A Literature Review of Physiological-Based Mobile Educational Systems

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Abstract—**This literature review explores prior research involving physiological-based mobile educational systems. Mobile computing is advancing, and implementations of ubiquitous systems for educational purposes are increasing. Another growing field is physiological computing, where the user's states are retrieved and applied as control inputs in applications. The integration of physiological signals such as electroencephalography (EEG), heart rate (ECG/EKG), and eye-tracking (EOG) to mobile learning (m-learning) applications can enhance the learning experiences to provide content tailored to the student's and educator's preferences. This article centers around a selection of core papers that represent the most relevant contributions to the research that falls at the intersection of m-learning and physiological computing. Specifically, this article presents an analysis and discussion of state-of-the-art mobile educational systems that leverage physiological technology.**

Index Terms—**Affective computing, education, mobile learning, physiological sensing, ubiquitous computing.**

I. Introduction

THE USE of mobile applications for learning has increased in recent years. Modern technologies allow students to leverage their mobile phones as a useful resource during their studies. Many different definitions have been attributed to the general term that describes the field: mobile learning (m-learning). Early work from O'Malley [1] defined the term as "Any sort of learning that happens when the learner is not at a fixed, predetermined location, or learning that happens when the learner takes advantage of learning opportunities offered by mobile technologies." Moreover, there have been many different interpretations of m-learning due to it being an immature field. Researchers have defined it in many ways to fit their specific needs, therefore developing categories such as those explored by Traxler [2], which to name a few include technology-driven mobile learning, informal mobile learning, and remote mobile learning. However, in this work, m-learning is defined as "the acquisition of knowledge and understanding through interactions with a mobile application" [3]. These types of devices provide students with the ability to learn topics anywhere and anytime. There is limited work surrounding the specified definition, and many of them use techniques from areas such as user interface/experience (UI/UX) design, machine learning (ML), and human-computer interaction (HCI) to improve the overall experience. Moreover, work is even more limited in m-learning applications applying physiological signals, which is a potential field that can improve educational experiences [4]. The field of physiological computing leverages the human physiological data as a control input, therefore making system interactions dependant on the user's state [5]. There are many different types of physiological signals that can be used in physiological-based applications, they include electroencephalography (EEG), electrocardiogram (ECG/EKG, also known as heart rate), electrooculography (EOG), and more. Thus, m-learning implementations involving physiological signals can provide access to the user's current state. Furthermore, the collected physiological data can be used to interactively adapt the application to enhance user experience. Recently, multiple studies featuring the use of physiological data have explored educational applications. The purpose of this literature review is to provide insights on research at the intersection of mobile learning and physiological computing. In particular, this review focuses on previous work that involve the use of physiological sensors to improve students' educational experience. This article presents a discussion of relevant papers, an analysis of their contributions, learning contexts, trends, and challenges. This review is based on four main research questions.

1) In which contexts are physiological m-learning being applied (e.g., formal, informal, and nonformal learning)? This article aims to advance knowledge regarding the settings in which physiological m-learning applications have been explored. Moreover, pedagogical approaches need to be explored to understand the state-of-the-art educational methodologies in the field.
2) What physiological m-learning applications exist and what are their objectives and contributions? This article aims to address this question through a critical discussion of the goals and contributions from the literature.
3) What system design trends exist in physiological-based mobile learning applications? The third question targets specific system implementations and architectures used in current applications. Information on existing designs and architectures provide insights that can inform future physiological-based mobile learning research.
4) What challenges exist for current physiological m-learning applications and how are these systems

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evaluated? The final question aims to shed light on the current state of physiological-based mobile learning applications. Furthermore, this article presents a discussion of common methods used to evaluate these applications and the challenges involved during implementation. Information on the growth of this interdisciplinary research is also provided.

The following sections discuss the selection and analysis of the relevant articles. In particular, previous contributions, learning contexts, challenges, and future directions are presented. Section II describes relevant background work and provides reflections on both m-learning and physiological signals. Afterward, Section III provides motivational scenarios to assist readers with envisioning how physiological sensors may be used in m-learning contexts. Section IV describes the methodology used to select relevant papers. Section V presents a statistical (publications) and thematic analysis of relevant articles. Subsequently, a synthesis of highly relevant articles and topics is provided in Section VI. This section also presents system design suggestions and revisits this article's research questions. This work concludes by suggesting future directions for physiological-based mobile learning research.

II. Background

A. Mobile Learning

1) Definition: Electronic learning (E-Learning) has advanced to become a very important part of many educational systems. This type of learning is often augmented with other factors such as mobile environments. The growing popularity of ubiquitous learning has recently inspired the emergence of the term mobile learning. In this field, research focuses on the use of mobile devices for educational purposes, taking advantage of their predominance and capabilities. This environment could help advance learning methodologies while being an accessible resource to students.

Many different definitions exist to reference the use of mobile applications in a learning context. The following sections will refer to this specific use case as "mobile learning" (m-learning for short), based on the definition by O'Malley *et al.* [1]. Multiple novel features have been integrated into mobile devices since this early definition. For example, hardware in smartphones currently supports processing of intensive tasks and include various sensors. Furthermore, internet connectivity on mobile devices has also improved. Prior work has also improved our understanding of ways to design and implement effective mobile user interfaces. Mobile computing has changed in multiple ways and it has the potential to change aspects of everyday life (as it already has). Therefore, a different definition is used in this review: "the acquisition of knowledge and understanding through interactions with a mobile application" [3].

2) Mobile Learning Systems: There are various existing m-learning systems. However, most of them involve the use of mobile devices to transmit information not necessary to involve interactivity. An example of an m-learning system developed before smartphones were created is [6], where they refer to the application as mobile even though it was implemented using a laptop. However, there are systems created in the correct context such as in [7] where the authors present a simulation-based application for students to learn about geographical locations. Moreover, in [8] the authors investigated m-learning as an alternative to e-learning and concluded that it should be a compliment instead of a replacement. The previous examples provide hints regarding how m-learning research is evolving. In this review, we focus on exploring work relevant to both m-learning and emerging physiological sensing technologies.

B. Physiological Computing

1) Definition: Physiological computing makes use of physiological information from humans to provide feedback that enhances their ability to complete a specific task. The general definition for physiological computing is any system that uses real-time physiological data to control a system [5]. The basis of physiological computing is to detect any type of signal from the user's central nervous system (CNS), somatic nervous system (SNS), and autonomic nervous system (ANS). These signals can be processed in many different ways, depending on their nature and architecture design. The use of these signals also varies by use case. In this work, there is no restriction in terms of real-time or postprocessed data. Due to the overall limitations and quantity of papers available, this article focuses on systems that retrieve physiological information to assist an application with its overall goal.

2) Types of Signals: As mentioned before, there are many types of physiological signals. This section details examples of the signals that are most common in previous m-learning literature. These can be electrical signals from the brain: EEG. This is a very popular type, due to its potential to capture covert user states [9]. Another type of signal is the electrocardiogram (ECG/EKG), which refers to heart rate. This type of signal is often leveraged in ubiquitous systems. Moreover, electrooculography (EOG) is used as a measure to perform eye-tracking. EOG allows for very specific details on the user's eye positions. Each signal needs a specific type of hardware device to capture it and communicate desired information about a user's state. For example, EEG requires electrodes placed on the human scalp to detect electrical brain activity. EOG normally requires sensors placed near the user's eyes. With the numerous available physiological sensors, numerous application concepts can have been developed. A subset of these applications is explored in the following subsection.

3) Physiological Systems: Multiple current systems take advantage of physiological signals. Since the origin of this area, there has been a focus on medical approaches. For example, prosthetic devices [10], brain-controlled wheelchairs [11], and medical education [12]. However, recent advances have taken the field into exploring more nonmedical applications. Examples of these include gaming with eye-tracking [13], drowsiness detection through heart rate (ECG/EKG) [14], workload estimation with EEG [15], and education with EEG [16]. The field is beginning to rise in terms of mobility, with emerging consumer-grade hardware and compatibility with more devices. Therefore, mobile computing leveraging such physiological data becomes an important topic since it can allow for user-centered experiences in many contexts, including education as this review discusses.

III. Motivation

Physiological data are a potential way of enhancing user experience during m-learning activities. Current research in both realms answers questions in different directions, without exploring the possibilities of a system involving their integration. In m-Learning, the trends are for applications with very limited interactivity. This is an unexplored, yet potentially beneficial component of m-learning applications due to the nature of such systems. Students can become more engaged through interactions with the interface instead of over-relying on the presentation of information through static mediums. Moreover, engagement can be measured and used through physiological sensing methods by leveraging EEG, heart rate, or eye gaze data. This technology can allow for customized learning experiences, taking into account student reactions and interactions with the interface to finally adapt to their preferences.

The idea of physiological-based mobile educational systems is interesting. However, many questions about this concept remain. Why can these applications be useful? How can they be used by students? What do these applications contribute? Therefore, both main components (educational mobile apps and physiological data) can be explored individually to gather information about their possible integration which can provide interesting results. First, mobile applications for learning are created to assist students to either study or achieve specific tasks assigned in class. An example is [17], where an m-learning application was developed to help students in their computer architecture course. This one incorporates a set of features such as flashcards, note-taking, and quizzes. Moreover, the author [18] focus on the use of microlectures and videos for the students to learn using their phone.

However, these are examples of how these systems could be much improved through the design of better interfaces and experiences. M-learning applications started evolving from static text, imagery, and quizzing to interactive displays. One example of this type of application is [19], where the objective is to have an intelligent system to assist students with their English pronunciation skills. Another example is [20], an application that uses gaming and multimedia for the teaching of the English language. Others used techniques such as user profiling to understand the preferences for each student and use the data for better user experiences [21]. This showcases how there is a need to understand individual student experiences to provide more effective activities suited to their preferences. Starting with universal, static information and subsequently creating adaptive models, there is potential for many methods to be applied into the m-learning field. The use of physiological sensing for this purpose has not been completely explored, and current trends are showing its potential.

