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**Author(s):** Silvennoinen, Minna; Parviainen, Tiina; Malinen, Anita; Karjalainen, Suvi; Manu, Mari; Vesisenaho, Mikko

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# Combining physiological and experiential measures to study the adult learning experience

Minna Silvennoinen <sup>1</sup> \*, Tiina Parviainen <sup>1</sup> \*\*, Anita Malinen \*\*\*, Suvi Karjalainen \*\*\*\*, Mari Manu \*\*\*\*\*, & Mikko Vesisenaho \*\*\*\*\*

\* Dr. (cognitive science), Senior researcher, JAMK University of Applied Sciences, School of Professional Teacher Education, PO Box 207, FI-40101 Jyväskylä, minna.silvennoinen@jamk.fi

\*\* Dr. (psychology), Associate professor, University of Jyväskylä, PO Box 35, FI-40014 University Jyväskylä, Finland, tiina.m.parviainen@jyu.fi

\*\*\* Dr. (adult education), Senior lecturer, University of Jyväskylä, PO Box 35, FI-40014 University Jyväskylä, Finland, anita.malinen@jyu.fi

\*\*\*\* M. Psych., Project researcher, University of Jyväskylä, PO Box 35, FI-40014 University Jyväskylä, Finland, suvi.k.karjalainen@jyu.fi

\*\*\*\*\* M. Ed., M.A., Project researcher, University of Jyväskylä, PO Box 35, FI-40014 University Jyväskylä, Finland, mari.j.manu@jyu.fi

\*\*\*\*\* Dr. (computer science), Adjunct professor, University of Jyväskylä, PO Box 35, FI-40014 University Jyväskylä, Finland, mikko.vesisenaho@jyu.fi

<sup>1</sup> These authors contributed equally to the work.

## Abstract

This chapter introduces methods for using an individual-level multimodal approach for studying the learning experience within the context of vocational education. There has recently been increased interest in recording physiological signals in pedagogical contexts. The current research literature on multimodal studies of adult learning experience is scarce and has been primarily applied and developed in studies of a preliminary nature and with varying combinations of modalities. Learning experience is a complex phenomenon which cannot be fully captured via a single-data modality. However, based on the reviewed literature, there is still a lack of larger datasets and strong empirical evidence to enable a comprehensive understanding of experiential learning as a phenomenon.

In addition to self-reported learning experiences, there is a need for theoretical development and a more holistic empirical approach that includes physiological and neurophysiological aspects involved in learning situation. We present a case example of simulation-based learning (SBL) of forestry skills, in which the modalities applied to explore the learning experience were video recordings, stimulated recall interviews, questionnaires, electrocardiography (ECG), and electroencephalography (EEG). Our example presents how multimodal research design can be used to study learning experience, by combining measurements of the human nervous system with subjective and observational data. It is too early to evaluate the practical impact of multimodal research for the field of adult education. Successful application of multimodal methods requires interaction across disciplines, harmonizing of conceptual frameworks and goals, as well as bringing together complementary, discipline-specific expertise to guarantee valid application of research methods. Opening of the disciplinary boundaries both at theoretical and methodological domains enables to increase discussion between researchers from different disciplines.

Keywords: multimodal measurements, adult learning, experiential learning, combined methods, research design, physiological measurement, heart rate variability, electroencephalography, EEG, learning experience, vocational education

## 1. Introduction

Traditionally, adult learning is considered to be a primarily cognitive process that can be studied with various quantitative or qualitative methods. However, research emphasis has recently shifted to a more holistic approach, whereby an individual is perceived as a whole, consisting of both mind and body (Papastamatis & Panitsides, 2014). Within this perspective, the cognitive, emotional, and also physical (the so-called embodied aspects) need to be considered in learning and reflection, with consequences for the research of learning experience. Closer integration of different methodological approaches capturing the cognitive, emotional, and embodied reflections of behavior has the potential to critically increase our understanding of the adult learning experience and learning interaction. Learning has been approached from different theoretical and scientific traditions that, to a large extent, have been developed independently from one another, for example, in the fields of education and psychology. Within these different scientific disciplines, there are also divergent methodological approaches to studying learning, which can be roughly categorized according to three different perspectives. Methods focusing on the self-reported experience of the learner, such as reflective assignments, questionnaires, or interviews, can capture the subjective first-person dimension of the experience (see experiential measures, e.g., Lumma & Weger, 2021). Additionally, learning is often studied by collecting quantified variables (e.g., reaction times or number of errors) or qualitative descriptions and interpretations of performance or experience by an external observer. These data offer a second-person perspective on experience. Finally, neuroscience adds a new, third dimension in the

exploration of the learning experience, as the recordings of the nervous system activity (i.e., quantitative third-person measurements that accompany the learning situation) form the biological basis of the various aspects within the learning experience (e.g., emotions, the level of effort or motivational state, and acquisition of new skills through experience; Ansari et al., 2011).

It is important to note that although we can collect these different data types, we have no straightforward way to directly map these different measurements with each other, and they need to be (and often are) treated as separate data approachable within distinct scientific paradigms (for a discussion of the case of neurophenomenology, see Varela & Shear, 1999). Therefore, neurophysiological measurements do not directly provide information about the experience itself but are rather correlates (i.e., external recordings of the underlying neural-level events) that give rise to the observed and experienced learning. These variables can, however, offer additional and complementary information to reach a more holistic understanding of learning and the learning experience.

Modern research technology allows for detailed monitoring of behavior outside laboratories in natural learning environments. Novel and fairly low-cost tools to record physiological and even neurophysiological signals in more natural settings have significantly increased the interest in recording these signals in pedagogical contexts (see van Atteveldt et al., 2018). In order to provide real added value, physiological measurements need to be sensibly linked to other indicators of the learning experience. However, this kind of research is challenged by a lack of methodological development in study design, data collection, and data analysis. Methodological approaches have not been developed to the same extent as the technological possibilities. To progress our understanding of the learning experience, research strategies need to combine laboratory and naturalistic research efforts (see Wilhelm & Grossman, 2010; Wilhelm et al., 2012). The combinations of quantitative and qualitative research designs, as well as different measurement technologies to explore learning and learning experiences (especially in natural contexts), are still fairly rare.

In this chapter, we introduce some new directions for using multimodal methods to study the adult learning experience in a natural context. We use a case example from a vocational education context of simulation-based learning (SBL) of forestry skills.

