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Use of wearable devices in the teaching-learning process: a systematic review of the literature

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Multimodal learning analytics (MMLA) has emerged as an encompassing approach to data collection, facilitating the analysis of student interactions across a variety of resources. MMLA capitalizes on data gleaned from diverse interactions, utilizing wearable devices to track physiological responses. This yields deeper insights into factors such as cognitive load, stress levels, interest, and other stimuli pivotal to the learning process. Nonetheless, it is crucial to acknowledge the theoretical and practical challenges underpinning the integration of wearable devices into learning experiences, both in academic settings and in everyday life activities. A systematic review of the literature (SLR) was conducted to identify the characteristics of studies that incorporate wearable devices into teaching-learning process analyses. The outcomes enabled us to discern key attributes such as participant descriptions, the activities implemented for data collection, and a broad spectrum of biometric indicators, with electrodermal activity (EDA) and heart rate (HR) among the most commonly employed methodologies in data analysis. Future endeavors should be centered on the formation of interdisciplinary teams. The objective is to devise novel methodologies for multimodal data collection and analysis that can discern performance variables, thereby enhancing learning in a manner conducive to more fluid, reflective educational experiences for all participants in the teaching-learning process.

KEYWORDS

wearable devices, multi-modal learning analytics, teaching-learning processes, biometric indicators, educational innovation

1. Introduction

The potential of learning analytics (LA) in education has been harnessed as a tool for the collection, measurement, and analysis of student data with the intent of understanding and constructing models that enhance learning experiences (Siemens and Long, 2011; Ferguson, 2012; Siemens and Gasevic, 2012). The data from LA have been utilized by various authors to explore and investigate factors that shape learning behavior in technology-mediated spaces (Lin and Hwang, 2018; Ullmann et al., 2019). Procedures carried out by institutions using learning analytics, which are based on clickstream data or the so-called time-stamped digital traces left by students during their interactions with the learning management system (LMS), have been recognized (Sedraz Silva et al., 2018). Given the ability to discern varied and intricate patterns regarding student behavior, the significance of other educational applications is also acknowledged (Cukurova et al., 2020). The potential of LMSs for early detection of students facing challenges in courses, predicting success, and promoting improved outcomes has been highlighted (Tempelaar et al., 2020).

Though LA has advanced the comprehension of students' learning processes (Avella et al., 2016), its limitations stem from the one-dimensional nature of its data collection (Rodríguez-Triana et al., 2017). Crucial contextual student data, vital for understanding behaviors and influential factors in their learning process, are often omitted (Eradze and Laanpere, 2017). To address these limitations, multimodal learning analytics (MMLA) has been introduced as a comprehensive approach to data collection (Giannakos et al., 2022; Monsalves et al., 2023). MMLA is characterized by the study of data from diverse sources stemming from student interactions in a range of environments beyond just the digital; this includes physical, physiological, psychometric, and environmental spaces (Worsley et al., 2016; Mu et al., 2020; Giannakos et al., 2022). Such data are captured, amalgamated, and analyzed to provide a holistic understanding of factors associated with the learning process (Quadri and Shukor, 2021).

Specifically, technological advancements have paved the way for wearable devices in the realm of capturing multimodal data pertaining to the physiological environment. These advancements have also simplified the storage of vast amounts of data in the cloud, easing their collection and subsequent analysis (DiMitri et al., 2018). Wearable devices, especially multimodal computerized biofeedback wristbands, have become pivotal for real-time data collection (Garbarino et al., 2014; Regalia et al., 2019). Their widespread adoption is attributed to their increasing popularity in health tracking and monitoring (Vos et al., 2023). Notably, the Empatica E4 wristband, known for its noninvasive nature, cost-effectiveness, and cloud storage capabilities, is prominently utilized (Ollander et al., 2016; Koskimäki et al., 2017). This device has been employed in diverse studies encompassing music, stress, and emotion management (Borrego et al., 2019; Bulagang et al., 2021; Chandra et al., 2021; Rahman et al., 2021).

Recently, there has been considerable interest in creating multimodal systems that automatically analyze students' states that are hard to observe directly, like cognitive load and stress levels, but can significantly affect their performance (Bustos-López et al., 2022). Some studies have focused on examining aspects such as self-regulation (Spann et al., 2017), motivation (Järvenoja et al., 2018), interest, and attention during activities (Tan et al., 2021). At this point, biometric data aids in managing learning-related information, such as assessment load (Hernandez-de-Menendez et al., 2021). Classroom biometric monitoring can usher in new learning approaches, as timely feedback to students with suitable teaching methods bolsters learning and retention (Ramírez-Moreno et al., 2021a,b).