Physiological computing has gone through many cycles during its existence, since its beginnings with medical applications to today's world of entertainment, education, and more. Current research presents many devices and signals that can be useful for the understanding of human feelings. EEG is widely used for the classification of cognitive states (anger, stress, engagement, etc.), and these are useful for a myriad of applications. In [22], an evaluation is conducted to understand if passive BCIs (using EEG) could be feasible to implement in autonomous driving contexts. The authors in [23] study the control of robots through adaptive interfaces by leveraging EEG data. But, one of the most relevant studies for this research field is [24], which implements adaptive agents using the student's EEG data to classify their attention levels and act accordingly. This system implementation represents one of the possibilities of m-learning applications, the capability of leveraging student physiological information to adapt to their needs leading to an improvement of their learning experiences and outcomes. There is a trend toward the need for learning personalization and interface adaptation using physiological data as input, which is an unexplored approach. To acknowledge how these applications can be used by students, and why it might be useful, a set of scenarios will be presented. These will be divided into two categories: Scenario 1 and Scenario 2. The first scenario will serve as a comparison point to why the second scenario is an improvement. There will be two sets of scenarios, each from a different perspective.

A. Learner Perspective Scenarios

1) Scenario 1: Ally downloaded the mobile application assigned by the professor for the Biology I course. Ally studies for the midterm exam, which covers the topics of DNA replication, translation, and transcription. The mobile application contains a section to study for these topics, and it includes definitions, images, videos, and quizzes. Ally keeps reading and watching the videos to answer the quizzes correctly, but she cannot do it for long hours. There is too much to read and the videos are not too entertaining. The quizzes include theoretical questions about the material, with minimum variation and interactivity. Ally is not too engaged in the study process, as she prefers practice problems and other activities to grasp the material. The time spent on the application is reduced and she starts to create her routine for a better learning outcome.

2) Scenario 2: Ally downloaded the mobile application assigned by the professor for the Biology I course. Ally also gets her EEG-capturing headset to use during the study session. She sits down to study for the midterm exam, which covers the topics of DNA replication, translation, and transcription. The mobile application contains a section to study for these topics, and it includes definitions, images, videos, and quizzes. However, each of the presented media types adapts to Ally's preferences. The application has a set of interface templates that change the way each section is presented as the data are analyzed and classified with the physiological information. Ally likes hands-on activities, therefore, based on her reactions to other interfaces, the app more frequently presents a mini-game where she can drag and drop nucleotides to their corresponding spots. Moreover, the application includes social features with multiplayer activites and communication systems that allow for student interactions. Ally is very engaged in the study process, as she can visualize and manipulate the topic information to her advantage. The time spent on the application is increased and she considers it an effective learning experience.

Both scenarios show how Ally feels during her study sessions using the corresponding m-learning application. The first scenario showcases more traditional means to display the information. Ally cannot feel engaged whenever having static text and imagery, and the videos are not entertaining to watch. She begins to create alternatives to the application, which is an example of the need to improve the experience. That is where the physiological-based m-learning application becomes useful (Scenario 2), since it provides dynamic interactions to teach the material. Nonetheless, the application also considers the students' preferences, which allows for an adaptation to other possible interfaces: static text for those who prefer reading, manipulative objects for those who like interactivity, adaptive quizzes for those who are motivated by rewarding systems, and more. These examples represent the need for adaptive learning experiences in the mobile environment, and the potential for physiological sensing to be implemented in these applications. Moreover, these are not the only scenarios possible, since other individuals are involved in the creation of physiological-based mobile educational systems: researchers.

B. Researcher Perspective Scenarios

1) Scenario 1: Juan is a graduate researcher working with m-learning applications and his advisor proposed the creation of an application that somehow leveraged user data to adapt the interface. Juan is reading about many different ways to achieve this, and finds some possibilities. Some of his findings include user profiling and physiological sensing. They are both very different approaches but could be complimented. Juan designs an application to teach the English language, but he cannot seem to find many resources for the implementation of physiological sensing into mobile environments. Similarly, since the physiological data are streamed and need to be classified, there are not many libraries or frameworks to support those activities in native mobile applications. After hard work getting connectivity resolved, Juan needs to decide the best techniques to build the application. What system design is most effective and in what context? Which physiological devices and/or signals should be used? How is this data used during an m-learning activity? How are these applications evaluated? Juan cannot easily find this information since the field is in its early stages.

2) Scenario 2: Juan is a graduate researcher working with m-learning applications and his advisor proposed the creation of an application that somehow leveraged user data to adapt the interface. Juan is reading about many different ways to achieve this, and finds some possibilities. Some of his findings include user profiling and physiological sensing. They are both very different approaches but could be complimented. Juan designs an application to teach the English language, and he finds libraries that allow him to continue his development. Some of the contributions include interface templates, physiological sensing libraries for the retrieval of data, and even datasets for his user profiling tasks. Finally, Juan can easily design his system based on research articles discussing the most effective architectures. He can also easily find information on m-learning activities using physiological signals and how to leverage these not only for educational purposes but also for system evaluations.

These scenarios represent the limited research in this research area and the difficulty of replicating these applications without a foundation. In the first scenario, Juan looks to get data streaming into mobile devices, which he thought would be a simple step. Moreover, he cannot encounter articles that have explored system designs, contexts, physiological data usage, or even evaluation methods. Due to the limited exploration of physiological-based mobile educational systems, there are no readily available resources to achieve his goal. However, in the second scenario, Juan can find some of these resources and research results that are feasible. He finds libraries to achieve the device connections and also encounters interface templates. This area has many possible contributions to the entire community, and the second scenario showcases examples of how it can provide useful tools for the future.

C. Literature Review Contributions

This article builds on the aforementioned trends, where there is a clear need for research in physiological-based mobile educational systems. With limited work done in the field, but literature supporting the potential of these types of applications, this literature review looks to provide a baseline for future work in the field. There are many areas in which this topic can help advance the scientific community, and its contributions to the field, along with those provided from this literature review, can be seen in Fig. 1 as well as listed in detail below.

1) The enhancement of learning experiences in the mobile learning realm by leveraging physiological computing.
2) Understanding of user experience and interface adaptation protocols using m-learning applications.
3) Architectural designs of physiological-based mobile educational systems.
4) User Interface and Experience guidelines for effective m-learning applications.
5) Reusable software for the development of physiological-based applications in mobile environments.
6) Evaluation methods for physiological-based mobile educational systems.
7) Libraries for machine learning, signal processing, and interface building in mobile environments.

IV. Methodology

To answer the research questions, a literature review was conducted. The approach was semisystematic, with publication statistical analysis and thematic content discussions. As discussed in [25] and [26], the first step to the review is paper

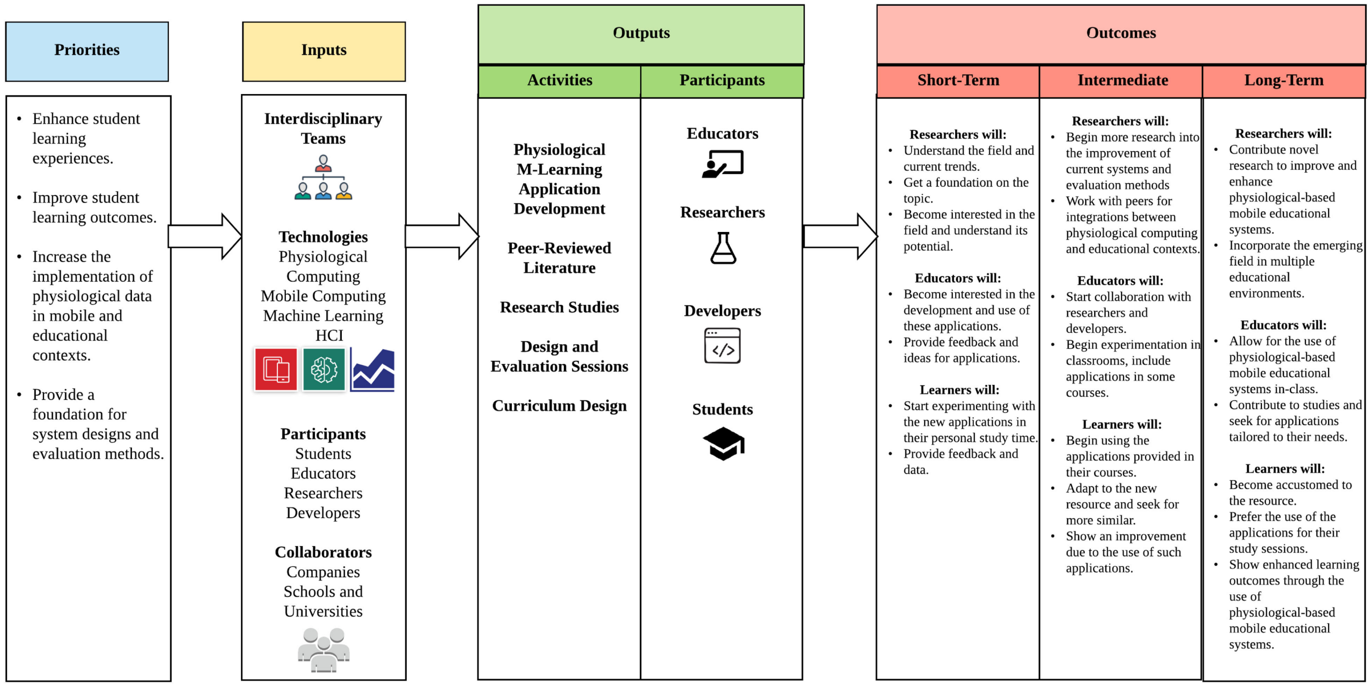

Fig. 1. Potential outcomes from additional physiological-based mobile educational research.