Before further discussing the different methodological ways to approach learning and specifically the learning experience, we must first define some key concepts used in this

chapter. First, by the **learning experience**, we refer to a specific combination of elements that together constitute the experience of learning. Learning experience, therefore, forms in the short and long term as an outcome of processes that govern physiological, cognitive-psychological, and social elements that co-occur in learning situations. These elements are discernible by verbal or non-verbal expressions and recordable biophysical signals, for example, visible facial expressions and gestures as well as neurophysiological and autonomic nervous system (ANS) recordings.

Second, various terminology is used to refer to research approaches and designs that combine methodologies from different disciplines. The multi-method approach in education sciences, similar to mixed methods more generally (see Johnson & Onwuegbuzie, 2004; Patton, 2002), typically refers to combining qualitative and quantitative methods (Hammond, 2005) or applying two or more sources of data to investigate the same phenomenon (Brever & Hunter, 1989). The mixing/combining of approaches can take place at different stages of analysis, and in most studies, the qualitative and quantitative data are analyzed separately and combined only at the interpretation stage. In some studies, combining physiological and self-reported data (see, e.g., Eteläpelto et al., 2018; Harley et al., 2015) is referred to as multicomponential research. We have chosen to use the term **multimodal** research to reflect the application of a combination of modalities, namely experiential data (first person), observations or interpretations of behavior (second person), and physiological data (third person), in data collection and analysis. This concept has been used when more than one data collection method was needed to measure learning-related experiences or emotions (see Giannakos et al., 2019; Harley et al., 2015). In our case example—SBL of forestry skills—the modalities applied were video recordings, stimulated recall interviews, questionnaires, electrocardiography (ECG), and electroencephalography (EEG).

In the first part of this chapter, we review current literature on multimodal studies of learning experience, including those in the SBL context. Then, we present our SBL research case, within which we combined a variety of methods and disciplinary expertise to study learning experience. The chapter ends with a discussion and suggestions for future directions concerning theoretical and methodological developments in researching the adult learning experience.

## 2. Adult learning research: From traditional to multimodal combinations of methods in researching learning experience

In the following section, we briefly summarize the traditional technique of combining methods for researching the adult learning experience and, subsequently, review the less familiar multimodal techniques for combining methods from these traditional disciplines with various other scientific fields, such as neuroscience.

### 2.1 Combining methods to explore learning experience

There has been growing interest in combining research approaches and methods in education, especially since the beginning of the previous decade (Gorard & Taylor, 2004). In education sciences, combining qualitative and quantitative approaches has a relatively short history compared to mono-method approaches. Appropriate combination and complementary utilization of methods provide increased value for both scientific and societal impact, resulting in stronger research arguments about the complex phenomenon in question (Gorard, 2002; Gorard & Taylor, 2004). Most of the studies researching the learning experience have relied on traditional qualitative approaches from education and social sciences (e.g., Daley et al., 2018; Gorard & Taylor, 2004), such as interviews and reflective writing. Of the quantitative research methods, questionnaires have mainly been used.

Thus far, few studies of the learning experience conducted in the educational context have complemented traditional educational research methods with recordings of body and brain signals. Brain information processing naturally provides the basis for learning, but this is primarily only possible in a laboratory context. The embodied learning view introduces concepts that are both attainable for more naturalistic, multimodal empirical research and also relevant for adult education scientists (Dirkx, 2008; Jordi, 2010). Embodied learning arises from the larger embodied cognition framework, which emphasizes the role of the entire organism (i.e., human body) and its immediate interaction with the environment, which can be used for studying cognitive functions (e.g., learning, experience, and emotions). From this point of view, learning as an experience is not only a rational analytical process but essentially involves the body as a producer of information related to learning and a tool for reflection (Dirkx, 2008; Fenwick, 2006; Jordi, 2010). Emotions are a good example of experiences (i.e., phenomena of the mind) that are intimately associated with physiological reactions (i.e.,

phenomena of the body; see Damasio, 1999; Hannaford, 1995). For example, memory formation is dependent on sensory (and motor) functions that ultimately bridge our brain with the contextual richness of experiential learning situations. Morris (2020) emphasized the importance of embodiment in the experiential learning process.

What kind of methodology is needed to understand the holistic nature of adult experiential learning? Daley et al. (2018) stated that “complex research questions are addressed by teams of researchers who understand and apply team science using quantitative, qualitative, and mixed methods” (p. 164). It is intuitively clear that adult learning poses complex research questions that cannot be comprehensively understood only by a single discipline. The challenge in designing this research is that it requires combining methodology with theories and concepts from different disciplines, such as education sciences, psychology, and cognitive neuroscience.

## 2.2 Multimodal research of the adult learning experience

We reviewed studies published between 2005 and 2021 that combined multimodal measurement techniques for studying adult learning-related experiences. We found 16 empirical research articles with varying modalities and learning contexts. The common ground for all studies was an interest in the learner experience and understanding this experience, in part by utilizing physiological recordings. In addition, we included a few papers that reported multimodal empirical studies without physiological recordings as well as a few that were more oriented toward methodology and technology. In addition, some purely theoretical papers on multimodal characterization of the learning experience are included in the literature review. We provide a brief overview of the literature found with the goal of introducing the current state of the topic rather than providing a deep analysis of the quality or validity of the findings.

### 2.2.1 Multimodal studies on learning experience and emotions

A holistic approach to learning (involving the whole body) must understand the role of emotions and affect as a natural and important part of the (reflective) learning experience (Dirkx, 2008; Jarvis, 2006). Researchers have shown increased interest in the contribution of emotions to learning (e.g., Calvo & D’Mello, 2011; Pekrun & Schutz, 2007; Picard et al., 2004). Indeed, the use of traditional self-reports are considered somewhat limited and

unreliable in their scope, and therefore, various additional signals (face, voice, body, and learning environment) as well as a combination of quantitative and qualitative methods have been suggested for more comprehensive exploration of emotions related to learning (see Bahreini et al., 2016; Zembylas, 2007). Emotional reactions are the most likely source of variation in the physiological responses of the learner; for example, HRV and electrodermal activity (EDA; sometimes referred as skin conductance response/level) are physiological changes essentially correlated with emotions.

