Neurophysiological Data Collection at the Digital Workplace

Till Bieg[1,2]*, Cornelia Gerdenitsch[1], Philip Schörpf[3,4], Anice Jahanjoo[5], and Nima Taherinejad[5]

[1] AIT Austrian Institute of Technology GmbH, Center for Technology Experience, Vienna, Austria {till.bieg,cornelia.gerdenitsch}@ait.ac.at
[2] Vienna University of Economics and Business, Institute for Marketing and Consumer Research, Vienna, Austria
[3] FORBA Working Life Research Center, Vienna, Austria
[4] University of Vienna, Institute of Sociology, Vienna, Austria {philip.schoerpf}@univie.ac.at
[5] Technical University of Vienna, Faculty of Electrical Engineering and Information Technology, Vienna, Austria {nima.taherinejad,anice.jahanjoo}@tuwien.ac.at

Abstract. Interest in the use of neurophysiological instruments for real-world studies in the workplace is increasing, also intensified by the simultaneously growing use of various commercial self-tracking technologies. However, the application of neurophysiological tools for real-world workplace research is associated with challenges - an aspect that has received little attention in previous research. This article outlines the key challenges encountered when applying neurophysiological measurements in the workplace, drawing on insights gained in an interdisciplinary research project on digital workplaces. We identify challenges along four main themes: technical tool requirements, data processing and interpretation, tool interaction, and organizational collaboration. Additionally, we discuss how these challenges were addressed within our case. As a contribution, this article offers important considerations and recommendations for the effective application of neurophysiological tools in real-world workplace research.

Keywords: Workplace Stress · Self-Tracking · Quantified-Self · Neurophysiological Measurement · Neuroergonomics · NeuroIS

1 Introduction

The widespread adoption of self-tracking technologies has made wearable devices a common tool for monitoring daily activities [1, 2]. Within the quantified-self movement [3], individuals track aspects such as sleep, mood, nutrition, or physical activity in their daily life [4–6]. As a result, the acceptance of neurophysiological tools for field research is likely to increase. While often used in controlled laboratory settings, their application extends to real-world situations [7, 8]. In this context, *neuroergonomics* - the study of the human brain in relation to performance at work - emerged as an interdisciplinary field [9, 10]. Indeed, there is a growing interest in using neurophysiological tools for real-world studies at the workplace [11–14], enabling to capture workers' reactions to varying working conditions (e.g., workload, interruptions [15, 16]) or to stress [17, 18] and attention levels across the workday. Considering this increasing interest, it is crucial to acknowledge the unique challenges inherent in designing and implementing studies using neurophysiological tools within the workplace – an aspect that has received little attention in existing literature.

In this article, we report on key challenges of applying neurophysiological measurements in the workplace, drawing on experiences from an interdisciplinary research project[1] that explores digital workplaces [19] through the lens of digital humanism [20, 21]. We discuss challenges across multiple themes, encompassing the selection of tools, data processing and interpretation, interaction with the tools/system, and coordination activities with organisations. Moreover, we describe how we addressed the challenges in our project and discuss potential benefits and drawbacks. Thus, our contribution lies in heightening awareness for practical challenges for applying neurophysiological tools within workplace settings and providing guidance for fellow researchers.

2 Challenges for Neurophysiological Data Collection

Due to the increasing integration of information and communication technologies into everyday work, work in organizations changes [22]. Working conditions including work intensification [23], digital interruptions [24], or fragmented work [25] emerge, contributing to work-related stress. In the interdisciplinary research project *ShapeTech*, we aim to capture workers' experiences in such digitized work environments and develop strategies for the humanization of work and technologies, in which the term 'humanization of work' refers to pursuing humane goals [21]. To achieve this, we research employees in two companies as case studies, equipping them with neurophysiological tools during their workdays.

