

Lecture Notes in Information Systems and Organisation 32

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Information Systems and Neuroscience

NeuroIS Retreat 2019

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Information Systems and Neuroscience

NeuroIS Retreat 2019

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Preface

NeuroIS is a field in Information Systems (IS) that makes use of neuroscience and neurophysiological tools and knowledge to better understand the development, adoption, and impact of information and communication technologies. The NeuroIS Retreat is a leading academic conference for presenting research and development projects at the nexus of IS and neurobiology (see <http://www.neurois.org/>). This annual conference has the objective to promote the successful development of the NeuroIS field. The conference activities are primarily delivered by and for academics, though works often have a professional orientation.

Since 2018, the conference is taking place in Vienna, Austria, one of the world's most beautiful cities. In 2009, the inaugural conference was organized in Gmunden, Austria. Established on an annual basis, further conferences took place in Gmunden from 2010 to 2017. The genesis of NeuroIS took place in 2007. Since then, the NeuroIS community has grown steadily. Scholars are looking for academic platforms to exchange their ideas and discuss their studies. The NeuroIS Retreat seeks to stimulate these discussions. The conference is best characterized by its workshop atmosphere. Specifically, the organizing committee welcomes not only completed research but also work in progress. A major goal is to provide feedback for scholars to advance research papers, which then, ultimately, have the potential to result in high-quality journal publications.

This year is the fifth time that we publish the proceedings in the form of an edited volume. A total of 40 research papers are published in this volume, and we observe diversity in topics, theories, methods, and tools of the contributions in this book. The 2019 keynote presentation entitled "How to Tell Your NeuroIS Story to an MIS Audience" was given by David Gefen, Prof. of MIS and Provost Distinguished Research Professor at the LeBow College of Business, Drexel University, USA. Moreover, Karin VanMeter, biologist and guest lecturer at the Austrian Biotech University of Applied Sciences, gave a hot topic talk entitled "The Importance of the Autonomic Nervous System for Information Systems Research."

Altogether, we are happy to see the ongoing progress in the NeuroIS field. More and more IS researchers and practitioners have been recognizing the enormous potential of neuroscience tools and knowledge.

Lubbock, USA
Steyr, Austria
Vaduz, Liechtenstein
Montreal, Canada
Kennesaw, USA
Steyr, Austria
June 2019

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David Gefen—Keynote: How to Tell Your NeuroIS Story to an MIS Audience

The philosophy of science and methodology of neuroscience, NeuroIS included, is different from that of the more “traditional” philosophies of science and methodologies in MIS such as surveys, design science, archival data analysis, and various types of ethnographic research. Telling a neuroscience research story and making the claim for its contribution to such an audience can be challenging. This talk will present the case, make suggestions, and open the floor to an honest conversation of those issues.

Karin VanMeter—Hot Topic Talk: The Importance of the Autonomic Nervous System for Information Systems Research

The autonomic nervous system (ANS), also referred to as the “involuntary nervous system,” is the part of the peripheral nervous system supplying internal organ systems and glands. It consists of three portions, the sympathetic, parasympathetic, and enteric divisions, all of which largely regulate bodily functions unconsciously. The ANS plays a major role in homeostasis and adaptive functions and thus a response to internal and external stimuli. Examples of external stimuli are changes in light, temperature, and general environment. The sympathetic branch regulates metabolic resources and coordinates the emergency response—“fight or flight.” The parasympathetic division is responsible for “rest and digest,” while the enteric branch is considered separately because of its location.

While sympathetic activity is increased during the day, the parasympathetic activity becomes more active during the night when regeneration occurs at the cellular and organ level, as well as the mental level. From an Information Systems (IS) perspective, the ANS is critical, for example, due to its role in stress processes. This talk describes the fundamentals of the functioning of the ANS. Because reviews of the literature revealed that measures of ANS activity (e.g., pupil dilation, heart rate, blood pressure, skin conductance) play a significant role in NeuroIS research, this talk deals with a fundamental NeuroIS research domain.

