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Mediators of the relationship between self-control and pathological technology use: Negative affect and cognitive failures, but not self-efficacy

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Preface

The proceedings contain papers presented at the 13th annual NeuroIS Retreat held June 1-3 2021. NeuroIS is a field in Information Systems (IS) that uses neuroscience and neurophysiological tools and knowledge to better understand the development, adoption, and impact of information and communication technologies (www.neurois.org).

The NeuroIS Retreat is a leading academic conference for presenting research and development projects at the nexus of IS and neurobiology. This annual conference promotes the development of the NeuroIS field with activities primarily delivered by and for academics, though works often have a professional orientation.

In 2009 the inaugural NeuroIS Retreat was held in Gmunden, Austria. Since then, the NeuroIS community has grown steadily, with subsequent annual Retreats in Gmunden from 2010-2017. Beginning in 2018, the conference is taking place in Vienna, Autria. Due to the Corona crisis, the organizers decided to host a virtual NeuroIS Retreat in 2021.

The NeuroIS Retreat provides a platform for scholars to discuss their studies and exchange ideas. A major goal is to provide feedback for scholars to advance their research papers toward high-quality journal publications. The organizing committee welcomes not only completed research, but also work in progress. The NeuroIS Retreat is known for its informal and constructive workshop atmosphere. Many NeuroIS presentations have evolved into publications in highly regarded academic journals.

This year is the seventh time that we publish the proceedings in the form of an edited volume. A total of 27 research papers were accepted and published in this volume, and we observe diversity in topics, theories, methods, and tools of the contributions in this book. The 2021 keynote presentation entitled "Decision Neuroscience: How it started and where we are today" is given by Antoine Bechara, professor of neuroscience and psychology at the University of Southern California (USC) in Los Angeles, USA. Moreover, Moritz Grosse-Wentrup, professor and head of the Research Group Neuroinformatics at the University of Vienna, Austria, gives a hot topic talk entitled "How (not) to interpret Multivariate Decoding Models in Neuroimaging".

Altogether, we are happy to see the ongoing progress in the NeuroIS field. Also, we can report that the NeuroIS Society, established in 2018 as a non-profit organization, has been developing well. We foresee a prosperous development of NeuroIS.

June 2021

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Antoine Bechara – Keynote

Decision Neuroscience: How It Started and Where We Are Today

Decision neuroscience is an emerging area of research whose goal is to integrate research in neuroscience and behavioral decision-making. Neuroeconomics is a more specialized field of study that seeks to bridge neuroscience research on human choice with economic theory, whereas neuromarketing addresses the neuroscience behind consumers' choices, including product branding, preference, and purchase decisions. More recent research seeks to include the field of information science by examining the impact of social media and other technology use on the human brain. All these areas capitalize on knowledge from the fields of neuroscience, behavioral economics, finances, marketing, and information science to explore the neural "road map" for the physiological processes intervening between knowledge and behavior, and the potential interruptions that lead to a disconnection between what one knows and what one decides to do. Thus, decision neuroscience is the domain that captures the interests of scientists who are attempting to understand the neural basis of judgment and decision-making in health as well as social behavior.

Moritz Grosse-Wentrup – Hot Topic Talk

How (not) to Interpret Multivariate Decoding Models in Neuroimaging

Multivariate decoding models are replacing traditional univariate statistical tests in the analysis of neuroimaging data. Their interpretation, however, is far from trivial. In this presentation, I outline various pitfalls and discuss under which conditions they can provide insights into the (causal) question of how neuronal activity gives rise to cognition and behavior.

