SIGHCI 2023 Proceedings

Special Interest Group on Human-Computer Interaction

1-25-2024

Keeping Calm in the Digital Age: Theorizing on a Self-Monitoring System of Technostress

Félix Giroux
HEC Montréal, felix.giroux@hec.ca

Sylvain Sénécal
HEC Montréal, sylvain.senecal@hec.ca

Constantinos Coursaris
HEC Montréal, constantinos.coursaris@hec.ca

Pierre-Majorique Léger
HEC Montréal, pierre-majorique.leger@hec.ca

Keeping Calm in the Digital Age: Theorizing on a Self-Monitoring System of Technostress

Research in Progress

Félix Giroux
HEC Montréal
felix.giroux@hec.ca

Sylvain Sénécal
HEC Montréal
sylvain.senecal@hec.ca

Constantinos K. Coursaris
HEC Montréal
constantinos.coursaris@hec.ca

Pierre-Majorique Léger
HEC Montréal
pierre-majorique.leger@hec.ca

ABSTRACT

People spend increasing time interacting with information technologies (IT) due to teleworking, which has become an important cause of psychological stress. Meanwhile, technological advances enable the monitoring of stress via methods that capture individuals' physiological states like automatic facial expression analysis (AFEA). This research-in-progress article proposes a novel theory that aims at explaining and predicting the impact of AFEA of stress self-monitoring systems on users' psychological stress. The theory proposes that AFEA of stress self-monitoring systems can increase facial expression self-awareness, and consequently inhibit users' facial expressions of stress, which can in turn decrease users' psychological stress. The theory has implications for the design science, affective computing, and technostress domains. It is hoped that the theory will generate discussions on the potential of stress self-monitoring systems in the workplace, education, and society.

Keywords

Technostress, Affective Computing, Design Science, Automatic Facial Expression Analysis, Self-Monitoring System, Objective Self-Awareness.

INTRODUCTION

The recent years have been characterized by a global teleworking culture where people spend increasingly more time interacting with IT. Teleworking blurs the line between work and personal life, thereby increasing the psychological stress of desk workers and students in organizations and in academia (Adedoyin and Soykan, 2020; Bojovic et al., 2020; Dragano and Lunau, 2020; Heiden et al., 2020). Due to its reliance on information technologies (IT), teleworking is also an important driver of technostress (i.e., stress that results from working with IT) (Taser et al., 2022). Past research on technostress has focused on identifying factors that explain the formation (i.e., creators) and outcomes of technostress (e.g., Salo et al., 2022; Nastjuk et al., 2023). However, there is a lack of research on ways to mitigate or inhibit technostress (e.g., Ragu-Nathan et al., 2008; Sarabadani et al., 2018; Ioannou et al., 2022).

Meanwhile, there is a growing trend towards the use of self-monitoring devices in modern society (Swan, 2013; Lupton, 2014; Crawford et al., 2015; Shin et al., 2019). Recent technological advances allow wearable devices to collect, monitor, and display information about their health such as their heart rate (Shin and Biocca, 2017; Jiang and Cameron, 2020; Marin-Farrona et al., 2020). Modern IT also has the capability to recognize users' emotional reactions via their facial expressions, gestures, voice, or other biological signals (e.g., heart rate) and respond via real-time feedback (Picard and Klein, 2002; Calvo et al., 2015). Research shows a growing interest in the assessment of stress in the workplace with devices like wearables that measure heart rate (Carneiro et al., 2017; Akbar et al., 2019; Booth et al., 2022; Castro-García et al., 2022). However, wearable devices that incorporate sensors may be expensive and intrusive (Greene et al., 2016; Sharma and Gedeon, 2012).

Automatic facial expression analysis (AFEA) from video recordings can also be used as an unobtrusive measure of physiological stress (Gavrilescu and Vizireanu, 2019). Most IT devices have built-in cameras, and the recent Covid-19 pandemic drove many organizations to provide their employees with web cameras to facilitate video calls (Chakraborti and Roberts, 2021). Therefore, due to the low-cost hardware material and important scaling potential of AFEA, this measure could be promising for IT-enabled self-monitoring systems.