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Circadian Rhythms and Social Media Information-Sharing



Rob Gleasure

Abstract Large amounts of information are shared through social media. Such communication assumes users are sufficiently aligned, not only in terms of their interests but also in terms of their emotional and cognitive states. It is not clear how this emotional and cognitive alignment is achieved for social media, given one-to-one interactions are infrequent and discussion often spans loosely connected individuals. This study argues that circadian rhythms play an important physiological role in aligning users for information-sharing, as information shared at different times of the day is likely to encounter users with common physiological states. Data are gathered from Twitter to examine patterns of sentiment and text complexity in social media, as well as how these patterns affect information-sharing. Results suggest the timing of a social media post, relative to collective patterns of sentiment and text complexity, is a better predictor of information-sharing than the sentiment and text complexity of the post itself. Put differently, information is more likely to be shared when it is posted at times of the day when other users are primed for emotion and concentration, independent of whether that posted information is itself emotional or demanding in concentration.

Keyword Circadian · Social media · Sentiment · Text complexity · Twitter

1 Introduction

Social media provides an important means of gathering and distributing information. Yet the sheer volume of information limits what individuals can consume and share, i.e. the amount of information users may ‘convey’ significantly exceeds the amount of information upon which they may ‘converge’ [c.f. 1]. Key determinants of convergence and information-sharing have been identified as *sentiment* [2, 3] and *text complexity* [4, 5]. These qualities influence a recipient’s motivation and capability to engage with particular pieces of information. The influence of *sentiment* and *text*

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complexity on information-sharing is not absolute; rather, their impact depends on their alignment with the needs of recipients at some particular time. Failure to match the *sentiment* of recipients may result in posts appearing out of sync or ‘tone deaf’ [6, 7]. Similarly, more complex information is often less welcome when discussion is adversarial [4, 5] and more welcome when discussion is collaborative [8–10].

This need for alignment between communicators and recipients is typically developed over the course of one-to-one symbolic interactions [11] and physiological mirroring [12]. Yet social media-based information-sharing is rarely one-to-one and often occurs between individuals who do not frequently interact [13]. Hence it is not obvious how users achieve the alignment to interact effectively.

This study proposes the alignment of social media users relies partly on common circadian rhythms, i.e. daily light-entrained physiological oscillations that help to ensure individuals are most active during the day and most restful at night [14, 15]. Studies have shown circadian rhythms produce predictable patterns in the sentiment of social media posts. Notably, an extensive study by Golder and Macy [16] found consistent circadian patterns in social media sentiment across countries, seasons, and days of the week. Previous research has also shown that information-sharing on social media is disproportionally between individuals in geographical proximity [17], hence in similar time zones. Thus, there is an intuitive role for circadian rhythms as a mechanism for creating alignment between social media users.

2 Social Media and Circadian Rhythms

Circadian rhythms encourage us to be active at the times best suited for our environment, e.g. to crave food and increase in activity when food sources are typically plentiful [18]. Circadian rhythms regulate a range of biological processes, from hormonal changes, to body temperature, to mood [14, 18–21]. These roughly 24-h cycles are coded into the cells of most living things, creating a natural clock that oscillates between wakefulness and restfulness—even when environments are artificially manipulated to make days seem longer or shorter [14, 22, 23].

For mammals such as humans, daily circadian cycles are entrained by light through the suprachiasmatic nucleus (SCN), which fires to dorsomedial areas of the hypothalamus and links to neural pathways involved in the release of mood and effort-related hormones such dopamine [24], serotonin [18], and cortisol [25]. The SCN simultaneously inhibits the pineal gland from secreting melatonin, the hormone that accumulates to promote sleep states [22]. This results in dual-process cycle (see [18]) where (i) the ascending arousal system triggers hormones to promote activity/inhibit the release of sleep-inducing melatonin via the pineal gland, while (ii) the competing homeostatic sleep system gradually builds up pressure until it can overwhelm sleep-inhibitors and produce enough melatonin to inhibit the SCN, resulting in a ‘flip flop’ switch between wake-sleep transitions. A summary of documented daily circadian hormonal patterns is illustrated in Fig. 1.