Panel Discussion

Success Factors in Publishing NeuroIS Research in Top IS Journals: Experiences of MIS Quarterly Editors and Reviewers

Moderator: Fred D. Davis
Panelists: Ofir Turel, Tony Vance, Adriane B. Randolph, Eric Walden

Table of Contents

6

Where NeuroIS Helps to Understand Human Processing of Text: A Taxonomy for Research Questions Based on Textual Data

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Abstract. Several research questions from information systems (IS) are based on textual data, such as product reviews and fake news. In this paper, we investigate in which areas NeuroIS is best suited to better understand human processing of text and subsequent human behavior or decision making. To evaluate this question, we propose a taxonomy to distinguish these research questions depending on how users' corresponding response is formed. We first review all publications about textual data in the IS basket journals from 2010–2020. Then, we distinguish text-based research questions along two dimensions, namely, if a user's response is influenced by subjectivity and if additional information is required to make an objective assessment. We find that NeuroIS research on textual data is still in its infancy. Existing NeuroIS studies focus on texts, where users' responses are subject to a higher need for additional data, which is not part of the text.

Keywords: Textual data · Taxonomy · Information processing · Decision-making · NeuroIS

Introduction

Social media and other forms of computer-mediated communication provide users with large amounts of textual data [1]. Text provides an unstructured and high-dimensional source of information as English texts can easily comprise vocabularies with tens of thousands of words [2]. So far, IS research has analyzed how users respond to texts of many types, such as fake news, online reviews, financial reports, spam emails, and computer-mediated communication. While the factors of a helpful product review are well understood (e.g., [3–5]), little is known of why users fall for deception in the form of fake news. Deciding if a news article is real or fake may be subjective and depends on prior beliefs and attitudes [6–8]. Making an objective veracity assessment of a news article may also require additional information from external sources, which is not part of the actual text [9]. Whether or not users invest cognitive effort into a critical assessment also depends on their mindset. Users in a utilitarian mindset are used to spending cognitive effort in reading the text as part of their daily (working) routines, whereas users in a hedonic mindset (e.g., when being active on social media) are less likely to carefully reflect on their actions [6]. As a

consequence, their behavior may be driven by unconscious processes, which can be studied by employing tools and theories from NeuroIS [10–13].

One possible reason for the limited understanding of specific IS phenomena based on textual data is that users' responses may exhibit higher degrees of subjectivity or that making an objective assessment requires additional information, which is not part of the text. In this study, we propose a taxonomy that distinguishes research questions based on textual data according to whether a user's response is driven by a low or high degree of subjectivity and the need for additional information in order to make an objective judgement. We specifically build our taxonomy for the research questions instead of the type of text themselves. The underlying reasoning is that the same type of text can be subject to different research questions. For instance, a news article can be categorized as positive or negative, or as real or fake. However, categorizing the article as positive or negative is less affected by political opinions and unconscious processes than categorizing an article as real or fake. The proposed taxonomy was developed based on all articles about text-related research questions from the IS basket journals published between 2010 and 2020. We categorized each of these studies along the dimensions "degree of subjectivity" and "need for additional information". In addition, we distinguish all studies according to (1) whether they collected user-specific data to account for individual beliefs and attitudes, and (2) studies that can be attributed to the field of NeuroIS. Taken together, we address the following research question:

"*For which research questions based on textual data should researchers employ methods from NeuroIS?*"

Literature Review

For our literature review about research on textual data, we consider all articles published in the IS basket journals between 2010 and 2020. We first read the title of all issues to determine whether an article is about textual data or not. Subsequently, we read the abstract of the remaining studies to validate our initial assessment. Thereby, we encountered 47 studies about text. We excluded nine of these studies [14–22] as they did not specifically analyze human behavior as a direct response to reading the text. Regarding the publication dates, we find that the number of studies about textual data and human responses has increased over the last few years. While 10 out of 38 papers were published in 2010–2015, the majority of 28 were published in the years 2016–2020. Finally, we scan the remaining 38 papers in regard to their collected data. We distinguish between (1) studies without user-specific data (e.g., political attitude, disposition to trust), (2) studies with user-specific data, and (3) studies with NeuroIS measurements.