Literature in psychology and psychiatry has shown that facial musculature can express, but also regulate one's emotions (Kleinke et al., 1998; Kraft and Pressman, 2012; Wollmer et al., 2012; Finzi and Rosenthal, 2014; Shafir, 2015; Söderkvist et al., 2018). Specifically, conscious inhibition of facial expressions of stress can result in reduced psychological stress. Therefore, self-monitoring systems based on AFEA could represent a low-cost and unobtrusive solution to monitor and regulate users' psychological stress.

This paper presents a novel idea of an IT artifact that has the potential to mitigate the stress it may induce via AFEA of stress self-monitoring. Inspired by the recent call for more relevant theorizing on our continually changing technological world, this paper theorizes about a potentially emerging information system (IS) phenomenon (Burton-Jones, 2018). Drawing on the theory of objective self-awareness (Duval and Wicklund, 1972; Wicklund, 1975) and the function of facial musculature in regulating one's emotions (e.g., Söderkvist et al., 2018), this paper develops a theory that explains and predicts the impact of AFEA of stress self-monitoring systems on users' psychological stress. The theory proposes that the presence and alert(s) of AFEA of stress self-monitoring systems may increase facial expression self-awareness, which may lead to conscious facial expressions of stress inhibition, and consequently reduced psychological stress.

Using a design science approach, future work will test the new theoretical development by evaluating the IT artifact in controlled laboratory experiments and case studies in organizations. This evaluation may have contributions in the field of affective computing by exploring the potential of a low-cost and unobtrusive way to monitor and regulate people's physiological stress by increasing facial expression awareness. The theoretical development may also contribute to literature on technostress in IS by focusing on an unexplored perspective where IT could be used as a way to mitigate or inhibit users' psychological stress.

THEORETICAL FOUNDATIONS

Emotion Expressing Function of Facial Movement

The science of facial expression was first introduced by Charles Darwin's (1872), who developed a taxonomy of facial expressions suggesting that specific human facial muscle configurations reflect specific emotions. Since then, scholars have traditionally used theories such as the Basic Emotion Theory (BET) to predict six basic emotions, namely happiness, anger, sadness, fear, disgust, and surprised, from specific facial muscle configurations known as facial Action Units (AUs) (Ekman, 1972; Ekman and Friesen, 1978). For instance, facial AU4, which refers to the act of lowering the brows down together or frowning, is known to be a component of the basic emotions of anger and sadness. Today, AFEA has become a popular method to detect facial emotion intensity from real-time facial micro-movement measurement. For instance, the validated AFEA software FaceReader (Noldus, Netherlands) allow classifying images from video recordings of facial expressions with artificial neural network trained with a large sample of images showing human faces mimicking the basic emotion (Skiendziel and Ro, 2019; FaceReader, Noldus). Facial expressions have also been used to predict various other emotional states, including depression, anxiety, or stress, which can manifest via unconscious facial movements (Liao et al., 2005; Garcia-Ceja et al., 2018; Gavrilescu and Vizireanu, 2019). Using artificial neural networks, Gavrilescu and Vizireanu, (2019) were able to predict the stress dimension of the Depression Anxiety Stress Scale (DASS) (Lovibond and Lovibond, 1995) with 90.2% accuracy via a combination of AU1 (i.e., inner brow raiser), AU6 (i.e., cheek raiser), AU12 (i.e., lip corner puller), AU15 (i.e., lip corner depressor). These results show the potential of dynamic facial movements corresponding to other states than the traditional six basic emotions in research using AFEA (Barrett et al., 2019; Krumhuber et al., 2023).

