They find that game players develop threat perceptions when they receive information about the negative consequences of problematic use. The threat perceptions (threat severity and vulnerability) invoke fear about suffering from the negative consequences, which disrupts the gaming habit and drives the intention to decrease use. They also find that users are motivated to decrease use if they believe that decreasing use is effective (response efficacy), not costly (response cost), and they have confidence in executing it (self-efficacy). Moreover, decreasing use is found to be influenced by individuals who are significant to the users and believe they should decrease use (subjective norms).

Replication studies allow for the validation of extant models and understanding of the phenomenon in new contexts (Dennis & Valacich, 2015; Xiao & Warkentin, 2021). This replication study seeks to examine the generalizability of Chen et al.'s (2020) theoretical model to the digital streaming service context. We chose to replicate Chen et al.'s (2020) study because digital streaming services and smartphone gaming are contextually similar in their hedonic nature. Similar to Chen et al.'s (2020) study on smartphone gaming, digital streaming services are also hedonic IS, where IS use is hedonically motivated and intrinsically rewarding (Arun, Singhb, Khanc, Akramd, & Chauhane, 2021; Pereira & Tam, 2021; Vaghefi, Lapointe, & Boudreau-Pinsonneault, 2017). Hedonic IS refers to a system that is primarily designed to provide self-fulfilling and intrinsic value to the user, as compared with utilitarian IS, which mainly affords instrumental values (Lowry, Gaskin, Twyman, Hammer, & Roberts, 2012). In both contexts, users engage in intrinsically rewarding behavior – playing smartphone games or watching a series back-to-back. The fun derived from these behaviors, accompanied by a release of dopamine, provides intrinsic rewards to the users (Wang & Hsu, 2016). To continuously receive such intrinsic rewards, people are prone to over-exercise these rewarding behaviors, resulting in problematic IS use (Turel, 2015; Venkatesh, Sykes, Chan, Thong, & Hu, 2019). The problematic use causes negative consequences that threaten users' wellbeing, which evokes negative emotional responses (Deng, 2017; Wang, Matook, & Dennis, 2021). To mitigate the threats, users are recommended to decrease their use. Thus, Chen et al.'s (2020) model is applicable to our study context and fits well with our goal.

The rest of the paper is structured as follows: research model and hypotheses, research method, results, discussion, and conclusion.

2 Research Model and Hypotheses

Based on the original study by Chen et al. (2020), we apply their theoretical model to the digital streaming service context. Our research model is depicted in Figure 1. We tested the same hypotheses from Chen et al. (2020) but in the context of streaming services. Table 1 shows the hypotheses.

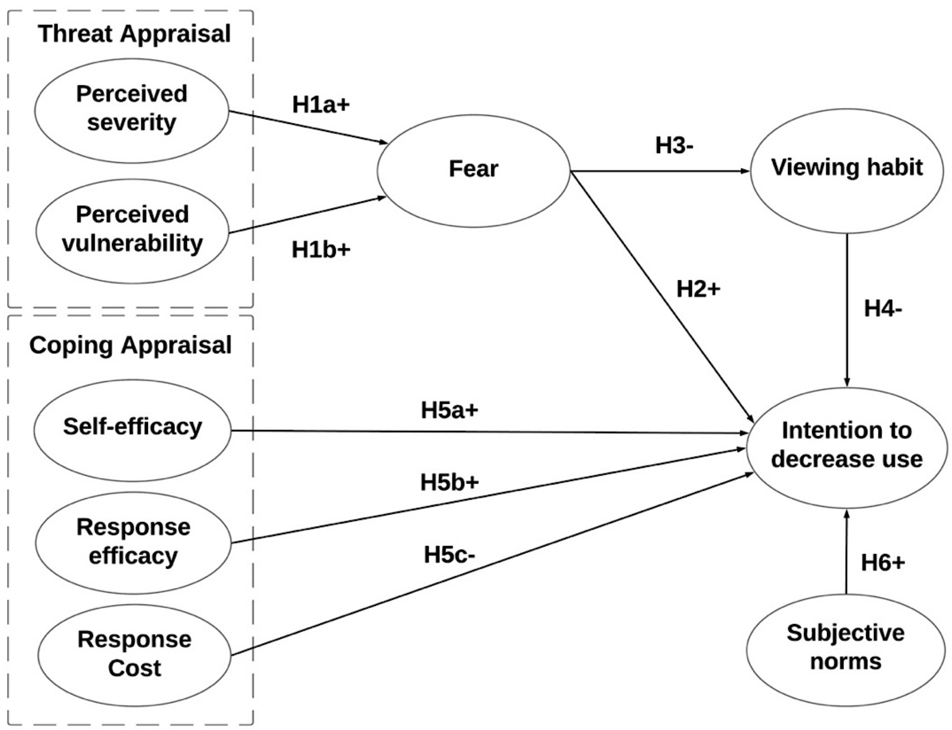

Figure 1. Research Model of the Replication Study (Adapted from Chen et al., 2020)

Table 1. Hypotheses (Adapted from Chen et al., 2020)

Hypothesis 1a	Perceived threat severity positively influences fear.
Hypothesis 1b	Perceived threat vulnerability positively influences fear.
Hypothesis 2a	Fear positively influences intention to decrease use.
Hypothesis 2b	Fear acts as a mediator between threat and intention to decrease use.
Hypothesis 3a	Fear acts as a mediator between perceived threat severity and viewing habit.
Hypothesis 3b	Fear acts as a mediator between perceived threat vulnerability and viewing habit.
Hypothesis 4	Viewing habit negatively influences intention to decrease use.
Hypothesis 5a	Self-efficacy positively influences intention to decrease use.
Hypothesis 5b	Response efficacy positively influences intention to decrease use.
Hypothesis 5c	Response costs negatively influence intention to decrease use.
Hypothesis 6	Subjective norms positively influence intention to decrease use.

3 Research Method

In this section, we describe the sampling and participants, fear appeal design and survey instrument, pretest and primary data collection.

3.1 Sampling and Participants

This replication study recruited participants among Netflix users in North America (the US and Canada). In the original study, participants were Chinese smartphone game players because "the phenomenon of problematic smartphone game use has been reported to be severe in China" (Chen et al., 2020, p. 503). We decided to conduct a survey in North America because the phenomenon of problematic Netflix use has become prevalent in North America during the COVID-19 pandemic (Statista, 2020). Statistics show that, as of July 2020, the subscribers in the US and Canada account for most of Netflix's subscribers worldwide (i.e., 74 million (Statista, 2021)). Notably, 69.5% of these users aged between 18 and 44 years old frequently binge-watch Netflix shows (Statista, 2020). Binge-watching Netflix has been recently recognized as an emerging problematic use phenomenon provoked by COVID-19 and related isolation measures (Rahman & Arif, 2021; Steins-Loeber et al., 2020). Literature shows that excessive binge-watching has negative effects on individuals' health, psychologically (e.g., causing stress, depression (Rahman & Arif, 2021)) and physically (e.g., causing diabetes, heart disease (Rogowsky & Donato, 2021)). Moreover, research finds that long hours spent binge-watching can intensify the negative effects (Rahman & Arif, 2021). During COVID-19, individuals reportedly spent more time binge-watching Netflix series (Rahman & Arif, 2021). Thus, they are likely to suffer from the adverse consequences of problematic use.

Following Lowry, D'Arcy, Hammer, and Moody's (2016) guidance, we recruited participants via an online panel provider, Prolific (https://www.prolific.co), to improve data quality. Prolific allows researchers to pre-screen potential participants who are suitable for our study. The selected participants were then invited to conduct the survey. We run two rounds of surveys on Prolific to recruit our participants. The first round was a short survey designed to screen participants of interest. The survey only contains questions about demographics and problematic streaming service use. Individuals aged between 18 and 44, who are Netflix users from North America and demonstrate problematic Netflix use behaviors, were identified as qualified participants. Then, we invited them to participate in the second round of data collection, where the complete survey was provided. Data were collected between November 28 2021 and December 3, 2021. Each participant was paid 0.90 USD for an 8-minute survey.