Consequently, wearable devices provide a range of measurements to acquire biometric data, including physiological responses such as electrodermal activity (EDA), also referred to as galvanic skin response (GSR). This measurement is intimately linked to the sympathetic nervous system (SNS), as skin conductance primarily arises from sweat glands under the exclusive control of the SNS. EDA is widely recognized as a direct method to gauge stress associated with responses

of the autonomic nervous system (ANS; Boucsein, 2012). In addition to this, these devices include other peripheral physiological measurements such as respiratory amplitude, skin temperature (ST), electrocardiogram (ECG), blood pressure volume (BVP), muscle electromyography (EMG), and electrooculogram (EOG; Koelstra et al., 2010).

Given the growing interest in wearable devices, it becomes imperative to undertake research in the field of education that addresses both the theoretical and practical issues and the current limitations of these tools. Consequently, this study attempts to pinpoint the characteristics of teaching-learning processes that integrate wearable devices for the collection of biometric data from students. The first section of the article provides an overview of the methodological strategy underpinning this research, based on a systematic literature review (SLR). The following section presents the results of the study, including analysis, interpretation, and findings. The final section addresses the central research question: What are the characteristics of studies that incorporate wearable devices into the analysis of teaching-learning processes?

2. Methodology

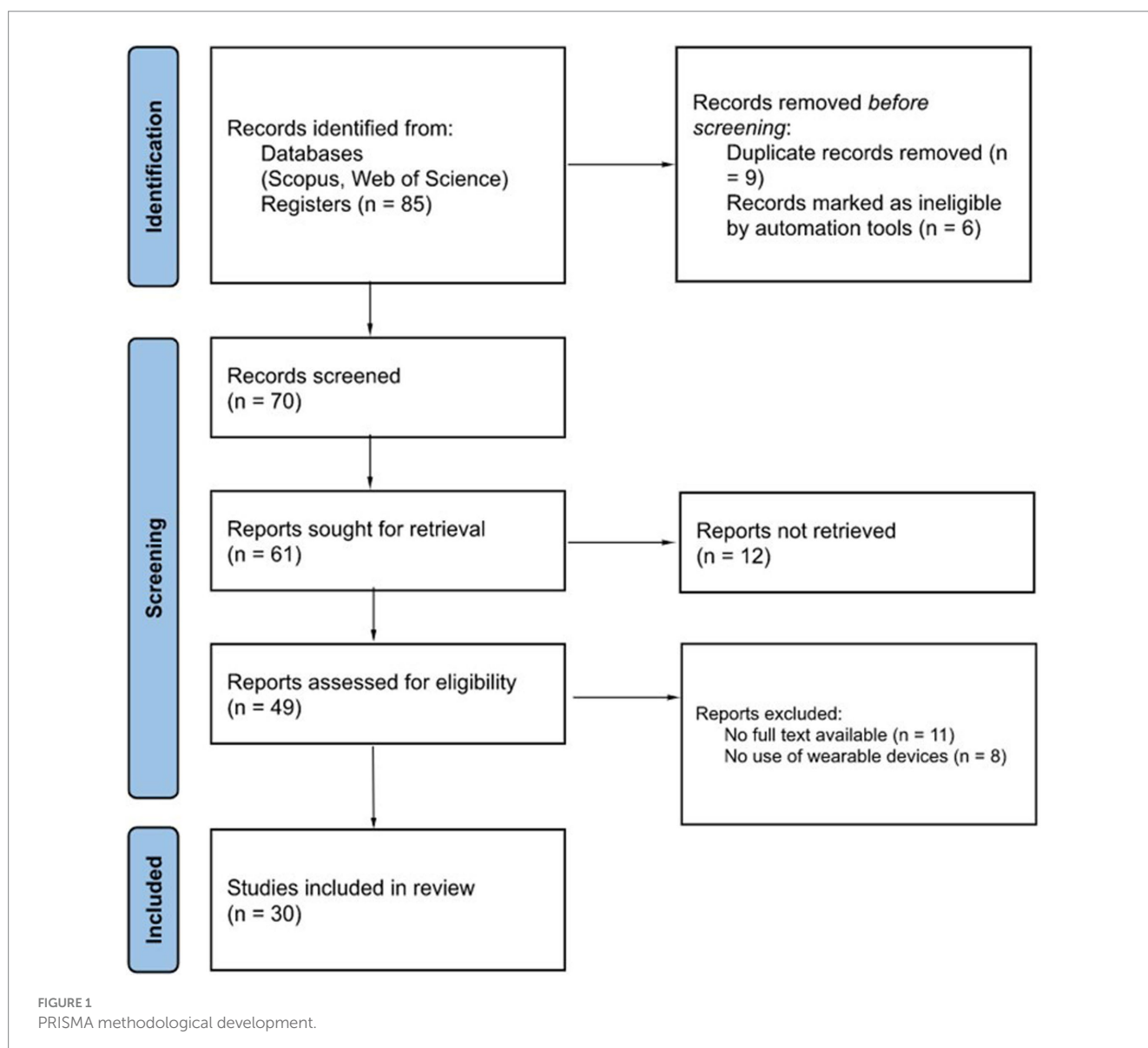
The systematic review was conducted using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021), facilitating the identification of potentially relevant articles. Extensive searches were performed in the Scopus and Web of Science (WoS) bibliographic databases to incorporate a wide range of scientific literature while excluding gray literature. Inclusion criteria were established to include peer-reviewed journal articles published in English between 2019 and 2022, spanning quantitative, qualitative, and mixed-methods studies. This approach ensured a comprehensive view of current research integrating wearable devices. Following the delineation of the study objectives, sub-research questions were subsequently defined to answer the main question (Table 1).