Emotion Regulating Function of Facial Movement

Literature in psychology and psychiatry suggests that facial expressions are used to communicate, but also regulate mood or emotions (Kleinke et al., 1998; Kraft and Pressman, 2012; Wollmer et al., 2012; Finzi and Rosenthal, 2014; Shafir, 2015; Söderkvist et al., 2018). For instance, Kleinke et al. (1998) had participants mimicking positive or negative facial expressions while viewing themselves in the mirror or not. They found that participants had increased positive emotions when mimicking positive facial expressions and decreased positive emotions when mimicking negative facial expressions. In addition, when viewing themselves in a mirror as a way to increase self-awareness, the previous effects of facial musculature on participants' subjective emotions were even stronger. Similarly, another study showed both physiological and psychological benefits of maintaining positive facial expressions during stressful event (Kraft and Pressman, 2012). Other clinical studies found positive outcomes of botox injection in depressed patients' glabellar frown lines to paralyze the corrugator supercilia face muscle (i.e., facial AU4) involved in frowning and negative emotions like stress (Wollmer et al., 2012; Finzi and Rosenthal, 2014; Söderkvist et al., 2018). Therefore, the literature suggests that physiological stress may be regulated by consciously relaxing facial muscles that can be contracted when experiencing stress.

Objective Self-Awareness Theory

The theory of objective self-awareness suggests that one's conscious attention can either be directed towards oneself or external environment (Duval and Wicklund, 1972). Objective self-awareness can be triggered by a stimulus such as a camera, a mirror, or the knowledge of being attended to by others (Wicklund, 1975). Once the individual's attention is self-focused, a self-evaluation of the discrepancy between aspiration and attainment occurs. When the discrepancy is negative, objective self-awareness may result in reducing this discrepancy (Wicklund, 1975). Therefore, the objective self-awareness theory can be used to predict user behavior with self-monitoring systems.

THEORETICAL DEVELOPMENT

The presented theory aims at explaining and predicting (Gregor, 2006) the impact of a hypothetical IT artifact (i.e., AFEA of stress self-monitoring system) on facial expression self-awareness, facial expressions of stress (i.e., physiological stress), and psychological stress. We develop an overarching proposition that explains how the theory's constructs are related (Cornelissen, 2017). Finally, we present the contextual boundaries of the new theoretical model.

Causal Model Development

The hypothetical IT artifact (i.e., AFEA of stress self-monitoring system) is a software or app that can automatically analyze users' facial expressions based on video recordings of their face behavior via a built-in or external camera. The IT artifact has a primary function of self-monitoring system presence. According to the theory of objective self-awareness (Duval and Wicklund, 1972; Wicklund, 1975), the self-monitoring system presence, hence the feeling of being continuously observed, may increase one's self-awareness. Self-monitoring system alerts are triggered when increased intensity or duration of facial expressions of stress is detected. These alerts act as an automatic evaluation of discrepancy between facial expressions of stress and desired state (i.e., neutral or relaxed facial expressions). Therefore, the present theory assumes that self-monitoring system presence and alerts both positively influence facial expression self-awareness by directing users' consciousness towards their facial expressions for self-evaluation.

Facial expression self-awareness is defined as the extent to which a user spends time being conscious about his or her facial behavior (Duval and Wicklund, 1972; Wicklund, 1975). During this time, users self-evaluate the state of their facial expression and compare it to a desired state to find discrepancy or not between the two. If a discrepancy is found, users may consciously engage in facial expression of stress inhibition by relaxing their facial muscles.

Facial expression of stress is defined as the extent to which the facial muscles associated with stress are contracted. Based on Jaccard and Jacoby's (2010) process in building causal models, the present theory includes Ekman and Friensen's (1978) FACS measurement system to determine the intensity of facial expressions of stress (i.e., physiological stress) via the combination of facial AU1 (inner brow raiser), AU6 (cheek raiser), AU12 (lip corner puller), and AU15 (lip corner depressor) (Gavrilescu and Vizireanu, 2019).

The present theory also includes Lovibond and Lovibond's (1995) stress dimension of the DASS in the model (i.e., psychological stress). Stress, anxiety, and depression are three interconnected emotional states that evolve sequentially (Friedman et al., 1992). Psychological stress has been defined as a state in which an individual has difficulty relaxing, has nervous arousal, and is easily agitated or upset (Lovibond and Lovibond, 1995; Gavrilescu and Vizireanu, 2019). The stress dimension of the DASS includes seven items assessing the extent to which the respondent felt (1) over-aroused, tense, (2) unable to relax, (3) touchy, easily upset (4) irritable (5) easily startled (6) nervy, jumpy, fidgety (7) intolerant of interruption or delay.