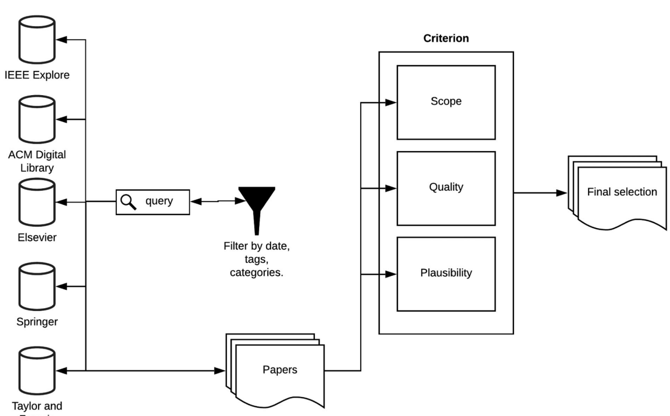

Fig. 2. Paper selection process for the literature review.

selection, which requires two substeps: a comprehensive search and an inclusion/exclusion criteria. The second step is to analyze all the selected papers providing a descriptive section of custom topic clusters and a thorough segment of the content discussion. The purpose of this review is to analyze all the relevant work in mobile learning using physiological signals and deliver a knowledge base while retrieving possibilities toward the future of this field.

First, a thorough search was conducted using a set of combinations between different concepts related to the topic. The overall process can be seen in Fig. 2 There were a total of five databases included in the process: IEEE Xplore, ACM Digital Library, Elsevier, Springer, and Taylor & Francis. The search query was constructed using different combinations of concepts, to find articles related to mobile computing, the following keywords were included in the search query: "mobile" OR "android" OR "iOS." To find articles that involved education, the following were included: "education" OR "learning." Finally, additional terms were added to include physiological computing in the results: "physiological" OR "sensors" OR "EEG" OR "EKG/ECG" OR "EOG" OR "EMG" OR "eye-tracking" OR "heart rate" OR "GSR" OR "skin conductance." Due to the many possibilities of physiological signals, this list was used to get a better collection of articles. These terms helped filter papers and journal articles for those that discuss mobile learning with applied physiological techniques, constructing different search queries using the aforementioned keywords (e.g., mobile learning or m-learning, mobile physiological education, EEG m-learning, and more). In the case of some databases, there were more specific search filters. Taylor and Francis required using the Computer Science tag to narrow down the results. Elsevier required category selections review articles and research articles along with the tags Computers & Education, Procedia Computer Science, and Neurocomputing. The search was made using exact matches for the concatenation of main concepts and additional terms. Moreover, the date range for all of the articles was from 2014 to the present (2019).

To better filter the research articles for the current topic, paper selection criteria were designed. For the literature to be relevant in this review, it must discuss both mobile computing and education with physiological signals or one of the main concepts along with physiological signals. Those that do not conform to these measures can be considered for background information during the review. Criteria examples can be seen in Table I. The criteria are defined as follows.

1) *Scope:* The article must include all three main concepts: mobile, education, and physiology. For example, an article discussing mobile learning techniques using heart rate sensors as input is considered in-scope and

TABLE I
INCLUSION/EXCLUSION CRITERIA EXAMPLES

Criteria	
Inclusion	**Exclusion**
The research provides relevant contributions to the mobile learning field.	The research involves physiological signals in a web-based environment.
The research involves physiological signals in an m-learning environment.	The research provides contributions in the mobile computing field.
The research shows thorough details on design, implementation, evaluation, and more.	The authors are not involved in other m-learning, physiological-based work.
The authors for such research have previous work in the field.	The research paper is a concept or demo without reproducible or thorough details on system design.
The research is relevant due to its sources.	The research is not well-received or cited amongst similar work.

should be included in the review. However, a paper that discusses EEG inputs applied to web technologies with no relevance to education is not in scope.

2) *Quality:* The article shall provide a thorough understanding of the presented topic. For example, a concept paper that proposes a mobile learning technique using physiological devices but does not contain any insight on design and implementation will not be considered in the review.
3) *Plausibility:* The article must be from a trustworthy source, meaning that its authors should be recognized or should have previous work in the field and their work is published in a suitable conference for the topic. For example, an author with previous work in mobile computing involving learning and physiological devices is an indicator of a knowledgeable source in the field. However, an author without experience in mobile learning should have their paper thoroughly analyzed before any inclusion in the review.

During the selection process each title, abstract, and conclusion were read to ensure their compliance with the standards. All three should have enough information to decide whether or not they belong in the review. After reading these sections, the article is analyzed with all three criteria: scope, quality, and plausibility. Whenever the article was fully compliant with all the standards, it was automatically included in the review. Nevertheless, those that do not were still considered for background information or analysis purposes. Included papers were inserted in a table that kept track of each title, keywords, author(s), publisher, venue type, venue name, and year. This would be used later in the analysis section for a thorough content examination. Furthermore, papers with similar topics were also filtered through for better results, in this case, those with more citations and overall relevance were selected over their duplicate. After the first search and filter, there was a paper count of fifty-four (54). Finally, after applying the same procedure for a second time, a total of thirty (30) relevant papers were selected as the base for this review.

TABLE II
PUBLICATIONS OF SELECTED ARTICLES BY YEAR

Year	Article(s)	Count	Percent
2014	[27], [4], [28]	3	10.00%
2015	[29], [30], [31], [32], [33], [34], [35], [36], [37]	9	30.00%
2016	[38], [39], [40], [41], [42]	5	16.67%
2017	[43], [44], [45], [46]	4	13.33%
2018	[47], [48], [49], [50], [51], [52], [53]	7	23.33%
2019	[54], [55]	2	6.67%

The following sections discuss the findings from the conducted literature review for physiological-based mobile educational systems. There is an analysis of the general results from the review, including details from paper publications over the years, and the most prominent conferences and journals. There is also an analysis of their contributions, along with details from learning contexts, physiological computing, and challenges. Contributions involve five types defined in this article: system implementation, architectural design, review, evaluation, and concept. Learning contexts are split into three categories: formal, informal, and nonformal (all defined in the previous section). Physiological signals were also found and there are a total of five categories: EEG, eye-tracking (EOG), photoplethysmogram (PPG), heart rate (ECG/EKG), and mixed (multiple signals). Mixed signals involve any of the other four categories used in the same context. The challenges section will cover the limitations mentioned in each paper, these are important since they provide a foundation for future research to improve the lacking characteristics of current work. There were two special cases: no challenges provided and implicit challenges. As for the first one, papers that did not include any explicit or implicit challenges were classified separately. The latter required paraphrasing using future work and results details to classify the challenges. Finally, a list of such problems in each paper was created and abstracted to a total of 22 categories, each with a count resembling the times they were identified as a limitation. The section provides statistical data on papers and their contents allowing for better visualizations of the current state of the field.

V. ANALYSIS

A. Publication Overview

The results of this review show that this research field is currently undeveloped. There is enough work to understand its significance and potential, however, there is room for improvement and expansion. After the review, the final selection of papers was a total of thirty (30) relevant articles published between 2014–2019. After analysis, there is a steady publication increase. Refer to Table II to see an overview of these results. From 2014 to 2015, there were three times as

TABLE III
REVIEWED PAPERS PUBLISHED PER DATABASE

Database	Article(s)	Count	Percent
ACM	[29], [38], [47], [43], [30], [39], [40], [31], [48], [49], [32], [33]	12	40.00%
IEEE	[44], [45], [27], [34], [46], [50], [51], [52], [41], [42]	10	33.33%
Springer	[4], [35], [36], [53], [54]	5	16.67%
Elsevier	[55], [37], [28]	3	10.00%
Taylor & Francis	N/A	0	0.00%

many publications, thirty percent (30%) of papers reviewed were published that year. Then, 2016 and 2017 showed a slowdown, but it maintained the count from the first year (three papers). During 2018, the count went up (seven; 23%) and it seems to be consistent going into 2019 (two; 6%), taking into account that the year had not ended and the typical conference/journal publication time cycles. The publication numbers from the past five years show a clear increase in research work in the area.

The papers were also analyzed in terms of their publishers, publication venues, and publication types. The publishers refer to the databases used in this review: ACM, IEEE Xplore, Springer, Elsevier, and Taylor & Francis. Please see Table III for an overview of papers published in each database. Most of the published work in this area can be found in the ACM DL (twelve; 40%). IEEE Xplore had ten (33%) of the reviewed articles. Furthermore, Springer and Elsevier contained multiple articles between them (five and three, respectively) whereas Taylor & Francis did not provide any papers compliant with the selection criteria.

In addition, another important detail to explore is the conferences and journals in which the papers were published. This allows for easy detection of a community for the topic. In Table IV, an overview of results for conference publications can be seen. There is a tendency toward publication in ACM conferences based on human-computer interaction (HCI) such as the International Conference on Human-Computer Interactions with Mobile Devices and Services (MobileHCI), the International Conference on Multimodal Interaction (ICMI), and the Conference on Human Factors in Computing Systems (CHI). The most prominent of these is ICMI with five papers (16%) and the second with most publications is MobileHCI with four (13%). The rest of the venues include at most two publications, and the most prominent of them is IEEE. Most of these conferences discuss HCI work, as well as ubiquitous computing and educational systems. There is also a set of articles published in journals, a total of five (16% of the total count) in three venues. Refer to Table V for details on the papers and the venues. The venue with the most journal publications in this area is Elsevier in Computers & Education with three papers. The other two were IEEE and Springer with one article each.

B. Learning Contexts

This section discusses the trends and findings of physiological m-learning applications learning contexts. *Formal learning* contexts are defined as systems that allow students to make use of the technology inside the classroom in a strict environment [56]. An example of this is [41], where the exergames application is created to be used during class. *Informal learning* is defined as nonstructured learning not provided by an educational or training institution, taking place spontaneously, and without a mediator [56]. An example of this learning context is [33]. This system does not need students to be inside a classroom, nor is it for a specific class either, therefore the users can utilize the application anytime and anywhere. Finally, *nonformal learning* occurs in a planned but highly adaptable manner in institutions, organizations, and situations outside of classrooms [56]. This type of learning can be seen in papers dealing with MOOCs, [30], [39], [43]. These are applications that can be created for specific classes but are not mediated as strictly as formal learning applications.