Researchers working with e-learning environments and learning applications have found that computerized learning environments (adaptive learning systems with sensors) could be improved by using affective or emotion-related information (e.g., Calvo & D'Mello, 2011; Fortenbacher & Yun, 2020). Multimodal physiological measurement settings have been developed for exploring the learning experience with the aim of customizing learning materials and improving the performance of e-learning environments based on students' emotional states (for a single-subject pilot, see Shen et al., 2009 for 1 subject pilot) or supporting learning applications with real-time biofeedback systems through wearable physiological sensors (see Schaaff et al., 2012). Furthermore, Hardy et al. (2013) tested the potential of EDA for providing additional insight into learners' affective and cognitive states in the context of learning programming skills.

It is, however, important to remember that an individual's own description is still the only way to capture an emotional experience, and the connection between experiential and physiological variables is still unclear. Eteläpelto et al. (2018) conducted a preliminary study aimed at understanding how self-reported and ANS indicators of emotions are related to each other in the context of professional learning. Hemingway et al. (2019) associated modulations of EDA during equine-assisted intervention with the significance of learning episodes (based on experiential interview data), but the data were only analyzed qualitatively. It is not always apparent that experiential measures of learners' emotional states co-vary with ANS-based assessments. Harley et al. (2015) showed that during complex learning situations, automatic facial recognition of emotions and self-report data were in agreement, but EDA was not correlated with these measures. Besides ANS recordings, one multimodal approach used cortisol measurements to explore students' emotions and coping in exam situations (Spangler et al., 2002).



It is known that specific affective states and emotions are related to learning experience (Pekrun & Schutz, 2007; Staus & Falk, 2017; Woolf et al., 2009). However, few studies on learners' emotional experiences have used multimodal recordings in real time or in informal learning contexts outside the classroom (see LeBlanc, 2019; Staus & Falk 2017). Most of the aforementioned empirical studies were preliminary in nature, focusing on learners' emotional reactions and associated physiological reactions. Earlier studies also indicated a need for larger-scale research to multimodally explore the relationship between physiological measures and subjective, emotional experiences (Hardy et al., 2013; LeBlanc, 2019; Shen et al., 2009).

### 2.2.2 Multimodal studies on learning experience and cognitive processes

Combined behavioral and body physiology measures have been used to explore metacognitive monitoring in the context of learning and cognitive behaviors, for example, in multimedia learning situations (Antonietti et al., 2015; Mudrick et al., 2019). Antonietti et al. (2015) recorded multimodal data within memory and problem-solving tasks with the aim of predicting correct responses according to the level of task-related cognitive effort as indicated by eye movement and EDA data. This study was not directly aimed at exploring learning experience but rather students' strategies during learning. The eye movement data were suggested to be useful in revealing participants' metacognitive monitoring (Antonietti et al., 2015). Similarly, Mudrick et al.'s (2019) study aimed at addressing how to identify behavior during meta-comprehension processes.

In a multimodal study on cognitive load during learning, Larmuseau et al. (2019) investigated the link between students' EDA and task-related self-reported cognitive load. They correlated physiological signals (EDA and skin temperature) recorded during a problem-solving task. Their preliminary results indicated no connection between the physiological data and task complexity, but a connection was found between EDA and mental effort during highly complex tasks. They thus suggested using EDA in combination with specific learning events for online determination of task-related cognitive load. Giannakos et al. (2019) explored the applicability of physiological recordings (via eye tracking, EEG, and video recordings) for understanding and supporting the learning experience when designing new learning technologies. Wang and Cesar (2015) explored the potential of physiological indicators (via GSR, video recording, and questionnaires) to provide feedback to teachers who teach in e-learning or distributed learning environments. Methodological combinations utilizing

physiological data in relation to self-regulation and monitoring behavior have shown promise for developing tools for immediate learning research and support in collaborative settings (e.g., Dindar et al., 2019; Haataja et al., 2018).

To sum up, the authors of the aforementioned studies found it useful to combine multiple data modalities (e.g., facial expression, eye movement, learner experiences, and EDA) to better understand learning behavior, providing the potential to shape future learning technologies to support both individual and collaborative learning processes. As with the studies on emotional experiences, these studies were exploratory in nature, and further studies with larger sample sizes and hypothesis-driven designs are needed to strengthen the validity of these findings.

### 2.2.3 The role of multimodality in studying SBL experience

SBL is a widely used and rather well-researched experiential learning method in healthcare (Husebø et al., 2015; Poore et al., 2014; Rogers et al., 2019) as well as other safety-critical contexts or contexts requiring repetitive training. SBL provides an ideal environment to perform multimodal studies of learning experience, but empirical studies of this kind are still scarce. There has been recent interest in using physiological recordings to study stress associated with SBL in different contexts (see LeBlanc, 2019). For example, experienced stress and HR were measured to determine the level of workload during SBL and specifically its relation with self-perceived learning (Girzadas et al., 2009). Additionally, experienced stress and HR were measured to compare the level of stress in real patient encounters vs. SBL situations (Judd et al., 2016). Furthermore, Kocialkowski et al. (2020) used an HR-based evaluation of stress response in their study to clarify the effectiveness of static vs. dynamic observational learning scenarios in medical students. Bhoja et al. (2020) reviewed and piloted the potential of using EDA and HRV measuring devices and video recordings during SBL situations to evaluate the level of stress and alertness for optimal learning in SBL. Despite the lack of physiological measures, Rogers et al. (2019) emphasized the importance of exploring emotional experiences and their relationship to learning within SBL scenarios (see also LeBlanc, 2019).

There have been some initiatives to utilize combined physiological and experiential data outside the stress domain, for example, in the context of technology-enhanced learning and so-called serious game development. By combining data from physiological recordings (EEG

and ECG) with self-reported data (questionnaires), Cowley et al. (2013) showed that HRV predicts learning effects in the serious game context. Simulated learning environments applying virtual reality (VR) or mixed reality technology have been shown to create powerful experiences (Vesisenaho et al., 2019), even though they are rarely designed for the process of experiential learning (Fromm et al., 2021; Birt et al., 2018). In their multimodal research, Aguayo et al. (2018) discussed the use of self-reported and biometric feedback data to design meaningful learning experiences in VR. While not directly related to learning experience, VR environments have been studied using multimodal methods to improve technologies and provide more immersive experiences (e.g., Marin-Morales, 2018; Stepanova et al., 2019). Thus, a more comprehensive understanding of learning experience via multimodal data could aid in creating SBL to better prepare learners for future professional practice. The presence of stress in particular should be acknowledged by instructors implementing SBL. Additionally, the physiological reactions in the SBL environment could provide an ideal basis for developing more reflective approaches to learning and for preparing for future performance in terms of stress/emotion regulation.