Table 1 shows the result of our literature review. We identified four studies from NeuroIS, from which three ([6, 23, 24]) are published in MIS Quarterly (MISQ) and one ([25]) in the European Journal of Information Systems (EJIS). Moravec et al. [6] analyzed the influence of IS design modifications on users' cognition when processing fake news. In their experiment, subjects were shown several online news

articles with and without warning messages, while their cognitive activity was measured with electroencephalography (EEG). The authors found that adding warning messages increases cognitive activity, but this has no impact on the final veracity assessment. Bera et al. [23] used eye tracking to explain cognitive processing of users in reading conceptual modeling scripts to perform problem solving tasks. Their results suggest that high task performance can be explained and detected by attention-based eye tracking metrics. Meservy et al. [24] studied how individuals evaluate and filter posts in online forums, while seeking the solution to a problem. For this purpose, the authors employed functional magnetic resonance imaging (fMRI) to measure the neural correlates that are involved in evaluating both solution content and contextual cues. Their results indicate that both content and contextual cues impact users' final filtering decisions. Finally, Brinton Anderson et al. [25] used text mining and eye tracking to study how users perceive security messages and found that habituation to security warnings significantly reduces the effect of such warnings.

Table 1. Studies about textual data in IS basket journals from 2010 to 2020.

Journal	No user-specific data	User-specific data	NeuroIS	Total
JMIS	[26–38]	[8]		14
MISQ	[39–44]	[7]	[6, 23, 24]	10
JAIS	[45–49]	[50]		6
ISR	[5, 51–53]			4
JIT	[54, 55]			2
JSIS	[56]			1
EJIS			[25]	1
ISJ				0
Total	31	3	4	38

We identified three studies which collected user-specific data, but without employing tools and theories from NeuroIS. For instance, Hong et al. [50] used a combination of surveys and text mining in order to explain and predict deviations in restaurant reviews based on cultural differences. Their findings suggest that users from a collectivist culture tend to agree with prior ratings. Kim and Dennis [8] collected users' political attitude and studied whether fake news can be mitigated by adding

user and expert ratings to the presentation of a news article. Their results suggest that expert ratings have a stronger impact in steering users to a correct veracity assessment. However, this only holds when the rating indicates low reliability, whereas ratings of high reliability have no effect. In another study on fake news, Kim et al. [7] studied the effects of alternating the presentation format. Their results suggest that presenting the source before the headline (instead of showing the headline before the source) makes users less likely to perceive fake news as real. In addition, the authors find that source reputation ratings have a stronger effect on the perceived believability. However, this only holds when the rating is low (i.e., indicating fake content).

All other studies did not collect user-specific data as part of their research design. Instead, they rely on statistical methods from text mining to empirically analyze how users respond to textual data. These studies covered consumer behavior [30, 33, 39, 40, 48, 49, 51, 53, 55, 56], financial decision-making [29, 31, 32, 35, 36, 43, 46, 47, 54], perception of online reviews [5, 26–28, 42, 45], deception detection [37, 38], and others [41, 52].

Taxonomy for Research Questions Based on Text

We now present our taxonomy to distinguish research questions based on textual data depending on whether users' response is influenced by subjectivity and if there is a need for additional information in order to make a correct assessment. Hereby, "degree of subjectivity" refers to the questions: How subjectively can the probands answer the (research) question? Would people with different prior experience or belief answer differently? "Need for additional information" on the other hand, refers to the questions: Would a proband's answer become better or more correct if they had additional information or additional knowledge? Is all relevant information that is needed for the proband to complete the task or answer the (research) question given in the text? Or is additional information, knowledge, or background required? We propose this taxonomy in order to address our research question. Based on the following cluster analysis, we identify areas in which NeuroIs seems best suited in order to understand human processing of text and their subsequent behavior or decision making? Figure 1 presents the proposed taxonomy along these two dimensions. All studies including user specific data from surveys are highlighted with a square, while all NeuroIS studies are highlighted with a circle. For the purpose of this study, we distinguish all studies from our literature based on our own reading. Overall, the NeuroIS studies were located in the upper part of Figure 1, which contains those research questions, where users have a higher need for additional information. The upper right corner of Figure 1 contains all studies analyzing research questions, where users' responses are driven by a high degree of subjectivity with a high need for additional information to make an objective assessment. Prominent examples are studies that analyze why users fall for fake news [6, 7, 7]. The decision if a news article is real of fake depends on users' individual political attitudes, while making an objective assessment generally requires users to research additional information.
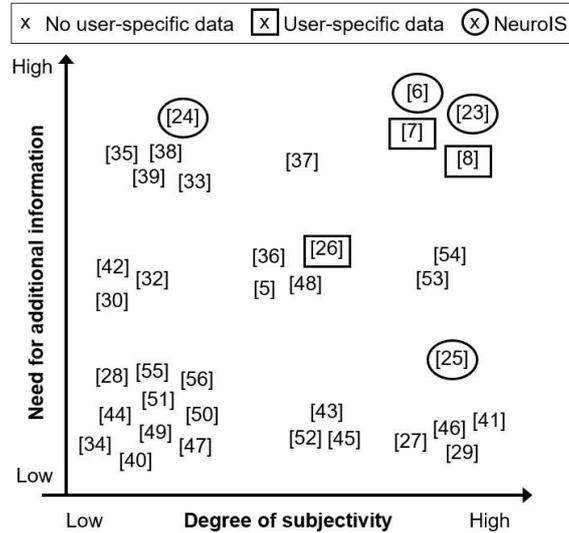
Fig.1. Taxonomy to distinguish research questions based on textual data depending on the characteristics of users' responses.