1) Formal, Informal, and Nonformal Contexts: A detailed view of all results can be seen in Table VI and the publication trends can be visualized in Fig. 3. Papers that presented informal learning are the most dominant, with well over a third of the total reviewed items (twelve; 40%). Abdelrahman *et al.* [29] presents a concept for a mobile learning application that uses EEG data to improve educational experiences in museums and Chen *et al.* [52] shows a similar system to enhance learning and engagement of museum visitors using eye-tracking. Other general examples include Shimoda *et al.* [49], Schiavo *et al.* [33], and the architectural implementation from Apostolidis and Stylianidis [27]. Finally, some analysis and evaluations were focused on informal activities, such as the EEG-based measurement for learner's interests by Moldovan [46] and the study on student response to neurofeedback using resting stage EEG by Eroğlu *et al.* [50]. There seem to be spikes of informal learning research between the years 2015 and 2018. There were no informal learning contributions in 2016 and only one in 2017, but 2018 had a total of 6 papers out of 12 total (50%). Though it is not steady, taking into account the publishing timelines and pauses, there is a clear trend of informal learning in the field.

Nonformal learning environments were the second most prominent (11; 36%). A set of papers comprises the majority in this learning context due to its focus: Massive Open Online Courses (MOOCs). These are classified as nonformal since they do not require a physical presence, an institution, or strict guidelines. Still, they are structured and the student's motivation is completely intrinsic. Out of the total 11 papers that fall into the nonformal category, eight of them are related to MOOCs (73%) [39], [40], [43]. These papers include [31], [40], and [43] . However, other papers also discuss this type of setting, for example an application for learning physics while using eye gaze data presented by Chanijani *et al.* [38]. Also, systems that explore serious games using eye-tracking technology [36]. There are publications for this context from 2015 to 2018, with two straight years of constant contributions

TABLE IV
REVIEWED ARTICLES PUBLISHED IN CONFERENCES

Venue	Conference Name	Article(s)	Count
ACM	International Conference on Multimodal Interaction (ICMI)	[30], [39], [40], [31], [48]	5
ACM	International Conference on Human-Computer Interactions with Mobile Devices and Services (MobileHCI)	[29], [38], [47], [32]	4
IEEE	International Conference on Interactive Mobile Communication Technologies and Learning (IMCL)	[27], [34]	2
ACM	Conference on Human Factors in Computing Systems (CHI)	[43]	1
ACM	International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp)	[49]	1
ACM	International Conference on Mobile and Ubiquitous Multimedia (MUM)	[33]	1
IEEE	International Symposium on Computer-Based Medical Systems (CBMS)	[44]	1
IEEE	Conference on e-Learning, e-Management and e-Services (IC3e)	[45]	1
IEEE	International Conference on Advanced Learning Technologies (ICALT)	[46]	1
IEEE	Medical Technologies National Congress (TIPTEKNO)	[50]	1
IEEE	Signal Processing and Communications Applications Conference (SIU)	[51]	1
IEEE	International Conference on Multimedia & Expo Workshops (ICMEW)	[52]	1
IEEE	International Conference on Cognitive InfoCommunications (CogInfoCom)	[42]	1
Springer	International Conference on Artificial Intelligence in Education (AIED)	[35]	1
Springer	International Conference on Mobile and Contextual Learning (mLearn)	[36]	1
Springer	International Conference on Intelligent Tutoring Systems (ITS)	[53]	1
Springer	European Conference on Computer Vision (ECCV)	[54]	1

TABLE V
REVIEWED ARTICLES PUBLISHED IN JOURNALS

Venue	Journal Name	Article(s)	Count
Elsevier	Computers & Education	[55], [37], [28]	3
IEEE	Transactions on Learning Technologies (TLT)	[41]	1
Springer	Universities and Knowledge Society Journal (RUSC)	[4]	1

TABLE VI
LEARNING CONTEXTS USED IN EACH SYSTEM CONTRIBUTING ARTICLE

Learning Contexts per Article	
Context	**Article(s)**
Informal	[29], [47], [49], [32], [33], [27], [34], [46], [50], [51], [52], [54]
Non-Formal	[38], [43], [30], [39], [40], [31], [48], [42], [35], [36], [53]
Formal	[44], [45], [41], [37], [28]
All Contexts	[4], [55]

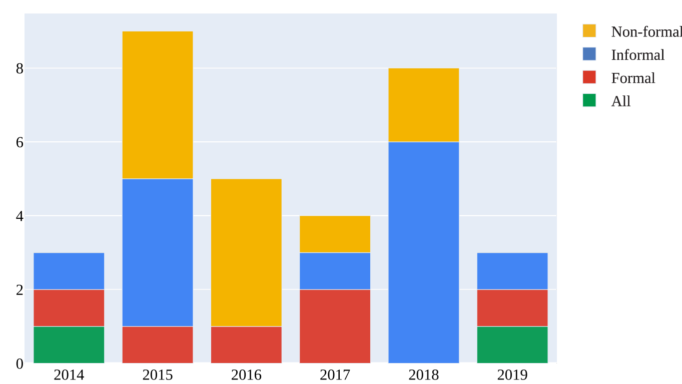

Fig. 3. Learning contexts publications throughout the years.

(2015 and 2016). These two years seem to be where nonformal approaches became apparent as an option for physiological m-learning. The publications started slowing down after 2016, with only one in 2017 and two in 2018, however, in general there is a trend for consistent contributions in the nonformal learning context.

Formal learning was found in almost a fifth of the reviewed literature (five papers; 16%). This learning context is explored on a smaller number of papers, a possibility for this is the medium in which the systems are being developed: mobile. Due to the nature of such ubiquitous experiences, the surest thing is that students would like to access information anywhere and anytime. However, this does not mean that formal learning happens strictly in physical classrooms, but the structure and academic influences require more specific interactions from the user. Siouli *et al.* [44] present the evaluation of an application for an elementary school class and Lindberg *et al.* [41] also explore a mobile board game to enhance physical education exergames. The formal learning context is also present consistently throughout the years, but with fewer amounts of publications having contributions from 2014 to 2019, excluding 2018. This shows how much work is being put into the context, but also demonstrating how hard it becomes to research such systems due to the need for strict classroom environments. This can slow down the process, and the amounts of articles dealing with formal contexts make it apparent since the only year with more than one contribution is 2017 (with two). Nonetheless, this is still an important area

TABLE VII
PEDAGOGICAL APPROACHES IN EACH OF THE CONTRIBUTING ARTICLES

Pedagogical Approaches per Article		
Approach	**Article(s)**	**Count**
Video Lectures	[43], [30], [39], [40], [31], [48], [49], [35], [53]	9
Game-based learning	[45], [27], [34], [46], [41], [36], [54]	7
Adaptive/Intervening Experience	[39], [40], [31], [48], [35]	5
Real World Interactive Experiences	[29], [32], [52], [41]	4
Traditional (Reading, Exams, etc.)	[57], [44]	2
Traditional Problem-Solving	[38]	1
Interactive App	[51]	1

of the field, and research could improve the current limitations involved.

Finally, two reviews discuss all three contexts due to their extensive studies exploring various implementations. First, a systematic literature review [55], and second a review for mobile learning applications and their future [4] (two papers; 7%). This review contains many systems, therefore, it represents the possibility of applications that target a combination of all learning contexts in the future. This category only has a total of two articles in 2014 and 2019.

2) Pedagogical Approaches: The results (Table VII) showed many different approaches to the learning activities. In this literature review, pedagogy refers to the teaching techniques applied to enable the acquisition of knowledge, skills, attitudes, and more [58]. Moreover, the types of approaches we present are referring to the methods in which information is transmitted to the learner, and the goal is to understand the many techniques applied in the studies. The most prominent approach is video lectures (nine; 30%), which correlates with the amount of articles that focus on MOOCs. The second most applied pedagogical strategy is game-based learning (seven; 23%), which is very popular in the educational field in general. These include gamified systems as well as interactive games. In education, a popular pedagogical technique is cooperative learning, and in this literature review there was one article that explicitly states the integration of both game-based and cooperative learning [41]. The other popular approaches are adaptive/intervening experiences (five; 17%) and real-world interactive experiences (four; 13%). The first involves adaptive user interfaces and interventions during the learning experience. For example, the authors in [40] detect disengagement and presents an intervening message. The real-world interactive experiences involve real objects mixed with the digital activities. Some examples include [29] and [52]. Finally, there are traditional skills (two; 7%) which involve reading and other examination techniques, traditional problem-solving (one; 3%), and interactive apps (one; 3%).

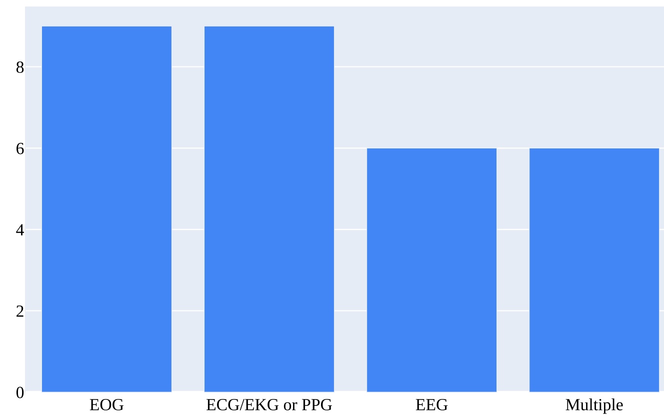

Fig. 4. Visual representation of physiological signal types used in the reviewed research.

C. Physiological Computing

This section analyzes all the physiological signal types and statistically represent their publication trends (see Fig. 4). The most dominant physiological signals used in mobile environments are EEG and eye-tracking (six and nine papers; 20% and 30%, respectively). First, papers that involve the use of EEG are Abdelrahman *et al.* [29] where the signals are used to detect engagement on museum learning activities, Shimoda *et al.* [49] where the user's state is detected to dynamically change the learning path and Eroğlu *et al.* [51] where the data are used to improve the cognitive functions of dyslexic children. Most of these are mobile-based in concept, however, they are missing completely ubiquitous implementations and they mostly mention it as future work. Second, papers that involve the use of eye-tracking (also known as EOG) are Chanijani *et al.* [38] where the signals are used in a physics learning application to analyze the user's preferences, Schiavo and Mana [33] use eye-tracking along with speech synthesis to adapt to the reader's pace and Juin *et al.* [45] provide suitable parameters for measuring learnability in mobile-game-based learning activities.