2.1. Selection criteria

Consequently, the titles and abstracts of potential studies were scrutinized to ensure they met the predetermined eligibility criteria. Thorough reviews were then performed to confirm the relevance of the included information to the study, namely, whether it contributed sufficiently toward addressing the objectives of the present research. Full versions of the articles were subsequently assessed independently using the following criteria: (1) intervention studies examining the impact of wearable devices on learning processes; (2) studies incorporating at least one control group; and (3) peer-reviewed studies.

TABLE 1 Sub-research questions.

ID	Question
RQ1	What is the research context that incorporates the use of wearable devices?
RQ2	Are wearable devices utilized to assess the development of any competency component, whether disciplinary or general?
RQ3	Which biometric indicators are associated with the use of wearable devices?
RQ4	What is the methodology for analyzing data gathered via wearable devices?



2.2. Data extraction

Data extraction from each database was independently executed by the authors. The principal metadata drawn from each study encompassed the following details: the first author, date and location of publication, authors' affiliations, journal details, keywords, and the country where the study was conducted. Additionally, specific labels analyzed by the researchers for each study were included, such as the academic level of the study (elementary school, middle school, high school, college, or undergraduate) and the pedagogical strategy or activity utilized. This data was assembled in standard MS Excel files. Any discrepancies encountered were resolved through author discussion.

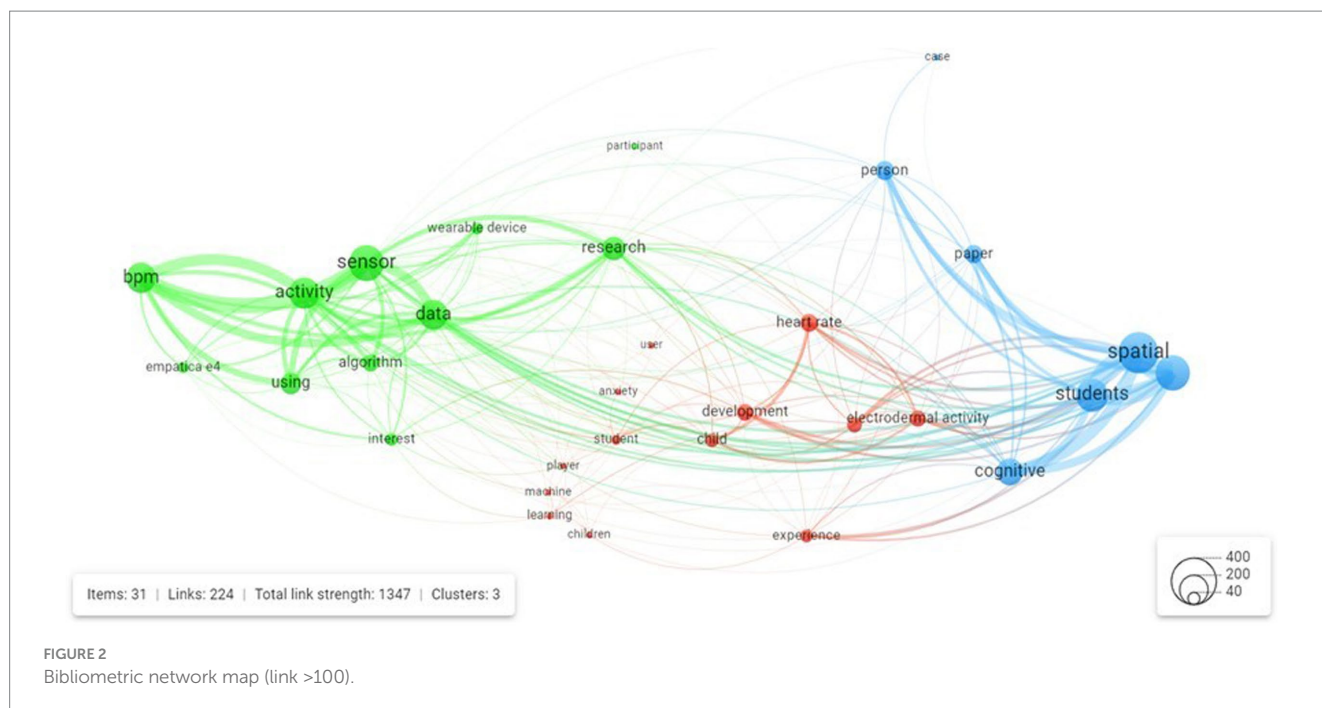
2.3. Identification and selection of the studies