3.2 Fear Appeal Design and Survey Instrument

Consistent with the original study, we used a two-group posttest-only randomized experimental design to test our research model. This experimental design included two groups of randomly assigned participants. Each group received a survey that contained a fear appeal manipulation. PMT research defines fear appeals as "persuasive messages designed to scare people by describing the terrible things that will happen to them if they do not do what the message recommends" (Witte, 1992, p. 329). Aligned with PMT, fear appeals were separated into two levels – high and low. To manipulate fear appeals, we designed two scenarios, each of which contains a level of fear appeal. The scenarios were then randomly assigned to the two groups of randomly assigned participants, labeled as high and low fear appeal groups, respectively. The high versus low manipulations of fear appeals are well-recognized practices in PMT studies, as opposed to the manipulations of the absence versus presence of fear appeals (Milne, Sheeran, & Orbell, 2000). According to PMT, only when a person is aware of a threat (i.e., fear appeal) and perceives it as relevant, a coping appraisal process can be triggered (Boss, Galletta, Lowry, Moody, & Polak, 2015; Rogers, Prentice-Dunn, & Gochman, 1997). Yet, the absence of fear appeals means that participants are entirely unaware of the threat, and thus may fail to experience fear, let alone respond to it. To ensure a base-level awareness of the threat, we, therefore, use a low fear appeal manipulation to provide a comparison group for the high fear appeal manipulation.

As the context of this replication study differs from the original study, we revised the scenarios to focus on the negative consequences of problematic use of streaming services (Netflix) as opposed to problematic smartphone gaming in the original study. In the high fear appeal group (scenario A), participants were presented with many explicit messages (six) about how negative consequences of problematic Netflix use could cause severe harm to their physical, psychological, and social wellbeing, followed by two recommended measures to mitigate the harm. The messages were presented in texts and relevant pictures. In the low fear appeal group (scenario B), participants were presented with short messages (two) about the importance of decreasing use, with no pictures. Participants were randomly assigned to one of the two fear appeal scenarios (see Appendix A) and were presented with the same survey questions.

As a conceptual replication, we primarily adapted measurement items from the original study (Chen et al., 2020) to our study context, with several exceptions. We included additional items for three constructs – perceived vulnerability (one item added), response costs (two items added), and subjective norms (three items added). The added items were adapted from existing studies to the streaming service context. Prior research recommends that each construct requires at least three items to ensure sufficient reliability of measurements (Anderson & Gerbing, 1988; Lin & Bhattacherjee, 2010). Thus, the addition of the items aims to improve the measurement reliabilities, evidenced by an increased Cronbach's α for each of the three constructs (see Table D1 in Appendix D). All constructs were measured using a 7-point Likert scale, ranging from strongly disagree to strongly agree. Table 2 shows instrument items used in the current study, in comparison with the items from the original study. The full instrument is provided in Appendix B.

Table 2. Instrument Items – Comparison of Original Study and Replication Study

Construct	Original study	Replication study	Differences in items
Dependent variable			
Intention to decrease use	Turel (2015); Verbeke and Viaene (1999)	Turel (2015); Verbeke and Viaene (1999)	Same
PMT factors – mediator			
Fear	Boss et al. (2015)	Boss et al. (2015)	Same
PMT factors – threat appraisal			
Perceived severity	Johnston and Warkentin (2010)	Johnston and Warkentin (2010)	Same
Perceived vulnerability	Boss et al. (2015); Johnston and Warkentin (2010)	Boss et al. (2015); Johnston and Warkentin (2010)	One item added
PMT factors – coping appraisal			
Self-efficacy	Kulviwat, Bruner II, and Neelankavil (2014)	Kulviwat et al. (2014)	Same
Response efficacy	Boss et al. (2015)	Boss et al. (2015)	Same
Response costs	Bulgurcu, Cavusoglu, and Benbasat (2010); Lee (2011)	Bulgurcu et al. (2010); Lee (2011); Yan et al. (2014); Vance et al. (2012)	Two items added
Non-PMT factors			
Viewing habit	Hsu, Chang, and Chuang (2015)	Hsu et al. (2015)	Same
Subjective norms	Turel (2016)	Turel (2016); Yoon (2011)	Three items added
Problematic use of IS (smartphone games/ digital streaming services (Netflix))	Lee, Cheung, and Chan (2014)	Flayelle et al. (2019; 2020b)	Different; a context-specified scale used.

As the construct 'problematic use of IS' is context-specific, we used a different scale to measure it, focusing on binge-watching behaviors. In Chen et al.'s (2020) study, problematic use is viewed more generally as an uncontrolled, impulsive behavior with negative consequences, including intrapersonal, interpersonal, and professional/academic related issues. Thus, they used scales adapted from Lee et al.'s (2014) work for measuring the problematic use of smartphone gaming, which emphasizes the negative consequences. The current study, however, focuses on excessive binge-watching, a specific form of problematic use recently provoked by the COVID-19 pandemic (Rahman & Arif, 2021). Binge-watching is defined as "the consumption of multiple episodes of a show in one sitting" (Rahman & Arif, 2021, p. 2720). To emphasize binge-watching as a unique form of problematic use, we sought for a scale that closely reflects the problematic viewing patterns of binge-watching. We thus turned to a scale proposed by Flayelle et al.'s (2019; 2020b) work. They measured binge-watching using a 6-item scale focusing on assessing the impulses of individuals to binge-watch. The adapted items include, for example, "*When an* *episode comes to an end, and because I want to know what happens next, I often feel an irresistible tension that makes me push through the next episode*" and "*I always need to watch more episodes to feel satisfied*."

We used SPSS to compute an average score of problematic use for each respondent. We used a 7-point Likert scale (from 1: strongly disagree to 7: strongly agree). Consistent with the original study, if a respondent scored higher than 4, it indicated the presence of problematic use. In the first round, we selected respondents with a score exceeding 4 for problematic use to ensure that only problematic Netflix users would be invited to the second round of data collection. Survey responses with a score below 4 were deleted.

3.3 Pretest and Primary Data Collection

We conducted a pretest for the fear appeal manipulation and corresponding survey (high vs. low fear appeal group) before the primary data collection. The purpose of this pretest was to 1) validate psychometric properties of the instrument (Straub, 1989); and 2) confirm the two scenarios could generate high and low fear appeals, respectively. The pretest participants were recruited through Prolific. We collected a total of 110 completed responses, 55 and 55 in the high and low fear appeal groups, respectively.

Instrument validation: We assess the reliability of the instrument items using Cronbach's α. Convergent and discriminant validity were tested using principal components analysis. The test results assured that the instrument items would generate satisfactory results in the primary data collection. Consistent with the original study, we utilized procedural remedies recommended by Lowry et al. (2016). These remedies include, for example, randomizing the order of survey questions; explaining the scientific importance of the survey at the beginning of the survey/ questions. Prolific ensures completeness by accepting the submission of full responses only. Some attention check questions were also included in the questions, such as "*It is important that you pay attention to the questions. Please select 'Strongly Disagree'*" and "*We need to ensure you are paying attention to the questions. For this question, you must select the answer option Green*."

Fear appeal manipulation testing: Following Chen et al. (2020), we tested for the effectiveness of fear appeal manipulations. The direct effects caused by fear appeals were compared (see Table C1 in Appendix C). Compared to the low fear appeal group, the results showed that the high fear appeal group consistently scored higher for the majority of constructs from both threat and coping appraisals, with one exception of self-efficacy. Overall, we concluded that the scenarios contained messages at two different levels of fear appeals, such that the fear appeals were effective in triggering threat and coping appraisals.

We conducted a two-round primary data collection using Prolific, applying the fear appeal manipulation and the survey instrument used in the pretest. The first round of data collection aimed to select problematic Netflix users who display problematic binge-watching behaviors. The survey was given to 1300 potential participants. 902 out of 1300 participants scored higher than 4 for problematic use of digital streaming service construct, and thus satisfied the criteria of being classified as problematic Netflix users. The 902 participants were then invited to the second round, where they were randomly assigned to one of the two fear appeal groups. A total of 451 participants received the high fear appeal scenario, while 451 participants received the low fear appeal scenario. The surveys were presented using Qualtrics, a web-based survey tool that ensures anonymity. Out of 902 participants, only 865 passed the attention check questions included in the survey. After deleting responses that failed the attention check questions, we obtained a final sample of 865 respondents, 437 in the high fear appeal group and 428 in the low fear appeal group. Table 3 presents the demographics of the two groups of the current study in comparison with that of the original study.