Heart rate signals are the third most used in the set of papers (nine; 30%). Pham and Wang [35] uses heart rate signals on unmodified smartphones to predict mind wandering events during MOOC sessions and follow-up quizzes, Lindberg *et al.* [41] use the signals to detect user activity during a mobile board game in a physical education setting and Xiao *et al.* [31] implement the signals to monitor user state during mobile MOOCs. Moreover, PPGs are also used as a method to capture heart rate physiological signals, the type was included in the count for heart rate (nine; 30%). Xiao *et al.* [43] use these signals to capture user disengagement in a mobile MOOC system, and Pham and Wang [59] combine the PPG signals with clickstreams and facial expressions to personalize reviews on mobile MOOCs. Finally, the rest of the papers involve multiple signals such as EEG, EOG, ECG/EKG, and PPGs in a single application (six; 20%).

1) Physiological Devices: A key part of these systems is the physiological sensor, the hardware that captures the

TABLE VIII
PHYSIOLOGICAL DEVICES USED IN EACH SYSTEM CONTRIBUTING ARTICLE

Physiological Devices per Article					
Device Name	**Article(s)**	**Device / Sensor Cost**	**Accuracy**	**Software**	**Portability**
Mobile Device	[43], [30], [39], [40], [35], [53], [54]	No extra cost	Accurate using LivePulse algorithm with 3.9% mean rate error estimating heart rate in resting conditions [60].	Custom Integration	Portable (Unmodified Mobile Device)
Emotiv	[29], [46], [51]	$849.00	128-256 Hz / Dry and Wet Electrodes available [61]	Available Proprietary Software	Portable (WiFi and Blutetooth)
iView X REDn	[38]	Price must be requested	60 Hz / 0.4°offset	Custom Integration with Python / Available Proprietary Software	Hybrid Portability
Tobii X60	[49]	$29,000.00	60 Hz / 0.5°offset	Available Proprietary Software	Hybrid Portability
g.Nautilus	[49]	$24,000.00	250-500 Hz	/ Dry and Wet Electrodes	Not Portable
EyeTribe	[33]	Regular: $99.00 / Pro: $199.00	60 Hz / 0.5°offset	Open API and SDKs (C++, C#, and Java)	Hybrid Portability
ChipSip SiME Smart Glasses	[52]	$550.00	Sampling rate not found / $<$ 3.2°offset	Custom Integration	Portable
PPG Sensor	[52]	Standard Pricing: approx. $20.00	Attention Estimations: 82.2%	Custom Integration	Portable
Microsoft Band (Wearable Watch)	[41]	$200.00	Data Not Available	Custom Integration	Portable
Custom Device	[34]	Low-cost custom materials (e.g. ARDUINO)	10 Hz	Custom Integration (Java)	Portable

necessary signals to analyze. Multiple systems in the field use different types of devices for different types of signals. Moreover, many signals can also share numerous types of sensors. To understand the state-of-the-art devices and trends for these in the field, the review explored the sensors used in each of the system contributing articles (see Table VIII). There are many factors to consider when selecting a sensor for mobile learning applications, therefore our analysis explored device costs, accuracy, software availability, and portability. Sensor costs for each device were compiled, for some the price was not publicly available, others did not require additional purchases (e.g., unmodified mobile devices). The accuracy column provides standard hardware specifications that determine how accurately the signals can be captured. EEG device accuracy can be established based on the sampling rate, electrode count/placement, and electrode types (wet or dry, both can be accurate with recent advances but wet usually provide more reliable data [62]). In this review, we decided to use sampling rate and electrode types, since electrode count or placement can vary based on the study and desired classifications. However, for some of the devices (e.g., mobile devices and custom hardware) the specifications had to be presented in terms of the reported results. Software availability is a necessary guide to understand if each device has supported APIs or SDKs. Finally, portability allows an understanding of how a device can be utilized in a ubiquitous environment, when it is classified as *Portable,* the device can be used comfortably anywhere, a *Hybrid Portability* means that the device could be integrated in a portable manner (e.g., an eye tracking camera attached to a custom tablet device), and a *Not Portable* classification would deem the device as difficult to carry and use anywhere.

A notable trend is the use of mobile devices as the primary physiological devices, with seven out of the sixteen system contributing articles (44%) employing this technique. This seems counter-intuitive since the understanding of physiological computing is that there is a need for a sensor to capture such signals. However, it does not only align with the needs of novel techniques for signal capturing, but it does specifically fit into mobile environments. Having ubiquitous applications, users must consider the use of third-party hardware. That is not only tedious for the user but also expensive. Therefore, the trend of novel approaches to capture physiological signals through the mobile device itself is not surprising but rather expected and important for the future of the field.

Some of the articles that experiment with this type of signal capturing include work from Pham, Wang, and Xiao in their MOOC applications using heart rate data (PPG) [35], [39], [40], [53]. The authors present systems that leverage the smartphone camera to capture images from the user's finger and use blood flow changes through the skin to calculate heart rate. The technique is based on their LivePulse algorithm [60], which minimizes noise by skipping the first and last thirty (30) seconds of captured data. This way the authors can extract many dimensions from the features, including average heart rate, temporal standard deviations of heartbeats, root mean squares of successive differences, and more [60]. This is not the only attempt to using mobile device sensors as physiological input methods since articles like [54] have presented the use of the smartphone front camera to record and recognize eye gaze and face data. This can replace expensive and inaccessible equipment that is normally required for eye-tracking technology, such as those used in [49] and [52]. The rest of the articles explore using different devices for their respective signals, the Emotiv headset being the second most prominent behind mobile devices (three papers; 19%), and the remaining eight devices tied with one article each (6%, respectively).

2) Physiological Signals: The signals are another important part of the process. They are used to analyze the user's physiological information, and they must be manipulated in the correct way to achieve the final goal. Some signals by themselves might provide more information than others, whereas in other cases there is a need for multiple data sources. As seen in Fig. 4 and discussed in the introduction to this section, the most prominent signals in the field are EOG (eye-tracking) and ECG/EKG/PPG (heart rate) with nine papers (30%) each. To understand this trend, this section will explore multiple articles and their purposes. Articles that implement eye-tracking technology include [32], [33], [36], [38], [45], [47], [49], [52], [54]. In [54], the system has the purpose of detecting and classifying the user's knowledgeability while using an m-learning application. The attempt to do so involves recording eye gaze and facial expressions, therefore using eye-tracking technology but without third-party hardware. The authors in [47] present a system that uses eye gaze data to understand the competence of the user in the current topic. This is a very similar concept from the previous paper, however, the authors use additional hardware to achieve their goal along with a tablet. The rest of the articles have very similar structures, all leveraging eye gaze data for the understanding of a user's interests and eventually their comprehension of presented topics. The main takeaway from this type of implementation is that eye gaze data are one of the easiest types of physiological information to capture without third-party hardware in mobile environments. Through the use of smartphone cameras, these signals can be acquired seamlessly. Moreover, the second most prominent, heart rate signals can be obtained through novel techniques presented by some articles [35], [39], [40], and [53], using the smartphone camera to analyze PPG data. The trend is clear to favor those signals easiest to capture without the need for additional hardware. Not only that, but they make for a better overall experience.

Other articles explore the use of other signals such as EEG. In the case of EEG, all of the systems rely on the use of external hardware to achieve their goals. Articles that implement these devices in their research include [28], [29], [44], [46], [50], [51], with a total of six papers (20%). In [29], the system presented uses an Emotiv headset to capture EEG signals. The Emotiv is a popular choice for applications involving this type of physiological data, because of its reliability and software support. In the same vein, [46], [51] present systems that use the same headset for EEG data processing and even classification. These signals provide the ability to detect engagement, boredom, interest, anxiety, and more. These articles all have a common problem that is natural to EEG signals in general: noise. Electrical signals from the brain depend on the user's entire body activity, and in ubiquitous environments, these can become noisy. This happens since these signals capture everything, and if the researcher is interested in engagement alone it becomes difficult to filter mostly whenever physical actions are present. This is not a problem with eye-tracking and PPG through smartphone sensors, even though those have their downsides: signal quality. Finally, articles also explore the use of multiple sensors at once, with six papers (20%) doing so in the literature. This can help increase efficiency and possibly fix some of the limitations introduced by single signals. Most of the research involving multiple signals are reviews, such as [4], [37], [55]. However, others introduce systems that explore the use of multiple signals [27], [34]. These introduce the use of galvanic skin response (GSR), HR, and temperature (TEMP) all in one to analyze the user's state. In [27], the system wants to try and regulate anxiety levels during the activities and this can be achieved if the user is closely monitored. That goal is achieved through the multiple signals, where all three provide insightful information about the desired feeling: anxiety. This is a small research area in the field, with only six papers (three being reviews) that explore the use of multiple signals.

3) Classification: This section will discuss the different classifications used in the system contributing articles. This is due to the nature of these papers, which is that they have employed the classifications whereas others evaluated or reviewed them. There are many different types of classifications based on the physiological signals used. A set of categories for classifications was compiled from the literature: affective states, eye gaze data, attention levels, exercise efficiency, and wellness of the brain. Each of these contains many subcategories that represent specific information from the user. An example of affective states is boredom, whenever a user feels bored the physiological data can provide the information on that state. These will be detailed along with their corresponding article(s) as follows.

