Towards a VR-BCI Based System to Evaluate the Effectiveness of Immersive Technologies in Industry

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Abstract: Industry 4.0 demands from its operators' knowledge and mastery of modern technologies, such as the Internet of Things and Virtual Reality, as these offer the Operator 4.0 intelligent tools to improve its daily operations and practices. Recent research shows promising results on immersive technologies, as they provide a safe and effective tool for representing hazardous environments that are often difficult to replicate in the real world. Nevertheless, there is a gap in research on behavioral changes in users while using these technologies, in addition to evaluating the effectiveness of industrial processes and training and the challenges to implement in the current Industry. This work seeks to evaluate and answer these questions by using modern technologies such as VR, BCI, Eye Tracking, and xAPI for this evaluation through the perspectives of attention and fatigue by capturing the user's behavior and physiological data inside a Virtual Environment so that in the future will be validated through a user test to evaluate and reflect on the effectiveness of using virtual reality in Industry.

1 INTRODUCTION

Safety training is crucial for companies globally as it impacts health, safety, and the environment by preventing accidents and promoting employee well-being (Villani et al., 2022). This training develops workers' skills and capabilities to analyze risk situations and make appropriate decisions. Recent research highlights promising outcomes with immersive technologies, which offer a safe and illustrative mechanism to simulate hazardous environments that are often challenging to replicate in real-world scenarios (Pedram et al., 2017). Furthermore, these technologies have been adopted across various industries, such as aviation (for landing scenarios) and firefighting (for the proper use of equipment), aiming to evaluate human behavior and train skills in high-risk situations (Scorgie et al., 2024).

As described by (Werbińska-Wojciechowska and Winiarska, 2023), Industry 4.0 introduces modern technologies into industrial processes, including the Internet of Things (IoT), Virtual Reality (VR), Augmented Reality (AR), Brain-Computer Interface (BCI), and Digital Security. These technologies provide Industry 4.0 operators with intelligent tools to enhance daily operations and practices. Notably, (Guo et al., 2020) emphasizes that immersive technologies are fundamental to implementing Industry 4.0, particularly when integrated with other modern technologies such as BCI, Blockchain, and IoT. According to (Douibi et al., 2021), using BCIs can contribute to workplace safety, adaptive learning, and remote control of devices.

However, as highlighted by (Stefan et al., 2023), there is a scarcity of studies at level 3 (Behavioral) of Kirkpatrick's model that evaluate users' behavioral changes following immersive training. This work aims to pioneer the application of modern technolo-

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gies such as VR and BCI to address this gap. While limited studies have explored the use of VR for assessing behavioral changes, what challenges might arise in implementing this technology in industrial processes and training? Moreover, what effects are perceived and recorded by users?

Thus, this work proposes a proof of concept to be presented as a framework for validating immersive technologies within industrial training scenarios. This prototype will be used in future research to validate its application through a case study in the industry. Therefore, the scope of this work does not include testing with participants but rather presenting a framework based on gaps identified in the literature. It incorporates the combined use of tracking and recording learning experiences with the xAPI, cognitive state analysis through a non-invasive BCI, immersive and personalized VR experiences, and attention analysis using eye tracking.

Finally, this paper is organized as follows: Literature Review, which addresses key concepts and foundations essential for the development of this work, along with related studies; Methodology, which presents the proof of concept of the framework and explains how each technology impacts the system; Experimental Design, detailing the plan for future testing; and finally, Partial Results, Conclusion, and Future Steps.

2 LITERATURE REVIEW

This section aims to define the theoretical concepts and related works that will be discussed throughout this research.

2.1 Challenges of Operator 4.0

The Kirkpatrick Model emerged from the need to evaluate training programs and was proposed by (Kirkpatrick and Craig, 1970) as a means to "assess effectiveness before conducting evaluations." Kirkpatrick's model divides training evaluation into four hierarchical levels:

1. **Level 1:** Measures participants' reactions to the training.
2. **Level 2:** Assesses the knowledge and skills acquired.
3. **Level 3:** Examines behavioral changes after training.
4. **Level 4:** Directly correlated with operational improvements, such as reduced incidents or increased revenue (e.g., productivity gains).