We also assessed the fear appeal manipulation for the main study dataset. The results are consistent with the pretest results, as per Table C2 in Appendix C.

Table 3. Demographics – Original Study vs. Replication Study					
Variable	Category	Original study		Replication study	
		High fear appeal (N)	Low fear appeal (N)	High fear appeal (N)	Low fear appeal (N)
Number of Respondents		420	494	437	428
Age (high & low group mean=30 years)	Below 18	7	12	-	-
	18 – 30	298	355	248	238
	31 – 40	103	114	158	150
	Above 40	12	13	31	40
Gender	Male	189	210	210	203
	Female	231	284	227	225
Use duration per day	Less than 3 hours	103	94	358	346
	3 – 5 hours	239	275	67	77
	Greater than 5 hours	78	125	12	5
Industry	Business Professional	17	11	155	94
	Government/ Civil Services	38	44	26	34
	Company Employee	242	283	113	112
	Freelancer	22	34	20	27
	Student	90	114	81	68
	Others	11	8	42	93

4 Results

The research model was tested using the same statistical analysis techniques as Chen et al.'s (2020) study – covariance-based structural equation modeling (CB-SEM) via LISREL. Consistent with Chen et al. (2020), we tested the research model following a two-stage analytical procedure (Anderson & Gerbing, 1988): 1) the measurement model assessment, and 2) the structural model assessment (i.e., hypothesis testing).

4.1 Measurement Model

To test the measurement model, we conducted confirmatory factor analysis with a maximum likelihood approach. As per Table 4, the goodness of fit indices suggests a reasonable fit of the model to the dataset in both high and low fear appeal groups (Straub, Boudreau, & Gefen, 2004). The measurement models were also tested for reliability and validity following the guidelines by Fornell and Larcker (1981).

Table 4. Measurement Model Fit Evaluation – Original Study vs. Replication Study					
Fit Index	Acceptable levels	Original study		Replication study	
		High fear appeal	Low fear appeal	High fear appeal	Low fear appeal
$\chi 2$	N/A	503.48	442.6	746.17	747.41
df	N/A	263	263	426	426
$\chi 2$ / df	< 3	1.914	1.681	1.752	1.754
RMSEA	< 0.08	0.047	0.037	0.041	0.042
NFI	> 0.90	0.950	0.950	0.944	0.941
CFI	> 0.90	0.980	0.980	0.975	0.973
SRMR	< 0.10	0.043	0.036	0.038	0.038
NNFI	> 0.90	0.970	0.970	0.971	0.969

Internal consistency reliabilities were evaluated using Cronbach's α and composite reliability measure using (*pc*). As per Table D1 (Appendix D), Cronbach's α and *pc* value exceeded 0.70 for all constructs (Straub et al., 2004). Thus, the internal consistency is satisfactory.

Convergent validity was assessed via three criteria recommended by extant studies (e.g., Carmines & Zeller, 1979; Fornell & Larcker, 1981): 1) all indicator factor loadings (λ) should be significant and surpass 0.50; 2) composite reliability (*pc*) should surpass 0.70, and 3) average variance explained (AVE) should surpass 0.50. Table D1 (Appendix D) shows that all three criteria were met for both groups. Thus, convergent validity is adequate.

Discriminant validity was evaluated by checking whether the square root of each construct's AVE surpasses the correlations of the construct with other constructs (Fornell & Larcker, 1981). As per Table D2 and D3 (Appendix D), the correlation matrix shows that the square root of AVE for each construct surpasses the off-diagonal correlations. Thus, discriminant validity is satisfactory.

We investigated the severity of potential multicollinearity issues via variance inflation factor (VIFs) (Shrestha, 2020; Thompson, Kim, Aloe, & Becker, 2017). The results in Appendix E show that the high fear appeal group has VIFs ranging from 1.11 to 2.22, while the low fear appeal group has VIFs ranging from 1.11 to 2.09, which are both below the 3.3 cutoff (Petter, Straub, & Rai, 2007). Thus, multicollinearity is unlikely a major issue in our data.

We assessed common method biases (CMB), following guidelines by Podsakoff, MacKenzie, Lee, and Podsakoff (2003) for procedural and statistical remedies. Procedural remedies included proximate separation and statistical remedies. To achieve proximate separation, we presented the survey questions on different pages. Statistical remedies included Harman's single factor test and a partial correlation procedure (using a marker variable). First, we performed Harman's single factor test (Harman, 1976; Matook, Wang, Koeppel, & Guerin, 2021). We loaded all factors into an EFA where the unrotated factor solution was examined. Nine factors emerged from each dataset (i.e., high and low fear appeals), which explained 82.23% and 82.54% of the variance, respectively. No single factor explained more than 50% variance. Consistent with Chen et al.'s (2020) study, we also added confirmatory factor analysis (CFA) as a more sophisticated test followed by the EFA (Podsakoff et al., 2003). Our results showed that the nine-factor model fitted the data significantly better than the single-factor model did.

Despite the fact that Harman's single factor test is a widely used diagnostic technique for evaluating the extent to which CMB may be an issue, some scholars argue that "this procedure [Harman's single factor test] actually does nothing to statistically control for (or partial out) method effects" (Podsakoff et al., 2003, p. 889). To control for the CMB effects, we thus turn to other statistical remedies. One remedy that has been employed to control the CMB effects is the partial correlation test (Lindell & Whitney, 2001). By partialling out the average correlation between the marker variable and other variables in the study, the potential contaminating effects of CMB can be controlled for (Podsakoff et al., 2003). We conducted a partial correlation test using a four-item construct not related to our topic, namely blue attitude (Schuetz, Lowry, Pienta, & Thatcher, 2021) as a marker variable to examine the influence of CMB on the observed relationships between constructs (Lindell & Whitney, 2001). The results showed that the marker variable had an insignificant effect on the dependent variable (High feal appeal group: $\beta = 0.031$, $p=0.420 > 0.050$; low feal appeal group: $\beta = 0.006$, $p=0.891 > 0.050$). There was no significant difference in variance explained of the endogenous construct after partialling out the marker variable, suggesting that the CMB effects had been statistically controlled for. Overall, our results indicate that CMB was unlikely to pose a serious threat to our dataset.

4.2 Structural Model and Hypothesis Testing

To test our hypotheses, we assessed the structural model in high and low fear appeal groups and compared the results. Specifically, we examined the significance of the path coefficients (including mediation testing), the coefficients of determination and effect sizes. The results are shown in Table 5.

Table 5. Results of Hypotheses Test – Original Study vs. Replication Study							
Hypothesized paths		**Original study**			**Replication study**		
		Overall	**High fear appeal**	**Low fear appeal**	**Overall**	**High fear appeal**	**Low fear appeal**
Testing the baseline PMT model							
H1a	Perceived severity →Fear	0.20***	0.21***	0.20***	0.15***	0.17***	0.11*
H1b	Perceived vulnerability →Fear	0.30***	0.35***	0.27***	0.61***	0.61***	0.61***
H2a	Fear → Intention to decrease use	0.35***	0.33***	0.27***	0.31***	0.26***	0.29***
H2b1	Perceived severity → Fear (mediator) → Intention to decrease use	Partial mediation	Partial mediation	Full mediation	Partial mediation	Partial mediation	Full mediation
H2b2	Perceived vulnerability → Fear (mediator) → Intention to decrease use	Partial mediation	Full mediation	Full mediation	Partial mediation	Partial mediation	Full mediation
H5a	Self-efficacy → Intention to decrease use	0.08*	0.20***	0.04	0.13***	0.14**	0.09
H5b	Response efficacy → Intention to decrease use	0.11**	0.11*	0.10	0.17***	0.28***	0.08
H5c	Response costs → Intention to decrease use	-0.03	-0.15**	0.02	-0.01	0.06	-0.09
Extensions to the baseline PMT model							
H3a	Perceived severity → Fear (mediator) → Habit	Full mediation	Full mediation	No mediation	No mediation	No mediation	No mediation
H3b	Perceived vulnerability → Fear (mediator) → Habit	Partial mediation	Full mediation	No mediation	Partial mediation	Partial mediation	No mediation
H4	Viewing habit → Intention to decrease use	-0.03	-0.13*	0.07	-0.10*	-0.14**	-0.07
H6	Subjective norms → Intention to decrease use	0.35***	0.34***	0.33***	0.37***	0.31***	0.44***
Variance explained (R^2)							
Fear		16.0%	20.0%	15.0%	47.3%	48.4%	43.6%
Habit (Gaming/Viewing)		19.0%	20.0%	20.0%	21.8%	21.8%	24.1%
Intention to decrease use		31.0%	44.0%	23.0%	37.3%	43.3%	30.1%
Note: * p<0.05, ** p<0.01, *** p<0.001							

In the high fear appeal group, perceived severity ($\gamma = 0.17$; $p < 0.001$) and perceived vulnerability ($\gamma = 0.61$; $p < 0.001$) significantly influenced fear. Thus, H1a and H1b are supported. The effect of fear on intention to decrease use was significant (β=0.26; p<0.001), and so was self-efficacy (β=0.14; p<0.01), response efficacy (β=0.28, p<0.001), viewing habit (β=−0.14, p<0.01), and subjective norms (β=0.31, p<0.001). Thus, H2a, H5a, H5b, H4, and H6 are supported. Yet, response costs (β=0.06, p>0.05) were not significant. Thus, H5c is not supported.