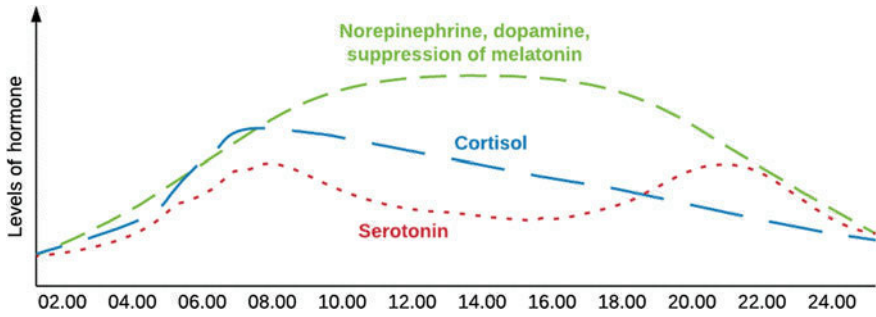


Fig. 1 Typical circadian levels of dopamine, serotonin, cortisol, and melatonin suppression

The role of these hormones in regulating engagement and energy means these patterns are relevant for social media information-sharing in two ways.

First, increased engagement and energy are linked to higher levels of emotional affect [26]. Hence circadian rhythms tend to influence the mood of individuals at different times of the day in a way that harmonizes that mood with other social actors [19], even in where no interaction has occurred.

Second, increased engagement and energy are associated with an individual's willingness to engage in challenging behaviors [27]. Communication via social media changes the nature of communication, wherein individuals must decide which communications to ignore, which to prioritize, and which to share with others [28, 29]. More complex communications increase mental load for the recipient [30], increasing the pressure on specific intrinsic and extrinsic rewards [31].

Circadian hormone patterns have been used to predict collective shifts in mood and information-processing in social media use. This includes daily contribution patterns to Wikipedia [32], seasonal changes in depression-related information search [33], and changes in word volume variation [34]. Most comprehensively, Golder and Macy [16] found strikingly consistent daily *sentiment* patterns on Twitter across countries, seasons, and days of the week.

Thus, circadian rhythms may conceivably have a direct impact on the *sentiment* and *text complexity* of social media posts, as well as subsequent information-sharing behaviors of users (as users will be in different, common physiological states at different times of the day). It may further moderate the relationship between *sentiment/text complexity* and information-sharing by extending alignment between the communicator and the recipients.

3 Method

Data were gathered from Twitter Data on 8th August and 6th December 2018. For both dates, 1000 English-language tweets were gathered from US social media users in each of the 50 states at 1-h intervals (total $N = 2,400,000$). Duplicates and retweets

were removed, as were tweets from private accounts or accounts with no followers, and tweets with no text. *Sentiment* for each tweet was analyzed at a word level using the AFINN sentiment lexicon for microblogs [35], accessed through the tidytext library¹ for R (an open source data processing platform). *Sentiment* was scored according to positive affect (PA), negative affect (NA), *valence* (PA – NA) and *arousal* (PA + NA). Tweets with no scores for *sentiment* were removed to allow analysis to focus on discussion with some emotional content. This resulted in a final set of 404,946 tweets. *Text complexity* was then scored using the Gunning FOG index [36], the Dale-Chall measure [37] (later dropped for convergence issues), the Flesch-Kincaid Reading Ease Index (FRE) [38], and the Simple Measure Of Gobbledygook (SMOG) [39] (accessed via the quanteda library²).