Neurophysiological tools include for example the electrocardiogram and electroencephalography [26]. These tools allow for the direct extraction of biometric data from an individual's body, serving as indicators for bodily reactions as well as cognitive and emotional processes, including stress levels and attention [27–29]. For instance, the electrical activity of the heart or the sweat levels in the eccrine glands of the palms can signal stress [30, 31]. As another example, the electrical activity on the skull surface indicates different levels of brain activity representing various cognitive and emotional constructs [32–34], such as attention. Commercially available tools for measuring these parameters are becoming widespread in the market (cf. [35]), falling

[1] ShapeTech: "Shaping technology: biometric data, collective empowerment and humanization of work" (2021 – 2024); shapetech.ict.tuwien.ac.at; Funded by Vienna Science and Technology Fund (WWTF) under project number ICT20-034.

under the realm of quantified-self technology (QST) [1, 3, 36]. Example QSTs include headsets (Neurosity[i], Flowtime[ii]), smartwatches (by Fitbit[iii], Apple[iv], Garmin[v]), shirts (Hexoskin Smart Shirt[vi], Sensoree GER Mood Sweater[vii]), or smart rings (Oura Ring[viii], RingConn[ix]). These technological trends are familiarizing people with tracking tools, so there seems to be a basis for neurophysiological measurements in the workplace. Moreover, research has indicated that these consumer-grade instruments can often be a viable alternative to high-quality research tools (e.g., for EEG [35]). However, commercial products cannot always be used for research studies – not only due to data security and privacy issues, but also because they influence user expectations in terms of user experience. Consequently, employing neurophysiological tools for workplace research entails challenges. We have outlined a collection of these challenges in the table below. In the remainder of this section, we will discuss how we answered these questions for our project.

Table 1. Questions relating to key challenges for neurophysiological data collection in real-world workplace settings.

Theme	Questions
Selection of tools	- How many different types of tools (e.g., smartwatch, headband) should be used and should they communicate? Is an overall system, like an app, needed to control the tools and provide feedback? - Do the tools provide adequate "real-world usability" in terms of comfort, maintenance, reliability, ease of use, movement, and visibility throughout the workday? - How many identical devices are needed for large-scale simultaneous testing? - How is the data stored to ensure data privacy and protection? - Should the tool provide raw data?
Data processing & interpretation	- How is the data processed? How transparent (disclosed underlying algorithms vs. black box) and valid are the metrics provided by commercial tools? Which methods (e.g., machine learning) are being used when processing raw data and what is the validity of the results? - How is the data contextualized in relation to reference groups (norms) or points in time? - What types of data is (needs to be) collected besides neurophysiological data? How are different types of data points aligned?
Tool/system interaction	- What interactions between user and tools are required; which ones are possible? What is the extent and the modality (input, output) of interaction? - If, how, and when is the data presented to participants? - How is the user experience (also compared to similar commercial products)? - Are there methodological implications (e.g., bias) of tool/system interaction?

Coordination with organizations	-	What coordination tasks are needed before, during, and after the study, including communication with management, works council, and workers?
	-	What agreements are necessary regarding data protection, managerial regulations, and privacy issues?

Selection of Tools: To capture workers' experiences in digitized work environments we provided office workers with *two neurophysiological tools* - the Empatica E4 smartwatch to identify stress [28–30] and the BrainLink Pro headband to measure attention levels [31] throughout multiple workdays. Additionally, we developed an Android app that enables participants to initiate data collection independently (switching tools on and off), a critical aspect for real-world research. It also provides awareness of battery status and sends notifications for time sampling methods. For project planning, it is important to consider that developing such an app requires resources. Alternatively, one could consider utilizing commercial products that come with accompanying apps. However, not all commercial products offer *real-time access to raw data*, essential for researching algorithms for infer stress from neurophysiological data. Also, not all available tools are suitable for measuring data throughout a whole workday. Moreover, some commercial products store data outside of Europe (e.g., America, Asia) which raises concerns regarding compliance with *data protection regulations* such as GDPR[2]. By developing our own system, we ensured that data is stored on the individual device.

One crucial requirement is *"real-world usability"* of the tools being used, meaning they should be comfortable, reliable, easy to maintain, and seamlessly integrate into the user's workday in terms of movement and visibility. However, meeting these standards can be challenging. For example, visibility issues may arise, particularly when wearing headbands during meetings or customer interactions. Comfort is challenged when tools interfere with other work equipment such as wearing headbands alongside headphones. Managing the devices during the workday may also present a logistical challenge for participants. In our study, devices needed to remain close together, so we supplied smartphone bands for this purpose. Unlike controlled laboratory environments where researchers can provide consistent support, studies in real-world require high device reliability. Poor reliability can impact data quality. Although participants may be able to address issues independently (depending on their digital skills), remote support is crucial for resolving any potential problems. Furthermore, the stability of the system during movement is to be addressed, as workers often stand up, move around inside and outside office buildings. In our studies, participants had to move between buildings, necessitating the maintenance of connections such as GPS, Internet, and Bluetooth.