To conclude, the literature reviewed shows that recent developments in sensor technology and analysis algorithms have enabled the recording of learners' physiological signals along with their varying emotional and cognitive states. The suitable paradigms and reliable measures in these different modalities still need to be established to determine the real benefit of this type of research. The current evidence is still very narrow, with varying and often modest sample sizes. The analysis of the physiological data is often limited, and various methods are used to collect data on learning situations. Previously published studies have varied in both theme and impact, ranging from high-level journals to non-peer-reviewed conference papers.

Regarding the scientific fields of the previously reviewed literature, it is noteworthy that the research has been carried out mainly by representatives of disciplines other than education science or neuroscience. Information and communication technology, psychology, and combined disciplines—such as educational technology or human–computer interaction with SBL-related studies in the fields of medical or health care education—are the most represented. Our research team combined educational sciences, psychology, neuroscience, signal processing, and cognitive science to produce a comprehensive perspective for the empirical understanding of experiential learning.

## 2.3 Building a theoretical framework for the multimodal study of learning

While studies have indicated the power of experience in learning (e.g., Illeris, 2018; Jarvis, 2005, p. 1), the complex and diverse processes of human learning are not well enough understood to produce a single comprehensive theory (Illeris, 2018; Jarvis, 2006; Malinen, 2000; Yang, 2006). In this chapter, we approach learning as a complex and multifaceted phenomenon aligning with the fundamental questions asked by Illeris (2018): How does learning take place in the human brain and body? What are the supposed mechanisms of experiential learning? Additionally, we explore the question asked by Jarvis (2006, p. 198): Is it possible to have a comprehensive theory of learning? Recent research has provided refreshing and valuable empirical approaches and new theoretical considerations to answer these questions. Experiential learning theory currently provides the most holistic conceptualization of (adult) learning.

Theory building attempts concerning adult experiential learning need to be examined more thoroughly. Few authors have combined the concepts of neuroscience with experiential learning or experiential education. Kolb and Kolb (2017) examined the contributions of neuroscience research to our understanding of experiential learning. They combined learning cycles and the brain, especially memory functions, within the experiential learning processes. Theoretically, they integrated the constructivist and embodied cognition perspectives into one balanced learning process (Kolb & Kolb, 2017, pp. 78–79). They argued, however, that “the promise of an evidence-based practice of neuroscience education currently offers more provocative possibilities than proven practices” (Kolb & Kolb, 2017, p. 56).

Schenck and Cruickshank (2015) re-conceptualized experiential learning theory by building on cognitive neuroscience knowledge. They developed a biologically driven model of teaching—co-constructed developmental teaching theory—and argued for neurobiology as the foundation for experiential learning. With a focus on the neurobiological basis of learning, they emphasized the need for empirical testing: “We need to better inform ourselves about the mind-brain processes that affect experiential learning” (Schenck & Cruickshank, 2015, p. 90).

Hagen and Park (2016) aimed to bridge the gap between adult learning theory and more recent scientific human resource development research and cognitive neuroscience. They argued that the four core assumptions of andragogy have connection to the neural networks

related to memory and cognition. They suggested a framework on how neuroscience knowledge can be used to understand prior experience in a learning process, problem-based learning, and experiential learning approaches, and they created a model of an adaptive cognitive neuroscience adult learning structure based on four andragogy assumptions: (1) self-directed learning, (2) experience-based learning, (3) adults' readiness for learning, and (4) application-focused learning (see also Lim et al., 2019). They also indicated that instructional techniques guided by andragogy can improve long-term memory and retention. They also suggested exploring the relationship of emotion and adult learning with neuroscientific methods.

To sum up, the current discussion around experiential learning theory clearly warrants efforts to develop a more holistic framework that can guide further experimental work at the intersection between educational sciences and cognitive neuroscience, especially regarding human physiology and neurophysiology. This development also needs to be informed by empirical evidence and research conducted more holistically on the process of learning, interfacing with research findings on the physiological and neurobiological basis of learning (Silvennoinen et al., 2020). In the next section, we introduce a case example of a multimodal study conducted in a vocational education context, SBL of forestry skills, that approached the learning experience in a holistic manner.

### 3. Case: Multimodal study of the forestry SBL experience

Our literature review indicated the need for integration of the research methodologies and frameworks of different disciplines to understand learning experience. Our case example from a vocational education context introduces an interdisciplinary research project utilizing expertise and methods of educational sciences, psychology, neuroscience, signal processing, and cognitive science. In order to understand determinants and elements of learning experience in different contexts, we acquired reports of subjective learning experience and teacher observations as well as physiological and neurophysiological signals associated with ongoing learning experience. This study therefore provides an example of multimodal research methods and the experiential learning environment that can be used to answer broad questions in the field of the adult learning experience. Next, we introduce the case, the applied methodology, data collection techniques, and some relevant points for conducting analyses of multimodal learning experience data.

### 3.1 Context and participants

The study participants were recruited from a vocational school at which students become qualified for forest-based energy production. Participants in this case were student–instructor dyads with six students and two instructors total. By the time of data collection in 2020, the students had already gained experience in the use of forestry simulators. SBL is an essential part of vocational studies, particularly when students begin to familiarize themselves with different forest machines. Pedagogically, SBL offers excellent possibilities in vocational education studies embodying strong elements of experiential learning (see, e.g., Clapper, 2014; Rogers et al., 2019). Each learning situation imitates an authentic environment, and learning tasks can vary according to the instructions (performed either by the simulator or instructor/teacher). Compared to traditional learning, such as lectures, simulations can create powerful experiences for learners due to their authentic connection to the emotions (Fromm et al., 2021) and reflections they stimulate and which are also debriefed (Bearman et al., 2019; Husebø et al., 2015; Lateef, 2010). From a research viewpoint, computer-based simulations offer optimally controlled situations to collect different kinds of data during the ongoing learning experience. Simulations combined with VR technology allow for data collection in a setting that is as close to natural and authentic as possible while still maintaining some control over the research design, providing maximal practical impact. However, learning in natural contexts is influenced by various uncontrolled variables, which poses a challenge for data collection and analysis.

### 3.2 Research data collection

We used video recordings, instructor observations (written notes), participating students' stimulated recall interviews and written notes, and interviews with teachers. For the autonomic and central nervous system reactions and ongoing signaling in the learning experience, we also recorded respiration using a respiratory belt HR and, HRV using ECG and ongoing brain activity using EEG.