According to the literature on the effect of facial musculature on emotion regulation, the presented theory assumes that the conscious inhibition of facial expressions of stress may reduce users' psychological stress. However, based on technostress literature, the theory acknowledges that IT artifacts with AFEA of stress self-monitoring systems may also have a direct positive effect on psychological stress. Indeed, technostress can be experienced over long periods of time due to ongoing IT use, or over short periods of time due to specific events like a system breakdown or an alert (Maier et al., 2022).

The theoretical model (see Figure 1) can be explained with the following overarching proposition. The presence and alert(s) of an AFEA of stress self-monitoring system will have a mediated negative effect on psychological stress via increased facial expression self-awareness but may also have a direct positive effect on psychological stress.

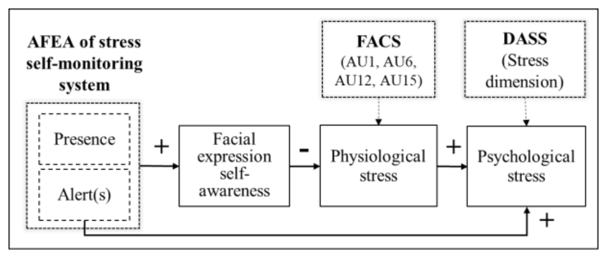

Figure 1. Theoretical framework on psychological stress regulation via an AFEA of stress self-monitoring system

The theory assumes a voluntary use of the IT artifact by users, such that they know if their facial expressions are being monitored. The theoretical model can be generalized to other contexts than working on a computer, such as car driving. Finally, although the current view on Artificial Intelligence-based emotion recognition and AFE-based affective computing in the workplace and education is concerned with ethical and privacy issues (e.g., Artificial Intelligence Act), this theory makes the important assumption that such technologies will be regulated and adopted in the next years (Andrejevic and Selwyn, 2020; Richardson, 2020).

CONCLUSION

This paper presents a theoretical model that explains and predicts the impact of the presence and alert(s) of AFEA of stress self-monitoring systems on users' psychological stress. The proposed theory may encourage research on AFE-based self-monitoring systems to regulate users' psychological stress while interacting with IT. Until other biosensors like smart watches become more affordable to enable multimodal emotion detection, research should explore the potential of physiological stress detection via AFEA alone. The theoretical development contributes to the fields of design science research and affective computing, as well as the technostress literature by studying the potential of self-monitoring systems for mitigating or inhibiting stress while interacting with IT.

REFERENCES

1. Adedoyin, O. B., & Soykan, E. (2020). Covid-19 pandemic and online learning: the challenges and opportunities. Interactive Learning Environments, 1-13.
2. Akbar, F., Mark, G., Pavlidis, I., & Gutierrez-Osuna, R. (2019). An empirical study comparing unobtrusive physiological sensors for stress detection in computer work. Sensors, 19(17), 3766.
3. Andrejevic, M., & Selwyn, N. (2020). Facial recognition technology in schools: Critical questions and concerns. Learning, Media and Technology, 45(2), 115-128.
4. Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., & Pollak, S. D. (2019). Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements. Psychological science in the public interest, 20(1), 1-68.
5. Bojovic, D., Benavides, J., & Soret, A. (2020). What we can learn from birdsong: Mainstreaming teleworking in a post-pandemic world. Earth System Governance, 5, 100074.
6. Booth, B. M., Vrzakova, H., Mattingly, S. M., Martinez, G. J., Faust, L., & D'Mello, S. K. (2022). Toward Robust Stress Prediction in the Age of Wearables: Modeling Perceived Stress in a Longitudinal Study with Information Workers. IEEE Transactions on Affective Computing, 13(4), 2201-2217.
7. Brocke, J. V., Riedl, R., & Léger, P. M. (2013). Application strategies for neuroscience in information systems design science research. Journal of Computer Information Systems, 53(3), 1-13.
8. Burton-Jones, A., Butler, B., Scott, S., & Xu, S. X. (2018). Next-generation information systems theories. MIS Quarterly Call for Papers.
9. Calvo, R. A., D'Mello, S., Gratch, J. M., & Kappas, A. (2015). The Oxford handbook of affective computing. Oxford University Press, USA.
10. Carneiro, D., Novais, P., Augusto, J. C., & Payne, N. (2017). New methods for stress assessment and monitoring at the workplace. IEEE Transactions on Affective Computing, 10(2), 237-254.
11. Castro-García, J. A., Molina-Cantero, A. J., Gómez-González, I. M., Lafuente-Arroyo, S., & Merino-Monge, M. (2022). Towards human stress and activity recognition: A review and a first approach based on low-cost wearables. Electronics, 11(1), 155.
12. Chakraborti, R., & Roberts, G. (2021). Learning to hoard: The effects of preexisting and surprise price-gouging regulation during the COVID-19 pandemic. Journal of Consumer Policy, 44, 507-529.
13. Cornelissen, J. (2017). Editor's Comments: Developing Propositions, a Process Model, or a Typology? Addressing the Challenges of Writing Theory Without a Boilerplate. Academy of Management Review, 42(1), 1–9.
14. Crawford, K., Lingel, J., & Karppi, T. (2015). Our metrics, ourselves: A hundred years of self-tracking from the weight scale to the wrist wearable device. European Journal of Cultural Studies, 18(4-5), 479-496.
15. Dragano, N., Lunau, T., (2020). Technostress at work and mental health. Current Opinion in Psychiatry, 33(4), 407-413.
16. Duval, S., & Wicklund, R. A. (1972). A theory of objective self-awareness. New York: Academic Press.
17. Ekman, P. & Friesen, W.V. (1978). Facial action coding system. Palo Alto: Consulting Psychologist Press.
18. Noldus FaceReader methodology, https://info.noldus.com/free-white-paper-on-facereader-methodology, last accessed 2023/05/02.
19. Finzi, E., & Rosenthal, N. E. (2014). Treatment of depression with botulinum toxin: A randomized, double-blind, placebo-controlled trial. Journal of psychiatric research, 52, 1-6.
20. Friedman, E. S., Clark, D. B., & Gershon, S. (1992). Stress, anxiety, and depression: Review of biological, diagnostic, and nosologic issues. Journal of anxiety disorders, 6(4), 337-363.
21. Garcia-Ceja, E., Riegler, M., Nordgreen, T., Jakobsen, P., Oedegaard, K. J., & Tørresen, J. (2018). Mental health monitoring with multimodal sensing and machine learning: A survey. Pervasive and Mobile Computing, 51, 1-26.
22. Gavrilescu, M., & Vizireanu, N. (2019). Predicting Depression, Anxiety, and Stress Levels from Videos Using the Facial Action Coding System. Sensors, 19(17), 3693.
23. Greene, S., Thapliyal, H., & Caban-Holt, A. (2016). A survey of affective computing for stress detection: Evaluating technologies in stress detection for better health. IEEE Consumer Electronics Magazine, 5(4), 44-56.
24. Gregor, S. (2006). The Nature of Theory in Information Systems. MIS Quarterly, 30(3), 611-642.
25. Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. MIS Quarterly, 37(2), 337-355.
26. Heiden, M., Widar, L., Wiitavaara, B., & Boman, E. (2021). Telework in academia: associations with

health and well-being among staff. Higher Education, 81, 707-722.