Finally, a *sufficient number of identical tools* and backup sets, ideally with similar age, usage levels, same batteries and sensors is necessary to ensure consistent performance. However, in studies requiring larger samples, as needed in real-world settings, obtaining a number of identical devices may not always be feasible.

Data Processing and Interpretation. Researchers may choose to use pre-calculated *metrics* provided by commercial tools for processing and interpreting

[2] General Data Protection Regulation (https://gdpr-info.eu/)

neurophysiological data (e.g., BrainLink offers pre-calculated metrics for attention levels). An advantage of this approach is that less effort is required in developing models. Challenges in this context relate to the *transparency of metrics* and how *valid interpretation* can be ensured. For commercial tools, vendors might not disclose underlying algorithms rendering the computation as a black box. If pre-calculated metrics are not used, researchers still need to choose methods that ensure valid results. In our project, one research objective was to improve existing stress detection algorithms. Thus, we did not rely on pre-calculated metrics. Instead, we trained machine learning models on established datasets [e.g., 28] and validated and refined them using data collected in our study.

Furthermore, *data needs to be contextualized*, for example, in relation to reference groups or different points in time. While some commercial tools provide norms for interpretation, this is not always the case. For example, the pre-calculated metric for attention provided by the BrainLink Pro headband is scaled to values between 0 and 100; however, how values are typically distributed remains unknown. This might be particularly problematic if metrics are based on black-box algorithms due to the additional lack of transparency. In comparison, the use of well-established datasets to develop custom models as in our project [38] - while more challenging - can provide more reliable reference points for interpreting data corroborated by academic research.

Researchers also need to consider *which other types of data need to be collected alongside neurophysiological data*. In our project, focusing on neurophysiological reactions to digitalized work, we included self-reports on subjective experience and contextual factors. Thus, following the approach of complementing NeuroIS and psychometric methods [24]. For that, participants filled out questionnaires at the beginning and end of each workday including a day reconstruction of their activities [39]. Given the continuous nature of neurophysiological measurements, another challenge concerns the *alignment of neurophysiological data with other types of data* collected at discrete points in time. For example, we decided to form averages across specific time periods to better understand the relation between neurophysiological data, subjective experience, and contextual factors.

Interaction with the Tools/System. Like most real-world studies, ours required participants to have *minimal interaction with the tools,* including charging them and turning them on and off. For our research, there was the requirement to collect data about stress, for which we used experience sampling [40–42] via app notifications with single-item measures at random points in time. When deciding for interaction with tools, it is important to balance the need for interaction with its *methodological implications*. Thus, in our research, participants could respond at their convenience to minimize bias in their interaction with the system.

Moreover, measurement tools can be used to *display information to participants*. Depending on research objectives, this could be used as a deliberate intervention. Additionally, participants' experiences with commercial QST might shape their *expectations regarding user experience*, including if and how data is visualized. In our study, we decided to keep feedback on the data during the study at a minimum to avoid introducing biases. Instead, each participant received an individual report visualizing data from different sources (neurophysiological data and self-reports) *after* the study for reflection purposes. In general, when presenting data to participants, it is important to manage potential expectations of participants emerging from commercial QSTs, consider how data is contextualized (e.g., comparison to norms), and find a balance between simplicity and sufficient information.

Coordinating activities with organizations: Conducting real-world workplace research demands elaborate management of the study process. Key stakeholders including management and the works council must be engaged and informed. This entails scheduling appointments for presenting the aim, methods, and results of the study, and discussing crucial aspects like data protection, storage, and access, ensuring compliance with regulations such as GDPR and company policies, and incentives for participation.

3 Conclusion

This work is situated in a context where QST use in daily life and neuroergonomics (i.e., using neurophysiological tools for workplace research) coexist. QST use affects participants' expectations regarding technical capabilities and user experience, which needs to be addressed in research studies. Drawing from our experience in a research project on work-related stress, we outline questions and describe our approaches to address them, thus providing a practical checklist to aid researchers in planning similar studies. Although a singular challenge in itself may seem obvious and manageable, it is the combination of a variety of different challenges that makes collecting neurophysiological data in the workplace so complex. We believe that by making this multitude of challenges salient, our article offers a valuable contribution to the NeuroIS community. In conclusion, we underscore the importance of neurophysiological tools to meet certain criteria for studies in the digital workplace. Ideally, these tools should be reliable, out-of-the-box solutions, provide transparency, and ensure full control over data.