However, how can traditional training methods (e.g., videos, slides, and quizzes) adapt to the rapid emergence of modern technologies? (Scorgie et al., 2024) highlights, in a meta-analysis of Virtual Reality (VR) for safety training, that these traditional methods are cost-intensive and often suboptimal in effectiveness. Nonetheless, immersive technologies have proven effective in military and industrial safety training for high-risk scenarios.

(Thorvald et al., 2021) describes the Operator 4.0 framework, detailing eight scenarios where Industry 4.0 improves the human workforce. Two notable examples are the Augmented Operator (accessing real-time information via overlays) and the Virtual Operator (replaces the physical world with a virtual one, enabling immersive experiences for training and design scenario development).

As human resources remain one of the most valuable and scarce assets in industrial environments, the concept of Operator 5.0 is emerging (Leng et al., 2022), bringing discussion involving operator ergonomics, accessibility, and even monitoring fatigue states through electrophysiological data.

2.2 Virtual Reality

The concept of Virtual Reality (VR) was introduced in the late 1980s by (Lanier and Biocca, 1992), envisioning the integration of the real and imaginary worlds. This technology offers limitless experiences, transcending physical limitations and fostering new forms of interaction.

In industrial and training applications, VR has shown positive results. For example, (Teodoro et al., 2023) utilized VR in energy concessionaire training, employing the Kirkpatrick Model to assess learning efficacy. Similarly, (Grabowski and Jankowski, 2015) used VR to train underground mining personnel in explosive handling, yielding increased confidence and knowledge. Systematic reviews, such as (Scorgie et al., 2024), emphasize the growing use of HMDs in various industries while also highlighting research gaps in mining, chemical, and electrical training contexts.

These examples underscore VR's potential beyond entertainment, establishing it as a cornerstone for advancing industrial tools and methodologies (Paszkiewicz et al., 2021; Pottle, 2019).

2.3 Eye Tracking

Eye tracking in VR hardware estimates gaze direction using cameras or infrared sensors. This technology is useful both for creating more realistic avatars and as a form of input and user movement within a VR environment (Adhanom et al., 2023). In (Jang, 2023), it is demonstrated how eye tracking can be used to define areas of interest in engagement studies, where attention and focus statistics analyze user involvement during an experience in a real clothing store. However, (Clay et al., 2019) discuss the lack of research utilizing eye tracking to analyze user behavior concerning what they observe within VR, as well as to evaluate where they looked in relation to their actions.

2.4 Brain-Computer Interface

With advances in medicine and technology and the need to understand and utilize the complex brain system, the first studies emerged in the 1970s using devices capable of extracting brain signals and sending them to external devices, such as a robotic arm (Kober and Neuper, 2012). According to (Yadav et al., 2020), these signals can be measured directly or indirectly from the brain, with electroencephalography (EEG) being one method of collecting brain activity using electrodes. Additionally, BCIs can be divided into invasive and non-invasive types, where non-invasive methods involve collecting EEG data from the scalp. In contrast, invasive methods use implanted electrodes directly on the cortical surface.

The capture of an EEG signal is based on the voltage difference between the active electrode and the reference electrode, and the signals can be categorized into specific bands according to their biological significance (Rashid et al., 2020). However, interpreting these data is challenging as signals can be contaminated by noise from various sources, such as facial muscle activity and eye movements (Porr and Bohollo, 2022).

Studies demonstrate an increase in spectral density in the Theta (4–8 Hz) and Alpha (8–13 Hz) bands when an individual is fatigued (Douibi et al., 2021) (Cao et al., 2014). The work of (Pooladvand et al., 2024) uses event estimation techniques from brain bands combined with machine learning to identify mental overload in workers, highlighting how time pressure and multitasking can impose negative factors on cognitive resources, affecting reflexes and information processing, which can be critical in high-stakes scenarios.