1) *Affective States:* A set of possible emotions that the user could present during the activity.
   a) *Engagement and disengagement:* It is normally classified using EEG data and a widely known formula presented by [29]. This type of classification can help detect attention levels. Articles applying engagement metrics include [29] with no accuracy results, [52] with detection accuracy of 82.2%, and [40] with a best engagement predictive accuracy of 76.85% using PPG signals outperforming their EEG-based method.
   b) *Confusion:* This affective state is also classified through multiple types of signals, in the literature normally through PPG and EEG. Articles applying confusion metrics include [30] with confusion

predictive accuracy of 81.96% and [53] with predictive accuracy of 74.4% overall (78.2% with PPG, 88.5% with FEA, and 84.6% with feature fusion).

c) *Boredom:* The boredom affective state can be detected with multiple types of signals, in this literature review it is apparent that most implementations use PPG. Articles applying boredom classification include [30] with the highest predictive accuracy of 78.56%, [40] with a best disengagement/boredom predictive accuracy of 68.33%, and [53] with an overall predictive accuracy of 70.5% (78.2% using PPG, 84.6% using FEA, and 83.3% using feature fusion).

d) *Frustration:* The frustration affective state would be detected using PPG in most of the literature. An article that classifies frustration data is [53] with an overall predictive accuracy of 78.2% (80.8% using PPG, 91.0% using FEA, and 91.0% using feature fusion).

e) *Concentration:* This affective state can be detected using EEG, per the literature in this review. Articles classifying this state include [49] which does not report accuracy data.

f) *Anxiety:* The affective state of anxiety can be detected using a variety of signals such as GSR, HR, and TEMP; per the literature in this review. Articles classifying this type of affective state include [34] with no reported accuracy results.

2) *Eye Gaze Data:* This represents the use of eye-tracking technology to detect the user's eye gaze on the system. It uses EOG or other details from the eye coordinates to achieve the data estimation. Articles including this type of classification include [38] compared novices to experts during a learning activity and used eye gaze data to analyze the participant competence while solving each problem, [49] used the participant looking away as the state of *distracted* which became input for the EEG classifier, [33] utilized eye gaze data as coordinates for the group of words that the TTS would read, and [52] implements eye data as part of the system to achieve visual focus point estimations with a view angle deviation of less than 3.2° and point-of-interest detection of up to 87.3%.

3) *Attention Levels:* This classification represents the user's level of attention to a specific activity. Normally detected using PPG, EOG, or EEG. Articles classifying attention levels include [43] which detected divided attention using PPG signals and achieved accuracies ranging from 50% (four different categories) to 83.3% (two mixed categories, e.g., full attention and external divided attention vs. low internal and high internal divided attention), [35] detected mind wandering events with a highest accuracy of 71.22% using PPG signals and a KNN classifier, and [54] used eye gaze data to predict knowledgeability and possible correct answers from a user with a 59.1% accuracy using SVM.

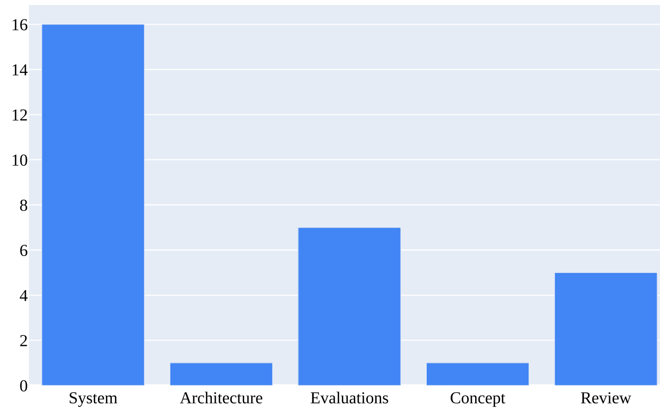

Fig. 5. Contributions types from the relevant papers in the field.

4) *Exercise Efficiency:* This is not a common type of classification in the physiological computing field. However, in the literature, a specific implementation [41] uses the data to detect student exercise efficiency during the learning activity in a PE class. This is done through heart rate sensing and no accuracy results were reported. The article considered previous studies to use heart rate as input for exercise efficiency calculations but they were not able to apply them due to many limitations (student ages, physical activity, etc.).

5) *Wellness of the Brain:* This is also a rare classification in the physiological computing field. In the literature, [51] leverages complexity/entropy, coherence, and relative Alpha bands from EEG data for the classification of wellness of the brain. However, no predictive accuracy results were reported.

There is a focus on the classification of affective states. The trend is clear in articles using different signals to perform classification, some using PPG, others EEG, and a few implement multiple signals (GSR, HR, TEMP). For articles using affective states in their applications, out of the 16 system contributing papers, they are the most prominent (nine; 56%). The second most common implementation is the eye gaze data classification (four; 25%). A close third is the classification of attention levels (three; 19%), fourth is a tie between exercise efficiency and the wellness of the brain (one each; 6%).

D. Contributions

A visual representation of paper contributions can be seen in Fig. 5. System implementation refers to those papers that created an original application as a solution to their stated problem. Architectural designs are papers that do not necessarily implement a system, but they provide a reproducible design for the application. A review includes all papers that gather knowledge from existing publications to discuss and synthesize the information. Evaluations are papers that focus on the assessment of systems and designs, they provide insights on the process from the setup to the results and their analysis. Finally, concepts are papers that do not provide insight on implementation or design, their focus is to propose an idea to tackle a presented problem.

TABLE IX
ARCHITECTURE COMPONENTS INCLUDED AND EXCLUDED FROM EACH SYSTEM CONTRIBUTING ARTICLE

Architecture Components per Article							
Article(s)	**Device**	**Signals**	**Intermediary SP**	**Mobile SP**	**Classification**	**Feedback**	**Analysis**
[29]	✓	✓	✓	✗	✓	✓	✗
[39], [40], [33], [51]	✓	✓	✗	✓	✓	✓	✗
[34]	✓	✓	✓	✓	✓	✓	✗
[46]	✓	✓	✓	✗	✓	✗	✓
[38], [43], [30], [52], [35], [36], [53]	✓	✓	✗	✓	✓	✗	✓
[41]	✓	✓	✓	✓	✓	✗	✓

First of all, articles that present architectural designs (one paper; 3%). Apostolidis [27] proposed an architecture for the implementation of biofeedback devices and mobile phones in learning activities for stress tracking. Second, system implementations were presented by the majority of the reviewed papers (sixteen; 53%). Schiavo and Mana [33] present an application using speech synthesis and eye-tracking to match the synthesized voice to a user's reading pace, Eroğlu *et al.* [51] proposed a system aimed at improving cognitive functions of dyslexic children, moreover, Pham and Wang [53], [59], and Xiao *et al.* [31] present many systems using different physiological signals [photoplethysmogram (PPG), heart rate] to implement better experiences in MOOCs by predicting learning outcomes. Third, a group of review papers was found (five papers; 16%). Blignaut [36] presents a systematic literature review on the use of eye-tracking when evaluating serious games for user learning experiences and Khamis [47] reviewed eye-tracking feasibility in handheld mobile devices. Fourth and finally, evaluations and analysis were found to be the second most dominant set of papers (seven; 23%). In this case, Siouli *et al.* [44] evaluate AffectureApp to find whether or not emotions and academic performances are related and Moldovan *et al.* [46] show an analysis on measurements of EEG devices, learner's interests, and (QoE) on mobile learning environments.

1) System Architecture Designs: After a thorough analysis of each system contribution, many similar core components were identified. These represent the state-of-the-art for a physiological-based mobile educational system, including variants of the same architecture depending on the use and compatibility issues, and we recommend following the core design of these applications. The main components are physiological sensor, physiological data, signal processor *(mobile or intermediary)*, classification, and either feedback or analysis. There are two components that can vary: signal processor (SP) and the analysis or feedback. The first refers to the device that receives and manages the raw physiological signals, processing these for later classification. The latter is the final step in the architecture, where the classification information is either used in real-time to adapt the experience (feedback) or it is stored and analyzed for use in future sessions (analysis). See Table IX for details on each paper with their system's components. Only one article, [49] did not provide details for their intermediary SP or mobile SP and was not included in the table.

In the reviewed literature, a total of two articles out of the sixteen system contributing papers (13%) exclusively used intermediary signal processors. In contrast, there were 11 out of the 16 (69%) that exclusively implemented mobile signal processors. Only two applied a hybrid system with both mobile and intermediary SPs (13%) and one did not provide details on their signal processor. Out of the 16 system contributing articles, a total of 10 (56%) applied the analysis component, including [49] that was excluded from the table due to its lack of information on signal processors. Finally, a total of six papers (38%) implemented the feedback component.

2) Evaluation and Analysis Methods: Another finding in the literature is the evaluation and analysis methods used in previous studies. This compliments system designs because feedback and analysis result in the fundamental understanding of individual components. Those results allow researchers to effectively and efficiently measure the performance from their system and how users respond to their experience. The literature shows that many studies focus on different methods, some applying classic techniques and others leveraging the physiological information to extract useful features. Table X presents the articles using each of the categorized methodologies. The identified categories will be listed and defined as follows.

1) *Subjective Feedback:* This category refers to the use of surveys, quizzes, or other classic methods of acquiring information directly from the user about their experience and/or knowledge gains.
2) *PPG Data, EEG Data, Eye-Tracking Data, Heart Rate Data, Face Expression Analysis Data:* This category refers to the use of any of the physiological signals (EEG, PPG, ECG/EKG, EOG, etc.,) to classify and analyze the user's experience and/or knowledge gains during the learning activity.
3) *Subjective Feedback and Physiological Data:* The category aims at those articles that utilize both classic techniques and the acquired physiological data to compliment each other and conclude on the user's experience and/or knowledge gains.

TABLE X
EVALUATION AND ANALYSIS METHODS USED IN EACH REVIEWED ARTICLE

Evaluation and Analysis Methods per Article		
Method(s)	**Article(s)**	**Count**
Subjective Feedback	[29], [43], [30], [39], [40], [31], [48], [44], [27], [46], [41], [53]	12
Subjective Feedback + Physiological Data	[29], [43], [30], [39], [40], [31], [48], [46], [41], [53]	10
No Evaluation	[47], [32], [33], [34], [42], [4], [36], [55], [37], [28]	10
PPG Data	[43], [30], [39], [31], [48], [35], [53]	7
EEG Data	[29], [40], [49], [46], [50], [51]	6
Eye-Tracking Data	[38], [52], [54]	3
Eye-Tracking Parameters	[45]	1
Heart Rate Data	[41]	1
Face Expression Analysis Data	[53]	1

4) *Eye-tracking Parameters:* The category was created specifically for one article that, instead of evaluating a system, contributed a set of parameters proven useful for eye-tracking analysis [45].
5) *No Evaluation:* The category serves as a way to identify articles that did not contribute any details or did not conduct studies directly evaluating a system.