References

1. Feng, S., Mäntymäki, M., Dhir, A., Salmela, H.: How Self-tracking and the Quantified Self Promote Health and Well-being: Systematic Review. J Med Internet Res. 23, e25171 (2021). https://doi.org/10.2196/25171.
2. Moore, P., Piwek, L., Roper, I.: The Quantified Workplace: A Study in Self-Tracking, Agility and Change Management. In: Ajana, B. (ed.) Self-Tracking. pp. 93–110. Springer International Publishing, Cham (2018). https://doi.org/10.1007/978-3-319-65379-2_7.
3. Hong, J.-K., Cho, J.-D.: The Quantified Self. In: Norman, K.L. and Kirakowski, J. (eds.) The Wiley Handbook of Human Computer Interaction. pp. 909–922. John Wiley & Sons, Ltd, Chichester, UK (2017). https://doi.org/10.1002/9781118976005.ch42.
4. Rivera-Pelayo, V., Fessl, A., Müller, L., Pammer, V.: Introducing Mood Self-Tracking at Work: Empirical Insights from Call Centers. ACM Trans. Comput.-Hum. Interact. 24, 1–28 (2017). https://doi.org/10.1145/3014058.

5. Avrahami, D., Williams, K., Lee, M.L., Tokunaga, N., Tjahjadi, Y., Marlow, J.: Celebrating Everyday Success: Improving Engagement and Motivation using a System for Recording Daily Highlights. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. pp. 1–13. ACM, Honolulu HI USA (2020). https://doi.org/10.1145/3313831.3376369.
6. Stephenson, A., Garcia-Constantino, M., Murphy, M.H., McDonough, S.M., Nugent, C.D., Mair, J.L.: The "Worktivity" mHealth intervention to reduce sedentary behaviour in the workplace: a feasibility cluster randomised controlled pilot study. BMC Public Health. 21, 1416 (2021). https://doi.org/10.1186/s12889-021-11473-6.
7. Niso, G., Romero, E., Moreau, J.T., Araujo, A., Krol, L.R.: Wireless EEG: A survey of systems and studies. NeuroImage. 269, 119774 (2023). https://doi.org/10.1016/j.neuroimage.2022.119774.
8. Ayaz, H.: Observing the "Brain at Work" in Everyday Life Using Optical Brain Imaging: Challenges and Opportunities for NeuroIS. , Vienna, Austria (2023).
9. Mehta, R.K., Parasuraman, R.: Neuroergonomics: a review of applications to physical and cognitive work. Front. Hum. Neurosci. 7, (2013). https://doi.org/10.3389/fnhum.2013.00889.
10. Dehais, F., Karwowski, W., Ayaz, H.: Brain at Work and in Everyday Life as the Next Frontier: Grand Field Challenges for Neuroergonomics. Frontiers in Neuroergonomics. 1, (2020).
11. Wascher, E., Reiser, J., Rinkenauer, G., Larrá, M., Dreger, F.A., Schneider, D., Karthaus, M., Getzmann, S., Gutberlet, M., Arnau, S.: Neuroergonomics on the Go: An Evaluation of the Potential of Mobile EEG for Workplace Assessment and Design. Hum Factors. 65, 86–106 (2023). https://doi.org/10.1177/00187208211007707.
12. Fischer, T., Riedl, R.: NeuroIS in situ: On the need for NeuroIS research in the field to study organizational phenomena. (2014). https://doi.org/10.13140/RG.2.1.2738.5200.
13. Fischer, T., Riedl, R.: Messung von digitalem Stress im organisationalen Umfeld: Erfahrungen aus einer Fallstudie. HMD. 57, 218–229 (2020). https://doi.org/10.1365/s40702-020-00596-w.
14. Fischer, T., Riedl, R.: Technostress Measurement in the Field: A Case Report. In: Davis, F.D., Riedl, R., Vom Brocke, J., Léger, P.-M., Randolph, A.B., and Fischer, T. (eds.) Information Systems and Neuroscience. pp. 71–78. Springer International Publishing, Cham (2020). https://doi.org/10.1007/978-3-030-60073-0_9.
15. Stangl, F.J., Riedl, R.: Interruptions in the Workplace: An Exploratory Study Among Digital Business Professionals. In: Nah, F. and Siau, K. (eds.) HCI in Business, Government and Organizations. pp. 400–422. Springer Nature Switzerland, Cham (2023). https://doi.org/10.1007/978-3-031-36049-7_29.
16. Stangl, F.J., Riedl, R.: Interruption science as a research field: Towards a taxonomy of interruptions as a foundation for the field. Front. Psychol. 14, 1043426 (2023). https://doi.org/10.3389/fpsyg.2023.1043426.
17. Gimpel, H., Regal, C.: Design Knowledge on Mobile Stress Assessment. ICIS 2019 Proceedings. (2019).
18. Schellhammer, S., Haines, R., Klein, S.: Investigating Technostress in situ: Understanding the Day and the Life of a Knowledge Worker Using Heart Rate Variability. In: 2013 46th