The studies in the bottom right area of Figure 1 consider research questions, where users' responses involve high degree of subjectivity without a need for additional information. One example is to explain why social media posts receive more likes (e.g., [40]). The decision of whether to like a social media post or not is subjective as it depends on personal tastes, while all relevant information based on which users decide to like a post is generally included in the text. The upper left corner of Figure 1 contains all studies analyzing research questions, where users' responses are driven by low degree of subjectivity, but with a high need for additional information. We classified all studies about fraud or deception detection as such [32, 34, 37, 38, 47]. Deciding if a message originates from a deceiver is generally not driven by personal attitudes. However, the decision is often made based on incomplete information. Ultimately, the studies in the bottom left area of Figure 1 consider research questions, where users' responses are not influenced by subjectivity without a need for additional information. For instance, this applies to the question of how daily deals impact a restaurant's online reputation [51]. The review text generally stands for itself, while the factors of a positive or negative review (length, number of arguments, high readability) are usually not influenced by subjectivity.

Conclusion and Future Research

Understanding how humans respond to textual data provides novel challenges for IS research and practice. We proposed a taxonomy to distinguish different forms of texts after reviewing recent studies from the IS literature according to their research design. In this taxonomy, we distinguish research questions based on textual data with respect

to the characteristics of users' responses. Specifically, we consider two dimensions, namely how much a user's response is driven by subjectivity and the need for additional information in order to make an objective assessment. We find that NeuroIS is used for research questions, where users arrive at conclusions based on incomplete information. All corresponding studies [6, 23–25] focused on users' cognitive processing. It appears that this is the area, where NeuroIS is best equipped to help understand human processing of text and help explain human behavior and decision making. However, the vast majority of existing studies in the IS literature considered texts where users' responses can be explained without user-specific data.

IS research on textual data should hence select their study design depending on the characteristics of users' responses. If users' conclusions exhibit only little subjectivity and the text contains all relevant information, there is no need for experiments and employing measurements from neuroscience. Conversely, if users' responses are driven by a higher degree of subjectivity and if additional information is required for an objective assessment, users may rely on unconscious and/or heuristic processes. For example, affective processes may not be fully reflected through self-reports, which requires IS researchers to employ neurophysiological measurements such as ECG or startle reflex modulation [13].

We plan to extend this study as follows. First, we need to evaluate our taxonomy by gathering feedback from external domain experts. Presenting our work at the NeuroIS retreat would be one important step in this direction. After this, we can perform a sequence of evaluation-improvement iterations until we reach an acceptable state. Second, we aim to extend our literature review to all studies in the existing IS literature to provide a full overview of IS studies on textual data. Third, we are planning to elaborate more on the specific tools from NeuroIS, in particular, how specific measurements can be applied to study users' responses to different types of text.