In the low fear appeal group, perceived severity ($\gamma = 0.11$; $p < 0.05$) and perceived vulnerability ($\gamma = 0.61$; $p < 0.001$) significantly influenced fear. Thus, H1a and H1b are supported. The effect of fear on intention to decrease use was significant (β=0.29; $p<0.001$), and so were subjective norms (β=0.44, $p<0.001$). Thus, H2a and H6 are supported. Yet, self-efficacy (β=0.09; $p>0.05$), response efficacy (β=0.08, $p>0.05$), response costs (β=−0.09, $p>0.05$), and viewing habit (β=−0.07, $p>0.05$) were not significant. Thus, H5a, H5b, H5c, and H4 are not supported. These results show relationships in the coping appraisal (i.e., self-efficacy, response efficacy, response costs) were not significant under the low fear appeal.

We tested the mediating effects of fear following a bootstrapping approach (Vance, Lowry, & Eggett, 2015). The results are presented in Appendix F. In both high and low fear appeal groups, we found fear was a mediator of the effect of threat perceptions (i.e., perceived severity and vulnerability) on intention to decrease use. Thus, H2b is supported in both fear appeal groups. In the high fear appeal group, fear partially mediated the effect of perceived vulnerability on viewing habit, but not that of perceived severity on viewing habit. Thus, H3b is supported, but H3a is not. In the low fear appeal group, however, fear was not a mediator of perceived threat on viewing habit. Thus, H3a and H3b are not supported.

Following Chen et al. (2020), we included four demographic variables – age, gender, industry and use duration per day – to control for their effects on viewing habit and intention to decrease use. In the high fear appeal group, only age showed significant impacts, negatively influencing intention to decrease use (β=-0.12, $p<0.01$). Gender (β=0.16, $p<0.01$) and Netflix use duration per day (β=0.37, $p<0.001$) showed significant impacts, positively influencing viewing habit. In the low fear appeal group, only Netflix use duration per day (β=0.38, $p<0.001$) showed significant impacts, positively influencing viewing habit. No controls showed significant impacts on the intention to decrease use.

We measured the coefficients of determination (R^2) to examine the influences of factors. The R^2 value represents the amount of explained variance of the endogenous variable. An R^2 value above 0.20 signifies the endogenous variable has an acceptable explanatory power (Zikmund, 2013). Structural model tests results (see Table 5) indicate that our model explained 48.4% and 43.6% of the variance in fear, for the respective group (high: $R^2 = 0.484$, low: $R^2 = 0.436$), 21.8% and 24.1% of the variance in viewing habit (high: $R^2 = 0.218$, low: $R^2 = 0.241$), and 43.3% and 30.1% the variance in intention to decrease use (high: $R^2 = 0.433$, low: $R^2 = 0.301$). The findings show that the low fear appeal group has lower explanatory power in explaining fear and intention to decrease use, but higher in explaining viewing habit.

We calculated and effect sizes of PMT factors and non-PMT factors to examine their influence on intention to decrease use. Following Cohen, West, and Aiken (2014), we tested three models to assess the effect size of PMT factors and non-PMT factors. Appendix G shows the test results of the three models. Model 1 was the control-only model. Model 2 added PMT factors into the control-only model. Model 3 was the full model that added PMT and non-PMT factors into the control-only model. The effect size f^2 was calculated (Cohen, 1988). The thresholds of 0.02, 0.15 and 0.35 are suggested to represent small, medium, and large effect sizes, respectively. Results show that PMT factors increased the predictive power of the high and low fear appeal model by 32.20% and 17.60%, respectively, with a large effect size (f^2=0.47) in the high fear appeal group and a medium effect size in the low fear appeal group (f^2=0.21). Non-PMT factors increased the predictive power of the high and low fear appeal model by 8.30% and 11.70%, respectively, with a small to medium effect size in both groups (high: f^2=0.09; low: f^2=0.13).

Furthermore, we tested an overall model with combined data from both groups. The results show the overall model has lower explanatory power in explaining fear and intention to decrease use than the high fear appeal. Thus, we conclude that the unexplained variance increases when the strength of fear appeals is not considered.

4.3 Results Differences between Original and Current Study

We compared the differences between the current study results of the hypothesis testing with the original study. Table 6 shows the comparison results.

In the high fear appeal group, we find support for 10 of the 12 hypotheses. In contrast with Chen et al.’s (2020) study, we find that the relationship between response costs and intention to decrease use (H6b) is not supported. We also find no mediation effect of fear on the relationship between perceived severity and viewing habit (H3a).

In the low fear appeal group, we find support for 6 out of 12 hypotheses. The results are consistent with Chen et al.'s (2020) study.

Table 6. Comparison of Model Results – Original Study vs. Replication Study

Hypotheses		High fear appeal		Low fear appeal	
		Original study	**Replication study**	**Original study**	**Replication study**
Testing the baseline PMT model					
H1a	Perceived severity →Fear	Supported	Supported	Supported	Supported
H1b	Perceived vulnerability →Fear	Supported	Supported	Supported	Supported
H2a	Fear → Intention to decrease use	Supported	Supported	Supported	Supported
H2b1	Perceived severity → Fear (mediator) → Intention to decrease use	Supported	Supported	Supported	Supported
H2b2	Perceived vulnerability → Fear (mediator) → Intention to decrease use	Supported	Supported	Supported	Supported
H5a	Self-efficacy → Intention to decrease use	Supported	Supported	Not Supported	Not Supported
H5b	Response efficacy → Intention to decrease use	Supported	Supported	Not Supported	Not Supported
H5c	Response costs → Intention to decrease use	Supported	Not Supported	Not Supported	Not Supported
Extensions to the baseline PMT model					
H3a	Perceived severity → Fear (mediator) → Viewing habit	Supported	Not Supported	Not Supported	Not Supported
H3b	Perceived vulnerability → Fear (mediator) → Viewing habit	Supported	Supported	Not Supported	Not Supported
H4	Viewing habit → Intention to decrease use	Supported	Supported	Not Supported	Not Supported
H6	Subjective norms → Intention to decrease use	Supported	Supported	Supported	Supported

5 Discussion

This study conceptually replicates Chen et al.'s (2020) model in a new context of digital streaming services. Our empirical results reveal many consistencies with the original study, with several exceptions. In this section, we discuss both consistencies and inconsistencies between the results of our replication study and the original study. Then, we discuss several implications of our key findings.

Consistent with Chen et al.'s (2020) study, we find that users' intention to decrease problematic use is determined by their perceptions of how serious and relevant the threat is, their beliefs regarding the protective behavior and the execution of it. We find that when the threat perceptions (severity and vulnerability) are high, users experience fear about suffering from the negative consequences, which motivates them to decrease use. When a strong threat is perceived, users are more motivated if they believe that decreasing use is effective (response efficacy) in mitigating the threats, and they have confidence in executing it (self-efficacy). Yet, when the threat perception is low, users' intention to decrease use is not driven by response efficacy or self-efficacy. In addition, the intention to decrease use is influenced by the expectations of individuals who are important to the users and believe they should reduce use (subjective norms). We also find that viewing habit inhibits the intention to decrease use, but only when the threat perception is high.