#### 3.2.1 Protocol

EEG, ECG, video recordings, and interviews were conducted simultaneously. The measurement period lasted on average three hours for each dyad, including preparations. The student performed the task with a VR headset, which provided a close to realistic impression

of being positioned in the cab of a forestry machine with a three-dimensional view of the control system and a virtual forest. The instructor sat beside the student and followed their performance (Figure 1). After all tasks were completed, the instructor used screen-recorded videos recorded during the task performance to give feedback to the student. Two video cameras recorded the student's performance on the simulator screen as well as the interaction between the student and the instructor. Discussions between the student and instructor were audio recorded.



Figure 1. Illustration of the research situation while testing the equipment. The student sat on the right (operating the simulator) and the instructor on the left, and both wore the EEG caps.

The SBL consisted of three phases: an introduction to the training task, the action (performing the training task within the simulator), and a debriefing discussion. During the introduction phase, the student and the instructor went through the structure and general instructions for the four forthcoming tasks. During the action phase, the student and the instructor watched the simulator's model video (one for each separate task) to gain an understanding of the optimal task performance, after which the student performed the task. The task difficulty progressively increased, and the students had little to no experience with

the actions in the final task. Along with the tasks, the instructor kept notes on the student's performance, which were later included in the data analysis as supplementary information on the SBL process and student performance. After each task, the student and the instructor briefly reviewed the task and the numerical performance levels offered by the simulator. After the four tasks, an in-depth debriefing discussion supported by the screen-recorded videos was done to gain a joint understanding of the overall SBL situation. Each student participated in a videorecorded stimulated recall interview (see details in Section 3.2.2) either on the same day or the following day after the SBL situation.

### 3.2.2 Data collection methods

We used **video recordings** to gather detailed information on the timeline and events during the simulation and to enable further investigation of different modalities of data related to specific events. In addition, we used the videos to analyze SBL situations (e.g., behavioral analysis of student–instructor interaction) and in the stimulated recall interviews, where the video material was examined and annotated by each student. Video recording is a frequently used method in learning science research and are particularly beneficial for data collection in complex learning environments (Derry et al., 2010), such as simulations involving rapidly changing situations and interactions between both technology and humans as well as learners and instructors. Video recording offers a method of collecting, sharing, studying, presenting, and archiving learning-related cases to support teaching, learning, and intensive study of those practices. Generally, video recordings can (1) provide detailed data of the timeline of events during learning, enabling combinations (annotations) of various other datasets or events; 2) enable behavioral analyses of occurrences during interaction and learning situations; and 3) aid the reflection process when applied as a stimulating material for interviews (self-reported data of the learning experience).

Each student was **interviewed** individually after the SBL situation on the same or following day via a stimulated recall method. First, the student and the interviewer discussed the training tasks performed in the SBL situation. Second, the student and the interviewer watched screenshot recordings of the training tasks, and the student annotated episodes that they felt were meaningful. Students also wrote down notes relating to the episodes. The instructors were interviewed individually in order to discuss their conceptions and opinions about the SBL situation along with their pedagogical thinking concerning SBL in general. We also used standardized **questionnaires** for the students to acquire information about their



temperament characteristics (adult temperament questionnaire, 77-item short form; Evans & Rothbart, 2007) and motivation (self-regulation questionnaire – learner; Black & Deci, 2000; Salmi et al., 2020) as well as non-standardized inquiries about the simulation training experience.

Interviews are a key source of experiential information on learning situations and often the most useful method for understanding experiences, opinions, values, etc. (Rowley, 2012). As another option, questionnaires may allow for faster collection of more precise or specific information, but they are always more formally structured and have limited space for participants to express information. These two data gathering methods can, however, complement each other. In **stimulated recall**, a video (or audio) recording is played to the participant to stimulate recollection of learning situation-related events in order to capture more accurate data explicated by the learner (Calderhead, 1981; Kagan et al., 1963). The stimulated recall method is a kind of think aloud technique, which has value especially in exploring cognitive strategies and learning processes (Lyle, 2003).

In recent years, the integrated efforts of neuroscience and educational sciences (i.e education neuroscience) have started to explore the brain basis of learning in increasingly natural settings (e.g., Ahonen et al., 2018; Dikker et al., 2017, van Atteveldt et al., 2018). In laboratory environments, the brain basis of learning and learning experience can be studied by several different types of brain research methods, such as brain structure via magnetic resonance imaging or electric signaling within networks of neurons via magnetoencephalography or EEG. In order to measure brain signaling during authentic learning experiences and interactions, the measurement equipment needs to be brought into natural learning environments. EEG is the most well-suited for this purpose, but it is only in the past 10 years that technological advances have enabled the measurement of reasonably good EEG signals from the brain during natural situations. In the forestry SBL case, we studied the ANS activity by recording **HR, HRV, and respiration**. Two HR measurement techniques were applied. First, continuous HRV measurement using a detection device (Firstbeat Technologies Ltd, Jyväskylä, Finland) was conducted for three to five days, including the day of the SBL. This measurement provided extensive information about the participants' baseline HRV over a long period of time (Firstbeat Technologies Ltd, 2014). Second, HR was recorded by ECG with the Bittium NeurOne system (Bittium Biosignals Ltd, Kuopio, Finland) during the SBL

situation. A flexible respiratory belt (Spes Medica, Genova, Italy) recorded the frequency and phases of respiration.

HRV is the temporal variation between successive heart beats reflecting the involvement of the parasympathetic division of the ANS and can thus be used to evaluate intra-subject levels of arousal, stress, and recovery. EDA provides a direct measure of the activity of sympathetic division. Despite their apparent simplicity, the use of ANS measures requires good understanding of both the physiological basis and the computations used for extracting reliable measures of ANS activity. Respiration is closely linked with and mainly controlled by ANS. However, unlike heartbeat, breathing can also be controlled voluntarily. Furthermore, the phase of respiration (i.e., inspiration vs. expiration) influences the timing of cardiac signals. This synchrony between respiration and HRV is defined as respiratory sinus arrhythmia (Shaffer & Ginsberg, 2017). Respiratory variables can be measured using an accelerometer or a respiratory belt. **Brain signals** were simultaneously recorded for the student-instructor dyad (Bittium Biosignals Ltd, Kuopio, Finland) using a 64-channel standard EEG cap (EASYCAP, BrainProducts GmbH, Gilching, Germany) for instructors and a 13-channel EEG cap (Neoprene Headcap with NG Geltrode electrodes and press stud cables, Neuroelectronics, Barcelona, Spain) adapted for the VR headset for the students. Prior to the SBL session, EEG caps, along with the ECG electrodes and respiratory belt, were individually fitted and prepared for the measurement and monitoring of autonomic and central nervous system activity. Synchronizing the EEG, ECG, and respiratory signals together and with the experiential measures was crucial for later integration of different data types, and thus a timestamp annotation was added to both EEG and video recordings. Also, other relevant annotations were added, such as when the SBL tasks began and when the feedback stage occurred.