Additionally, there is a growing trend in studies involving EEG as a tool for simultaneous monitoring across individuals in a group, known as hyperscanning (Gumilar et al., 2021). For example, this method is employed by (Toppi et al., 2016) to evaluate pilot behavior during emergency landing situations. However, the development of software capable of analyzing and interpreting these data and research emphasizing the nuances of brain activity are complex endeavors. This complexity is compounded by the fact that BCI equipment has become popular and accessible to end users as a closed product in recent years (Janapati et al., 2023), restricting its use to a highly specialized audience.

2.5 Evaluation Methods

(Slater et al., 1994) presents in their infuential work that the subjective sense of presence experienced by a group of volunteers in a Virtual Research Environment (VRE) can be measured through a questionnaire comprising six or more questions, using the Likert scale (Jebb et al., 2021). As Slater described, these questions address the feeling of being in the represented virtual environment or even recalling it as a visited place.

In a recent review of their work, (Slater et al., 2022) conclude that it is necessary to combine different methods to validate participants' experiences, utilizing some of the following tools:

1. **Questionnaires:** While helpful, questionnaires have several limitations when used in isolation, as they are generally administered after the experience and may influence the sense of presence by prompting participants to consider feelings they may not have experienced.
2. **Physiological or Behavioral Analysis:** This includes the measurement of brain waves using BCIs or skin resistance in response to stress-inducing situations within the simulation. However, this type of analysis may be problematic if the simulation does not contain scenarios that trigger measurable effects.
3. **Configuration Transitions:** This method exposes participants to variations of the same scenario (such as differences in lighting or virtual body configurations) to validate the perception of presence and the events occurring. Subsequently, participants control these factors randomly, allowing researchers to estimate the likelihood of a specific factor being present in the final configuration for each participant. This method is noteworthy as it does not require participants to provide opinions or ratings but to make decisions about the best configuration for themselves.

3 METHODOLOGY

This section presents the proof of concept of the proposed framework, outlining how each technology will provide the necessary information and function in an integrated manner.

The Kirkpatrick model serves as the foundational basis for training level evaluation in the proof of concept. Virtual Reality (VR) technology enables a degree of immersion and presence (Slater et al., 1994) in training scenarios that are both realistic and free of physical risk to humans while being fully controllable. Human fatigue, though not the only factor, significantly increases risk, particularly in hazardous environments. Fatigue can alter behavior, which in turn impacts productivity and exposure to risks inherent in industrial processes. Therefore, to identify human behavior as proposed in level three of Kirkpatrick's model, we propose a framework that provides a sense of presence and immersion without physical exposure to risks. This framework simultaneously measures an operator's level of physical or mental fatigue through the Chalder Fatigue Questionnaire (Cella and Chalder, 2010). Additionally, the xAPI library is used to infer whether human behavior changes based on training or after prolonged operational use of industrial equipment. The xAPI can record both expected user actions and reactions (e.g., in risky situations) that may vary depending on the individual's fatigue state.

Combining attention measures obtained through the eye-tracking capability of the Meta Quest Pro with variations in Alpha and Theta brainwave bands collected via the Unicorn BCI provides valuable cognitive and physiological data. These data are analyzed alongside self-reported physical and mental fatigue from the questionnaire.

The following sections outline the proposed proof of concept and the technologies employed.

3.1 Proof of Concept

The proof of concept involves the development of a prototype that utilizes learning systems based on user records, integrating BCI and eye-tracking technologies, as illustrated in Figure 1.

According to (Slater et al., 2022), VR scenarios should be designed to stimulate participants sufficiently to record individual user perceptions. This study utilizes technologies such as BCI (to capture changes in brainwave bands) and xAPI (to log user actions and reactions), enabling a more personalized experiment recording process.