During the identification phase, a total of 85 records were initially recognized and subsequently imported for the construction of the database, sourced from Scopus (42) and Web

of Science (43). With the use of Parsifal automation tools, these records were consolidated, resulting in the identification and removal of nine duplicates and six unsuitable records. This process yielded 70 articles for the subsequent screening phase. Nine articles written in Russian and Chinese were eliminated, leaving 61 reports for recovery. Of these, only 49 were evaluated for eligibility based on the application of selection criteria. Ultimately, the final review incorporated 30 articles that included the use of wearable devices. A depiction of this methodological process is provided in [Figure 1](#).

3. Results

The subsequent key findings were derived from the sub-research questions (RQ1). What is the research context that incorporates the use of wearable devices? (RQ2) Are wearable devices utilized to assess the development of any competency component, whether disciplinary or general? (RQ3) Which biometric indicators are associated with the use of wearable



devices? (RQ4) What is the methodology for analyzing data gathered via wearable devices?

3.1. Context of the development of studies that integrate the use of wearable devices

The context for the development of the selected studies was analyzed from two viewpoints. The first viewpoint encompasses the use of text mining to construct and visualize networks of co-occurring terms extracted from the chosen scientific literature. The second viewpoint pertains to descriptive variables, such as the academic level of the study and the employed pedagogical strategy or activity. Using VOSViewer software, terms drawn from the title and abstract fields of all articles were scrutinized employing a full-count method, where every occurrence of a term in a document is accounted for (Figure 2). Access to the interactive version is provided here: interactive bibliometric network.

The results of the terms linked to each database demonstrate the relationship between the variables that are part of the analyzed articles, where the key and relevant concepts of these studies are verified. The primary bibliometric network map generated a total strength of 1,347 links, which we classified into three clusters. The main findings identify the first cluster (colored in green) with 11 items and the highest number of occurrences (O), which indicates the number of documents in which a keyword occurs (55), links (L) (27), understood like a connection or a relation between two items, and total link strength (LS), which indicates the total strength of the co-authorship links of a given researcher with other researchers (176). It comprises terms that relate to the implementation and use of devices, such as activity, data, sensors, and research. The second cluster, highlighted in red, contains the concepts of anxiety, children, development, electrodermal activity, experience, learning, and user. The third cluster (blue) highlights the terms cognitive, case, test, person, and student.

The data amassed from the results of the biometric map enable the discernment of the interaction of the most pertinent constructs of the investigations. This is based on the data procured from the frequency of occurrence, links, and total strength of the data extracted from the titles and abstracts of each study. Notably, there is a conspicuous absence of terms that are connected with the constructs of pedagogical processes. However, the body of information provided by each cluster is underscored. In the green cluster, activities utilizing sensors to compute beats per minute (BPM) in various research activities are emphasized. Meanwhile, in the red and blue clusters, the student is recognized as the central figure and user in experiences that allude to physiological indicators such as the heart rate (HR).