EEG is a non-invasive method for recording electrical activity of the brain with high temporal and adequate spatial resolution. It is based on monitoring the voltage differences between the electrodes placed on the surface of the scalp. Although typically used in laboratories, it is possible to conduct EEG measurements in naturalistic settings. The most robust element in EEG recording is the rhythmic activation occurring at a frequency of ~10 Hz (i.e., one cycle about 10 times/second), called alpha oscillation or alpha rhythm. Since alpha rhythm has been associated with arousal, attention allocation, and task engagement, it is a reasonable measure of brain activation for the study of learning experience. However, there are

numerous other measures that can be calculated from the EEG signal that may be useful for studying the learning experience.

### 3.3 Data analysis

The combination of methods described above, including interviews, questionnaires, learners' and instructors' notes, and physiological and neurophysiological measures, enabled us to explore the manifold nature of experiential learning. A multimodal study, however, requires tackling methodological challenges separately for each modality first and then integrating the data of the different modalities.

#### 3.3.1 Analysis of interview data

We had two aims for the qualitative analysis of the interview data. First, we wanted to explore participants' experience of SBL through data-driven analysis, and second, we wanted to construct the course of the events as a temporal continuum.

The student interviews were first transcribed and placed into a table format as a linear continuum of events. It was important to maintain the order of the SBL event description from the perspective of the participants. The interview questions followed the SBL structure. Qualitative data, such as interview transcripts, are textual, non-numerical, and thus unstructured. Coding is probably one of the most sensible ways to organize and make sense of interview data. Coding allows researchers to communicate and connect with the data to facilitate the comprehension of the emerging phenomenon and to generate theory grounded in the data (Basil, 2003). Codes can be certain types of experiences, feelings, or emotions or more content-structured, such as task-related events. In our research process, the interview texts were first carefully scrutinized by one researcher to gather all expressed utterances into a table format. Each utterance was then supplemented with a short clarification and the phase of the SBL situation, for example: "The student describes success in a task. / Action, Task 1." Then, these entities were given a code that described them in terms of content. Two researchers independently generated the codes for the content and then jointly discussed each code to reach common agreement. Researcher triangulation is a recommended way to increase the credibility of data interpretations. Another way to increase credibility of the analysis is to consult professional experts in the vocational field. In this case, a forestry teacher could be consulted in cases where the interviewees used professional vocabulary and

terms that were unfamiliar to the researchers. Thematic entities that emerged as a result of the coding process described the main elements of the SBL experience.

### 3.3.2 Preparing interview data for multimodal integration

For the purpose of multimodal integration of the research data, it is necessary to maintain the temporal dimension of the learning experience. We started by creating a timeline of the interview data (transcribed text) and continued with generating data-driven codes for participants' expressed utterances through researcher triangulation.

At this stage of the analysis, we used video data and participants' written notes to construct the timeline of the events. Some of the selected thematic entities, such as successes or failures elaborated by the interviewee, were placed in a temporal time continuum based on the video data and the time-stamped written notes. Thus, the temporal structure of the SBL experience was constructed for these thematic entities, such as task variation, successes, failures, and aspects of student–instructor interactions. The video recordings enabled us to review the authentic situation. Video data were utilized to check the accuracy of the timeline in relation to SBL events, such as guidance or interaction situations.

### 3.3.3 Analysis of physiological and neurophysiological data

EEG data analysis consists of two main stages: preprocessing and the extraction of the signal of interest. Natural research environments cause specific challenges and potential caveats for both of these stages. First, the quality of the recordings in natural learning environments is usually poorer than in laboratory settings (van Atteveldt et al., 2018) since the recordings are conducted without any shielding against electromagnetic interference. Natural movements and interactions between the student and the instructor can also weaken the quality. Besides clearly recognizable artifact types, such as movement or eye blinks, there are many other sources of artifacts in the EEG recordings that can be easily mixed with those caused by neural activity. Therefore, advanced methods and experience in EEG data processing are needed to gain reliable results. Recent state-of-the-art analysis methods allow for precise pre-processing of the data to reduce these artifacts.

Second, no detectable features in the signals can be directly associated with a particular experience, let alone learning. However, some well-studied characteristics can be extracted from the physiological measurements, and to some extent also from neurophysiological

recordings (see above), which are linked to particular states, such as arousal, vigilance, and stress (Berntson et al., 1997; Quintana et al., 2012).

Third, one of the core problems in analyzing and interpreting the neurophysiological data in complex learning situations is the continuous nature of the task, unlike in controlled experimental designs, where specifically defined stimuli or tasks are used. This requires careful design of the data analysis stage.

In our case example, we focused on extracting reliable, artifact-free electrophysiological signatures that reflect both the state and reactivity of the central nervous system and ANS during different phases of the SBL situation. The EEG data were first visually inspected, and electrodes with poor signal quality were excluded. Physiological artifacts such as ocular and cardiac activity were removed using independent component analysis. After filtering and re-referencing, alpha activity was extracted via fast Fourier transform, which converts the data from the time domain to the frequency domain. Heart rate-related data were preprocessed and analyzed using Kubios HRV software (Biosignal Analysis and Medical Imaging Group, University of Eastern Finland, Kuopio, Finland), which provides standard and validated protocols for calculating measures of HR and HRV (Tarvainen et al., 2014). Both time-domain (e.g., mean, minimum, and maximum HR; mean and standard deviation of the time interval between successive heart beats) and frequency-domain (e.g., high and low frequency components of HRV) measures of HR and HRV were calculated and extracted from the HR-related data.