Another consistent finding is that threat perceptions have limited explanatory power in explaining viewing habit. Only a small amount of the variance in viewing habit is explained by the threat perceptions and fear (high fear appeal=21.8%; low fear appeal=24.1%). This denotes that there are other factors that are not captured in the model, but also influence the viewing habit. Research on IS use behavior suggests that habit can be strengthened by factors such as prior IS use, user satisfaction, and hedonic motivation (Jeyaraj, 2022). Yet, little is known about factors that may inhibit IS use habits. Thus, we suggest future research may explore other factors that lead to the breaking of viewing habits.

We observe several findings that are inconsistent with Chen et al.'s (2020) study. First, we find that users' intention to decrease problematic use is not significantly influenced by the personal costs (e.g., time, effort, or trouble) incurred by decreasing use (response cost). This non-significant relationship may be due to the low response costs perceived by the users. Indeed, our data shows that participants in our study on average perceive low response costs from decreasing use (mean=3.45, SD=1.24). A plausible reason for this may be that the benefits users perceive from decreasing use outweigh its costs. Extant research (Granow, Reinecke, & Ziegele, 2018; Groshek et al., 2018) and media outlets (Birch, 2019) have recently advocated the benefits of reducing streaming service use, such as improved health condition, decreased mental stress, and enhanced social relationships. As users are constantly exposed to such information, they may perceive decreasing use as more beneficial than costly. Thus, the response costs are, in general, perceived low, while users' intentions to decrease use vary. This implies the impact of response costs on intention to decrease use is too small to be considered meaningful. Empirical studies on IS security (e.g., Herath & Rao, 2009; Ifinedo, 2012) support our findings by showing that response costs have no significant effect on IS security compliance intentions.

A second inconsistent finding pertains to the influence of threat perceptions on breaking viewing habits. We find that if users believe the negative consequences of problematic use are likely to occur, then fear is induced, which triggers changes in their viewing habits. Yet, inducing fear is not sufficient for breaking the viewing habit if users only acknowledge the seriousness of the negative consequences (threat severity) but perceive the consequences as less personally relevant (threat vulnerability). A plausible reason for this may be that some users have prior knowledge about the threat severity of problematic use. This means the level of severity they perceived may not just be realized by receiving a fear appeal manipulation, but also influenced by their prior knowledge about it. Research on health communication (e.g., Davis & Jansen, 2016) suggests prior knowledge about the threat severity has a positive impact on the threat severity perceived from a fear appeal. In the current context, users with more prior knowledge about the threat severity of problematic use may perceive higher levels of threat severity from the fear appeals. Thus, it is possible for different users that threat severity stays high, while their viewing habits vary. Perceived threat severity alone, thus, may not be sufficient for breaking the viewing habit. Future research may explore the interaction effect of threat severity and vulnerability on fear.

A third inconsistent finding is the predictive power of threat perceptions is higher in this replication study than in the original study. Specifically, our study has a significantly greater amount of variance in fear explained by threat perceptions, especially by threat vulnerability (increased by 140% under high fear appeal; 193% under low fear appeal). PMT research suggests that a weaker fear appeal manipulation can increase unexplained variance in fear, undermining the power of threat perceptions in predicting fear (Boss et al., 2015). The higher variance explained in fear suggests that the fear appeal manipulations used in this replication study were stronger than the ones in the original study. A plausible reason for this may be the fear appeal messages are perceived as more believable when the source of the messages is presented. In the replication study, the fear appeal messages (i.e., news stories) were presented with the sources (i.e., web links), making them more believable than the messages with no source presented. Research suggests that users are more likely to act on a news story (e.g., click the link and read about it) when they perceive it to be believable (Kim & Dennis, 2019). This may help users better understand the threat provided in the fear appeal, leading to a stronger perception of the threat and emotional response (Boss et al., 2015). Whereas in the original study, the source links of the fear appeal messages were absent. This may reduce the believability of the messages, subsequently diminishing the effect of the fear appeal manipulation. Thus, the predictive power of threat perceptions is lower in the original study.

Our findings have several implications for governments and streaming service providers. First, our results show that users who perceive a higher threat from persuasive messages about the negative consequences of problematic use are more motivated to decrease their use. These persuasive messages are designed to induce fear in people and persuade them to take a protective measure (Witte, 1992). Research suggests that crafting messages that explicitly communicate threats can induce high levels of fear, and thereby elicit high protection motivation (Schuetz, Lowry, Pienta, & Thatcher, 2020). Governments should motivate users to reduce use by exposing them to persuasive messages that contain information about the threats and recommendations to mitigate the threats. Social media are effective channels for making these persuasive messages publicly accessible (Marett, Vedadi, & Durcikova, 2019; Matook, Dennis, & Wang, 2022). For example, governments can make Facebook posts or YouTube videos to inform users that problematic use is prevalent and may have severe effects on their wellbeing. Through this approach, governments can increase users' overall level of concern for threats posed by problematic use, and consequently promote behavioral changes.

Second, we note that users are more motivated to decrease problematic use if they believe the threats can be mitigated by use reduction, and they have sufficient confidence in decreasing the use. IS security research suggests that awareness training of the threats can help individuals develop a sense of responsibility in controlling their technology use (Mwagwabi, McGill, & Dixon, 2018; Puhakainen & Siponen, 2010). The governments should support educational institutions in implementing training programs for streaming service users. Through these programs, users can learn more about the threats and recommended actions to mitigate the threats, and build confidence in their ability to recover healthy levels of streaming service use.

Third, our finding suggests that fear appeals are effective in activating users' motivation to decrease problematic use. Streaming service providers can make use of fear appeals to inspire protective responses from users who exhibit problematic use. For instance, service providers can post information on their websites about serious consequences associated with excessive binge-watching and measures that help mitigate such consequences. This approach can motivate users to take protective measures to proactively control their binge-watching behaviors. Examples of these protective measures include turning off autoplay while watching a Netflix series (Castro, Rigby, Cabral, & Nisi, 2021), or using an internet or app blocker that disables their access to Netflix after a specific period. By implementing these measures, users can take control of their impulsive viewing behaviors and recover healthy use levels.

Fourth, given the importance of subjective norms in users' behavioral changes, people who are important to the users should be encouraged to assist users to regulate viewing time and promote protective measures to recover healthy viewing habits. These people may be friends, family, or colleagues who have close relationships with the users (Madsen & Matook, 2010). For example, these referents may help distract users from binge-watching by engaging them with other forms of entertainment, such as listening to podcasts or reading books together. They can also remind users of the importance of reducing viewing time to avoid potential adverse effects. This approach helps keep users accountable when controlling their problematic use, especially for digital streaming services – an IS used for individual purposes rather than organizational ones (Krell, Matook, & Rohde, 2011).

Fifth, streaming service providers have a moral obligation to encourage the healthy use of the technology. The service providers can implement features to discourage users' excessive use. Research suggests that warning messages can influence behaviors (Bansal-Travers, Hammond, Smith, & Cummings, 2011; Moravec, Kim, & Dennis, 2020). For example, warning messages are helpful in promoting responsible use and healthy behaviors (Auer & Griffiths, 2015; Wohl, Gainsbury, Stewart, & Sztainert, 2013). To promote a healthy service use, streaming services should consider displaying periodic warning messages when an excessive use is detected (e.g., watching multiple episodes in one setting). Furthermore, IS use behavioral research recommends that visually pleasant features can promote desirable use behaviors (Deng & Poole, 2010). Service providers should adopt more visually pleasing designs for the warning messages to evoke positive user responses, thereby promoting a healthy service use. They should also enable tailored design, allowing users to specify where, when and how long the warning message should emerge. In doing so, the service providers demonstrate their adaptability to changing users' needs (Esswein & Zumpe, 2002), leading to increased customer satisfaction (Zumpe & Ihme, 2006).

Our findings reinforce the applicability of PMT in motivating streaming service users to decrease problematic use in a different context, population, and time. Chen et al.'s (2020) study applies PMT to the smartphone game use context, using empirical data from Chinese smartphone game players. Whereas this replication study tests Chen et al.'s model in the digital streaming service context, with a different population, i.e., Netflix users from North America. Despite the population difference, our results support most of the hypotheses. This shows that PMT is appropriate for explaining decreasing problematic use in a different context and is not limited by the population. Moreover, unlike Chen et al.'s (2020) study conducted prior to 2017, this study was conducted in 2021. The time difference is notable as our results become even more significant in light of the year 2021, an atypical year in which COVID-19 was prevalent. The onset of COVID-19 provoked the problematic binge-watching phenomenon. The COVID-19-related lockdown measures limited individuals' options for entertainment (Rahman & Arif, 2021). Binge-watching on streaming services is one of the few avenues to have fun and escape from stress and misery (Raza et al., 2021). As such, it is difficult for individuals to control their impulses to binge-watch. Our findings are therefore pivotal and timely in helping users control their problematic use and recover healthy use levels.

6 Conclusion

This study conceptually replicates Chen et al.'s (2020) study on intention to decrease problematic IS use in a new context of digital streaming services. Overall, we show that Chen et al.'s (2020) model is useful for examining intention to decrease problematic streaming service use, albeit it offers opportunities for further refinement. Our findings support that the intention to decrease problematic streaming service use is influenced by PMT factors (except for response cost), subjective norms, and viewing habits. These influences increase when the fear appeal level is high. Our findings also suggest that high threat perceptions can break the viewing habit, but the effects are limited. Further research is needed to explore other factors contributing to the disruption of viewing habits.

Acknowledgments

The author is grateful to the Senior Editor and the review team for their constructive and insightful suggestions. The author thanks Sabine Matook and Alan R. Dennis for their support and feedback on earlier versions of this paper. We also appreciate the helpful comments we received from participants at the Ph.D. Student Colloquium 2021, held by UQ Business School, the University of Queensland, where the author presented this study.

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Appendix A: Survey Scenarios

Table A1. Survey Scenarios – High vs. Low Fear Appeals

Scenario A – High fear appeal group	Please read the news stories below regarding watching Netflix shows that happened in real-life: 1. A 20-year-old woman who binge-watched 18 episodes of Korean dramas on Netflix over the weekend was diagnosed with acute glaucoma, an irreversible disease that can lead to blindness. (Source: Web Link) 2. The Netflix documentaries and drama series of charming killers, brutal crimes, and tragic victims has led to a rise in violence or even copycat crimes in real life. (Source: Web Link) 3. Binge-watching Netflix series has been closely linked to an increased risk of health issues including Alzheimer's, diabetes, heart disease, and cancer, even if the person also exercises regularly. (Source: Web Link) 4. Binge-watching can lead to cognitive decline. Research shows that watching more than 3.5 hours of Netflix daily was associated with poor verbal memory after six years. (Source: Web Link) 5. Research finds watching back-to-back episodes of violent crime series on Netflix can cause "mean world syndrome", a phenomenon that indicates the viewer sees the world as meaner and scarier than it really is. (Source: Web Link) 6. A University of Texas at Austin study found that those who binge-watch were more likely to admit to feelings of depression, lack of self-regulation or loneliness. (Source: Web Link) 7. Balance Netflix-viewing with other activities, such as physical exercise, seeing friends and reading, is a method to decrease individuals' binge-watching Netflix. (Source: Web Link) 8. Setting up a time limit when watching Netflix shows may help decrease problematic viewing behaviors to prevent negative consequences described above. (Source: Web Link)
Scenario B – Low fear appeal group	Please read the news stories below regarding watching Netflix shows that happened in real-life: 1. Research finds that binge-watching may result in undesirable outcomes, like decreased physical activity, erratic sleep schedules, increased fatigue, and an increased likelihood of making poor eating decisions during a binge. 2. To reduce the effect of binge-watching, health experts recommend people to decrease their viewing hours of Netflix.
Note: For scenario A, relevant pictures were presented to the respondents. For scenario B, no pictures were presented to the respondents.	

Appendix B: Survey Items

Table B1. Constructs and Survey Items

Current variable	Item code	Current study	References
Problematic use of digital streaming services (Netflix)	BIGW_1	When an episode comes to an end, and because I want to know what happens next, I feel an irresistible tension that makes me push through the next episode.	Flayelle et al. (2019; 2020b)
	BIGW_2	I usually spend more time watching Netflix series than planned.	
	BIGW_3	I often need to watch the next episode to feel positive emotions again and to relieve frustration caused by the interruption in the storyline.	
	BIGW_4	I don't sleep as much as I should because of how much time I spend watching Netflix series.	
	BIGW_5	I always need to watch more episodes to feel satisfied.	
	BIGW_6	I cannot help feeling like watching Netflix series all the time.	
Perceived severity	PRSV_1	If the negative effects of watching Netflix on mental and physical health were to happen to me, the consequences would be severe.	Johnston and Warkentin (2010)
	PRSV_2	If the negative effects of watching Netflix on mental and physical health were to happen to me, the consequences would be serious.	
	PRSV_3	If the negative effects of watching Netflix on mental and physical health were to happen to me, the consequences would be significant.	
Perceived vulnerability	PRVL_1	I am likely to suffer from the physical, mental, or social negative effects of watching Netflix.	Boss et al. (2015); Johnston and Warkentin (2010)
	PRVL_2	It is likely that I suffer from the physical, mental, or social negative effects of watching Netflix.	
	PRVL_3	My physical and mental wellbeing or social relationships are at risk for interruption due to watching Netflix.	
	PRVL_4	It is possible that I suffer from the physical, mental, or social negative effects of watching Netflix.	
Fear	FEAR_1	I am worried that I may suffer from the physical, mental, or social negative effects of watching Netflix.	Boss et al. (2015)
	FEAR_2	I am frightened that I may suffer from the physical, mental, or social negative effects of watching Netflix.	
	FEAR_3	I am anxious that I may suffer from the physical, mental, or social negative effects of watching Netflix.	
	FEAR_4	I am scared that I may suffer from the physical, mental, or social negative effects of watching Netflix.	
Self-efficacy	SLEF_1	I am able to reduce my use of Netflix without the help of others.	Kulviwat et al. (2014)
	SLEF_2	I have the skills, knowledge or determination required to reduce my use of Netflix.	
	SLEF_3	I am able to reduce my use of Netflix on my own.	
Response efficacy	RSEF_1	Decreasing the usage of Netflix works to protect me from the negative consequences of problematic Netflix watching.	Boss et al. (2015)
	RSEF_2	Decreasing the usage of Netflix is effective for protection from the negative consequences of problematic Netflix watching.	
	RSEF_3	When the usage of Netflix is decreased, I am more likely to be protected from the negative consequences of problematic Netflix watching.	

Table B1. Constructs and Survey Items – Continued			
Current variable	**Item code**	**Current study**	**References**
Response costs	RSCO_1	It takes effort to decrease the time I spend watching Netflix.	Bulgurcu et al. (2010); Lee (2011); Yan et al. (2014); Vance, Siponen, and Pahnila (2012)
	RSCO_2	Negative emotions (e.g., agitation, unhappiness and anxiety) emerge when I decrease the time I spend watching Netflix.	
	RSCO_3	I will miss the enjoyment if I decrease the time watching Netflix.	
	RSCO_4	Decreasing the time I spend watching Netflix would require considerable investment of effort other than time.	
Viewing habit	HABT_1	Watching Netflix is something I do frequently.	Hsu et al. (2015)
	HABT_2	Watching Netflix is second nature to me.	
	HABT_3	Watching Netflix is something I do without thinking.	
Subjective norms	SUNO_1	People who influence my behaviour think that I should decrease the time I spend watching Netflix.	Turel (2016); Yoon (2011)
	SUNO_2	Most people who are important to me think that I should decrease the time I spend watching Netflix.	
	SUNO_3	If I decrease the time I spend watching Netflix, most of the people who are important to me would approve.	
	SUNO_4	Most people who are important to me think it is a good idea to decrease the time I spend watching Netflix.	
	SUNO_5	My friends think decreasing the time I spend watching Netflix is important.	
Intention to decrease use	DUSE_1	I intend to decrease my Netflix usage in the next 3 months.	Turel (2015); Verbeke and Viaene (1999)
	DUSE_2	I predict I will decrease the time I spend watching Netflix within the next 3 months.	
	DUSE_3	I plan to decrease the time I spend watching Netflix within the next 3 months.	
Maker variable: Blue attitude	CMB_1	I like the color blue.	Schuetz et al. (2021)
	CMB_2	Blue is a beautiful color.	
	CMB_3	I enjoy the color blue.	
	CMB_4	Blue is a pleasant color.	