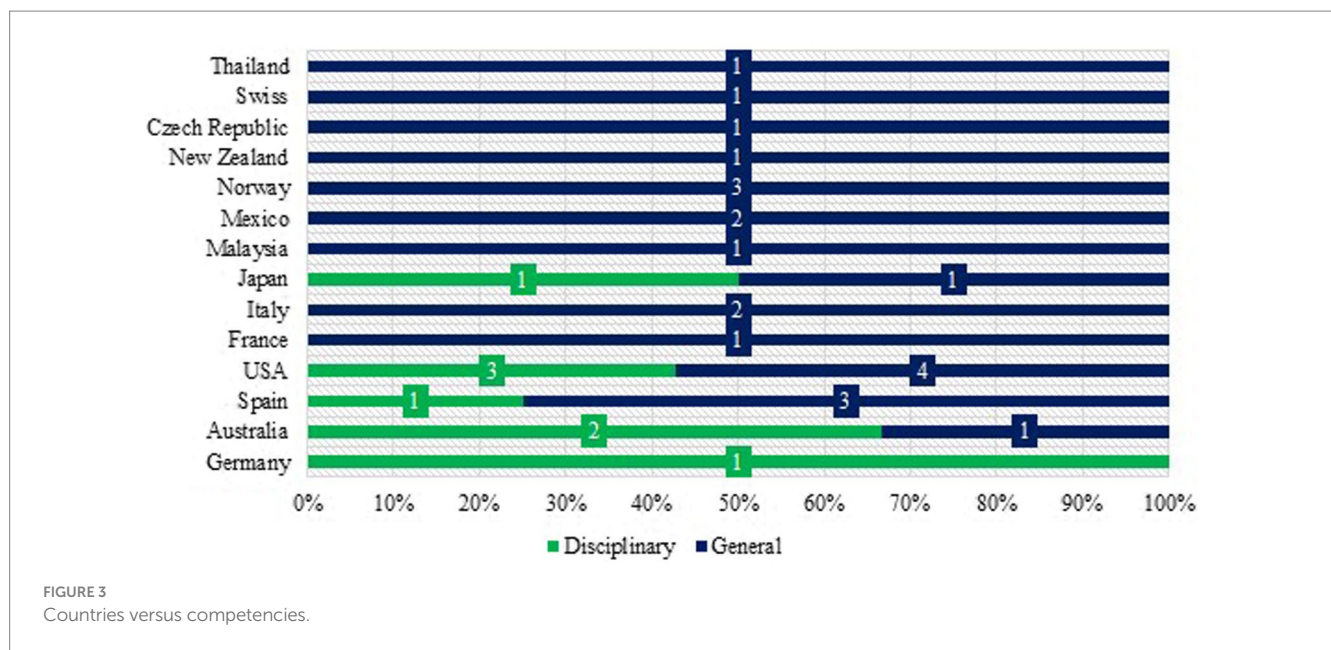
Regarding the descriptive variables, Table 2 assembles information concerning the authors, the research objective, the methodology for data collection, the participant profiles, and the descriptions of activities involving wearable devices. It also includes biometric indicators, whose abbreviations are further detailed in Section 3.3.

From the preliminary investigation of the profiles of the participants, it was found that university students constituted the highest percentage (23.3%). In some of the studies, the characteristics of the participants were not mentioned (16.6%), while an equal percentage involved working with volunteers. Studies mentioned users involving children under 12 years of age (10%). The least represented participants were physicians (6%), office and industrial workers (6%), graduate students (3%), children with special educational needs (3%), and patients (3%).

Subsequent examination of portable device activities revealed that controlled studies and simulated activities were performed (33.3%). Virtual reality environments were involved (6.6%), as were activities in authentic contexts (13.3%), such as emergency rooms and courts. Other activities included activities of daily living (10%), games that integrate motion-based touchless games (MBTG), games with different ASRs (avatar representation), movement-based educational games (MBEG; 10%), pedagogical activities aimed at developing data analysis tools (6.6%), and standardized tests (3.3%).

TABLE 2 Description of linked items.