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Mediators of the Relationship Between Self-Control and Pathological Technology Use: Negative Affect and Cognitive Failures, But Not Self-Efficacy

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Abstract. The widespread adoption of technologies such as smartphones, the Internet, and social media has been associated with the emergence of pathological technology use (e.g., Internet addiction). Prevalence rates of pathological technology use vary widely across age groups, cultures, and medium, although it is not uncommon for rates of mild to moderate pathological use to exceed 20%-30%. These relatively high prevalence rates have motivated researchers to identify the predictors of pathological use. The current study focuses on the relationship between self-control and pathological technology use, and demonstrates that negative affect and cognitive failures, but not self-efficacy, partially mediate the association between self-control and pathological technology use. These findings reveal some of the pathways by which poor self-control could lead to elevated levels of pathological technology use.

Keywords: self-control, negative affect, pathological technology use

Introduction

The widespread adoption of smartphones and the technologies that they provide access to (e.g., the Internet and social media) over the last two decades has revolutionized the way we interact with friends and family, conduct business, pursue an education, and spend our leisure time [1]. In contrast to the many benefits these technologies have brought to our lives, there are also significant personal and social costs associated with the abusive (e.g., cyberbullying) and pathological (e.g., Internet addiction) use of technology [2-3]. Estimates of the prevalence of pathological technology use vary widely across medium, although it is not uncommon for rates to fall between 20%-30% or higher depending upon the sample and form of technology [4-6]. These high prevalence rates have motivated extensive work seeking to identify the causes and consequences of pathological technology use [3,6,7]. This research reveals that pathological technology use is consistently associated with diminished self-control [8] and poor mental health outcomes including increased depression, anxiety,

stress, and suicidal ideation [9]. The current study sought to extend upon the extant literature by examining whether the relationships between aspects of self-control and pathological technology use (i.e., smartphone, Internet, social media) are partially or fully mediated through effects on negative affect, cognition, and self-efficacy.

Studies have consistently demonstrated that poor self-control is associated with an increase in pathological technology use [7] and addiction more generally [10]. As an example, Kim et al. [11] found that individual differences in self-control and impulsivity were unique predictors of smartphone pathology. Consistent with this finding, individuals with attention deficit hyperactivity disorder (ADHD) experience higher levels of pathological smartphone use than typically developing individuals [12]. Poor self-control may also account for the association between pathological technology use including video games [13], social media [14], and the Internet [15] and poor decision making in the Iowa Gambling Task (IGT) reported in a number of studies. These findings are consistent with work using electrophysiological and neuroimaging methods demonstrating that pathological technology use is associated with attenuated neural activity related to reward processing [16] and to reduced brain volume in a number of structures within the reward network [17]. The disruption of neural activity and alternations in brain volume and connectivity within the fronto-striatal reward/control network are commonly implicated in disorders of self-control, emotion dysregulation, and addiction [18].

Self-control is a complex construct that represents aspects of impulsivity, risk-taking, and emotion regulation [19,20]. Poor self-control is associated with increases in negative affect (i.e., depression, anxiety, stress), poor cognitive control, and reduced self-efficacy [19,21-22], and each of these are themselves associated with pathological technology use. Therefore, an important question represents the degree to which the influence of self-control on pathological technology use may be mediated through its influence on negative affect, cognitive control, and self-efficacy. To address this question, the current study examined three hypotheses related to possible mediators of the relationship between self-control and pathological technology use:

H1: Poor self-control is associated with increases in negative affect, cognitive failures, pathological technology use, and decreases in self-efficacy.

H2: Negative affect, cognitive failures, and self-efficacy are associated with pathological technology use.

H3: The relationship between self-control and pathological technology use is mediated through negative affect, cognitive failures, and self-efficacy.

To examine these hypotheses, individuals completed measures of pathological technology use (i.e., smartphone, Internet, social media), a multidimensional measure of self-control, a measure of negative affect tapping depression, anxiety and stress, and a measure of cognitive failures. We did not include a measure of pathological Internet gaming as in some previous research an effect of gender has been observed in this domain [12,23], wherein pathology is much more common in males than in females, an interaction we hoped to avoid in the current dataset. The multidimensional measure of self-control allowed us to distinguish between the influence of aspects of self-control that were differentially related to impulsivity and emotion regulation, and risk-taking on pathological technology use.