4 Findings

Data show reliable circadian patterns of *sentiment* and *text complexity*, consistent with existing research (see Figs. 2 and 3) [c.f. 16]. The predicted *sentiment* and *text complexity* at different times were estimated using separate locally weighted regression (LOESS) curves for each measure of *sentiment* and *text complexity*. These curves were tested against the patterns and effect size of comparative polynomials to ensure reliability. A series of negative binomial regressions (see Tables 1 and 2) also compared the impact of a tweet’s *sentiment* and *text complexity* with the predicted *sentiment* and *text complexity* based on the time of day it was posted, i.e. the qualities of the tweet versus the daily aggregate qualities of Twitter discussion at the time of posting. Hierarchical models were introduced that predicted information-sharing by adding the *sentiment/text complexity* of a tweet (model 1), then the circadian predicted

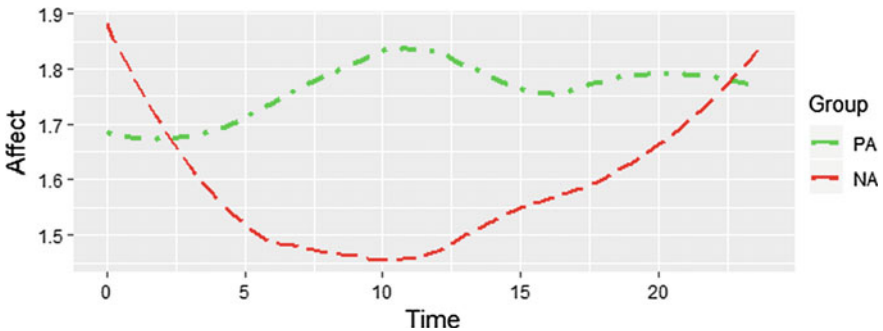


Fig. 2 LOESS curves for *positive affect* (PA) and *negative affect* (NA) based on avg. *sentiment* for time

¹Tidytext version 0.1.8, available at <https://cran.r-project.org/web/packages/tidytext/index.html>.

²quanteda ver. 1.3.4, available at <https://cran.r-project.org/web/packages/quanteda/index.html>.

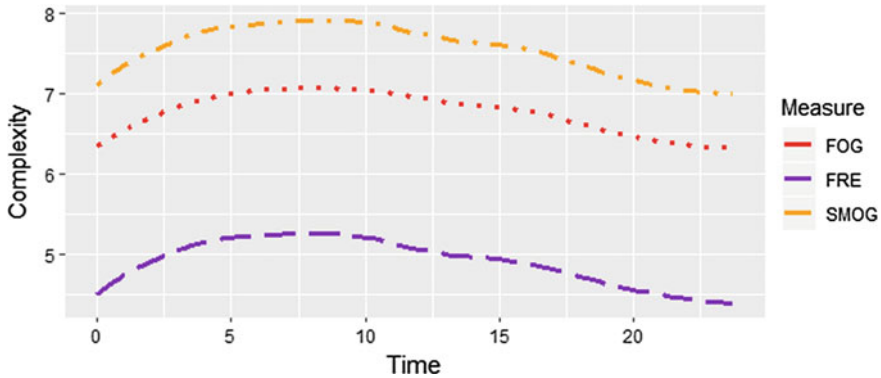


Fig. 3 LOESS curves for FOG, FRE, and SMOG, based on avg. text complexity for time

sentiment/text complexity at the time that tweet was posted (model 2), then finally the interaction term (model 3).

5 Discussion

Findings from this study support previous observations of circadian patterns in the *sentiment* of social media discussion. They also extend these patterns to *text complexity*, the first study to do so, to the author's knowledge.

More importantly, findings from this study suggest collective circadian patterns of *sentiment* and *text complexity* provide stronger predictions of information-sharing than the *sentiment* and *text complexity* of individual posts. Put differently, information is more likely to be shared when it is posted at times of the day when other users are primed for emotion and concentration, independent of whether that posted information is itself emotional or demanding in concentration.

More broadly, this study provides an explanatory physiological mechanism for how loosely connected individuals can achieve the emotional and cognitive alignment required for information-sharing. This has obvious practical implications for social media, e.g. perhaps posted information should be delayed for users in other time zones. However, this finding also has implications beyond social media discussion. For example, the circadian model proposed in this study may help to explain communication and relationship-building difficulties in distributed organizational teams.

Table 1 Results of negative binomial regression for circadian predicted sentiment on retweets

	Model 1			Model 2			Model 3		
	<i>B</i>	<i>SE</i>	<i>exp</i>	<i>b</i>	<i>SE</i>	<i>exp</i>	<i>B</i>	<i>SE</i>	<i>Exp</i>
Arousal	0.026**	0.006	1.026	0.024***	0.006	1.024	−0.531**	0.189	0.588
Predicted arousal				0.817***	0.134	2.257	NS	–	–
Ar * Predicted Ar							−0.165**	0.056	0.848
Hashtags	0.131***	0.014		0.135***	0.014		0.135***	0.141	
Mentions	−0.291***	0.018		−0.289***	0.018		−0.289***	0.178	
Urls	0.319***	0.025		0.336***	0.025		0.335***	0.025	
Log (followers)	0.557***	0.009		0.559***	0.009		0.559***	0.009	
Log (activity)	−0.179***	0.009		−0.181***	0.009		−0.181***	0.009	
AIC	77,604			77,563			77,563		
Valence	−0.011**	0.004	0.989	−0.010	0.004	0.990	NS	–	–
Predicted valence				−1.122***	0.101	0.320	−1.118***	0.101	0.321
Val * Predicted Val							NS	–	–
Hashtags	0.131***	0.014		0.133***	0.014		0.133***	0.014	
Mentions	−0.291***	0.018		−0.285***	0.018		−0.285***	0.018	
Urls	0.312***	0.025		0.339***	0.025		0.339***	0.025	
Log (followers)	0.557***	0.009		0.562***	0.009		0.563***	0.009	
Log (activity)	−0.181***	0.009		−0.187***	0.009		−0.188***	0.009	
AIC	77,615			77,492			77,492		
PA	NS	–	–	NS	–		NS	–	–
Predicted PA				−2.785***	0.296	0.053	−2.469***	0.399	0.075

(continued)

Table 1 (continued)

	Model 1			Model 2			Model 3		
	<i>B</i>	<i>SE</i>	<i>exp</i>	<i>b</i>	<i>SE</i>	<i>exp</i>	<i>B</i>	<i>SE</i>	<i>Exp</i>
PA * Predicted PA							NS	–	–
Hashtags	0.128***	0.014		0.123***	0.014		0.123***	–0.014	–
Mentions	–0.294***	0.018		–0.288***	0.018		–0.288***	0.018	
Urls	0.308***	0.025		0.309***	0.025		0.309***	0.025	
Log (followers)	0.556***	0.009		0.559***	0.009		0.559***	0.009	
Log (activity)	–0.179***	0.009		–0.185***	0.009		–0.185***	0.009	
AIC	77,623			77,535			77,535		
NA	0.029***	0.069	1.029	0.027***	0.006	1.027	NS	–	–
Predicted NA				1.182***	0.122	3.277	1.159***	0.153	3.218
NA * Predicted NA							NS	–	–
Hashtags	0.134***	0.014		0.138***	0.014		0.138***	0.014	–
Mentions	–0.287***	0.018		–0.285***	0.018		–0.285***	0.018	
Urls	0.319***	0.025		0.346***	0.025		0.346***	0.025	
Log (followers)	0.558***	0.009		0.563***	0.009		0.563***	0.009	
Log (activity)	–0.182***	0.009		–0.186***	0.009		–0.186***	0.009	
AIC	77,602			77,512			77,514		

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, † $p < 0.1$, NS = not significant

Table 2 Results of negative binomial regression for circadian predicted sentiment on retweets

	Model 1			Model 2			Model 3		
	<i>B</i>	<i>SE</i>	<i>exp</i>	<i>b</i>	<i>SE</i>	<i>Exp</i>	<i>B</i>	<i>SE</i>	<i>Exp</i>
FOG	0.017***	0.003	1.017	-0.012***	0.003	1.012	NS	-	
LOESS FOG				-0.259***	0.046	1.308	-0.238**	0.084	1.287
FOG * LOESS							NS	-	
Hashtags	0.129***	0.014		0.133***	0.014		0.133***	0.141	
Mentions	-0.288***	0.018		-0.287***	0.018		-0.287***	0.178	
Urls	0.286***	0.025		0.303***	0.025		0.303***	0.025	
Log (followers)	0.553***	0.009		0.555***	0.009		0.555***	0.009	
Log (activity)	-0.178***	0.009		-0.179***	0.009		-0.179***	0.009	
AIC	77,603			77,574			77,576		
FRE	0.018***	0.003	1.018	0.019***	0.003	1.019	NS	-	
LOESS FRE				-0.251***	0.049	1.299	-0.229**	0.079	1.267
FRE * LOESS							NS	-	
Hashtags	0.132***	0.014		0.136***	0.014		0.136***	0.014	
Mentions	-0.285***	0.018		-0.284***	0.018		-0.285***	0.018	
Urls	0.279***	0.025		0.294***	0.025		0.294***	0.025	
Log (followers)	0.552***	0.009		0.554***	0.009		0.554***	0.009	
Log (activity)	-0.177***	0.009		-0.178***	0.009		-0.178***	0.009	
AIC	77,594			77,570			77,572		
SMOG	0.015***	0.004	1.015	0.016***	0.004	1.016	NS	-	
LOESS SMOG				-0.372***	0.055	1.464	-0.338**	0.125	1.416

(continued)

Table 2 (continued)

	Model 1			Model 2			Model 3		
	<i>B</i>	<i>SE</i>	<i>exp</i>	<i>b</i>	<i>SE</i>	<i>Exp</i>	<i>B</i>	<i>SE</i>	<i>Exp</i>
SMOG * LOESS									
Hashtags	0.131***	0.014		0.135***	0.014		NS	–	
Mentions	–0.289***	0.018		–0.288***	0.018		0.135***	0.014	
Urls	0.286***	0.025		0.305***	0.025		–0.288***	0.018	
Log (followers)	0.552***	0.009		0.555***	0.009		0.305***	0.025	
Log (activity)	–0.177***	0.009		–0.179***	0.009		0.555***	0.009	
AIC	77,609			77,567			–0.179***	0.009	
							77,569		

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, † $p < 0.1$, NS = not significant

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Does a Social Media Abstinence Really Reduce Stress? A Research-in-Progress Study Using Salivary Biomarkers



Eoin Whelan

Abstract There is much scientific evidence in recent years indicating that our ‘always on’ culture powered by platforms such as Facebook, LinkedIn, Instagram, Twitter, and WhatsApp, is leading to negative health outcomes, particularly stress. To mitigate social media induced stress, people are being advised to abstain from using social media for a period of time. However, the effectiveness of such breaks is open to question. As many people are heavily dependent on social media, the inability to access these platforms for a period of time could actually create stress and anxiety. To determine if and how social media abstinence relates to stress, this project will investigate the role of passion as a mediating variable. Stress will be measured using a combination of the salivary biomarkers cortisol and alpha amylase, with psychological scales. Ultimately, this study aims to determine the boundary conditions under which an abstinence from social media use will either increase or decrease stress levels in working professionals.

Keywords Social media · Stress · Abstinence · Cortisol · Alpha amylase

1 Introduction

Combining biomarkers of stress (cortisol and alpha amylase) with psychological measures, the objective of this study is to determine how an abstinence from social media use affects the wellbeing of working professionals. This proposed study will focus on working professionals as they are a population who are heavily dependent on social media for work, family, and leisure activities, yet are understudied in terms of the resulting health implications [1].