There are trends in the literature showing the usefulness of subjective feedback by itself. A total of 12 papers (40%) used the technique during their studies. These papers explore the user's perception of the overall experience while also analyzing the learning gains through every individual's responses. Other articles tend to leverage the physiological information to detect and classify specific features to indicate user experience during each learning activity. These also explore the classification of either learning gains or competence for topics. The articles falling under these categories (PPG, EEG, eye-tracking, heart rate, and FEA data) represent a total of 18 papers (60%), with the most prominent data type being PPG (seven papers out of eighteen; 39%). Nonetheless, most of these articles employed both subjective feedback and physiological data in their studies, as a mixture of techniques that seems to be very effective for analysis purposes. Therefore, another category was created to cover these papers, and there are ten (33%) that leverage both subjective feedback with different types of physiological information to evaluate their systems. One article was specifically contributing parameters that were proven effective for evaluation of systems using eye-tracking technology, and it is listed under its own category eye-tracking parameters [45]. There are multiple data types to detect and classify to understand what the user is experiencing during these activities, and those were explored in Section V-C.

E. Challenges

This section will discuss the challenges mentioned in each paper, these are important since they provide insights for future physiological-based m-learning research. Challenges were identified thoroughly, each publication was read and every mentioned drawback was included. There were two special cases: no challenges provided and implicit challenges. As for the first one, papers that did not include any explicit or implicit challenges were classified separately. The latter required paraphrasing using future work and results from the articles to classify the challenges. Finally, a list of such problems in each paper was created and abstracted to a total of 22 categories, each with a count resembling the times they were identified as a limitation.

To discuss the retrieved list of challenges, the top ten were: no issues specified (eleven), environment (six), personal and aggregated learning events (four), physiological data management and visualizations (four), equipment (four), nonreal-time feedback (three), security/privacy (three), varying engagement (two), mobile implementation (two) and lack of adaptiveness (two). For an overview of such results, please refer to Table XI. As seen in the list, 11 papers (34%) did not explicitly or implicitly provide challenges to their research work. However, six papers (19%) mentioned the environment as their main issue. This is due to the nature of such implementations, where ubiquitous devices allow users to use the applications anytime and anywhere. It is also difficult to simulate environments for studies since there are many different possibilities for students to use the apps. Moreover, the set of challenges including personal and aggregated learning events, physiological data management and visualizations, and equipment were all mentioned in four papers (13%). Personal learning events can provide better learning outcomes since students are heavily influenced by their experiences, this data can be difficult to capture but would prove more than helpful in studies like these. Also, physiological data are invisible to the user and this could cause confusion during the use of an application. The management and visualization of such data provide important feedback that users can use to perform accordingly during the learning experience. Equipment is a big concern in the mobile setting since wearable devices are expensive, could be uncomfortable if not carefully considered and it brings possible technical faults to the process.

Also, nonreal-time feedback and security/privacy were mentioned in three papers (9%). Most applications in this literature review had an issue with real-time feedback. This is expected due to the processing time and nature of some physiological signals (e.g., EEG) that require an amount of time to provide clear patterns. Other systems encountered users that were particular about their privacy and security. This was a problem mostly with eye-tracking applications, that would need to use the camera to see a person's face and classify different states. Finally, the top ten concludes with varying engagement, mobile implementation, and lack of adaptiveness; all mentioned in two papers (6%). The problem with

TABLE XI
CHALLENGES PRESENTED BY THE AUTHORS IN THE REVIEWED PAPERS

Category	Count	Article(s)	Description
No issues specified	11	[31], [32], [33], [45], [50], [51], [42], [4], [35], [36], [53]	N/A
Environment	6	[29], [30], [48], [28], [55], [44]	Students use the m-learning application with EEG devices in public spaces, increasing noise and, therefore, inaccuracy.
Personal and Aggregated Events	4	[30], [44], [41], [43]	Applications use the physiological information without leveraging personal and contextual information from the user to improve accuracy.
Physiological Data Management and Visualizations	4	[30], [48], [34], [41]	Applications do not provide users with useful visualizations of their physiological data and do not use the data to its full potential (e.g. adaptiveness).
Equipment	4	[27], [41], [55], [28]	Applications require third-party hardware (physiological devices, computers) to function, increasing the cost, discomfort, and inconvenience of the system.
Non-Real-Time Feedback	3	[29], [39], [40]	Applications gather and analyze physiological information but do not have the capacity to use it in real-time for the enhancement of the learning experience.
Security/Privacy	3	[55], [30], [41]	Some applications might employ the capturing of finger and eye data (such as [30], [39], [54]) can worry users about their privacy and security.
Varying Engagement	2	[29], [55]	Applications using EEG data are subject to the nature of humans varying in their engagement from day to day, sometimes multiple times per day.
Mobile Implementation	2	[29], [27]	Some applications heavily depend on the use of additional computers or, as defined in this review, intermediary signal processors. Most of these are due to difficulties with compatibility and limited software availability.
Lack of Adaptiveness	2	[38], [40]	Applications that do not use the physiological data to adapt the applications for better learning experiences.

varying engagement measures is being replicated in the mobile learning setting. Moreover, another issue is the implementation process on mobile devices using such physiological devices. This implies new hardware and possible compatibility issues between devices that could become a major limitation in most designs. Last, the lack of adaptiveness is a drawback for some papers. A possible relation with the real-time feedback limitation, adaptiveness is important since users expect instant replies from the system to improve as they go instead of waiting until they are finished to get an assessment on their performance.

Finally, the remaining 12 challenges are as follows: state classification (2), user-independent classification (2), UI/System functionality (2), lack of interactivity (1), fatigue (1), competitiveness versus cooperativeness (1), long-term versus short-term evaluations (1), small population (1), multiple inputs for effectiveness improvements (1), pre and postdata comparisons (1), engagement self-reporting (1), and data analysis for student anxiety (1). Most of these target the topic of finding more data and better managing it to perform better at specific implementations. Others focus on the evaluations for these systems, such as long-term versus short-term and pre and postdata comparisons. However, challenges such as user-independent classification, lack of interactivity, and state classification provide interesting takes on possible future work in the mobile learning realm that can drastically change current designs.

VI. DISCUSSION

This literature review presents a total of 30 papers that discuss the topic of physiological-based mobile educational systems. This section will explore the information provided by the reviewed articles, answering the proposed research questions (RQs) through the synthesis of all the papers. Most of the reviewed system designs use smartphones as their main device [30], [41], [43], [46], [59], but there are cases where the researchers also include a tablet to evaluate the difference between both mobile environments [46]. The interfaces created for most applications are simple, there is mostly static content (text, images, and videos) and straightforward interactivity. For example, in [30], [43], and [59], the type of interactivity involves users going through lectures and possibly answering short quizzes. Nevertheless, in [41], a mobile game incorporates students playing the game both on their phones and in-person. Therefore, interactivity is much higher compared to the other applications which only require linear actions. As defined earlier in this review, the goal of m-learning is to enhance learning through interactions with mobile applications [3], and after this analysis, it is clear that more dynamic environments improve the value of such systems. This analysis provides an understanding of the types of systems and their contributions to the field, answering RQ2 and RQ3.

A. M-Learning Systems

The most dominant type of physiological-based m-learning applications is MOOCs. Dr. Jingtao Wang leads a laboratory on mobile educational systems, with extensive work on MOOCs, which represent 8 (27%) out of the 30 articles in this review. Existing literature shows mostly positive reactions to the usability of these applications [30]. The interaction is straightforward, the content is adequately shown, and users showed learning improvements [30], [43], [59]. Still, these implementations exhibit the same problem mentioned earlier: lack of interactivity. MOOCs are effective and useful in most cases, but they could integrate dynamic activities to enhance student learning experiences. This analysis allows for an understanding of the current state-of-the-art systems, contributing to the overall answer to RQ2 and RQ3.

In the current literature, there is minimal discussion on pedagogical approaches. Some articles implicitly employ specific techniques such as [41] with collaboration and [27] with game-based learning. However, the lack of discussion of pedagogical approaches is a current limitation in the field. Therefore, this review focused on the learning contexts of each article, which, due to the abundance of MOOCs, lean toward nonformal environments. There are few formal learning contexts, with informal and nonformal showing dominance throughout the years. This helps answer RQ1, providing an understanding of the current learning context trends. The analysis presents the abundant use of subjective feedback as an evaluation method, but many papers implement physiological data into their results to either strictly determine the student's performance or to contrast with the provided feedback. There are different approaches to evaluate these systems, current research leans toward the use of both surveys (for subjective information) and the captured physiological data to understand the learning experience from the user. This information contributes to the answer of RQ4, identifying the trends of current evaluation techniques in the research area. Furthermore, these applications introduce an important component: physiological computing.