Method

Participants

The sample included 210 individuals from the Prolific registry. To participate in the study, individuals had to be 18 years of age or older and have an IP address registered in the United States. The average age of the sample was 31 years (SD=11 years), with 43% females, 49% males, 4% gender non-conforming, 2% trangender, and 1% other. The sample was predominantly white (63%), followed by Asian (13%), Black or African American (11%), Hispanic or Latinx (10%), Indigenous (1%), and other (2%); 19% had not completed any college, 31% had completed 1-2 years of college, 8% had completed 3 years of college, 28% had completed 4 years of college, and 14% had completed some graduate training. Individuals were compensated $5 US for participation in the study through their Prolific account.

Materials and Procedure

Cronbach's α was used to estimate the reliability (internal consistency) of the scales for the data obtained for the study, these values are reported in the text. The self-control scale measures six aspects of self- control (Impulsivity α=.82, Risk-taking α=.85, Self concern α=.78, a preference for Simple tasks α=.87, a preference for Physical activity over mental activity α=.78, Tempe (emotion regulation) α=.80)[20]; for the Self-control scale higher scores represent lower self-control. Pathological technology use was measures with the Internet Addiction Test-Short Version (α=.86)[24], Smartphone Addiction Scale-Short Version (SAS-SV, α=.87) [25], and Bergen Social Media Addiction Scale (BSMAS, α=.86)[26]. Negative affect was measured with the Depression, Anxiety and Stress Scale-21 (DASS-21-Depression α=.93, Anxiety α=.86, Stress α=.89)[27]. The Cognitive Failures Questionnaire (CFQ, α=.94)[28] was used to assess cognitive control. Self-efficacy was measured with the General Self-Efficacy Scale (GSF, α=.91) [29] and Short Grit Scale (perseverance subscale α=.76) [30]. Individuals also completed demographic measures including age, gender, education, and race and ethnicity, and other scales not relevant to the current project. There were three attention check questions distributed across the study materials, these included "Which of the words is presented in upper case letters? – cat, RAT, bat, sat; "Which of the words is a color?" – red, grass, sky, water; "Which word is an animal?" – water, pan, cup, fox.

Individuals completed the study through a link posted on the Prolific website. The study materials were presented using Google Forms. At the beginning of the study, individuals read a consent form and checked a box indicating their willingness participant in the study and then continued with the survey materials. Completion of the study materials required 15 to 30 minutes across participants.

Data Cleaning and Preparation

All participants answered the three attention check questions correctly and were therefore retaining in the sample. Some participants were missing responses for an item from an individual scale or subscale. These missing values were imputed with the participants mean for the scale or subscale, thereby allowing us to estimate reliability in the entire sample without impacting individual scores for the measures or the pattern of correlation across the measures. For the analyses, scale level measures were formed by calculating the average response across items for each of the scales or subscales (Self-control scale). Additionally, composite measures were formed by averaging scores for the three pathology measures (smartphone, internet, social media pathology) and the three negative affect measures (depression, anxiety, stress) given the higher degree of correlation among the relevant measures.

Results

Scores for the three pathology measures were highly correlated, as was the case for the measures of negative affect (Table 1). Self-efficacy and perseverance for the Grit scale were also highly correlated ($r = .58$, p<.001); therefore, a composite variable was formed representing the average Z-score for the two measures as they are on different scales. The six subscales of the self-control scale revealed a mixed pattern of correlations (Table 2). A principal component analysis [31] was performed for the Self-control scale in an effort to reduce the number of variables included in the analyses, while capturing the underlying structure within the six subscales. Consistent with previous research [32], the PCA revealed two components with Eigenvalues greater than 1.0 that accounted for 61% of the variance, and were moderately correlated ($r = .24$). The first component (SC1) represented impulsivity (component loading = .76), self-concern (component loading = .64), simple task (component loading = .84), and tempe (component loading = .72), and the second component (SC2) represented risk-taking (component loading = .68) and physical tasks (component loading = .87). Two composite variables were formed that represented the average of impulsivity, self-concern, simple task, and tempe, or risk- taking and physical tasks.