The case study depicted in Figure 1 can represent any immersive scenario developed within the Unity game engine proposed by industrial stakeholders. These scenarios may range from simulations of hazardous environments (challenging to replicate in a controlled, real-world setting) to rehabilitation of techniques or processes by operators in specific industrial sectors.

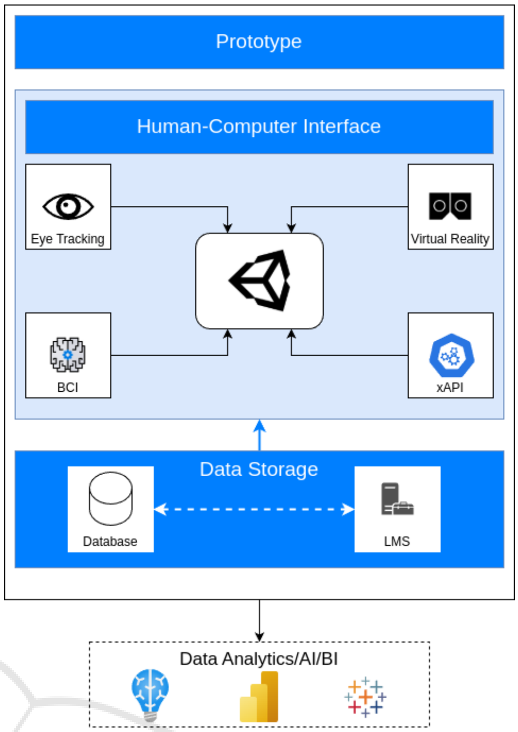

Figure 1: Proposed system for user's data collection in immersive scenarios.

Unity was chosen as the game engine due to its wide array of tools for VR development, active community, and compatibility with various immersive devices available in the market. The VR hardware selected is the Meta Quest Pro, which offers comfort, fidelity, performance, and high-resolution display improvements. Its eye-tracking functionality enables attention data collection through defined targets in VR scenarios, leveraging Meta's native SDK for Unity. The Unicorn Hybrid Black was chosen as the BCI device for its non-invasive design, eight-electrode configuration, multiple language APIs, and Unity integration. This BCI offers a range of customizable software environments and tools while eliminating the need for data transmission cables, using radio signals for improved usability and user mobility.

Participant actions and response times are tracked using the xAPI. Key advantages of xAPI include its ability to capture detailed learning activity data beyond traditional e-learning platforms and its interoperability with different systems and tools through

APIs in multiple languages, including Unity. A secure server architecture for the LRS and database will allow precise and standardized data capture through xAPI. Additionally, an optimized SQL-based database, separate from the LRS, will be implemented to facilitate future analyses of the collected data, which could employ Business Intelligence (BI) techniques, Machine Learning, or other Artificial Intelligence (AI) methods.

3.2 Materials and Methods

3.2.1 Unity

Unity is a comprehensive game development platform offering tools for physics simulation, collision detection, and immersive technologies such as Virtual Reality (VR) and Augmented Reality (AR). It supports a variety of devices (ISAR, 2018). According to (Nguyen and Dang, 2017), Unity is widely chosen for its extensive community, diverse model library, support for popular programming languages (e.g., C#, JavaScript, and Java), and its flexibility as the most recognized game engine for VR development.

(Kuang and Bai, 2018) emphasize the importance of detailed modeling for VR scenario development to ensure optimized scene performance (free of crashes or loss of immersion) alongside immersive features such as audio and interactions.

3.2.2 xAPI

The Experience API (xAPI) is a learning architecture designed to capture user-generated data through interactions with a Learning Management System (LMS) or VR application. The LMS serves as a software platform for educators or trainers to create, organize, deliver, and monitor educational courses and training programs. It provides tools to track student progress and detailed reports on individual performance and effectiveness. These data are stored in a specific database architecture known as a Learning Record Store (LRS), enabling a comprehensive and interoperable view of progress and behavior during training sessions, which can later be processed and analyzed using analytical tools and techniques (Nouira et al., 2018).