B. Physiological Computing in M-Learning Systems

There are various types of physiological signals and many ways to collect the data. In a ubiquitous setting, many challenges could arise while integrating these features. First of all, the most common signal used was heart rate [30], [41], [43], [59]. Tied with eye-tracking, which was also used in most of the reviewed articles [33], [38], [45], [54]. They are both widely used in mobile because of the many ways to capture the signals. Nowadays smartphones, and wearables (smartwatches) include sensors that detect heart rate; therefore it is not necessary to add any external devices. These signals are captured through PPG, which is not as effective as ECG/EKG but it is still very useful. Moreover, if the smartphone does not have such sensors and there are no wearable available, the research presents methodologies using the camera to retrieve the heart rate signals [30], [43], [59]. Similarly, the eye-tracking glasses are some of the most comfortable hardware to

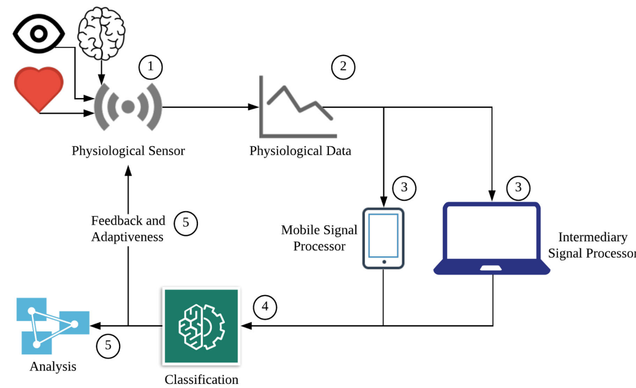

Fig. 6. Generic architecture design for physiological-based mobile educational systems.

interact in a ubiquitous environment. In general, it is very convenient to detect those signals in a mobile environment, and methods are being developed for easier, nonintrusive ways of doing so in the future.

There is also the use of EEG signals [46], and the trend is to analyze the data after the learning activities. However, this data could contribute more if it was utilized during the activities (real-time). An example would be to have adaptive user interfaces [35] or interventions [40], but the current literature explores these approaches in a limited manner. Most studies are exploring early technology, therefore their goal is to collect high quality data and perform predictive classifications with high accuracy. However, others explore the use of interventions during the educational experience [40], detecting user disengagement and presenting a feed-forward reminder catching the learner's attention. Another example is [59] where the application intervenes to present a topic review based on the user data during the video lectures. Moreover, there is a need for external devices to retrieve the EEG signals and most can be portable and accurate [46], but expensive. As consumer-grade EEG devices become more accurate (e.g., Muse headset), these implementations will become feasible. Using physiological signals also requires monitoring possible data perishability due to external factors such as caffeine intake and stress. During this review, only one article considered this as a variable during their study [42]. More studies need to include these stimulants to understand their effects during the learning experience since most students are in uncontrollable environments. This analysis helps answer RQ2 and RQ3 due to contributions made in terms of physiological computing and system architectures, which need to take into account the signals as an input to the application.

C. System Design Recommendations

This generic architecture serves as a guide to create systems adapting to specific needs and compatibility. Fig. 6 illustrates a design diagram including all of the components and their variations. However, they all have the same underlying components and purpose. Some systems might want to use devices that can require changes in their overall structure due to the lack of compatibility between the hardware and mobile devices. Therefore, such implementations would want to use an intermediary signal processor, either a computer or cloud service, to connect with the mobile device. In the case of [33], the system uses a tablet with a custom-mounted eye-tracking device called EyeTribe.[1] This device can directly transmit the necessary information to the device, it sends x and y coordinates of the user's eyesight on the screen. Since the application only needs that data to synthesize speech during reading activities, the architecture works well without an intermediary signal processor. However, other applications like [46] have presented the need for an external device as their signal processor. Here, the authors use a laptop to receive and analyze the data from the user instead of feeding it directly to the smartphone. They present the use of an Emotiv SDK[2] to process and classify affective states through their proprietary algorithms. This situation occurs in a few of the reviewed systems (five; 17%), but it can still become a concern with specific hardware.

The other variable component in the generic architecture is the analysis or feedback process. The application will continue to process its signals and classify the desired features, but the final step needs to determine what to do with the acquired information. The purpose of such applications is to improve the user experience during learning, and the reviewed literature shows two possibilities: analysis with future enhancements or feedback with real-time adaptiveness. The first refers to capturing the results and analyzing the data to improve the system and help the learners with their experience in future activities. The second is the real-time use of information to adapt the application while the user is learning. In [54], the application captures face and eye data to classify the user's reactions to the information and later classifying their knowledgeability. This information can be used to better adapt future implementations of the application depending on their physiological data. Therefore, this represents an architecture with the final step being an analysis. On the other hand, the authors in [39] contribute a system that detects, analyzes, and classifies the PPG signals of users learning in mobile MOOC courses to automatically provide them with reviews of the most difficult topic. This leverages the physiological data to instantly give users a better experience during their learning activity. This is an example of the architecture with a final step of feedback.

The final component in a physiological-based mobile learning application is the educational activity. The literature showed a myriad of pedagogical approaches. Research shows that video lectures are an effective, and easy to implement technique for mobile environments. However, the ubiquitous nature of these applications allows for opportunities to increase interactivity. For example, game-based learning is a big area in the field and some studies explored the use of real-world objects to increase the students' interests. Moreover, they can include other learners and integrate cooperation or competitiveness. Nonetheless, this generic system design allows for the exploration of more educational activities since there are no physical limitations. The addition of physiological data is useful to adapt or suggest content. Additionally, more intervention techniques can be explored to help students either maintain or increase their attention levels. Therefore, the educational component is open to many implementations, using all of the available components to create a more interactive and interesting experience for the learners.

[1] [Online]. Available: https://theeyetribe.com
[2] [Online]. Available: https://www.emotiv.com/

D. Challenges

Common challenges discussed in this topic include the aforementioned capturing and analysis of the physiological data. Heart rate signals are normally captured through PPG and EEG (requires external devices). The need for third-party hardware can become tedious for the learner since they would need to include extra weight and cost. Furthermore, it can also be a problem for the developer due to possible problems with hardware and software compatibility issues, proprietary licenses, and more. Nonetheless, this has inspired research on ways to create methods that allow for the capturing of the data through available devices. An example is the tangible video control interface from [30], [43], [59], in which users must use their finger to play/pause videos through the camera lens. They leverage PPG to capture the signals. In summary, more methods can be developed to further improve the usability and experiences of physiological-based mobile educational systems.

There are other important challenges found in the physiological computing area, including feedback and multimodal implementations. This review discussed systems that do not show users their current states, and it has been shown that such information is important for them to possibly adjust and understand how the current activity influences them during learning. One specific paper provides users with a view of the signals as they are being recorded [48], whereas from the others there are only two with a visual representation of the learner's state (blinking indicator showing important cognitive states). The other important finding is that papers in this review did not use multiple physiological signals in their systems. Each application utilized one type of data, either heart rate [30], [41], [43], or EEG [46], [59], but there is no discussion on the possibility of multimodal implementations. The use of multiple signals can improve results on the learning experiences, as well as predictions for those systems that rely on the data to classify different reactions from the user. This shows a lack of exploration for multimodal systems that can leverage many physiological attributes to better adapt to the learner. Challenges are explored in detail, and they help comprehend the current maturity of the systems presented in the research papers, including their evaluation methods and implementation limitations. Therefore, such analysis contributes to the answer to RQ4.

E. Future Directions

Physiological data can and has improved learning experiences and outcomes. As presented in most reviewed articles [30],

[33], [34], [43], [49], there are various ways to enhance the learner's performance. The use of such physiological data can show the needs or preferences of the user, in the case of [43] and [46], there is a need for adaptiveness to tackle the detected divided attention and interest levels. The application can change the type of activity to become more active (for uninterested learners) or passive (for overly excited learners) in real-time. There is a lack of exploration of interventions during these learning activities. The same applies to the use of the data to provide recommendations on topics to study for self-improvement [48]. Current implementations of recommendations use overall information on broad topics, and this can become better by focusing on the individual and their features. A common challenge is a generalized approach to teaching the material, and this can be refined through the adaptiveness to a user's preferences. Physiological information along with context can provide much insight into a learner's style. However, personalization is not the only necessary course of action, since aggregation demonstrated being a powerful piece of data. A user is influenced by their teacher and peers, therefore it is very useful to take into account how other learners are performing to correctly assess the current student. In summary, the user should be the centerpiece of such applications, through individual and general performances the system can adapt and recommend the user better content as it enhances their learning outcome.

Finally, physiological-based mobile educational systems need a deep understanding of the learner for effective knowledge transmission. There is a need for more interactive, dynamic applications that can provide content through various means. Evaluations for such applications should become longitudinal, instead of instant and fast studies where the student cannot effectively show progress. The physiological signals used can be expanded to other types, as background literature reveals possibilities for eye-tracking to be included in the spectrum. Not only this, but more methods to capture the signals are becoming available to eliminate third-party hardware. M-learning applications can provide customizable options for users to choose their preferred studying methods. Learners also have different motivations (intrinsic, extrinsic), and preferred peer interaction modes (cooperation and competition). Furthermore, the applications in this field must use inputs from physiological data, user preferences, and their contexts to fully adapt to their needs. The implementation of these systems should make the learner their most important component and, through the aforementioned methods, enhance their learning experiences for effective transmission of knowledge.

VII. Conclusion

This article presents a literature review of physiological-based mobile educational systems. Multiple research papers were selected through specified criteria, and then detailed analysis was provided to understand the current state of the field. The main discussion is on the state-of-the-art of the field as of the present day. In this section, the focus is to define current solutions, along with information about topics stated as important during the statement of research questions. These include contributions, learning contexts, physiological signals, and challenges from every relevant paper in the field. All of the aforementioned data leading to a synthesis of the ideas and topics researched during the review.

There are many important findings to consider whenever discussing physiological-based mobile education. The field is in very early stages, which provides an opportunity to contribute in various ways. It was found that the dominant type of physiological m-learning applications was MOOCs. Which, even though proven effective in learning outcomes, are not known for many interaction-based activities. Therefore, there is a need for such adaptive applications that leverage physiological signals for interactivity. Another finding presents that the capture of the physiological signals in mobile environments is a prominent research area due to the difficulties that it entails. Such ubiquitous applications make the use of external devices an uncomfortable task. Moreover, these signals are a useful resource to detect and classify a learner's state, thus providing possibilities for personalized systems. The use of this data has not been used to its full potential, and it can become the main tool for better, adaptive learning applications. In general, there is a potential left to uncover inside physiological data for mobile educational systems, such as predictions, adaptiveness, multimodal implementations, aggregate recommendations, and more.

This literature review provides a basis for state-of-the-art research in this area. Educational applications can become a useful class resource, thanks to the rising market of smartphones. