The Infamous “Like” Feature: A Neuro Perspective

Helmi Issa, CEREN EA 7477, Burgundy School of Business, Université Bourgogne Franche-Comté, Dijon, France*
Rachid Jabbouri, CEREN EA 7477, Burgundy School of Business, Université Bourgogne Franche-Comté, Dijon, France

ABSTRACT

With the recent rise of excessive use of social media and its damaging effects, there is an urgent need to systematically recognize how users behave towards the “Like” button, which has been considered the most toxic feature on social media. To date, scholars know little about the neurophysiological responses of users towards the “Like” feature despite its pervasiveness. Thus, through the lens of cybernetic theory, this research measured user behavior towards the “Like” feature by experimenting with two neuro tools (i.e., electrocardiogram [EKG/ECG] and electroencephalography [EEG]). Sixteen participants, allocated within three separate groups, completed a simple experimental task of “liking” content. Unexpectedly, the findings revealed that participants who frequently and infrequently received “Likes” shared similar biometrics (i.e., high neurophysiological activities). Furthermore, this research raised concerns over the underlying AI algorithms related to recommendation engines/systems.

KEYWORDS

Cybernetic Theory, NeuroIS, Neurophysiological Responses, Social Media

INTRODUCTION

Technology innovations may be of various forms (i.e., disruptive, incremental, radical, or architectural). Regardless of the types, technologies support our daily tasks. Among the many recent trends in innovations, the “Like” button (feature) is considered a type of disruptive innovation for businesses (Sullivan, 2016).

Numerous social media platforms (e.g., Facebook, YouTube, Twitter, LinkedIn, Instagram, TikTok) introduced the “Like” feature (in one form or another) to solve problems and save time, but it ended up creating more challenges and unintended consequences. Numerous empirical and theoretical studies focused on the perceived outcomes of the “Like” feature (e.g., intention, service quality) (e.g., John, Emrich, Gupta, & Norton, 2017; Schondienst, Kulzer, & Gunther, 2012), on its social aspects (Eranti & Lonkila, 2015), and the motives behind its specific or general use (e.g., Ozanne, Navas, & Mattila, & Van Hoof, 2017; Kim, Sohn, & Choi, 2011).

Nevertheless, despite the growing body of knowledge on social media use (generally) and the “Like” feature (specifically), there is a dearth of research focusing on the underlying behavioral mechanisms of the “Like” feature, especially since academic publications in this research area are relatively scarce. Research studies conducted by health experts (e.g., Royal Society for Public Health, 2018) have shown that the “Like” button is the most toxic feature on social media by triggering...
undesirable reactions, emotions, memories, stress, and pressure (Moffat, 2019). Such behavioral experiences/reactions are challenging to be measured by traditional/commonly used methodologies (e.g., interviews, surveys), which led to inaccurate behavioral mappings and unreliable findings. One approach to effectively measure behavioral (neurophysiological) reactions to the “Like” button is through the neuroIS perspective, which this research adopted. NeuroIS refers to applying cognitive neuroscience methods and tools in IS research (Dimoka, Pavlou, & Davis, 2007).

The “Like” feature, a simple yet innovative method of gathering data of individuals’ interests and activities, has shown to be beneficial for businesses but damaging to users’ well-being (Moffat, 2019). Yet, no study in the literature investigated users’ behavioral responses (from a neurophysiological perspective) towards the “Like” feature. Thus, this research attempted to address “How do users neurophysiologically behave or respond towards the ‘‘Like’’ feature?”

This research delivers three modest contributions. First, neuroIS research is relatively new and underdeveloped (Riedl, Fischer, Leger, & Davis, 2020). Therefore, through the theoretical lens of cybernetics, this neuroIS research is the first in the literature to investigate how users neurophysiologically behave or respond towards the “Like” feature. This research experimented with two different neurophysiological tools (i.e., electrocardiogram (EKG/ECG) and electroencephalography (EEG)). Second, this research delivered a simplified yet comprehensive understanding of users’ neurophysiological responses by challenging the complexities (e.g., costly and complicated experimental designs) of previous neuroIS experimental studies; thus, capturing a broader range of audiences. Besides, such an attempt supports higher potentials of replicability and reproducibility to develop neuroIS research. Third, to date and up to the authors’ knowledge, two neuroIS studies investigated users responses towards the “Like” feature but with the use of fMRI rather than EEG or EKG/ECG (i.e., Sherman, Hernandez, Greenfield, & Dapretto, 2018; Sherman, Payton, Hernandez, Greenfield, & Dapretto, 2016). However, fMRI focuses on spatial (which area of the brain is active) rather than temporal resolution (when activation occurs). The temporal resolution of fMRI has shown to be inaccurate due to the rapid circulation of blood (Fomby & Cherlin, 2011). Besides, fMRI is more fit for studies related to memory and cognition (Pandarinathan et al., 2018). Accordingly, this research provided a novel and better understanding of users’ responses towards the ‘‘Like’’ feature from the temporal perspective. Subsequently, a complete road map of both resolutions (spatial and temporal) will be available for future studies to build on.

Furthermore, the “Like” feature tracks and monitors users through pre-determined algorithms (Reflectiz, 2019; Eranti & Lonkila, 2015). As a result, throughout the last decade, the “Like” feature drew privacy scrutiny (i.e., sharing user information/data to third parties). This research further raised concerns over the underlying AI algorithms that partially function within “recommendation engines”.

The rest of the research is structured as follows: the following section reviews the theoretical backgrounds on the concept of user behavior, social media in the information systems (IS) discipline, the “Like” feature, neuroscientific methods, and cybernetic theory. Then, the authors discuss the methodology section that involves a detailed experimental protocol. The authors then elaborate on the findings and conclude with limitations and future research directions.

THEORETICAL BACKGROUND

The Concept of User Behavior

Behavior, ubiquitous in nature, is defined as an individual’s action or reaction towards stimuli in the environment (Cao, 2010). Behavior is vastly used for multifaceted problem-solving within virtual-physical environments and widely studied in multiple research disciplines (i.e., behavioral science, computer science, social networks, social computing).

In general, behaviors are categorized as either qualitative (characterized by user actions) or quantitative (quantified by entities). In the social media research area, user behavior implicates two types (i.e., individual and collective). Individual user behavior consists of user-user behavior, user-
entity behavior, and user-community behavior. Collective behavior, directed by team dynamics, refers to social actions/incidents that emerge impulsively or unexpectedly (e.g., user migration behavior) (Safari, Rahmani, & Alizadeh, 2019). Despite the general similarities among the main and sub-types, only the individual user behavior is examined in this research (see Figure 1).

**Figure 1. Mapping of the behavior concept in social media research**

---

### Social Media

From a general standpoint, social media (or social networking sites, platforms, or apps) refers to digital media that allows for peer-to-peer interactions over an internet-based (Web 2.0) environment; thus, creating a rich social structure. Social media is a type of social medium that builds over innovative foundations through which participants or users freely exchange content, information, music, comments, photos, videos, and creations (Kaplan & Haenlin, 2010).

Nevertheless, given the significance of social media to various industries and businesses, it received much consideration from scholars of different disciplines, including marketing and IS (Kapoor et al., 2018). This research followed the definitions of social media related to IS rather than marketing discipline (see Table 1). Furthermore, social media research is growing exponentially. Thus, Table 2 shows the distinction between the features of this research and previous IS studies that examined the concept of social media.
Table 1. Various definitions of social media in the IS discipline

| Authors | Definitions of social media |
|---------|----------------------------|
| Kapoor et al. (2018) | - Various user-driven platforms that ease diffusion of fascinating content, dialogue creation, and communication to a wider audience  
- A digital space created by the people and for the people, and provides an environment that is conducive for interactions and networking to occur at different levels (for instance, personal, professional, business, marketing, political, and societal) |
| Lundmark, Oh, & Verhaal (2016) | - A unique form of communication that integrates various sources of legitimacy, and offers a unique context. 
- Means for the diffusion of both internally and externally generated data relating to all stakeholders |
| Schlagwein & Hu (2016) | - It constitutes internet-based communication and collaboration channels 
- Its tools and the adjoining organizational and managerial structures constitute social IS |
| Wakefield & Wakefield (2016) | - IS artifact consisting of technical, informational, and relational subsystems that interact based on the context 
- Social media networks as specific types of social media platforms and Internet sites with common attributes |
| Miranda, Young, & Yetgin (2016) | - A medium where ordinary people in ordinary social networks can create user-generated news |
| Spagnoletti, Resca, & Saebo (2015) and Xu & Zhang (2013) | - Set of internet-based technologies/applications that aim at stimulating the creation, modification, update, and exchange of user-generated content, while creating new links between the content creators |
| Bharati, Zhang, & Chaudhury (2014) | - A technology not focused on transactions but collaboration and communication across users/groups inside and outside the firm |
| Tang, Gu, & Whinston (2012) | - User-generated media that is a source of online information created, initiated, circulated, and used by consumers with intentions of educating each other about products, brands, services, personalities, and issues |

Table 2. A systematic comparison between the current research and previous IS studies

| Authors – Methodologies | Issues addressed |
|-------------------------|------------------|
| Ozanne, Navas, Mattila, & Van Hoof (2017) - Qualitative (interview)  
Turel (2015) - Quantitative (survey)  
Chiu & Huang (2015) - Qualitative (survey)  
Chen & Sharma (2015) – Quantitative (survey)  
Xu, Xu, & Li (2016) - Quantitative (survey) | Social Media Use Behaviors and Consequences |
| Zhang & Piramuthu (2016) – Quantitative (web crawling)  
Centeno, Hermoso, & Fasli (2015) – Quantitative (analytical) | Reviews and Recommendations on Social Media Sites |
| Lundmark et al. (2016)- Quantitative (analytical)  
Mettler & Winter 2016) – Quantitative (Design science approach)  
Schlagwein & Hu (2016) – Qualitative (interview)  
Greenwood & Gopal (2015) - Quantitative (analytical) | Social Media and Associated Organizational Impact |

Table 2 continued on next page
### Table 2 continued

| Authors – Methodologies | Issues addressed |
|-------------------------|------------------|
| Dennis, Minas, & Lockwood (2016) - Qualitative (conceptual) | Social Media and Participation in Online Communities |
| Goes, Guo, & Lin (2016) - Quantitative (analytical) | |
| Khansa, Ma, Liginlal, & Kim (2015) - Quantitative (web crawling) | |
| Zhang, Zhou, Kehoe, & Kilic (2016) – Quantitative (content analysis) | Risks and Concerns with the Use of Social Media |
| Burtch, Ghose, & Wattal (2016) - Quantitative (analytical) | |
| Vishwanath (2015) – Quantitative (laboratory experiment) | |
| Cao, Guo, Liu, & Gu (2015) - Quantitative (survey) | Negative Stigma Attached to Social Media Use |
| Huang, Baptista, & Newell (2015) – Quantitative (case study) | |
| Barrett, Oborn, & Orlikowski (2016) - Qualitative (interview) | Social Media and Value Creation |
| Dong & Wu (2015) – Qualitative (event study) | |
| Oh, Eom, & Rao (2015) – Quantitative (natural experiment) | Role of Social Media During Critical/Extreme Events |
| Ling, Pan, Ractham, & Kaewkitipong (2015) - Mixed (interviews) | |
| Spagnoletti et al. (2015) – Qualitative (content analysis) | Social Media for Help/Support |
| Maier, Launer, Eckhardt, & Weitzel (2015) - Quantitative (survey) | |
| Baur (2017) – Qualitative (design science) | Public Bodies and Social Media Interaction |
| Rosenberger, Lehrer, & Jung (2017) | |
| Dwivedi, Kapoor, & Chen (2015) | |
| Miranda et al. (2016) - Quantitative (content analysis) | Traditional v/s Social Media |
| Chung, Tyan, & Han (2017) - Quantitative (survey) | |
| Stanko (2016) – Mixed (analytical & fuzzy set QCA) | |
| Kekolahi, Karikoski, & Riikonen (2015) - Quantitative (survey) | |
| Stanko (2016) – Mixed (analytical & fuzzy set QCA) | |
| Testa (2016) – Quantitative (survey) | |
| **This research – NeuroIS (use of neurophysiological tools)** | **The neurophysiological responses of users towards the “Like” feature** |

*Only the most recent publications are shown (studies before 2015 were not included since they share similar methodologies, examinations, and contributions) (Egebark & Ekstrom, 2011)*

*Studies related to the marketing discipline were excluded (Wai Lai & Liu, 2020)*

### The “Like” Feature

The “like” button, represented by a visible thumbs-up gesture/emoticon/feature, was first introduced by Facebook in 2010 and later adopted by almost all digital and social media platforms. It is considered an easy way to comment on any shared content. The “Like” feature has taken various shapes and symbols (e.g., stars or hearts); nevertheless, all share the same purpose, use, and intention. The “Like” feature witnessed changes from specific to general and private to public. In other terms, the “Like” feature was initially visible only for individual posts and links among friends but later evolved to a fundamentally public gesture visible to all users. Nowadays, liking any content (photo, videos, comments, posts) on any digital platform is the most used activity. Thus, the “Like” feature is currently the most common type of online communication and interaction among users.
In principle, the “Like” button is a binary feature. That is, the user either likes a specific content or remains neutral. The “Dislike” button is non-existent except for a few platforms (e.g., YouTube). Nevertheless, remaining neutral (i.e., not “liking” a certain content) has shown to have undesirable effects on users since it takes the form of “ignoring” the other individual/user who posted the content (that could be a friend or stranger) (Eranti & Lonkila, 2015).

In literature, the use of the “Like” feature has shown to have economic (e.g., business modeling, advertisements), political (political discussions, movements, and campaigns), and social (interactions and participations) implications (Eranti & Lonkila, 2015; Kristofferson, White, & Peloza, 2014; Gerlitz & Helmond, 2013). This research examined the social use of the “Like” feature. Such an aspect shows that users’ behaviors influence other users’ actions/behaviors; hence, linear-sequential patterns emerge from the observed social (nano-level) interactions (e.g., use of gestures and emoji similar to the case of the “Like” button) (Eranti & Lonkila, 2015).

Neuroscientific Methods

Data generated from neuroscientific tools are generally not prone to subjectivity bias, social desirability bias, and demand effects. Such neuroscientific tools a) support, complement, or oppose existing sources of data (e.g., self-reporting, observations, or secondary data); b) triangulate across measurement data; c) reduce common method bias; d) collect data continuously and accurately; and e) infer causal relationships among IS constructs (Dimoka, Pavlou, & Davis, 2011; Zheng & Pavlou, 2010).

Specifically, in the neuroIS and neuromarketing literature, different types of neuroscientific methods and tools have been proposed as implicit measures of human behavior (e.g., Durantin, Gagnon, Tremblay, & Dehais, 2014; Kivikangas et al., 2011; Glockner & Herbold, 2011; Sequeira, Hot, Silvert, & Delplanque, 2009) (see Figure 2).

A recent literature review has shown that neuroIS studies focus on either the PNS or the CNS tools (Al Mamun, David, Mai, Kim, & Parsons, 2018). This research used both types (i.e., ECG/EKG and EEG). ECG/EKG measures and records the electrical activity of the heart by placing sensors on the skin. EEG delivers valuable data by analyzing the brain’s electrical activity. This method identifies changes in the electrical currents of brain waves.

Figure 2. Types of neuroscientific methods
Cybernetic Theory

In the IS discipline, multiple theories were used to examine the technological aspects, perceptions, and uses of social media (e.g., innovation diffusion theory, social exchange theory, network theory, IS success model, organization theory, learning theory, uses and gratifications theory, elaboration likelihood model theory, rational choice theory, attribution theory, social capital theory, the theory of planned behavior) (e.g., Burtch, Ghose, & Wattal, 2016; Zhao, Detlor, & Connelly, 2016; Schlagwein & Hu, 2016; Turel, 2015; Yan, Peng, & Tan, 2015; Chen & Sharma, 2015; Chiu & Huang, 2015). Nevertheless, this research adopted a different and multi-disciplinary theory that explains the actual behavioral responses in which users experience when using a technology device/app integrated with social media features.

Systems theories deliver a general framework for many scientific concepts. Such theories explain what types of patterns might exist between interconnected/interrelated systems (physical, biological, psychological, or social) with similar structures and interacting rather than found in isolated conditions. Applied psychology theories, among a few, have followed the same systematic and holistic approach to examine how dynamic interactions produce a specific behavior, discover general patterns, and unite scientific principles. Their characteristics maintain balanced and adjusted levels (equilibrium) to their current situation; hence, the systems are self-stabilizing or self-regulating through continuous communication flow. This specific type of systems theory, cybernetics, is reflected in the early work on physiological responses to threat (Cannon, 1915), the general adaptation syndrome (Selye, 1983), and the general theory of human behavior (Carver & Scheier, 1982).

The cybernetic theory is a transdisciplinary approach that implies control of any system using technology (Muller, 2000) and focuses on how anything (digital, mechanical, or biological) reacts to changes in information (Kelly, 1995). The cybernetic theory permits individuals to respond differently to similar situations (Le Fevre, Matheny, & Kolt, 2003); can be applied to organizational systems and social-individual structures (Le Fevre et al., 2003); and is widely accepted as a theoretical framework for understanding human behavior (Edwards, 1992).

METHODOLOGY

Generally, experiments in IS research focus on examining users’ perceptions and behavior, whereas in neuroIS research, researchers often investigate how users interact with systems (e.g., processing information or executing a cognitively challenging task). Besides, to effectively examine the human-computer interaction, neurophysiological processes must be accessible with different emerging scenarios (Teubner, Adam, & Riordan, 2015). This research met such conditions.

Numerous software and platforms are existent in earlier and recent experimental studies (mainly neuro-related) (e.g., E-prime, PsychoPy, Superlab, PsyToolkit) (e.g., Kim, 2019; Sherman, Hernandez, Greenfield, & Dapretto, 2018; Sherman, Payton, Hernandez, Greenfield, & Dapretto, 2016; Peirce, 2007). Nevertheless, such interfaces are either expensive, time-consuming, or complicated (i.e., require coding and scripting); thus, leading to a low number of replicated experimental studies. Therefore, to overcome such limitations, the experiment team decided to use Facebook as an ideal ground for experimentation.

The experiment team experimented inside an independent computer-science laboratory under the supervision of two senior medical personnel. The experiment team independently bought the neurophysiological tools for the experiment (i.e., SpikerBox tool). SpikerBox tool has shown to be scientifically adequate in a groundbreaking experimental study conducted by DeBoer, Haney, Atiq, Smith, & Cox (2017). Furthermore, such inexpensive and non-medical neuro tools are reliable for investigational designs in the neuroIS field (e.g., Wang & Hsu, 2014). Figure 3 shows a complete mapping of the experimental protocol and research method.
The experiment team recruited the participants through announcements at a single French business school. The experiment team randomly chose nineteen participants from the initial thirty-four applications. The experiment team chose students for the experiment since social media is used by students for multiple purposes (e.g., online learning, interactivity with friends, online knowledge sharing behavior, and engagement) (e.g., Ansari & Khan, 2020). Thus, they are considered the most knowledgeable in terms of social media use. Upon arrival, each participant completed written consent with guaranteed anonymity. Due to time and budget constraints, the experiment team managed nineteen participants (maximum capacity). The number of participants \( n = 19 \) is considered an adequate sample size in neuroscience studies (Lieberman, Berkman, & Wager, 2009).

Before the experiment, each participant filled out a short questionnaire (e.g., age, gender, nationality, social media experience, and medical condition). The participants (i.e., final sample) were 5 males and 14 females; ages between 19 and 23; an average of 6 years of social media use; none had any serious medical condition; and various nationalities (French (x6), Chinese (x4), German (x2), African (x3), Arabian (x3), and Spanish (x1)).

*(1)* The experiment team notified all participants that the experiment was investigating user behavior towards general social media use (photo-sharing content). Thus, the participants were unaware that the focus was on investigating behavioral responses towards the “Like” feature. Before the experimentation, the experiment team randomly assigned each participant to either treatment group 1 \( (n = 7; \text{frequently receiving “Likes”}) \), treatment group 2 \( (n = 7; \text{less frequently receiving “Likes”}) \), or focus group \( (n = 5; \text{moderate/average “Likes” submissions}) \). Random assignment is the most effective method to isolate the causal effects of the treatment from other factors affecting the outcome (Handke & Herzog, 2019). This method leads to an equal probability for each participant to receive either group.

*(2)* Regardless of each participant’s number of followers on social media, the experiment team requested each individual to send 30 different images (pictures) of himself/herself before the experiment. The participants should have recently posted these specific images on any social media platform. This way, the participants were not at risk of submitting private images by mistake. Their images were inserted and mixed within a private channel with images of other participants (i.e., only selected users can see the images; invisible/unreachable by external users). The experiment team notified each participant that other distant participants were either “Liking” or “Skipping” their images.
Furthermore, during the experiment, a “web push notification pop-up” would appear on the bottom-right of the screen. The pop-up showed the number of received “Likes” and the positioning of each participant in comparison to others. In reality, the experiment team digitally simulated and planned the notifications ahead of time.

*(3)* Step 1= Before attaching the neurophysiological tools, the experiment team indeed notified each participant that other participants were also rating (liking or skipping) his/her photos; however, in reality, the experiment team already assigned the ranking and number of “Likes.” Each participant skimmed through other participants’ photos; however, regardless of what they chose, it wouldn’t affect the outcome since all rankings were pre-determined by the experiment team. In other words, the participants were not in control.

Step 2= Treatment group 1: 4 out of the 7 participants connected to the EEG test (brain activity measurement); 3 out of the 7 participants connected to the EKG/ECG test (heart action activity measurement).

Treatment group 2: 4 out of the 7 participants connected to the EEG test (brain activity measurement); 3 out of 7 participants connected to the EKG/ECG test (heart action activity measurement).

Focus group: 3 out of the 5 participants connected to the EEG test (brain activity measurement); 2 out of 5 participants connected to the EKG test (heart action activity measurement).

Neuro measurement procedure for EKG/ECG= two adhesive electrodes on each inner wrists and one adhesive electrode on the back of the left palm.

Neuro measurement procedure for EEG= EEG headband with two electrodes centered on the top back of the head and one electrode behind the ear.

Step 3= Start of the task (Liking/skipping other participants’ photos). Furthermore, the experiment team provided each participant with a separate worksheet (short guide) concerning the rankings (Less than 10 “Likes”= unpopular; between 11 and 20 “Likes”= average; more than 20 “Likes”= popular).

*(4)* For treatment group 1, the experiment team systematically provided to each participant a high frequency of “Likes” and top-level ranking (i.e., more than 20 “Likes”) (see Figure 4).

For treatment group 2, the experiment team systematically provided each participant a low frequency of “Likes” and low-level ranking (i.e., less than 10 “Likes”) (see Figure 5).

For the focus group, the experiment team systematically provided each participant an average frequency of “Likes” and moderate-level ranking (i.e., between 11 and 20 “Likes”) (see Figure 6).

*(5)* For all participants, the experiment team ended the task after approximately 4-to-5 minutes.

*(6)* The experiment team debriefed and financially rewarded each participant.
Figure 4. Push notification for treatment group 1

![Push notification for treatment group 1]

Figure 5. Push notification for treatment group 2

![Push notification for treatment group 2]

Figure 6. Push notification for focus group

![Push notification for focus group]
FINDINGS

To interpret the generated values and graphs (see Table 4), Table 3 serves as a guide for biometrics. The biometrics relate to average/regular rather than abnormal/irregular conditions. Nevertheless, the experiment team eliminated three findings (i.e., two related to technical difficulties and one linked with improper biometric data generation). Thus, the final sample consisted of sixteen rather than nineteen observations, which is still adequate for the current experiment (e.g., Dimoka, 2010: n=15; Dimoka, Pavlou, & Davis, 2011: n=6; Dimoka & Davis, 2008: n=6; Vance, Jenkins, Anderson, Bjornn, & Kirwan, 2018: n=15).

There was no need for statistical methods to alleviate the validity challenges of the results (Handke & Herzog, 2019) since the experiment team used the random assignment approach to solve non-equivalent groups (i.e., treatment and focus groups).

Table 3. Biometric guide

| Neuro Tool | Biometrics |
|------------|------------|
| ECG/EKG    | Normal: EKG rhythm is regular with a heart rate that is normal (60-100 bpm). The P wave features: normal (positive & precedes each qrs). PR interval is normal (0.12-0.20 sec). The QRS complex is normal (0.06-0.10 sec). Tachycardia: EKG rhythm is regular with a fast heart rate (> 100 bpm). The P wave features: normal, may merge with t wave at very fast rates. PR interval is normal (0.12-0.20 sec). The QRS complex is normal (0.06-0.10 sec). QT interval shortens with increasing heart rate. Bradycardia: EKG rhythm is regular with a slow heart rate (< 60 bpm). The P wave features: normal. Notice that the PR interval is normal (0.12-0.20 sec). The QRS complex will usually be normal (0.06-0.10 sec) |
| EEG        | Delta: has a frequency of 3 Hz or below. It tends to be the highest in amplitude and the slowest waves. It is normal as the dominant rhythm in infants Theta: has a frequency of 3.5 to 7.5 Hz and is classified as “slow” activity. It is perfectly normal in children up to 13 years Alpha: has a frequency between 7.5 and 13 Hz. It is the major rhythm seen in normal relaxed adults. Beta: is a “fast” activity. It has a frequency of 14 and greater Hz. It is the dominant rhythm in patients who are alert or anxious. |

*All figures are universally acknowledged by the scientific domain
Table 4. Experiment findings

| Figure | Group       | Neuro Tool | Findings                      | Similarity rate among the participants |
|--------|-------------|------------|-------------------------------|----------------------------------------|
| 7a     | Focus       | EKG        | Normal – Heart rate @ 87 bpm  | (2/2) 100%                             |
| 7b     | Treatment 1 | EKG        | Tachycardia – Heart rate @ 125 bpm | (2/3) 66%                     |
| 7c     | Treatment 2 | EKG        | Tachycardia – Heart rate @ 152 bpm | (2/2) 100%                     |
| 8a     | Focus       | EEG        | Alpha activity                | (2/2) 100%                             |
| 8b     | Treatment 1 | EEG        | Beta activity                 | (3/3) 100%                             |
| 8c     | Treatment 2 | EEG        | Beta activity                 | (3/4) 75%                              |

*Before the experiment: Treatment group 1: 4 EEG tests, 3 EKG tests; Treatment group 2: 4 EEG tests, 3 EKG tests; Focus group: 3 EEG tests, 2 EKG tests (TOTAL 19 observations)

**After the experiment (after 3 eliminations): Treatment group 1: 3 EEG tests, 3 EKG tests; Treatment group 2: 4 EEG tests, 2 EKG tests; Focus group: 2 EEG tests, 2 EKG test (TOTAL 16 observations)
Figure 7(c) Treatment group 2 – EKG

Figure 8(a) Focus group – EEG
It is evident from the observed results that treatment groups 1 and 2 (most of the participants) shared similar biometrics. Whether the user is receiving a high or low number of “Likes”, up to a certain degree, the neurophysiological responses were identical. The main difference between the two is that receiving more “Likes” is usually accompanied by positive emotions, whereas receiving fewer “Likes” is supplemented with negative emotions. In the medical and psychology fields, regardless of the types of emotions involved, high levels of neurophysiological activities (i.e., elevated heart rates and beta brain activities) have shown to lead to anxiety disorders, chronic stress, anger, and shame.
Algorithmic Bias

Sherman et al. (2016) showed that users are more likely to like or share content depicted with many likes than content with few likes. However, the ‘most liked’ contents are systematically ranked and classified through artificial intelligence (AI) algorithms. One form of such a classification is the recommendation engines/systems.

Search engines acquire information with numerous results. However, searching for relevant data became a struggle. Consequently, social media giants (and similar tech corporations) developed recommendation systems. A recommendation engine/system is an algorithm that analyzes the user behavior to recommend content based on his/her preference. Recommendation engines motivate demand for marketers (profits in sales) and satisfy users (interesting content; saves time). Such innovations consist of different types (i.e., content-based, collaborative filtering, demographic recommender, utility-based, hybrid-based, and knowledge-based) (Fang, Zhang, & Chen, 2016; Bindra, 2012).

In social media and regardless of the type of recommendation systems, the users are systematically profiled/personalized (by collecting their data) based on their use/interaction history, number of views, tags, ratings, and number of followers. But what if the algorithms in such engines no longer satisfy the users but rather keep them engaged? In other terms, the systems may provide users with content that may not benefit them, but in reality, keep them concerned with other users. Thus, users who receive more “Likes” are recommended by the engines to other users (friends or otherwise) that will lead to more “Likes” and shares. On the other hand, users who receive fewer “Likes” will not be shared or recommended by the engines; thus, not gaining popularity nor given a chance. Such inconsistencies relate to “algorithmic bias.”

LIMITATIONS & FUTURE RESEARCH DIRECTIONS

In experimental studies, scholars have identified three significant criteria to claim a causal explanation(s) or relationship(s) (i.e., association, time order, and nonspuriousness) (Chambliss & Schutt, 2012). This research met all three conditions. This research established a) association by comparing two or more groups, b) time order by observing variations in the independent variables before and after changes were identified in the dependent variable, and c) nonspuriousness by the use of random assignment (Chambliss & Schutt, 2012).

Nevertheless, despite the modest contributions offered by this research, few limitations are existent. First, the neuro tools may not have been sensitive enough to provide robust findings. Future studies may replicate the same experiment (preferably with a longitudinal design) with more advanced tools. Second, the authors were unable to specifically identify the meaning and characteristics of the behavioral (neurophysiological) responses (especially between treatment groups 1 and 2) during the high and low “Liking” developments. Additional series of analyses are required to interpret if the responses are explicit or implicit and whether the behaviors are emerging because of social (peer) pressure, personality traits, or visual perceptions. Third, the time and budget constraints led to a relatively small sample. Future studies are encouraged to target a larger specimen. Lastly, few participants had social ties (i.e., few were friends since they were from the same business school), which may have affected the ‘liking’ choices. Besides, the authors did not control reciprocal liking (a tendency for users to like others who liked their content) (Balakrishnan & Griffiths, 2018). Thus, future studies may select participants based on specific criteria (i.e., either as friends or as strangers), especially since social media users tend to “Like” content of their friends more frequently than strangers (Greenfield, Evers, & Dembo, 2017). Future studies are encouraged to build on these limitations as research opportunities.
RECOMMENDATIONS AND CONCLUSION

This research suggests two potential solutions. The first solution is reducing the degrees of AI bias through proper data management (i.e., monitoring of input codes, data refinement, and data modeling). Second, few social media platforms are in the progress of entirely removing the “Like” feature. Nevertheless, most users are socially and psychologically attached (in the form of addiction) to the “Like” feature. Such radical and sudden decisions may create psychological issues and concerns for the users. Instead, the second solution is substituting the “Like”/“Dislike” with ‘agree +’ or ‘hide -’. Users will be either acknowledged by other users for their creative content or disregarded without causing any disruption or harm.

The use of digital media (related to social media and its features) does not affect only psychological well-being but also neurophysiological welfare (among others, such as education, social interaction, and politics) (Korte, 2020). This research validated the existence of the neurophysiological manifestation that received little attention in the literature.

ACKNOWLEDGMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ADDITIONAL FUNDING INFORMATION

The publisher has waived the Open Access Processing fee for this article.
REFERENCES

Ansari, J. A. N., & Khan, N. A. (2020). Exploring the role of social media in collaborative learning the new domain of learning. Smart Learning Environments, 7(9), 9. Advance online publication. doi:10.1186/s40561-020-00118-7

Balakrishnan, J., & Griffiths, M. D. (2018). An exploratory study of ‘selfitis’ and the development of the selfitis behavior scale. International Journal of Mental Health and Addiction, 16(3), 722–736. Advance online publication. doi:10.1007/s11469-017-9844-x PMID:29904329

Barrett, M., Oborn, E., & Orlikowski, W. (2016). Creating value in online communities: The sociomaterial configuring of strategy, platform, and stakeholder engagement. Information Systems Research, 27(4), 704–723. doi:10.1287/isre.2016.0648

Baur, A. W. (2017). Harnessing the social web to enhance insights into people’s opinions in business, government and public administration. Information Systems Frontiers, 19(2), 231–251. doi:10.1007/s10796-016-9681-7

Bharati, P., Zhang, C., & Chaudhury, A. (2014). Social media assimilation in firms: Investigating the roles of absorptive capacity and institutional pressures. Information Systems Frontiers, 16(2), 257–272. doi:10.1007/s10796-013-9433-x

Bindra, A. (2012). Social LDA: Scalable topic modeling in social networks (Master’s thesis). University of Washington.

Burtch, G., Ghose, A., & Wattal, S. (2016). Secret admirers: An empirical examination of information hiding and contribution dynamics in online Crowdfunding. Information Systems Research, 27(3), 478–496. doi:10.1287/isre.2016.0642

Cannon, W. B. (1915). Bodily changes in pain, hunger, fear and rage: An account of recent researches into the function of emotional excitement. Appleton-Century-Crofts. doi:10.1037/10013-000

Cao, L. (2010). In-depth behavior understanding and use: The behavior informatics approach. Information Sciences, 180(17), 3067–3085. doi:10.1016/j.ins.2010.03.025

Cao, X., Guo, X., Liu, H., & Gu, J. (2015). The role of social media in supporting knowledge integration: A social capital analysis. Information Systems Frontiers, 17(2), 351–362. doi:10.1007/s10796-013-9473-2

Carver, C. S., & Scheier, M. F. (1982). Control theory: A useful conceptual framework for personality–social, clinical, and health psychology. Psychological Bulletin, 92(1), 111–135. doi:10.1037/0033-2909.92.1.111 PMID:7134324

Centeno, R., Hermoso, R., & Fasli, M. (2015). On the inaccuracy of numerical ratings: Dealing with biased opinions in social networks. Information Systems Frontiers, 17(4), 809–825. doi:10.1007/s10796-014-9526-1

Chambliss, D. F., & Schutt, R. K. (2012). Making sense of the social world: Methods of investigation. SAGE Publications. https://www.sagepub.com/sites/default/files/upm-binaries/23639_Chapter_5___Causation_and_Experimental_Design.pdf

Chandra, S., Jaiswa, A. K., Singh, R., Jha, D., & Mitta, A. P. (2017). Mental stress: Neurophysiology and its regulation by Sudarshan Kriya Yoga. International Journal of Yoga, 10(2), 67–72. doi:10.4103/0973-6131.205508 PMID:28546676

Chen, R., & Sharma, S. K. (2015). Learning and self-disclosure behavior on social networking sites: The case of Facebook users. European Journal of Information Systems, 24(1), 93–106. doi:10.1057/ejis.2013.31

Chiu, C. M., & Huang, H. Y. (2015). Examining the antecedents of user gratification and its effects on individuals’ social network services usage: The moderating role of habit. European Journal of Information Systems, 24(4), 411–430. doi:10.1057/ejis.2014.9

Chung, N., Tyan, I., & Han, H. (2017). Enhancing the smart tourism experience through geotag. Information Systems Frontiers, 19(4), 731–742. doi:10.1007/s10796-016-9710-6

DeBoer, J., Haney, C., Atiq, Z., Smith, C., & Cox, D. (2017). Hands-on engagement online: Using a randomised control trial to estimate the impact of an at-home lab kit on student attitudes and achievement in a MOOC. European Journal of Engineering Education, 44(1-2), 1–2. doi:10.1080/03043797.2017.1378170
Dennis, A. R., Minas, R. K., & Lockwood, N. S. (2016). Mapping the corporate blogosphere: Linking audience, content, and management to blog visibility. *Journal of the Association for Information Systems, 17*(3), 162–193. doi:10.17705/1jais.00425

Dimoka, A. (2010). What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study. *Management Information Systems Quarterly, 34*(2), 373–396. doi:10.2307/20721433

Dimoka, A., & Davis, F. D. (2008). Where does TAM reside in the brain? The neural mechanisms underlying technology adoption. *Proceedings of the 29th International Conference on Information Systems, 1–18.*

Dimoka, A., Pavlou, P. A., & Davis, F. (2007). Neuro-IS: The potential of cognitive Neuroscience for Information Systems research. *Proceedings of the 28th International Conference on Information Systems, 11–14.*

Dimoka, A., Pavlou, P. A., & Davis, F. D. (2011). NeuroIS: The potential of cognitive Neuroscience for Information Systems research. *Information Systems Research, 22*(4), 687–702. doi:10.1287/isre.1100.0284

Dong, J. Q., & Wu, W. (2015). Business value of social media technologies: Evidence from online user innovation communities. *The Journal of Strategic Information Systems, 24*(2), 113–127. doi:10.1016/j.jsis.2015.04.003

Durantin, G., Gagnon, J. F., Tremblay, S., & Dehais, F. (2014). Using near infrared spectroscopy and heart rate variability to detect mental overload. *Behavioural Brain Research, 259,* 16–23. doi:10.1016/j.bbr.2013.10.042 PMID:24184083

Dwivedi, Y. K., Kapoor, K. K., & Chen, H. (2015). Social media marketing and advertising. *The Marketing Review, 15*(3), 289–309. doi:10.1362/146934715X14441363377999

Edwards, J. R. (1992). A cybernetic theory of stress, coping, and well-being in organizations. *Academy of Management Review, 17*(2), 238–274. doi:10.2307/2587722

Egebark, J., & Ekstrom, M. (2011). Like what you like or like what others like? Conformity and peer effects on Facebook. Research Institute of Industrial Economics. IFN Working Paper No. 886.

Eranti, V. O., & Lonkila, M. K. (2015). The social significance of the Facebook Like button. First Monday (Chicago), 6. Advance online publication. doi:10.5210/fm.v2016.5505 doi:10.5210/fm.v2016.5505

Fang, Z., Zhang, L., & Chen, K. (2016). Hybrid recommender system based on personal behavior mining. https://arxiv.org/abs/1607.02754

Fomby, P., & Cherlin, A. J. (2011). Family instability and child well-being. *NIH Public Access, 72,* 181–204. PMID:21918579

Gerlitz, C., & Helmond, A. (2013). The Like economy: Social buttons and the data intensive Web. *New Media & Society, 15*(8), 1.348–1.365. 10.1177/1461444812472322

Glockner, A., & Herbold, A. K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making, 24*(1), 71–98. doi:10.1002/bdm.684

Goes, P. B., Guo, C., & Lin, M. (2016). Do incentive hierarchies induce user effort? Evidence from an online knowledge exchange. *Information Systems Research, 27*(3), 497–516. doi:10.1287/isre.2016.0635

Greenfield, P. M., Evers, N. F. G., & Dembo, J. (2017). What kind of photographs do teenagers “like”? *International Journal of Cyber Behavior, Psychology and Learning, 7*(3), 1–12. doi:10.4018/IJCBPL.2017070101

Greenwood, B. N., & Gopal, A. (2015). Research note—Tigerblood: Newspapers, blogs, and the founding of information technology firms. *Information Systems Research, 26*(4), 812–828. doi:10.1287/isre.2015.0603

Handke, C., & Herzog, C. (2019). Testing for causality in data: Experiments. In H. Van den Bulck, M. Puppis, K. Donders, & L. Van Audenhove (Eds.), *The Palgrave Handbook of Methods for Media Policy Research* (pp. 233–247). Palgrave Macmillan. doi:10.1007/978-3-030-16065-4_13

Huang, J., Baptista, J., & Newell, S. (2015). Communicational ambidexterity as a new capability to manage social media communication within organizations. *The Journal of Strategic Information Systems, 24*(2), 49–64. doi:10.1016/j.jsis.2015.03.002
Izard, C. E. (2009). Emotion theory and research: Highlights, unanswered questions, and emerging issues. *Annual Review of Psychology, 60*(1), 1–25. doi:10.1146/annurev.psych.60.110707.163539 PMID:18729725

Jamieson, J. P., Koslov, K., Nock, M. K., & Mendes, W. B. (2013). Experiencing discrimination increases risk-taking. *Psychological Science, 24*(2), 131–139. doi:10.1177/0956797612448194 PMID:23257767

John, L. K., Emrich, O., Gupta, S., & Norton, M. I. (2017). Does “liking” lead to loving? The impact of joining a brand’s social network on marketing outcomes. *JMR, Journal of Marketing Research, 54*(1), 144–155. doi:10.1509/jmr.14.0237

Kaplan, A. M., & Haenlin, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons, 53*(1), 59–68. doi:10.1016/j.bushor.2009.09.003

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present, and future. *Information Systems Frontiers, 20*(3), 531–558. doi:10.1007/s10796-017-9810-y

Kekolahti, P., Karikoski, J., & Riikonen, A. (2015). The effect of an individual’s age on the perceived importance and usage intensity of communications services—A Bayesian network analysis. *Information Systems Frontiers, 17*(6), 1313–1333. doi:10.1007/s10796-014-9502-9

Kelly, K. (1995). *Out of control: The new biology of machines*. Social Systems and the Economic World. Paperback.

Khansa, L., Ma, X., Liginlal, D., & Kim, S. S. (2015). Understanding members’ active participation in online question-and-answer communities: A theory and empirical analysis. *Journal of Management Information Systems, 32*(2), 162–203. doi:10.1080/07421222.2015.1063293

Kim, J., Gabriel, U., & Gygax, P. (2019). Testing the effectiveness of the Internet-based instrument PsyToolkit: A comparison between web-based (PsyToolkit) and lab-based (E-Prime 3.0) measurements of response choice and response time in a complex psycholinguistic task. *PLoS One, 14*(9), e0221802. doi:10.1371/journal.pone.0221802 PMID:31483826

Kim, Y., Sohn, D., & Choi, S. M. (2011). Cultural difference in motivations for using Social Network Sites: A comparative study of American and Korean college students. *Computers in Human Behavior, 27*(1), 365–372. doi:10.1016/j.chb.2010.08.015

Kivikangas, J. M., Chanel, G., Cowley, B., Ekman, I., Salminen, M., Jarvela, S., & Ravaja, N. (2011). A review of the use of psychophysiological methods in game research. *Journal of Gaming & Virtual Worlds, 3*(3), 181–199. doi:10.1386/jgvw.3.3.181_1

Korte, M. (2020). The impact of the digital revolution on the human brain and behavior: Where do we stand? *Dialogues in Clinical Neuroscience, 22*(2), 101–111. doi:10.31887/DCNS.2020.22.2/mkorte PMID:32699510

Kristofferson, K., White, K., & Peloza, J. (2014). The nature of slacktivism: How the social observability of an initial act of token support affects subsequent prosocial action. *Journal of Consumer Research, 40*(6), 1,149–1,166. 10.1086/674137

Le Fevre, M., Matheny, J., & Kolt, G. S. (2003). Eustress, distress, and interpretation in occupational stress. *Journal of Managerial Psychology, 18*(7), 18. doi:10.1108/02683940310502412

Lieberman, M. D., Berkman, E. T., & Wager, T. D. (2009). Correlations in social neuroscience aren’t voodoo. *Perspectives on Psychological Science, 4*(3), 299–307. doi:10.1111/j.1745-6924.2009.01128.x PMID:26158967

Ling, C. L. M., Pan, S. L., Racthem, P., & Kaewkitipong, L. (2015). ICT-enabled community empowerment in crisis response: Social media in Thailand flooding 2011. *Journal of the Association for Information Systems, 16*(3), 174–212. doi:10.17705/1jais.00390

Lundmark, L. W., Oh, C., & Verhaal, J. C. (2016). A little birdie told me: Social media, organizational legitimacy, and underpricing in initial public offerings. *Information Systems Frontiers, 1*, 1–16. doi:10.1007/s10796-016-9654-x

Maier, C., Laumer, S., Eckhardt, A., & Weitzel, T. (2015). Giving too much social support: Social overload on social networking sites. *European Journal of Information Systems, 24*(5), 447–464. doi:10.1057/ejis.2014.3
Mendes, W. B., Major, B., McCoy, S., & Blascovich, J. (2008). How attributional ambiguity shapes physiological and emotional responses to social rejection and acceptance. *Journal of Personality and Social Psychology, 94*(2), 278–291. doi:10.1037/0022-3514.94.2.278 PMID:18211177

Mettler, T., & Winter, R. (2016). Are business users social? A design experiment exploring information sharing in enterprise social systems. *Journal of Information Technology, 31*(2), 101–114. doi:10.1057/jit.2015.28

Miranda, S. M., Young, A., & Yetgin, E. (2016). Are social media emancipatory or hegemonic? Societal effects of mass media digitization. *Management Information Systems Quarterly, 40*(2), 303–329. doi:10.25300/MISQ/2016/40.2.02

Moffat, B. (2019). *The power of likes on social media: Friend or foe?* Retrieved from https://www.the-future-of-commerce.com/2019/10/07/the-power-of-likes-on-social-media/

Muller, A. (2000). A Brief history of the BCL. *Österreichische Zeitschrift für Geschichtswissenschaften, 11*(1), 9–30.

Oh, O., Eom, C., & Rao, H. R. (2015). Research note—Role of social Media in Social Change: An analysis of collective sense making during the 2011 Egypt revolution. *Information Systems Research, 26*(1), 210–223. doi:10.1287/isre.2015.0565

Ozanne, M., Navas, A. C., Mattila, A. S., & Van Hoof, H. B. (2017). An investigation into Facebook “Liking” behavior: An exploratory study. *Social Media + Society, 3*(2). Advance online publication. doi:10.1177/2056305117706785

Pandarinathan, G., Mishra, S., Nedumaran, A. M., Padmanabhan, P., & Gulyas, B. (2018). The potential of cognitive neuroimaging: A way forward to the mind-machine interface. *Journal of Imaging, 4*(5), 70. doi:10.3390/jimaging4050070

Peirce, J. W. (2007). PsychoPy: Psychophysics software in Python. *Journal of Neuroscience Methods, 162*(1-2), 8–13. doi:10.1016/j.jneumeth.2006.11.017 PMID:17254636

Rosenberger, M., Lehrer, C., & Jung, R. (2017). Integrating data from user activities of social networks into public administrations. *Information Systems Frontiers, 19*(2), 253–266. doi:10.1007/s10796-016-9682-6

Safari, R. M., Rahmani, A. M., & Alizadeh, S. H. (2019). User behavior mining on social media: A systematic literature review. *Multimedia Tools and Applications, 78*(23), 33747–33804. Advance online publication. doi:10.1007/s11042-019-08046-6

Schlagwein, D., & Hu, M. (2016). How and why organizations use social media: Five use types and their relation to absorptive capacity. *Journal of Information Technology, 32*(2), 194–209. doi:10.1057/jit.2016.7

Schondienst, V., Kulzer, F., & Gunther, O. (2012). *Like versus dislike: How Facebook’s like-button influences people’s perception of product and service quality*. Retrieved from https://aisel.aisnet.org/icis2012/proceedings/DigitalInnovation/4/

Selye, H. (1983). The stress concept: Past, present and future. In C. L. Cooper (Ed.), *Stress Research Issues for the Eighties* (pp. 1–20). John Wiley & Sons.

Sequeira, H., Hot, P., Silvert, L., & Delplanque, S. (2009). Electrical autonomic correlates of emotion. *International Journal of Psychophysiology, 71*, 50–56. doi: 2008.07.00910.1016/j.ijpsycho
Sherman, L. E., Hernandez, L. M., Greenfield, P. M., & Dapretto, M. (2018). What the brain ‘Likes’: Neural correlates of providing feedback on social media. *Social Cognitive and Affective Neuroscience, 13*(7), 699–707. doi:10.1093/scan/nsy051 PMID:29982823

Sherman, L. E., Payton, A. A., Hernandez, L. M., Greenfield, P. M., & Dapretto, M. (2016). The power of the Like in adolescence: Effects of peer influence on neural and behavioral responses to social media. *Psychological Science, 27*(7), 1027–1035. doi:10.1177/0956797616645673 PMID:27247125

Spagnoletti, P., Resca, A., & Saeb, O. (2015). Design for social media engagement: Insights from elderly care assistance. *The Journal of Strategic Information Systems, 24*(2), 128–145. doi:10.1016/j.jsis.2015.04.002

Stanko, M. A. (2016). Toward a theory of remixing in online innovation communities. *Information Systems Research, 27*(4), 773–791. doi:10.1287/isre.2016.0650

Sullivan, J. (2016). *Facebook’s new Like buttons are a disruptive innovation for advertisers.* Retrieved from https://www.bandt.com.au/facebooks-new-like-buttons-disruptive-innovation-advertisers/

Tang, Q., Gu, B., & Whinston, A. B. (2012). Content contribution for revenue sharing and reputation in social media: A dynamic structural model. *Journal of Management Information Systems, 29*(2), 41–76. doi:10.2753/MIS0742-1222290203

Teubner, T., Adam, M. T. P., & Riordan, R. (2015). The impact of computerized agents on immediate emotions, overall arousal and bidding behavior in electronic auctions. *Journal of the Association for Information Systems, 16*(10), 838–879. doi:10.17705/1jais.00412

Turel, O. (2015). Quitting the use of a habituated hedonic information system: A theoretical model and empirical examination of Facebook users. *European Journal of Information Systems, 24*(4), 431–446. doi:10.1057/ejis.2014.19

Vance, A., Jenkins, J. L., Anderson, B. B., Bjornn, D. K., & Kirwan, C. B. (2018). Tuning out security warnings: A longitudinal examination of habituation through fMRI, eye tracking, and field experiments. *Management Information Systems Quarterly, 42*(2), 355–380. doi:10.25300/MISQ/2018/14124

Vishwanath, A. (2015). Diffusion of deception in social media: Social contagion effects and its antecedents. *Information Systems Frontiers, 17*(6), 1353–1367. doi:10.1007/s10796-014-9509-2

Wai Lai, I. K., & Liu, Y. (2020). The effects of content likeability, content credibility, and social media engagement on users’ acceptance of product placement in mobile social networks. *Journal of Theoretical and Applied Electronic Commerce Research, 15*(3), 1–19. Advance online publication. doi:10.4067/S0718-1876202000300102

Wakefield, R., & Wakefield, K. (2016). Social media network behavior: A study of user passion and affect. *The Journal of Strategic Information Systems, 25*(2), 140–156. doi:10.1016/j.jsis.2016.04.001

Wang, C. C., & Hsu, M. C. (2014). An exploratory study using inexpensive electroencephalography (EEG) to understand flow experience in computer-based instruction. *Information & Management, 51*(7), 912–923. doi:10.1016/j.im.2014.05.010

Xu, B., Xu, Z., & Li, D. (2016). Internet aggression in online communities: A contemporary deterrence perspective. *Information Systems Journal, 26*(6), 641–667. doi:10.1111/isj.12077

Xu, S. X., & Zhang, X. M. (2013). Impact of Wikipedia on market information environment: Evidence on management disclosure and investor reaction. *Management Information Systems Quarterly, 37*(4), 1043–1068. doi:10.25300/MISQ/2013/37.4.03

Yan, L., Peng, J., & Tan, Y. (2015). Network dynamics: How can we find patients like us? *Information Systems Research, 26*(3), 496–512. doi:10.1287/isre.2015.0585

Zhang, D., Zhou, L., Kehoe, J. L., & Kilic, I. Y. (2016). What online reviewer behaviors really matter? Effects of verbal and nonverbal behaviors on detection of fake online reviews. *Journal of Management Information Systems, 33*(2), 456–481. doi:10.1080/07421222.2016.1205907

Zhang, J., & Piramuthu, S. (2016). Product recommendation with latent review topics. *Information Systems Frontiers, 1–9*. doi:10.1007/s10796-016-9697-z
Zhao, L., Detlor, B., & Connelly, C. E. (2016). Sharing knowledge in Social Q&A sites: The unintended consequences of extrinsic motivation. *Journal of Management Information Systems, 33*(1), 70–100. doi:10.1080/07421222.2016.1172459

Zheng, E., & Pavlou, P. A. (2010). Toward a causal interpretation for structural models: A new bayesian networks method for observational data with latent variables. *Information Systems Research, 21*(2), 365–391. doi:10.1287/isre.1080.0224