Appendix C: Fear Appeal Manipulation Test

Table C1. Fear Appeal Manipulation Pretest Results

Construct	High fear appeal	Low fear appeal	T value (test of significant)
N	55	55	
Perceived Severity	4.485 (1.305)	2.600 (1.104)	8.176*** (p<0.001)
Perceived Vulnerability	2.059 (1.047)	1.605 (0.735)	2.634** (p=0.005)
Fear	2.405 (1.380)	1.359 (0.490)	5.295*** (p<0.001)
Self-Efficacy	6.485 (0.532)	6.273 (1.008)	1.380ns (p=0085)
Response Efficacy	5.200 (1.218)	4.527 (1.347)	2.747** (p=0.004)
Response Cost	2.277 (1.084)	1.914 (0.570)	2.202* (p=0.015)

Table C2. Fear Appeal Manipulation Main Study Results

Construct	High fear appeal	Low fear appeal	T value (test of significant)
N	437	428	
Perceived Severity	4.377 (1.376)	3.910 (1.412)	4.932*** (p<0.001)
Perceived Vulnerability	3.180 (1.375)	2.900(1.388)	2.983** (p=0.001)
Fear	3.301 (1.593)	2.751 (1.447)	5.318*** (p<0.001)
Self-Efficacy	6.017 (0.777)	6.015 (0.855)	0.034ns (p=0.486)
Response Efficacy	5.097 (1.209)	4.943 (1.228)	1.861* (p=0.032)
Response Cost	3.440 (1.248)	3.282 (1.240)	1.871* (p=0.031)

Appendix D: Measurement Reliability and Validity Results

Table D1. Reliabilities and Validity of Measurements

Construct	**Item**	**Mean**	**SD**	**Factor loadings [p< .001]**	**Cronbach's α**	**PC**	**AVE**
High Fear Appeal Group							
Intention to decrease use	DEUS_1	3.89	1.62	0.85	0.96	0.90	0.74
	DEUS_2	3.90	1.61	0.87			
	DEUS_3	3.89	1.62	0.86			
Fear	FEAR_1	3.47	1.69	0.84	0.97	0.92	0.74
	FEAR_2	3.13	1.60	0.87			
	FEAR_3	3.44	1.72	0.85			
	FEAR_4	3.25	1.64	0.87			
Perceived severity	SEVE_1	4.17	1.50	0.88	0.94	0.92	0.80
	SEVE_2	4.43	1.44	0.92			
	SEVE_3	4.52	1.45	0.88			
Perceived vulnerability	VULR_1	3.32	1.51	0.79	0.93	0.86	0.61
	VULR_2	3.17	1.50	0.82			
	VULR_3	2.95	1.47	0.73			
	VULR_4	3.38	1.57	0.77			
Viewing habit	HABT_1	5.68	1.02	0.78	0.77	0.86	0.67
	HABT_2	5.06	1.26	0.86			
	HABT_3	5.01	1.32	0.82			
Subjective norms	NORM_1	2.89	1.41	0.87	0.92	0.91	0.68
	NORM_2	2.85	1.42	0.88			
	NORM_3	4.03	1.51	0.64			
	NORM_4	3.16	1.53	0.87			
	NORM_5	3.00	1.45	0.85			
Self-efficacy	SLEF_1	5.94	1.02	0.85	0.87	0.88	0.72
	SLEF_2	5.98	0.92	0.85			
	SLEF_3	5.96	0.96	0.84			
Response efficacy	RSEF_1	5.04	1.27	0.91	0.96	0.94	0.83
	RSEF_2	5.05	1.28	0.90			
	RSEF_3	5.10	1.27	0.92			
Response costs	RSCO_1	3.59	1.69	0.71	0.83	0.83	0.56
	RSCO_2	2.90	1.41	0.78			
	RSCO_3	4.32	1.48	0.71			
	RSCO_4	2.96	1.57	0.78			
Blue attitude	CMB_1	6.01	0.91	0.90	0.94	0.96	0.84
	CMB_2	6.14	0.75	0.90			
	CMB_3	6.03	0.87	0.94			
	CMB_4	6.10	0.81	0.93			

Table D1. Reliabilities and Validity of Measurements – Continued							
Construct	**Item**	**Mean**	**SD**	**Factor loadings [p< .001]**	**Cronbach's α**	**PC**	**AVE**
Low Fear Appeal Group							
Intention to decrease use	DEUS_1	3.25	1.51	0.90	0.95	0.92	0.79
	DEUS_2	3.35	1.55	0.90			
	DEUS_3	3.22	1.49	0.87			
Fear	FEAR_1	2.95	1.61	0.84	0.96	0.91	0.71
	FEAR_2	2.56	1.43	0.85			
	FEAR_3	2.82	1.61	0.85			
	FEAR_4	2.68	1.50	0.83			
Perceived severity	SEVE_1	3.60	1.54	0.88	0.91	0.92	0.79
	SEVE_2	3.97	1.53	0.92			
	SEVE_3	4.15	1.54	0.87			
Perceived vulnerability	VULR_1	3.00	1.49	0.81	0.93	0.88	0.64
	VULR_2	2.80	1.48	0.83			
	VULR_3	2.68	1.53	0.75			
	VULR_4	3.12	1.58	0.81			
Viewing habit	HABT_1	5.74	1.00	0.80	0.82	0.89	0.72
	HABT_2	4.94	1.45	0.89			
	HABT_3	4.85	1.53	0.86			
Subjective norms	NORM_1	2.57	1.35	0.86	0.91	0.91	0.66
	NORM_2	2.54	1.34	0.89			
	NORM_3	3.74	1.52	0.57			
	NORM_4	2.81	1.48	0.85			
	NORM_5	2.71	1.43	0.86			
Self-efficacy	SLEF_1	6.00	0.93	0.87	0.92	0.92	0.79
	SLEF_2	6.00	0.93	0.91			
	SLEF_3	6.04	0.89	0.88			
Response efficacy	RSEF_1	4.91	1.32	0.93	0.95	0.95	0.86
	RSEF_2	4.96	1.28	0.94			
	RSEF_3	4.96	1.27	0.91			
Response costs	RSCO_1	3.29	1.68	0.70	0.82	0.81	0.51
	RSCO_2	2.79	1.42	0.73			
	RSCO_3	4.28	1.58	0.79			
	RSCO_4	2.76	1.45	0.64			
Blue attitude	CMB_1	5.91	0.88	0.91	0.94	0.95	0.83
	CMB_2	5.98	0.83	0.91			
	CMB_3	5.93	0.88	0.92			
	CMB_4	6.00	0.86	0.90			
Note: Intention to decrease use=DEUS; Fear=FEAR; Perceived severity=SEVE; Perceived vulnerability=VULR; Viewing habit=HABT; Subjective norms=NORM; Self-efficacy=SLEF; Response efficacy=RSEF; Response costs=RSCO; Blude attitude=CMB							

Table D2. Inter-Construct Correlations – High Fear Appeal Group

	DEUS	FEAR	SEVE	VULR	HABT	NORM	SLEF	RSEF	RSCO	CMB
DEUS	0.86									
FEAR	0.45*	0.86								
SEVE	0.31*	0.42*	0.89							
VULR	0.43*	0.65*	0.42*	0.78						
HABT	-0.11*	-0.03	-0.02	0.14*	0.82					
NORM	0.48*	0.37*	0.29*	0.46*	-0.02	0.82				
SLEF	0.01	-0.23*	-0.04	-0.27*	-0.09	-0.18*	0.85			
RSEF	0.45*	0.32*	0.31*	0.34*	-0.06	0.32*	0.04	0.91		
RSCO	0.21*	0.44*	0.30*	0.47*	0.20*	0.30*	-0.41*	0.14*	0.75	
CMB	0.04	0.04	0.03	-0.01	0.04	-0.03	0.13*	0.01	0.06	0.92