Author	Research objective	Data collection method	Participants description	Activity description	Biometric indicators
Martinez (2019)	To develop a mobile artificial pancreas based on an Android smartphone and evaluate its safety and efficacy in patients with type 1 diabetes	Quantitative	Patients with type 1 diabetes	Activity in real context	GSR
Jenks et al. (2020)	Examine trends in the frequency and severity of stress during the work shift	Quantitative	Physicians		HR
Peters et al. (2020)	To characterize the physical activity of emergency physicians during their shifts	Quantitative			ACC
Novak (2019)	Describe how Czech courts evaluate and consider the influence of acute stress in cases of necessary defense	Quantitative	N/A		EDA
Fucci et al. (2019)	Replicate a previous study using fMRI to classify the types of comprehension tasks performed by developers and relate their results to their experience	Quantitative	University students	Educational activity	EEG, EDA, BVP, HR, and HRV
Wang et al. (2020)	To identify the unique design considerations for affect sensors that consider student capacities and challenges and explore the potential of the sensors to support students' self-learning	Mixed methods			ACC, ST, BVP, and GSR
Rivers (2022)	Assessing anxiety through subjective experience versus observable behavior and the efficacy of anxiety recording tools	Quantitative		Simulated activity	HRV and EDA
Alfredo et al. (2023)	Designing a stress analysis dashboard to visualize physiological data during an authentic team simulation in the context of nursing education	Mixed methods	ACC, ST, BVP, and EDA		
Ronda-Carracao et al. (2021)	Identify whether arousal levels match faculty expectations at each stage of the simulated scenario	Mixed methods	EDA, ACC, ST, and BVP		
Climent-Pérez et al. (2022)	Provide an annotated data set for automatic evaluation of daily activities and applications of behavioral analysis and evaluation of measurement devices	Quantitative	Volunteers	Activities of daily living	ACC
Choksatchawathi et al. (2020)	Evaluate and correct the heart rate estimation provided by four popular wearable devices	Quantitative			HR
Poli et al. (2020)	Investigate the influence of device characteristics and measurement uncertainty on classification accuracy	Quantitative			EDA and ACC
Ghandi (2019)	Linking human emotions and cognition with the built environment to improve users' mental health and wellness	Quantitative	Patients	Adaptive cyber-environments	GSR and HR
Magaki and Vallance (2019)	Develop a reliable and straightforward measurement of cybersickness for VR application developers and educators	Quantitative	Users	Virtual reality environment	HR
Perales et al. (2019)	Assess user-perceived pain in a controlled virtual reality environment	Quantitative			EDA and HR
Bulagang et al. (2021)	To investigate whether emotions can be classified using HR as a predictor in a virtual reality (VR) environment with machine learning	Quantitative	Not mentioned		HR
Collins et al. (2019)	Exploring the merits of physiological measures in assessing emotional responses in virtual environments	Quantitative	Not mentioned		EDA and HR
Aguilar-Herrera et al. (2021)	To develop a web platform using the IoT and ML architecture to predict students' performance, analyze mental fatigue, and provide real-time quantitative biofeedback to identify the best learning modality	Mixed methods	Volunteers	Controlled study	EEG, BVP, EDA, and ST
Wampfler et al. (2019)	To accurately predict the affective states of participants solving tablet-based math tasks using low-cost mobile biosensors	Quantitative	Users		EDA, IBI, HR, and ST
Raju et al. (2022)	To explore differences in self-reported and recorded stress levels using an Empatica E4 device	Mixed methods	University students		EDA
Ragot et al. (2018)	Evaluating the accuracy of emotion recognition between laboratory sensors and wearable devices	Quantitative	Not mentioned		EDA and HR
Iadarola et al. (2021)	Highlight features related to acoustic stimulation		Volunteers		GSR
Cored Bandrés et al. (2021)	To evaluate the impact of using portable devices in interventions to improve social skills	Mixed methods	Children under 12 years old	Data analysis tools	ED and HR
Tan et al. (2021)	Deepen the understanding of the value of interest in learning		University students		EDA
Ramírez-Moreno et al. (2021a,b)	To evaluate the efficacy of a mental fatigue assessment tool based on biometric signals and inter-subject models		University students and office and industrial workers		EEG, HR, HRV, and EDA
Gouverneur et al. (2017)	Develop an algorithm for the classification of physiological data for emotion recognition	Quantitative	Not mentioned		EDA
Lee-Cultura et al. (2020a,b)	Investigating how player motion data collected during interactions with motion-based educational games can predict performance and enhance the educational experience		Users		GAZE, EDA, BVP, HRV, and ST
Lee-Cultura et al. (2021)	To combine traditional video annotations and MMD to understand children's behavior as they interact with educational technology		Children under 12 years old		HRV, EDA, movement, and gaze
Lee-Cultura et al. (2020a,b)	To evaluate the effect of different ASR on children's stress, attention, and cognitive load during MBTG games				HRV, EDA, ST, and BVP
Hardacre et al. (2021)	To identify background variables, language characteristics, and psychological or physiological factors related to anxiety in ethnic minority teacher candidates	Mixed methods	Postgraduate Students	Standardized tests	HR



3.2. Development of competencies through the use of wearable devices

In response to the second research sub-question (RQ2), competencies (C) are distinguished and classified into two categories: general (G) and specific (E). General competencies (G) are referenced as the extensive skill sets required across various professions, encompassing aspects like teamwork, working toward objectives, initiative, leadership, time management, and independence. The analyzed studies found that the development phase of these general competencies was in progress (60%). Specific or disciplinary competencies refer to skills unique to particular disciplines, such as using data analysis programs and programming abilities. In the collected studies, these competencies were exhibited through practices prevalent across different fields, such as the creation of technological tools and the analysis of physiological attributes and states like stress, mental processes, concentration, and memory (27%). Furthermore, it was noted that a segment of the studies could not be categorized (13.3%) owing to the lack of processes that were directly connected with the teaching-learning paradigm. In addition, information pertaining to the competency analysis was cross-verified with the country in which each study was conducted (Figure 3).

This analysis facilitated the understanding that the emphasis was predominantly on the development of general competencies. In terms of disciplinary competencies, they accounted for all studies conducted in Germany, followed by Australia (65%), Japan (50%), the United States (42%), and Spain (24%).

Specifically, in the studies that refer to formal educational contexts, the different educational levels are linked to specific pedagogical activities. Undergraduate-level studies (11) are primarily related to simulated activities such as controlled studies (45%), virtual reality environments (9%), and activities in a real context (9%), among others. The elementary level (three studies) all linked games with different ASR (avatar representation); motion-based educational games (MBEG) and high school technologies defined a study with controlled variables. On the other hand, studies linked to