Hawaii International Conference on System Sciences. pp. 430–439. IEEE, Wailea, HI, USA (2013). https://doi.org/10.1109/HICSS.2013.365.

19. Schörpf, P., Gaitsch, M., Flecker, J., Gerdenitsch, C., Bieg, T., Sellitsch, D., Jahanjoo, A., TaheriNejad, N.: Shaping technology in the immaterial labour process: Empowerment instead of self-optimisation - Wearables and self-monitoring as a means of humanising office jobs – an empirical case study. Presented at the (2023).
20. Fuchs, C.: Digital humanism: a philosophy for 21st century digital society. Emerald Publishing, [Bingley],UK (2022).
21. Kreikebaum, H., Herbert, K.-J.: Humanisierung der Arbeit. Gabler Verlag, Wiesbaden (1988). https://doi.org/10.1007/978-3-322-84005-9.
22. Cascio, W.F., Montealegre, R.: How technology is changing work and organizations. Annual Review of Organizational Psychology and Organizational Behavior. 3, 349–375 (2016). https://doi.org/10.1146/annurev-orgpsych-041015-062352.
23. Mauno, S., Herttalampi, M., Minkkinen, J., Feldt, T., Kubicek, B.: Is work intensification bad for employees? A review of outcomes for employees over the last two decades. Work & Stress. 37, 100–125 (2023). https://doi.org/10.1080/02678373.2022.2080778.
24. Puranik, H., Koopman, J., Vough, H.C.: Pardon the Interruption: An Integrative Review and Future Research Agenda for Research on Work Interruptions. Journal of Management. 46, 806–842 (2020). https://doi.org/10.1177/0149206319887428.
25. Mark, G., Gonzalez, V.M., Harris, J.: No task left behind?: examining the nature of fragmented work. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. pp. 321–330. ACM, Portland Oregon USA (2005). https://doi.org/10.1145/1054972.1055017.
26. Dimoka, A., Banker, R.D., Benbasat, I., Davis, F.D., Dennis, A.R., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P.A., Riedl, R., Vom Brocke, J., Weber, B.: On the Use of Neurophysiological Tools in IS Research: Developing a Research Agenda for NeuroIS. MIS Quarterly. 36, 679–702 (2012). https://doi.org/10.2307/41703475.
27. Papousek, I., Wimmer, S., Lackner, H.K., Schulter, G., Perchtold, C.M., Paechter, M.: Trait positive affect and students' prefrontal EEG alpha asymmetry responses during a simulated exam situation. Biological Psychology. 148, 107762 (2019). https://doi.org/10.1016/j.biopsycho.2019.107762.
28. Katmah, R., Al-Shargie, F., Tariq, U., Babiloni, F., Al-Mughairbi, F., Al-Nashash, H.: A Review on Mental Stress Assessment Methods Using EEG Signals. Sensors. 21, 5043 (2021). https://doi.org/10.3390/s21155043.
29. Vanhollebeke, G., De Smet, S., De Raedt, R., Baeken, C., van Mierlo, P., Vanderhasselt, M.-A.: The neural correlates of psychosocial stress: A systematic review and meta-analysis of spectral analysis EEG studies. Neurobiology of stress. 18, 100452 (2022).
30. Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., Tsiknakis, M.: Review on Psychological Stress Detection Using Biosignals. IEEE Trans. Affective Comput. 13, 440–460 (2022). https://doi.org/10.1109/TAFFC.2019.2927337.
31. Kim, H.-G., Cheon, E.-J., Bai, D.-S., Lee, Y.H., Koo, B.-H.: Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 15, 235–245 (2018). https://doi.org/10.30773/pi.2017.08.17.

32. Angelidis, A., Van Der Does, W., Schakel, L., Putman, P.: Frontal EEG theta/beta ratio as an electrophysiological marker for attentional control and its test-retest reliability. Biological Psychology. 121, 49–52 (2016). https://doi.org/10.1016/j.biopsycho.2016.09.008.
33. Krigolson, O.E., Williams, C.C., Colino, F.L.: Using Portable EEG to Assess Human Visual Attention. In: Schmorrow, D.D. and Fidopiastis, C.M. (eds.) Augmented Cognition. Neurocognition and Machine Learning. pp. 56–65. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-58628-1_5.
34. Müller-Putz, G.R., Riedl, R., Wriessnegger, S.C.: Electroencephalography (EEG) as a Research Tool in the Information Systems Discipline: Foundations, Measurement, and Applications. CAIS. 37, (2015). https://doi.org/10.17705/1CAIS.03746.
35. Riedl, R., Minas, R.K., Dennis, A.R., Müller-Putz, G.R.: Consumer-Grade EEG Instruments: Insights on the Measurement Quality Based on a Literature Review and Implications for NeuroIS Research. In: Davis, F.D., Riedl, R., vom Brocke, J., Léger, P.-M., Randolph, A.B., and Fischer, T. (eds.) Information Systems and Neuroscience. pp. 350–361. Springer International Publishing, Cham (2020). https://doi.org/10.1007/978-3-030-60073-0_41.
36. Gerdenitsch, C., Bieg, T., Gaitsch, M., Schörpf, P., Tscheligi, M., Kriglstein, S.: Tracking to Success? A Critical Reflection on Workplace Quantified-Self Technologies from a Humanistic Perspective. In: Proceedings of the 2nd Annual Meeting of the Symposium on Human-Computer Interaction for Work. pp. 1–7. Association for Computing Machinery, New York, NY, USA (2023). https://doi.org/10.1145/3596671.3597653.
37. Schmidt, P., Reiss, A., Duerichen, R., Marberger, C., Van Laerhoven, K.: Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection. In: Proceedings of the 20th ACM International Conference on Multimodal Interaction. pp. 400–408. ACM, Boulder CO USA (2018). https://doi.org/10.1145/3242969.3242985.
38. Jahanjoo, A., TaheriNejad, N., Aminifar, A.: High-Accuracy Stress Detection Using Wrist-Worn PPG Sensors. In: 2024 IEEE International Symposium on Circuits and Systems (ISCAS) (2024).
39. Kahneman, D.: A survey method for characterizing daily life experience: the day reconstruction method. Science. 306, 1776–1780 (2004). https://doi.org/10.1126/science.1103572.
40. van Berkel, N., Ferreira, D., Kostakos, V.: The Experience Sampling Method on Mobile Devices. ACM Comput. Surv. 50, 93:1–93:40 (2017). https://doi.org/10.1145/3123988.
41. Myin-Germeys, I., Oorschot, M., Collip, D., Lataster, J., Delespaul, P., Os, J. van: Experience sampling research in psychopathology: opening the black box of daily life. Psychological Medicine. 39, 1533–1547 (2009). https://doi.org/10.1017/S0033291708004947.
42. Volsa, S., Lewetz, D., Mlakic, V., Bertagnoli, C., Hochstöger, S., Rechl, M., Sertic, H., Batinic, B., Stieger, S.: Development of an open-source solution to facilitate the use of one-button wearables in experience sampling designs. Behav Res. (2024). https://doi.org/10.3758/s13428-023-02322-y.

[i] https://neurosity.co/

[ii] https://www.meetflowtime.com/
[iii] https://www.fitbit.com/
[iv] https://www.apple.com/watch
[v] https://www.garmin.com/
[vi] https://hexoskin.com/
[vii] https://www.sensoree.com/
[viii] https://ouraring.com/de
[ix] https://ringconn.com/products/smart-ring