27. Ioannou, A., Lycett, M., & Marshan, A. (2022). The role of mindfulness in mitigating the negative consequences of technostress. Information Systems Frontiers, 1-27.
28. Jaccard, J., and Jacoby, J. (2010). Theory Construction and Model-Building Skills: A Practical Guide for the Social Scientist, New York: The Guilford Press.
29. Jiang, J., & Cameron, A. F. (2020). IT-Enabled Self-Monitoring for Chronic Disease Self-Management: An Interdisciplinary Review. MIS Quarterly, 44(1).
30. Kleinke, C. L., Peterson, T. R., & Rutledge, T. R. (1998). Effects of self-generated facial expressions on mood. Journal of Personality and Social Psychology, 74(1), 272.
31. Kraft, T. L., & Pressman, S. D. (2012). Grin and bear it: The influence of manipulated facial expression on the stress response. Psychological science, 23(11), 1372-1378.
32. Krumhuber, E. G., Skora, L. I., Hill, H. C., & Lander, K. (2023). The role of facial movements in emotion recognition. Nature Reviews Psychology, 1-14.
33. Liao, W., Zhang, W., Zhu, Z., & Ji, Q. (2005). A real-time human stress monitoring system using dynamic Bayesian network. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)-Workshops (pp. 70-70). IEEE.
34. Lovibond, S.H. & Lovibond, P.F. (1995). Manual for the Depression Anxiety Stress Scales. Psychology Foundation of Australia: Sydney, Australia.
35. Lupton, D. (2014). Self-tracking cultures: towards a sociology of personal informatics. In Proceedings of the 26th Australian computer-human interaction conference on designing futures: The future of design (pp. 77-86).
36. Marin-Farrona, M., Leon-Jimenez, M., Garcia-Unanue, J., Gallardo, L., Crespo-Ruiz, C., & Crespo-Ruiz, B. (2020). Transtheoretical model is better predictor of physiological stress than perceived stress scale and work ability index among office workers. International journal of environmental research and public health, 17(12), 4410.
37. Nastjuk, I., Trang, S., Grummeck-Braamt, J. V., Adam, M. T., & Tarafdar, M. (2023). Integrating and Synthesising Technostress Research: A Meta-Analysis on Technostress Creators, Outcomes, and IS Usage Contexts. European Journal of Information Systems, 1-22.
38. Picard, R. W., & Klein, J. (2002). Computers that recognise and respond to user emotion: theoretical and practical implications. Interacting with computers, 14(2), 141-169.
39. Ragu-Nathan, T., M. Tarafdar, B. S. Ragu-Nathan and Q. Tu (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. Information systems Research, 19(4), 417-433.
40. Richardson, S. (2020). Affective computing in the modern workplace. Business Information Review, 37(2), 78-85.
41. Salo, M., Pirkkalainen, H., Chua, C. E. H., & Koskelainen, T. (2022). Formation and mitigation of technostress in the personal use of IT. MIS Quarterly, 46.
42. Shafir, T. (2015). Movement-based strategies for emotion regulation. Handbook on emotion regulation: Processes, cognitive effects and social consequences, 231-249.
43. Sarabadani, J., Carter, M., & Compeau, D. (2018). 10 years of research on technostress creators and inhibitors: synthesis and critique. AMCIS 2018 Proceedings. 23.
44. Sharma, N., & Gedeon, T. (2012). Objective measures, sensors and computational techniques for stress recognition and classification: A survey. Computer methods and programs in biomedicine, 108(3), 1287-1301.
45. Shin, D. H., & Biocca, F. (2017). Health experience model of personal informatics: The case of a quantified self. Computers in Human Behavior, (69), 62-74.
46. Shin, G., Jarrahi, M. H., Fei, Y., Karami, A., Gafinowitz, N., Byun, A., & Lu, X. (2019). Wearable activity trackers, accuracy, adoption, acceptance and health impact: A systematic literature review. Journal of biomedical informatics, 93, 103153.
47. Söderkvist, S., Ohlén, K., & Dimberg, U. (2018). How the experience of emotion is modulated by facial feedback. Journal of nonverbal behavior, 42(1), 129-151.
48. Swan, M. (2013). The quantified self: Fundamental disruption in big data science and biological discovery. Big data, 1(2), 85-99.
49. Taser, D., Aydin, E., Torgaloz, A. O., & Rofcanin, Y. (2022). An examination of remote e-working and flow experience: The role of technostress and loneliness. Computers in Human Behavior, 127, 107020.
50. Wicklund, R. A. (1975). Objective Self-Awareness. Advances in Experimental Social Psychology Volume 8, 233–275.
51. Wollmer, M. A., de Boer, C., Kalak, N., Beck, J., Götz, T., Schmidt, T., ... & Sönmez, D. (2012). Facing depression with botulinum toxin: a randomized controlled trial. Journal of psychiatric research, 46(5), 574-581