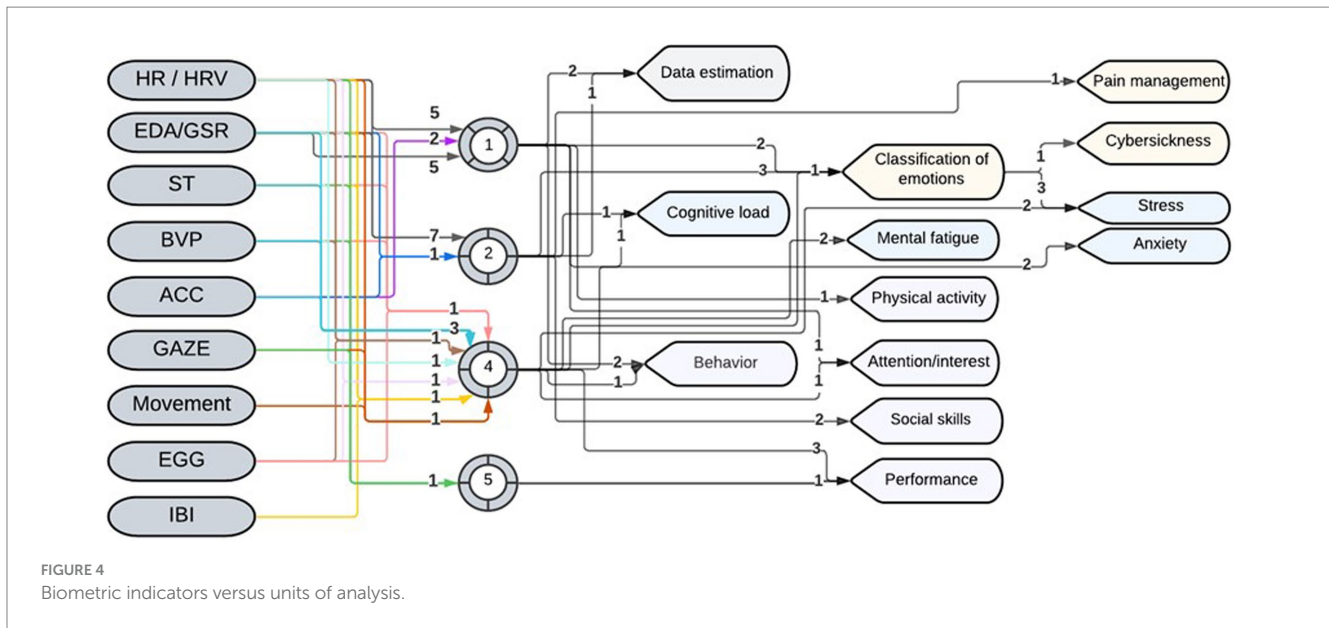
non-educational contexts involved daily life activities (25%), real-world contextual activities (18%), the development of data analysis tools (8%), and the use of controlled environments with virtual reality (7%).

3.3. Biometric indicators linked to the use of portable devices

The biometric indicators gleaned from the studies relevant to this analysis are depicted (Figure 4). These biomarkers are highlighted on the left side of the diagram, set against a gray backdrop. The four central circles represent various combinations of biometric indicators, indicating the number of different biomarkers examined in tandem within each study (1, 2, 4, 5). The smaller numbers represent the total number of studies according to their respective combinations, while the labels on the right depict the meta-skills, understood as the foundational knowledge, abilities, and experiences upon which all life-acquired skills (both soft and hard) are built for each study.

Biometric indicators recognized within these studies include heart rate (HR), its variation (HRV), and electrodermal activity (EDA), also known as galvanic skin response (GSR). Each of these indicators was used in five different studies, with their combination proving to be the most common (seven studies). Only a single study combined EDA and accelerometer (ACC) data. A significant discovery was that seven studies incorporated four distinct physiological indicators, with the most frequently used (three studies) being electrodermal activity (EDA), skin temperature (ST), blood pressure volume (BVP), electroencephalography (EEG), and accelerometer (ACC). The other seven studies combined four indicators, linking others such as gaze, movement, and interbeat interval (IBI). It is worth noting that a single study combined five indicators.

These findings imply that various studies integrate biometric indicators and propose constructs, viewed in this research as units of analysis, to imbue the collected data with meaningful interpretation.



Three primary categories integrating meta-skills stand out: data estimation (three studies) and behavior (three studies), incorporating performance analysis (four studies), alongside social skills (two studies), attention/interest (two studies), and physical activity (one study). The third category is cognitive load as a unit of analysis (two studies), comprised of emotion classification (six studies), mental fatigue (two studies), pain management (one study), cyber sickness (one study), stress (five studies), and anxiety (two studies).