One advantage of xAPI lies in its well-defined formalization and semantics, facilitating integration and interoperability between systems (Vidal et al., 2015). Furthermore, the standard has been applied in various emerging technologies, including mobile learning and serious games (Farella et al., 2021).

xAPI has been utilized in both industrial and academic contexts. Studies such as (Schardosim Simao et al., 2018) and (Viol et al., 2024) demonstrate its application in virtual laboratories to log interactions between trainers and student groups.

3.3 Proposed Architecture

In this section, we present each of the technologies used in this research and their respective functionalities.

3.3.1 Technology to Capture Time Response

The capture of behavioral records and response times of participants in immersive scenarios is performed using xAPI technology, employing the TinCan API for the C# language[1]. For permanent storage of this information, the YetAnalytics LRS[2] was selected. This choice was based on its open-source nature and the possibility of hosting the SQL database autonomously, unlike other cloud-based solutions.

The data collected by xAPI in the test scenarios, recorded in the LRS, will be analyzed later to assess whether participants' reaction times vary over time and to evaluate expected behaviors within the prototype. In an immersive training environment, the instructor must be able to assess individual user behaviors, and xAPI facilitates this by modeling custom statements within the environment.

3.3.2 Implementation of Attention Monitoring

The eye-tracking functionality integrated into the Meta Quest Pro VR hardware was utilized to monitor users' attention. This feature estimates user attention during immersive scenario usage by defining targets of interest within the scenarios for data collection reference (within the user's field of vision). These targets serve as a basis for determining which position within the 3D VR simulation the participant is focusing on, leveraging the Eye Gaze API available in the Meta Movement SDK[3].

The API implements individual eye movements captured by the sensors of the Meta Quest Pro. Based on these movements, a raycast (a projected line originating from the eyes) detects collisions with solid objects, in this case, predefined targets in the immersive environment. By identifying these targets, it becomes possible to estimate how long the user focused on key elements necessary for training. This allows

[1] xAPI TinCan C#: https://rusticisoftware.github.io/TinCan.NET/

[2] SQL LRS: https://www.yetanalytics.com/sql-lrs

[3] Movement SDK: https://developer.oculus.com/documentation/unity/move-overview/

the instructor to accurately evaluate, alongside other technologies, whether the user directed their attention where required during training.

3.3.3 Registering EEG Data During Experiment

EEG data collection during immersive scenario usage was conducted using the non-invasive Unicorn Hybrid Black BCI device[4]. This device was selected due to its wide range of available libraries in various programming languages (for both data collection and processing) and its ready-to-use integration library for Unity.

The Unicorn Hybrid Black allows for the recording, visualization, and exportation of EEG data in common formats such as CSV. Additionally, it includes native high-pass and low-pass filters, as well as feedback on the signal quality of each electrode. Among the applications available in the device's software suite is Unicorn Bandpower, which provides users with a real-time view of brain waves at the eight electrode positions on the head. It also continuously estimates the power of Delta (1–4 Hz), Theta (4–8 Hz), Low Beta (12–16 Hz), Mid Beta (16–20 Hz), High Beta (20–30 Hz), and Gamma (30–50 Hz) bands.

For subsequent EEG data analysis, signal processing techniques will be employed using open-source libraries such as BrainFlow[5] and MNE-Python[6]. These libraries provide APIs for various devices, including the Unicorn Hybrid Black, in multiple programming languages (e.g., C++, Python, Rust, and JavaScript).

3.3.4 Recording Personal Experiences after the Experiment

The Chalder Fatigue Questionnaire, adapted for Brazilian Portuguese by (Cho et al., 2007), will be used to document participants' experiences regarding physical and mental fatigue during the immersive scenarios. This questionnaire will provide critical information on participants' perceptions of fatigue, complementing the analysis of the collected brain data. The complete questionnaire is included in the Appendix.