Social media use is increasing across society, and its association with mental wellbeing remains unclear. Some recent social media studies report on its harmful association with stress [2], anxiety [3], and depression [4]. Other studies conclude the health implications of social media use to be minimally detrimental [5, 6], and

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even beneficial in some cases [7, 8]. Notwithstanding the lack of scientific clarity, many national and organisational health policies have emerged, as well as a sizable digital detox industry, advising social media users to abstain from use for a period of time. For example, the Royal Society for Public Health now advocate a “Scroll Free September”. While such policies may be well intentioned, they are in essence untested medical interventions.

Given the contemporary nature of the phenomena, there is a limited body of knowledge pertaining to the health implications of social media abstinence. Many people are heavily dependent on social media [9, 10]. Thus, removing access to a person’s social media accounts for a period of time may actually increase stress and anxiety. Indeed, recent studies have validated the link between the inability to access digital technology and stress [11], anxiety [3, 12], and sleep difficulties [13]. In the context of working professionals, one study found some employees worked for longer stretches when online distractions were blocked, a consequence of which was increased stress [14]. Likewise, the withdrawal symptoms of craving and boredom have been reported by participants while abstaining from social media [15]. Involuntary abstinence has also been studied, with research showing that participants who lost their smartphones reported negative feelings, such as boredom, anxiety, and loneliness [16]. On the bright side, an experiment with 1095 participants in Denmark, demonstrated that taking a one week break from Facebook had positive effects on life satisfaction and emotions, and such benefits were significantly greater for heavy Facebook users [17].

To determine why people respond differently to a social media abstinence, this study will examine the passion a worker has for social media, and if that explains increases or decreases in stress levels. Vallerand and colleagues [18–20] have conceptualised the passion a person feels for an activity, such as social media, as a duality. The dual model of passion (DMP) posits that an individual can have a strong inclination toward a self-defining activity that is loved, but that activity is comprised of both harmonious and obsessive dimensions [21, 22]. Both forms of passion describe a “*strong inclination toward an activity that people like, that they find important, and in which they invest time and energy*” [21, p. 756]. However, the opposing dimensions of passion differ in how they become internalised in the identity of an individual. A harmonious passion is adaptive and reflects a level of control to engage in the activity. The internalisation of the activity into the person’s identity is autonomous [20]. A person demonstrating harmonious passion is not compelled to do the activity and can stop at any time. Harmonious individuals observe the activity as a supplement to a well-balanced lifestyle and are not consumed by a sense of “I must, I need to” engage with the activity. They are able to bound the activity (e.g., set limits), set personal goals which are consistent with their own strengths and weaknesses, and can align and/or prioritise the activity, thus, reducing conflict with other life domains (e.g., work, family). In other words, the respective activity is in “harmony” with other aspects of person’s life [23].

In cases of obsessive passion, the internalisation is driven by intrapersonal or interpersonal pressures, such as heightened self-esteem or social acceptance within a specific group [24]. People demonstrating obsessive passion experience an internal

compulsion to engage in the activity even when not appropriate to do so, as it goes beyond the person's self-control [23]. Obsessive passion is maladaptive and is related to negative emotions such as shame [21]. The activity dominates the person's identity to the extent it conflicts with other aspects of the person's life [20]. IS scholars have drawn from the DMP to shed light on the effects of online gaming [24, 25], social media use [26], and internet activities [27].

To extend state-of-the-art knowledge of the health effects of social media abstinence, this proposed study will combine physiological data with psychological data to measure stress. Both approaches are susceptible to validity issue, such as subjectivity, social desirability, and common method bias for psychological measures [28, 29], and construct reliability [30]. Physiological approaches are particularly well equipped for measuring constructs people are unable to accurately self-report, such as stress [28]. Previous technostress studies have used cortisol measures to determine the stress effects of systems breakdown [31], extensive media use [1], and interruptions [32]. That is not to say that such physiological approaches are better than traditional self-reported methods. As physiological data cannot be manipulated by the subject, or susceptible to social desirability bias, triangulation with additional data sources can result in a more holistic representation of research constructs [28, 30]. As advocated by Tams et al. [30], to improve validity and reliability, this study will combine physiological data with self-reported psychological measures of well-being.

2 Proposed Methods

Sixty volunteers who are fulltime working professionals will be recruited for this study. It is envisioned participants will be recent graduates of NUI Galway's MBA program. If required, snowball sampling techniques will also be employed to recruit more participants (e.g., postings on Facebook and newspapers). Working professionals are the focus of this study as some organisations have or are considering implementing social media blocking apps to reduce distractions and stress [14]. Applicants will be screened for suitability against the following criteria;

- Regularly using social media at least 1 h per day.
- Not required by employer to use social media for work purposes.
- No recent infections, or suffering from a chronic illness, or a heavy smoker, or receiving hormonal replacement treatment (all affect hormonal stress measures).

Selected volunteers will be randomly split into a control group of 30, who do not abstain from using social media, and an experimental group of 30, who will abstain from social media use. The ecological momentary intervention (EMI) method will be adopted to achieve the project objectives i.e. experimental intervention in the natural setting during participants' everyday lives. This involves gathering data over; (a) a 2 day baseline phase where all participants use their social media as normal, (b) for the experimental group, a 2 day intervention phase where access to social

media is blocked, while experimental group continue use as normal (c) a 2 day post intervention where social media can be used as normal again by all participants. To ensure consistency, data gathering for each phase will take place on the same workdays, Tuesday and Wednesday over 3 weeks.

Prior to commencing the EMI, participants will complete psychometric tests to measure variables which previous studies suggest may influence reaction to social media abstinence e.g. personality, emotional characteristics, fear of missing out, preoccupation with social media, work-family segmentation preferences, boredom proneness. Harmonious and obsessive passion for social media will be measured using the 14 item DMP scale [21]. For the physiological measures of stress, each day participants will passively drool into a small vial they will be provided with. Following best practice in saliva collection and analysis [1, 31], samples will be collected immediately upon waking in the morning before feet touch the floor, 30 min after waking, at noon (before lunch), and right before bedtime. Participants will be instructed how to freeze their saliva samples. This will result in 1,440 samples. Samples will be sent securely to the Biomarker Lab in Anglia Ruskin University for analysis. Stress is measured by calculating the change in levels of salivary cortisol and alpha amylase from morning to evening (i.e. the diurnal slope). The project is focusing specifically on cortisol and alpha amylase as previous studies found links between these stress biomarkers and digital technology use [1, 11].

Across all three phases of the EMI, the smartphone app 'Moment' will be used to objectively track social media usage. For the experimental group in the abstinence phase, the 'Freedom' app will be used to block access to social media, which participants can override if necessary. From these apps, the research team will have documented evidence if the experimental group successfully completed the social media abstinence. Participants will also complete a daily questionnaire, to be completed at a specific time during each work day, designed to measure psychological perceptions of wellness including stress, anxiety, mood, and life satisfaction using well established scales [33–35]. The questionnaire will also require participants to reflect on their behaviours during the abstinence. This will allow the researchers to determine if any compensatory behaviours emerged. In keeping with the objective of the project, the questionnaires will be paper based as opposed to computer mediated.

3 Expected Outcomes

This project will determine;

- The efficacy of a social media abstinence as a workplace health intervention.
- If rebound effects are prevalent when users end a social media abstinence.
- If possessing a harmonious or obsessive passion for social media explains why different groups of people respond differently to a social media abstinence.

- If a more nuanced intervention is needed to reduce the harmful effects of social media use on well-being, whilst also developing the framework for such interventions.

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