Supporting Hypotheses 1 and 2, the correlations between pathology and the predictors were medium to large, except for the SC2 composite where the correlation was small (Table 3); all correlations were significant. Pathology increased with greater negative affect and cognitive failures, and less self-control, and decreased with greater self-efficacy. The correlations between the SC1 composite and the mediators were also medium to large, and significant. The correlations between the SC2 composite and the mediators were small, and the correlation with negative affect was not significant.

Table 1. Pearson correlations between measures of pathology (left side) and negative affect (right side)

Pathology	1	2	3	Negative Affect	4	5	6
1. Internet				4. Depression			
2. Smartphone	.69			5. Anxiety	.71		
3. Social Media	.63	.71		6. Stress	.71	.82	

Note: All correlations are significant at p<.001.

Table 2. Pearson correlations among the subscales of the self-control scale.

	1	2	3	4	5	6
1. Imp.	--					
2. Risk	.40**	--				
3. Self	.29**	.22*	--			
4. Simple	.51**	.05	.35**	--		
5. Physical	.006	.29**	.15#	-.16#	--	
6. Tempe	.40**	.26**	.50**	.35**	.05	--

Note: # p< .05, * p<.01, **p<.001

Table 3. Pearson correlations between pathology and the predictor variables.

	1	2	3	4	5	6
1.Pathology						
2. SC 1	.50**					
3. SC 2	.17#	.21*				
4. Negative Affect	.52**	.48**	.11			
5. CFQ	.46**	.46**	.19*	.57**		
6. Self-efficacy	-.31**	-.45**	.17*	-.35**	-.31**	

Note: # p< .05, * p<.01, **p<.001

We tested a set of four mediation models to determine whether the relationship between self-control and pathology was fully or partially mediated by negative affect, cognitive failures, or self-efficacy. The models were fit using the Mediation Model in JASP (0.14, JASP Team 2020) based upon the Lavaan SEM package with R [33]. Maximum likelihood estimation was used. For the direct and indirect effects, we report the z-test for the parameter estimates along with the 95% confidence interval based upon 1000 Bootstrap samples with the Bias-corrected percentile [34]. An initial set of models including both components of self-control revealed that the total effect of SC2 was not significant (p=.28). Therefore, this variable was dropped from the analyses to simplify the models. The individual mediator models provided partial support for Hypothesis 2, revealing that both negative affect and cognitive failures were partial mediators of the relationship between self-control and pathology (Table 4). In contrast, although self-efficacy was correlated with both self-control and pathology, the indirect effect was not significant in the self-efficacy model. When negative affect and cognitive failures were included in a combined model, there were significant unique indirect effects for both mediators from self-control to pathology (Table 4, Full model).

Table 4. Standardized path coefficients, z-test, and bootstrap 95% confidence interval for the individual and combined mediator models. The direct effect from SC1 to pathology and the indirect effects through the mediators.

	Direct effect	z	Indirect effect	z	R-squared
Affect	.34[.22-.46]	5.18**	.18[.11-.27]	4.58**	.35
Cognition	.36[.25-.52]	5.73**	.14[.07-.23]	3.84**	.32
Self efficacy	.47[.32-.62]	6.80**	.05[-.02-.14]	1.58	.26
Full model	.30[.17-.44]	4.46**			.37
Affect			.14[.06-.23]	3.52**	
Cognition			.08[.006-.17]	2.24#	

Note: #p=.025, * p <.01, ** p < .001. The 95% confidence intervals for the Bootstrap for direct and indirect effects are reported in the [].