After preprocessing the data, two analysis pipelines were designed to obtain central nervous system and ANS measures that are associated with learning experience (Figure 2). First, based on the analysis of the video recordings, different states (e.g., rest, simulation task, and feedback) were timestamped to the neurophysiological and physiological data. This was supported by a well-defined structure for the SBL situation, reflecting behaviorally and pedagogically distinct phases. A rudimentary timeline was created, providing an anchor for integrating the qualitative and quantitative data for the **state-based analysis**. The purpose of the state-based analysis was to enable us to focus on physiological and neurophysiological characteristics in distinct behavioral states (i.e., time periods that were defined by the experimental protocol). Both EEG measures and HRV were investigated in these specific states at both the individual subject level and as group averages. Comparison of these different behavioral states can be used to extract information about the engagement of

nervous system resources for attention allocation during cognitively different task requirements. Furthermore, if reliable measures can be verified, it is possible to examine how the nervous system indices of attention engagement during pedagogically different stages in SBL align with the observed or experienced indices of learning.

While the first analysis pipeline was based on the experimental conditions (rest, instruction, task performance, and feedback), the second ***continuous data-driven analysis*** pipeline focused on the time-varying nature of physiological and neurophysiological signals. In this approach, the data are represented as a continuously varying trajectory, enabling the investigation of possible intra- and inter-subject synchrony between the ongoing brain activity and ongoing bodily physiology during the evolution of the learning experience. Indeed, there is an emerging field of research utilizing synchrony measures across individuals to determine behaviorally meaningful associations (see Dikker et al., 2017).

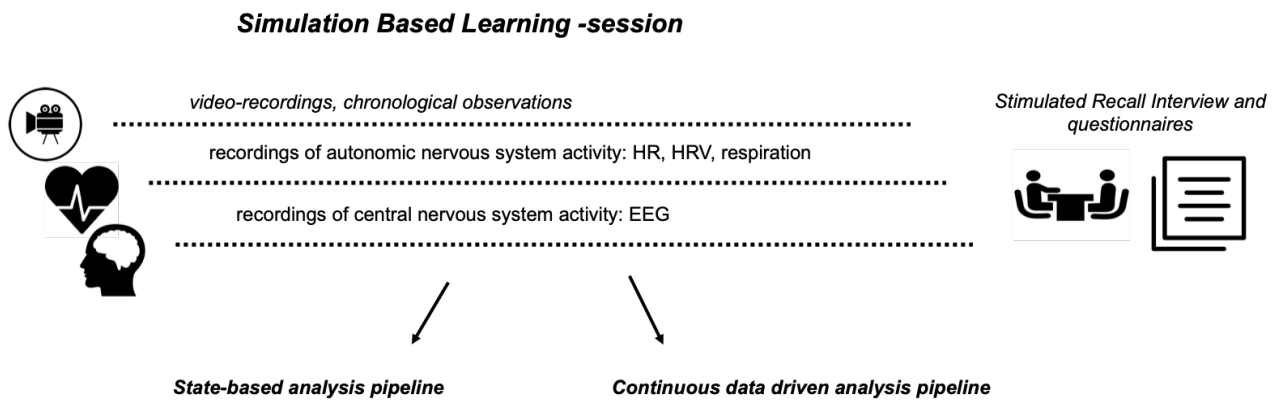


Figure 2. Data collection methods

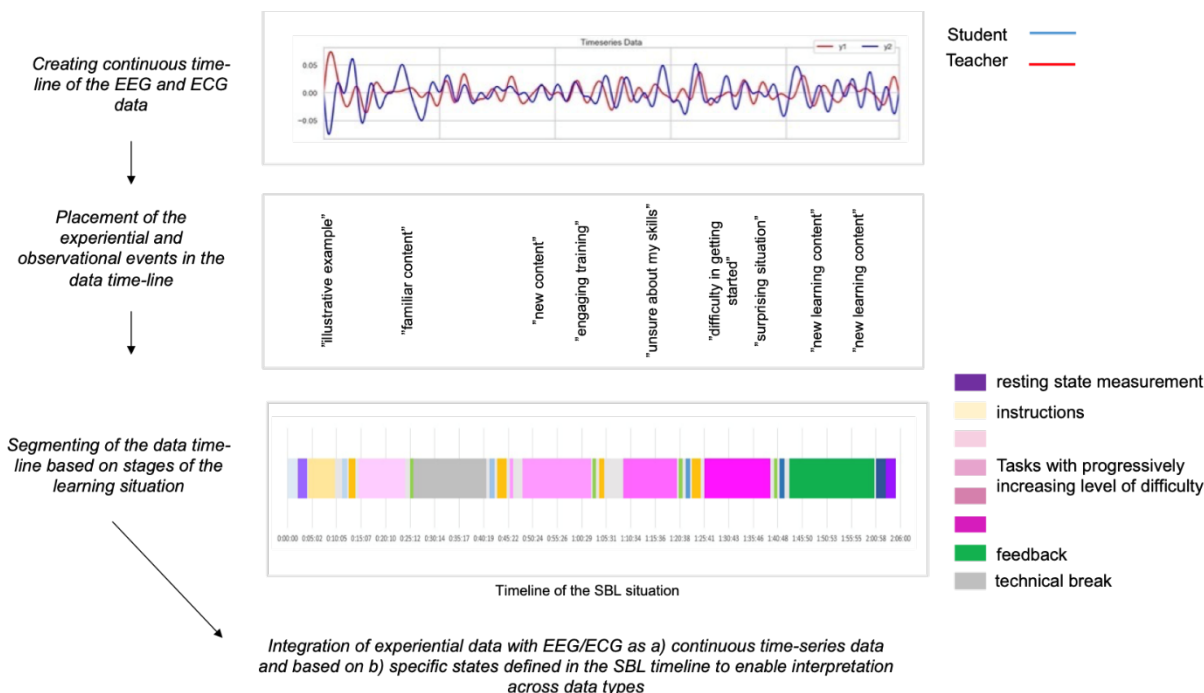


Figure 3. Analysis pipeline

### 3.3.4 Approaching integration across data modalities

These timelines representing changes in the physiological, neurophysiological, and self-expressed experiential level as well as in the pedagogic interaction were used to pinpoint causal associations and dependencies between events within and across individuals. The integration of multimodal data allowed us to identify reproducible elements reflecting phases of experiential learning and student–instructor interaction. This analysis was conducted separately for each student and instructor as well as for the interaction in each student–instructor dyad. This modality-specific analysis enabled us to test the reliability and reproducibility of measures collected during the naturalistic SBL situations (Figure 3). Additionally, we were able to extract features from each modality that were linked to meaningful episode events during SBL and to structure the data in a way that enabled integration between modalities within the quantitative measures (EEG measures and HRV) and across modalities (self-expressed experiences as well as observational, physiological, and neurophysiological measures). The timestamp annotations (see Section 3.3.2) in the neurophysiological and video recordings were of critical importance, as temporal synchronization of datasets (EEG, HRV, observational data, and experiences described in the interview) enabled data integration.