Note: Square root of the average variance extracted (AVE) is the diagonal. * $p \leq 0.05$
Intention to decrease use=DEUS; Fear=FEAR; Perceived severity=SEVE; Perceived vulnerability=VULR; Viewing habit=HABT; Subjective norms=NORM; Self-efficacy=SLEF; Response efficacy=RSEF; Response costs=RSCO; Blude attitude=CMB

Table D3. Inter-Construct Correlations – Low Fear Appeal Group

	DEUS	FEAR	SEVE	VULR	HABT	NORM	SLEF	RSEF	RSCO	CMB
DEUS	0.89									
FEAR	0.40*	0.84								
SEVE	0.20*	0.35*	0.89							
VULR	0.30*	0.62*	0.41*	0.80						
HABT	0.00	0.13*	0.07	0.26*	0.85					
NORM	0.49*	0.43*	0.15*	0.35*	0.12*	0.81				
SLEF	-0.06	-0.27*	-0.14*	-0.38*	-0.08	-0.28*	0.89			
RSEF	0.24*	0.27*	0.18*	0.15*	-0.03	0.27*	0.03	0.93		
RSCO	0.14*	0.40*	0.18*	0.49*	0.23*	0.40*	-0.50*	0.16*	0.71	
CMB	0.02	0.05	-0.02	0.08	0.18*	0.04	0.07	-0.02	0.08	0.91

Note: Square root of the average variance extracted (AVE) is the diagonal. * $p \leq 0.05$
Intention to decrease use=DEUS; Fear=FEAR; Perceived severity=SEVE; Perceived vulnerability=VULR; Viewing habit=HABT; Subjective norms=NORM; Self-efficacy=SLEF; Response efficacy=RSEF; Response costs=RSCO; Blude attitude=CMB

Appendix E: Multicollinearity Diagnostics

Table E1. Multicollinearity Diagnostics – VIF and Tolerance

Variable	High fear appeal group		Low fear appeal group		Test result
	Tolerance	VIF	Tolerance	VIF	
Fear	.51	1.96	.54	1.87	Passed
Perceived severity	.74	1.34	.81	1.24	Passed
Perceived vulnerability	.45	2.22	.48	2.09	Passed
Viewing habit	.90	1.11	.90	1.11	Passed
Subjective norms	.74	1.36	.72	1.38	Passed
Self-efficacy	.79	1.27	.70	1.42	Passed
Response efficacy	.80	1.26	.85	1.17	Passed
Response costs	.63	1.59	.59	1.70	Passed

Note: Test result = ‘Passed’: VIF < 3.3 and Tolerance > 0.1; Test result = ‘Failed’: VIF > 3.3 or Tolerance < 0.1.

Appendix F: Mediation Test Results

Table F1. Mediation Test Results – Bootstrapped CI Tests (Overall, High Fear Appeal, Low Fear Appeal)						
Mediator (M) fear		**Mediation test (indirect)**				
Independent variable (X)	**Dependent variable (Y)**	**Indirect effect of X on Y**	**Bias-corrected 95% confidence intervals for indirect effect**		**Zero included?**	**Mediation?**
		Effect (SE)	**Lower bound**	**Upper bound**		
Overall						
Perceived severity	Intention to decrease use	0.176*** (0.022)	0.135	0.222	No	Yes
Perceived vulnerability		0.251*** (0.035)	0.184	0.321	No	Yes
Perceived severity	Viewing habit	0.017ns (0.011)	-0.005	0.039	Yes	No
Perceived vulnerability		-0.062*** (0.022)	-0.107	-0.019	No	Yes
High fear appeal group						
Perceived severity	Intention to decrease use	0.185*** (0.033)	0.124	0.255	No	Yes
Perceived vulnerability		0.221*** (0.051)	0.129	0.328	No	Yes
Perceived severity	Viewing habit	-0.007ns (0.016)	-0.039	0.023	Yes	No
Perceived vulnerability		-0.098** (0.031)	-0.161	-0.038	No	Yes
Low fear appeal group						
Perceived severity	Intention to decrease use	0.133*** (0.027)	0.085	0.190	No	Yes
Perceived vulnerability		0.226*** (0.042)	0.180	0.350	No	Yes
Perceived severity	Viewing habit	0.034ns (0.016)	-	-	-	No
Perceived vulnerability		-0.029*** (0.032)	-0.093	0.031	Yes	No
Mediator (M) fear		**Full/partial mediation test (direct)**				
Independent variable (X)	**Dependent variable (Y)**	**Direct effect of X on Y**	**Bias-corrected 95% confidence intervals for direct effect**		**Zero included?**	**Type of mediation?**
		Effect (SE)	**Lower bound**	**Upper bound**		
Overall						
Perceived severity	Intention to decrease use	0.128*** (0.036)	0.058	0.199	No	Partial Mediation
Perceived vulnerability		0.171*** (0.044)	0.085	0.256	No	Partial Mediation
Perceived severity	Viewing habit	0.010ns (0.028)	-	-	-	No Mediation
Perceived vulnerability		0.224*** (0.031)	0.160	0.289	No	Partial Mediation
High fear appeal group						
Perceived severity	Intention to decrease use	0.162** (0.053)	0.058	0.266	No	Partial Mediation
Perceived vulnerability		0.267*** (0.063)	0.143	0.391	No	Partial Mediation
Perceived severity	Viewing habit	-.009ns (.037)	-	-	-	No Mediation
Perceived vulnerability		0.198*** (0.043)	0.113	0.283	No	Partial Mediation
Low fear appeal group						
Perceived severity	Intention to decrease use	0.077ns (0.049)	-0.019	0.172	Yes	Full Mediation
Perceived vulnerability		0.087ns (0.059)	-0.030	0.203	Yes	Full Mediation
Perceived severity	Viewing habit	-	-	-	-	No Mediation
Perceived vulnerability		-	-	-	-	No Mediation

Appendix G: Stepwise Results

Table G1. Effects of PMT and non-PMT Factors on Intention to Decrease Use

Factors	**DV: Intention to decrease use**		
High fear appeal group			
	Model 1 – Control-only model	**Model 2 – PMT model**	**Model 3 – Full model**
Controls			
Age	-0.04***	-0.12*	-0.12**
Gender	-0.15	-0.03	0.03
Use duration	0.11	0.03	0.06
Industry	-0.02	-0.03	-0.06
PMT factors			
Fear		0.33***	0.26***
Self-efficacy		0.12**	0.14**
Response efficacy		0.35***	0.28***
Response cost		0.10	0.06
Non-PMT factors			
Viewing habit			-0.14**
Subjective norms			0.31***
R^2	**2.8%**	**35.0%**	**43.3%**
R^2 Change		**32.20%**	**8.30%**
Effect size (f^2)	**0.03**	**0.54**	**0.76**
Effect size (f^2) Change		**0.47**	**0.09**
Low fear appeal group			
	Model 1 – Control-only model	**Model 2 – PMT model**	**Model 3 – Full model**
Controls			
Age		-0.03	-0.02
Gender		-0.00	0.04
Use duration		0.02	0.02
Industry		-0.00	-0.01
PMT factors			
Fear		0.39***	0.29***
Self-efficacy		0.06	0.09
Response efficacy		0.14**	0.08
Response cost		0.02	-0.09
Non-PMT factors			
Viewing habit			-0.07
Subjective norms			0.44***
R^2	**0.80%**	**18.40%**	**30.1%**
R^2 change		**17.60%**	**11.70%**
Effect size (f^2)	**0.01**	**0.23**	**0.43**
Effect size (f^2) change		**0.21**	**0.13**

About the Author

Yazhu (Maggie) Wang is a Ph.D. student in Information Systems at the UQ Business School, The University of Queensland, Brisbane, Australia. She holds a degree in Master of Commerce (Information Systems) from The University of Queensland and a degree in Bachelor of Economics (Finance) from The University of International Business and Economics, Beijing, China. Before commencing her doctoral studies, she worked as an academic tutor for two postgraduate courses at the UQ Business School and as a data analyst for a data science team at the Information Services Branch of Brisbane City Council. Her research interests focus on the adoption and use, and consequences of use of artificial intelligence systems, social media platforms, and educational technologies. Methodologically, she uses both qualitative and quantitative methods in her studies. Her work has appeared in the *Journal of Management Information Systems*. She has presented research papers at esteemed conferences, including the *International Conference on Information Systems* and the *Australasian Conference on Information Systems*.