3.4. Methods of analysis of data collected by wearable devices

Regarding the methods of data analysis, the use of quantitative approaches that include automated and continuous monitoring of physiological response data through the use of biometric sensors has been indicated (66.6%). Among the most prominent analysis methods, classification models such as support vector machines (SVM), k nearest neighbors (kNN), random forests (RF), extra trees (ET), and gradient boosting (GB) are declared. Furthermore, machine learning includes models (Fucci et al., 2019; Wampfler et al., 2019), algorithms (Collins et al., 2019), and techniques (Lee-Cultura et al., 2020a,b; Aguilar-Herrera et al., 2021). In addition, the need to incorporate technological innovations to capture, measure, and analyze physiological data was recognized. Wearable devices mentioned in the research include Wristband Empatica E4 (Gouverneur et al., 2017; Ragot et al., 2018; Jenks et al., 2020; Poli et al., 2020; Cored Bandrés et al., 2021; Iadarola et al., 2021; Climent-Pérez et al., 2022; Raju et al., 2022), Biopac MP150 (Ragot et al., 2018), Fitbit Charge HR, Apple Watch Series 4, and TicWatch Pro (Choksatchawathi et al., 2020).

On the other hand, 33.3% of the studies accounted for were classified as mixed-type. In these cases, physiological parameters were measured, and these studies included data from self-report questionnaires and the results of standardized tests (Hardacre et al., 2021). Likewise, it is acknowledged that the studies analyzed the recording of biometric signals and conducted correlational analysis with self-report information (Ramírez-Moreno et al., 2021a,b).

Additionally, the use of techniques such as questionnaires (Alfredo et al., 2023), for example, the Fatigue Assessment Scale questionnaire and Enophones (Wang et al., 2020), systematic observation (Cored Bandrés et al., 2021; Tan et al., 2021), and semi-structured interviews and surveys is recognized.

4. Discussion

Wearable devices have been an alternative to identifying performance characteristics in activities contributing to teaching-learning. The study results allowed recognition of the main characteristics of research, such as describing the participants in the activities developed for data collection, the wide range of physiological indicators, and the methodologies to analyze multimodal data. These findings are consistent with those of the study by Giannakos et al. (2022) since they highlight the use of multiple sources of data obtained from the interactions of students using different resources such as videos, e-books, games, and attending face-to-face classes, among others. The wide range of activities associated with collecting multimodal data highlights the relevance of linking and generating multidisciplinary spaces for a better understanding of developing the teaching-learning process in both pedagogical and real-world contexts. Similarly, a variety of biometric indicators are recognized, including the HR, its variation (HRV), and electrodermal activity (EDA), also known as galvanic skin response (GSR), skin temperature (ST), blood pressure volume (BVP), and accelerometer (ACC), with some being related to the development of disciplinary competencies, such as data estimation, while others focus on generic variables, such as attention, stress, and anxiety. This understanding is in line with the findings described by Hernandez-de-Menendez et al. (2021), who highlighted the potential of biometric data in managing information related to learning. There has been a demonstrated interest in creating multimodal systems that automatically analyze student states that are difficult to observe with the naked eye, such as cognitive load and stress levels (Bustos-López et al., 2022). At this point, the significance of comprehending how data collected through portable devices in

pedagogical contexts can serve as a support tool for learning management is emphasized, considering that its collection, fusion, and analysis pose challenges for integration.

5. Conclusion

This review was initiated with the question, “What are the characteristics of studies that incorporate portable devices in the analysis of teaching-learning processes?” This question led to the development of a methodology that identified the most relevant characteristics responsive to the objectives framed in each investigation. At a general level, the types of participants have been recognized, with university students, graduate students, volunteers, physicians, office and industrial workers, children under 12 years old, children with special educational needs, and patients being among the most prominent ones. It is also acknowledged that these participants were involved in simulated activities, controlled studies, and pedagogical activities aimed at developing data analysis tools and standardized tests. The technological linkage between activities in virtual reality environments and authentic contexts, such as emergencies and courts, is highlighted.

Additionally, other activities encompassed activities of daily living, games that integrate motion-based touchless games (MBTG) with different avatar representations (ASRs), and educational games based on movement (MBEG). Moreover, the trend of utilizing biometric data such as the HR, its variation (HRV), and electrodermal activity (EDA) is highlighted. This is done to measure and detect stress, enable intervention, and improve attention and working memory. Additionally, it emphasizes the easy and portable use of sensors for measuring emotions and physical characteristics. Thus, the usefulness of technology (in this case, wearables) as tools for assessing the impact of an educational intervention is confirmed by our review.

Regarding the limitations of this research, an area of opportunity is identified in research sub-question number four. While the methods of multimodal data analysis are acknowledged, the characteristics considered for applying machine learning techniques to data gathered via wearable devices could be more comprehensively elucidated. Likewise, it is recognized that in this research, it is impossible to demonstrate the direct impact of interventionist improvements in the various integrated contexts. It is proposed that future work should focus on the generation of multidisciplinary teams that can understand performance variables, aiming to create new methods for multimodal data collection and analysis that promote personalized learning.

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Furthermore, research should be encouraged to identify factors that affect learning to promote more fluid and reflective educational experiences for all those involved in the teaching-learning process.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

LG-M and MC-A contributed to the conception and design of the study. JR-R organized the database. CA-N wrote the first draft of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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