## 4. Discussion

In this chapter, we introduced techniques to apply multimodal methods in the study of the adult learning experience. The learning experience is a complex phenomenon that cannot be fully captured via a single-data modality (Aguayo et al., 2018; Giannakos et al., 2019; Larmuseau et al., 2019). Different methodological explorations have recently emerged using multimodal combinations of cognitive and physiological measures together with self-reports and interviews to capture various aspects of the learning experience. Despite increasing interest in methodological combinations, multimodal studies of the learning experience are still scarce and have mostly been preliminary in nature. Indeed, there is still a lack of larger-scale studies, and an accumulation of empirical evidence is needed to provide comprehensive understanding of experiential learning. Interestingly, many of the scholars who have approached the learning experience multimodally represented fields other than education and neuroscience, and the current focus seems to be more on technological aspects and learning environment development than on theoretically grounded empirical research. In our case example of SBL, we aimed to develop a multimodal research design that takes into account the complex nature of experiential learning and supports both theoretical and methodological development.

### 4.1 Understanding learning experience requires crossing disciplinary boundaries

Recently, cross-disciplinary and trans-disciplinary research has become more frequent, for example, to approach so-called wicked problems of societal issues and overarching research questions (Bore & Wright, 2009; Stadler et al., 2021). It is clear that the study of naturally occurring behaviors benefits from integration of cross-disciplinary understanding. Referring to Rosenfield's (1992) taxonomy of the level of integration between disciplines, it seems necessary to address learning experience with a transdisciplinary approach, with "researchers working jointly using a shared conceptual framework and drawing together disciplinary-specific theories, concepts, and approaches" (p. 1351). In other words, it is not enough to work



in parallel (multidisciplinary) or even jointly (interdisciplinary) to address the questions of learning if the research still builds on a discipline-specific basis.

However, numerous challenges arise in transdisciplinary approaches, for example, from different research designs and traditions in data collection methods (Aagaard-Hansen, 2007). Methodologies are not separable from underlying theoretical assumptions, which inevitably differ between disciplines, for example, between natural sciences (neuroscience) and education sciences. Indeed, discipline-specific expertise is crucially needed for multimodal research approaches. Researchers are not and should not be experts in all fields, but high-quality multimodal research should be the result of cooperation between experts in the fields in which it takes place.

## 4.2 Combining traditional approaches with physiological and neurophysiological recordings

The learning experience forms via a complex process. Indeed, multimodal studies of the learning experience present a good example of phenomena that would require both theoretical and methodological integration of lines of work across disciplines that seem far removed from each other (such as neuroscience, psychology, education science, and data science). Physiological measures may reveal, for example, the neural basis or arousal level that contributes to learning, but they do not capture the subjectively experienced elements revealed through the self-reports or via interviews. To best support learning, the experience needs to be understood as a phenomenon in which important factors can be captured at multiple levels, such as physiological contributors, emotional or cognitive significance, subjectively perceived implications, and the determinants of interaction. The multidisciplinary research design of our SBL case exemplifies how a combination of quantitative, third-person measures of human nervous system signaling can be combined with the first-person experiential data of the ongoing learning experience. We have also demonstrated the many challenges, including technological, methodological, and conceptual, in the multimodal research of the learning experience in natural settings.

Currently, technological possibilities seem to antecede methodological development. Advanced technologies are naturally needed to conduct measurements in natural learning situations, but for successful knowledge building, it is crucial to develop methods of valid data integration. There is, for example, a risk of making oversimplifications in the interpretation

of physiological signals if discipline-specific background knowledge is not correctly applied in the data analysis. The problem of synchronizing across modalities goes beyond technological and methodological tools, as the meaningful phenomena in each modality differ in crucial ways. For example, the different dimensions of experience do not evolve and manifest themselves in similar ways, especially in the time domain. Unlike for physiological and neurophysiological signals, it is not conventional in educational research to organize data sequentially with detailed temporal dimensions. As pointed out by Eteläpelto et al. (2018), questions related to methodological complementarity, interchangeability, validity, and reliability should be addressed. The adoption of new multimodal methods and research designs will also necessitate new analytical and statistical techniques (Azevedo & Alevén, 2013). A multimodal approach also requires deeper interaction across disciplines at the conceptual level, which would in the long run facilitate the use of common terminology.

#### 4.3 A new theoretical framework requires building consistent empirical evidence of learning experiences in natural contexts

As discussed in Section 2.3, there exists no unifying theory of adult learning, which reflects the complexity of learning as a phenomenon (Yang, 2006). Experience itself is a complex phenomenon since it is both longitudinal and episodic and relates to various cognitive domains, such as awareness and perception (Jarvis, 2005). It is also too early to evaluate the practical implications of multimodal research for the development of experiential learning and education. Each study and theory add a little more to our understanding of the phenomenon, and the relationships between theory, practice, and ideology should be made the central focus not just for philosophical purposes but also to achieve greater empirical precision (Baldwin et al., 2004).

The core challenges for future studies can be summarized as follows. **First**, multimodal approaches have thus far been used to study learning and related experiences (e.g., emotions), not specifically *experiential* learning. Consequently, the contexts vary from using the measures as indicators of stress in exam situations to emotion recognition in a gaming environment.

**Second**, these studies have been performed in various contexts and with different interpretations and meanings given both for experience and learning and for the physiological measures. Specifically, the concept of the learning experience and the elements involved in it

varies across disciplines. Harmonizing the methodology and use of concepts would facilitate the accumulation of scientific knowledge.

**Third**, and perhaps most importantly, the experimental literature has so far not given rise to a novel theoretical framework in the field of education that would incorporate, and thus give integrative concepts and designs for, both experiential and physiological measures. There do exist theories that build on embodied learning and thus acknowledge the role of body (and brain) systems involved in the experience. These are, however, often rather unspecific, especially regarding the physiological and neurophysiological concepts and processes. The lack of a coherent theoretical basis is of course not a trivial problem, and development of novel theoretical concepts needs to be done in connection with experimental work. Therefore, now is the optimal time to increase discussion among researchers utilizing multimodal methods to understand learning and more broadly human experience and interaction.

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