4 EXPERIMENTAL DESIGN

The proposed experimental design involves several well-defined stages, starting with a pre-test phase conducted by the authors to adjust the experiment's duration. A group of voluntary participants will be formed after obtaining approval from the university's Ethics Committee.

Before beginning the experiment, participants will be briefed on the procedures and provided with the Informed Consent Form (ICF) detailing the data to be collected and the experiments to be conducted. An initial familiarization stage will be carried out, particularly for participants with no prior experience with the technology.

Data will be collected using the technologies described in previous sections during the experiment's execution within the developed scenarios. EEG data collected by the BCI will be synchronized with reaction times and response data recorded through xAPI, enabling a correlational analysis between the duration of the experiment, participants' focus, and their reactions. Eye tracking will also supply data on participants' visual behavior. Furthermore, the Chalder Fatigue Questionnaire (CFQ) will be administered to assess participants' personal perceptions of their mental and physical fatigue during the experiment, providing additional insights into the effectiveness of the VR scenarios.

5 RESULTS AND CONCLUSIONS

This work proposes a VR-BCI-based system to evaluate the effects of integrating immersive technologies in industrial operators. It is also a way to fill a significant gap in research on training and immersive environments capable of inducing behavioral changes, as the Kirkpatrick Model recommends.

The theoretical basis of this work involves the challenges of the 4.0 operator in the industry, which requires knowledge and mastery of modern market technologies, such as Virtual Reality, Cybersecurity, and the Internet of Things. These and other disruptive technologies offer the 4.0 operator intelligent tools to improve day-to-day operations and practices.

Thus, this work proposes a framework that integrates VR, BCI, xAPI, and eye-tracking technologies. Figure 2 displays the working version of the proposed system. As displayed, the proposed framework is fully integrated and ready for users' tests. The following stages include the execution of user's experience tests. The experiments are already approved by the institution's ethics committee and are scheduled to begin in further stages of this research.

[4]Unicorn BCI: https://www.unicorn-bi.com/
[5]Brainflow: https://brainflow.org/features/
[6]MNE-Python: https://mne.tools/stable/index.html

Figure 2: Proposed VR-BCI based system working in a virtual scenario of an industrial process.

6 GENERATIVE AI USAGE

The authors state that generative AI was only used for translation and proof-reading. All presented text is originally written by the authors.

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REFERENCES

Adhanom, I. B., MacNeilage, P., and Folmer, E. (2023). Correction to: Eye tracking in virtual reality: a broad review of applications and challenges. *Virtual Reality*, 27(2):1569–1570.

Cao, T., Wan, F., Wong, C., da Cruz, J., and Hu, Y. (2014). Objective evaluation of fatigue by eeg spectral analysis in steady-state visual evoked potential-based brain-computer interfaces. *Biomedical engineering online*, 13:28.

Cella, M. and Chalder, T. (2010). Measuring fatigue in clinical and community settings. *Journal of Psychosomatic Research*, 69(1):17–22.

Cho, H. J., Costa, E., Menezes, P. R., Chalder, T., Bhugra, D., and Wessely, S. (2007). Cross-cultural validation of the chalder fatigue questionnaire in brazilian primary care. *Journal of Psychosomatic Research*, 62(3):301–304.

Clay, V., König, P., and Koenig, S. (2019). Eye tracking in virtual reality. *Journal of Eye Movement Research*, 12.

Douibi, K., Le Bars, S., Lemontey, A., Nag, L., Balp, R., and Breda, G. (2021). Toward eeg-based bci applications for industry 4.0: Challenges and possible applications. *Frontiers in Human Neuroscience*, 15:705064.

Farella, M., Arrigo, M., Chiazzese, G., Tosto, C., Seta, L., and Taibi, D. (2021). Integrating xapi in ar applications for positive behaviour intervention and support. In *2021 International Conference on Advanced Learning Technologies (ICALT)*, pages 406–408. Tartu, Estonia.

Grabowski, A. and Jankowski, J. (2015). Virtual reality-based pilot training for underground coal miners. *Safety Science*, 72:310–314.

Gumilar, I., Sareen, E., Bell, R., Stone, A., Hayati, A., Mao, J., Barde, A., Gupta, A., Dey, A., Lee, G., et al. (2021). A comparative study on inter-brain synchrony in real and virtual environments using hyperscanning. *Computers & Graphics*, 94:62–75.

Guo, Z., Zhou, D., Zhou, Q., Zhang, X., Geng, J., Zeng, S., Lv, C., and Hao, A. (2020). Applications of virtual reality in maintenance during the industrial product lifecycle: A systematic review. *Journal of Manufacturing Systems*, 56:525–538.

ISAR, C. (2018). A Glance into Virtual Reality Development Using Unity. *Informatica Economica*, 22(3):14–22.

Janapati, R., Dalal, V., and Sengupta, R. (2023). Advances in modern eeg-bci signal processing: A review. *Materials Today: Proceedings*, 80:2563–2566.

Jang, J. Y. (2023). Analyzing visual behavior of consumers in a virtual reality fashion store using eye tracking. *Fashion and Textiles*, 10(1):24.

Jebb, A. T., Ng, V., and Tay, L. (2021). A review of key likert scale development advances: 1995–2019. *Frontiers in Psychology*, 12.

Kirkpatrick, D. L. and Craig, R. (1970). Evaluation of training. *Evaluation of short-term training in rehabilitation*, page 35.

Kober, S. E. and Neuper, C. (2012). Using auditory event-related eeg potentials to assess presence in virtual reality. *International Journal of Human-Computer Studies*, 70(9):577–587.

Kuang, Y. and Bai, X. (2018). The research of virtual reality scene modeling based on unity 3d. In *2018 13th International Conference on Computer Science & Education (ICCSE)*, page 611 – 613. Cited by: 15.

Lanier, J. and Biocca, F. (1992). An insider's view of the future of virtual reality. *Journal of Communication*, 42(4):150–172.

Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D., and Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, 65:279–295.

Nguyen, V. T. and Dang, T. (2017). Setting up virtual reality and augmented reality learning environment in unity. In *Adjunct Proceedings of the 2017 IEEE International Symposium on Mixed and Augmented Reality, ISMAR-Adjunct 2017*, pages 315–320. Institute of Electrical and Electronics Engineers Inc.

Nouira, A., Cheniti-Belcadhi, L., and Braham, R. (2018). An enhanced xapi data model supporting assessment analytics. *Procedia Computer Science*, 126:566–575. Knowledge-Based and Intelligent Information And Engineering Systems: Proceedings of the 22nd International Conference, KES-2018, Belgrade, Serbia.

Paszkiewicz, A., Salach, M., Dymora, P., Bolanowski, M., Budzik, G., and Kubiak, P. (2021). Methodology of implementing virtual reality in education for industry 4.0. *Sustainability*, 13(9).

Pedram, S., Perez, P., Palmisano, S., and Farrelly, M. (2017). Evaluating 360-virtual reality for mining industry's safety training. In *HCI International 2017–Posters' Extended Abstracts: 19th International Conference, HCI International 2017, Vancouver, BC, Canada, July 9–14, 2017, Proceedings, Part I 19*, volume 713, pages 555–561. Springer Verlag.

Pooladvand, S., Chang, W.-C., and Hasanzadeh, S. (2024). Identifying at-risk workers using fnirs-based mental load classification: A mixed reality study. *Automation in Construction*, 164:105453.

Porr, B. and Bohollo, L. M. (2022). Bci-walls: A robust methodology to predict success or failure in brain computer interfaces. *arXiv preprint arXiv:2210.16939*.

Pottle, J. (2019). Virtual reality and the transformation of medical education. *Future healthcare journal*, 6(3):181.

Rashid, M., Sulaiman, N., P. P. Abdul Majeed, A., Musa, R. M., Ab. Nasir, A. F., Bari, B. S., and Khatun, S. (2020). Current status, challenges, and possible solutions of eeg-based brain-computer interface: A comprehensive review. *Frontiers in Neurorobotics*, 14.

Schardosim Simao, J. P., Mellos Carlos, L., Saliah-Hassane, H., Da Silva, J. B., and Da Mota Alves, J. B. (2018). Model for recording learning experience data from remote laboratories using xapi. In *Proceedings - 13th Latin American Conference on Learning Technologies, LACLO 2018*, page 450 – 457. Cited by: 7.

Scorgie, D., Feng, Z., Paes, D., Parisi, F., Yiu, T. W., and Lovreglio, R. (2024). Virtual reality for safety training: A systematic literature review and meta-analysis.

Slater, M., Banakou, D., Beacco, A., Gallego, J., Macia-Varela, F., and Oliva, R. (2022). A separate reality: An update on place illusion and plausibility in virtual reality. *Frontiers in Virtual Reality*, 3.

Slater, M., Usoh, M., and Steed, A. (1994). Depth of presence in virtual environments. *Presence: Teleoperators & Virtual Environments*, 3:130–144.

Stefan, H., Mortimer, M., and Horan, B. (2023). Evaluating the effectiveness of virtual reality for safety-relevant training: a systematic review. *Virtual Reality*, 27(4):2839 – 2869. Cited by: 1; All Open Access, Hybrid Gold Open Access.

Teodoro, P. N. B., Cardoso, A., and Ramos, D. C. (2023). Combinação do framework 70-20-10 com kirkpatrick model para construção e avaliação de treinamentos apoiados por realidade virtual. *Revista Científica Universitas*, 10(1):73–87.

Thorvald, P., Fast Berglund, Å., and Romero, D. (2021). The cognitive operator 4.0. In *18th International Conference on Manufacturing Research, ICMR 2021, incorporating the 35th National Conference on Manufacturing Research, 7–10 September 2021, University of Derby, Derby, UK*, volume 15, pages 3–8. IOS Press.

Toppi, J., Borghini, G., Petti, M., He, E. J., De Giusti, V., He, B., Astolfi, L., and Babiloni, F. (2016). Investigating cooperative behavior in ecological settings: an eeg hyperscanning study. *PloS one*, 11(4):e0154236.

Vidal, J. C., Rabelo, T., and Lama, M. (2015). Semantic description of the experience api specification. In *Proceedings - IEEE 15th International Conference on Advanced Learning Technologies: Advanced Technologies for Supporting Open Access to Formal and Informal Learning, ICALT 2015*, page 268 – 269. Cited by: 10.

Villani, V., Gabbi, M., and Sabattini, L. (2022). Promoting operator's wellbeing in industry 5.0: detecting mental and physical fatigue. In *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 2030–2036.

Viol, R. S., Fernandes, P. C., Lacerda, I. I., Melo, K. G. F., Nunes, A. J. D. A., Pimenta, A. S. G. a. M., Carneiro, C. M., Silva, M. C., and Delabrida, S. (2024). Eduvr: Towards an evaluation platform for user interactions in personalized virtual reality learning environments. In *Proceedings of the XXII Brazilian Symposium on Human Factors in Computing Systems*, IHC '23, New York, NY, USA. Association for Computing Machinery.

Werbińska-Wojciechowska, S. and Winiarska, K. (2023). Maintenance performance in the age of industry 4.0: A bibliometric performance analysis and a systematic literature review. Ler os artigos 146, 158, 176, 187, 188, 189, 190.

Yadav, D., Yadav, S., and Veer, K. (2020). A comprehensive assessment of brain computer interfaces: Recent trends and challenges. *Journal of Neuroscience Methods*.