Discussion

Here we replicated the finding that lower self-control is associated with increased levels of pathological technology use in an adult, community-based sample, with roughly equal numbers of males and females [7]. Our measure of self-control represented two distinct, but correlated, factors. One that was primarily related to impulsivity and emotion regulation (tempe) and one that was primarily related to risk taking. The impulsivity/emotion regulation component was more strongly related to pathology technology use and the three predictors (i.e., negative affect, cognitive failures, and self-efficacy) than the risk-taking component. Additionally, the impulsivity/emotion regulation component was a unique predictor of pathological technology use, while risk- taking was not. These findings provide some refinement of our

understanding of the nature of the relationship between pathological technology use and self-control by demonstrating a specific association with impulsivity/emotion regulation. This finding is interesting within the broader literature indicating that pathological technology use may in some instances serve a compensatory role in the context of anxiety and negative affect [35].

We also observed that pathological technology use was associated with elevated negative affect and cognitive failures, and lower self-efficacy. These findings are consistent with previous research [5,11-12] and provide the foundation for testing the hypotheses related to mediation of the association between self-control and pathological technology use. The mediation analyses revealed that negative affect and cognitive failures were unique partial mediators of the association between self-control and pathological technology use. In contrast, self-efficacy did not mediate the relationship between self-control and smartphone pathology, although it was significantly correlated with both variables. This finding may indicate that high self-efficacy could provide a buffer against pathological technology that operates outside of the influence of self-control. These findings move beyond the simple observation of associations between self-control and pathological technology use by revealing potential pathways by which this association is manifest. For instance, the mediated path from self-control to negative affect to pathology, may reveal how a reduction in emotion regulation could lead to increased depression, anxiety and stress, that in turn leads individuals to utilize the Internet in an attempt to boost their mood. Likewise, poor impulse control may contribute to lower cognitive control (i.e., increased cognitive failures) making it difficult to resist the temptation to frequently check social media [19,22].

The current findings may be of interest to Information Systems researchers and professionals alike in demonstrating that there are multiple routes to understanding, and possibly disrupting, the link between self-control and pathological technology use. As an example, based upon our findings, intervention programs designed to reduce pathological technology use may be most successful when focused on both the affective and cognitive aspects of self-control. This suggestion is consistent with some literature examining factors that led to both the emergence of pathological technology use within individuals and also one's ability to overcome pathological use [35]. For instance, in this study individuals reported that pathological use was related to reducing negative affect or creating positive affect consistent with the link for self-control to negative affect to pathological use. Also, others reported that intrinsic and extrinsic motivation that could be related to both self-control and self-efficacy were important in overcoming pathological technology use. Our findings are also interesting within the context of programs designed to disrupt pathological technology use that have a focus on providing resources for monitoring and limiting use [36], possibly serving as a surrogate for endogenous self-control. Together, the current findings and extant literature may demonstrate the important interplay between research designed to both characterize and then reduce pathological technology use.

There are some limitations of the current research worth considering. First, the three measures of pathological technology use were highly correlated, making it difficult to examine unique predictors of different forms of pathology as has been done in some previous research [23]. This might be possible with a larger sample that would

be appropriate for estimating what are likely to be small unique effects and would also allow us to examine potential gender differences across the three forms of technology considered in the study. Second, the measures of negative affect were also highly correlated, making it difficult to consider possible unique influences of depression, anxiety, and stress. Again, a larger sample could be useful in addressing this limitation. Third, given the nature of the dataset it is impossible to fully understand the direction or nature of the causal effects reflected in the correlations observed between self-control, negative affect, cognitive failures, and pathological technology use, although we may be able to conclude that the effects of self-control and self-efficacy arise from different sources. The direction of the causal effects could be examined with either longitudinal studies over short or long periods of time, or through targeted intervention studies.

In conclusion, the current study provides a number of insights into the relationship between self-control and pathological technology use. First, we demonstrated that pathological technology use is more strongly related to aspects of impulsivity and emotion regulation rather than risk-taking within the context of self-control. Second, we observed that negative affect and cognitive failures, but not self-efficacy, were partial mediators of the association between self-control and pathological technology use. Together our findings lead to the suggestion that there are multiple pathways by which variation in self-control is associated with pathological technology use.

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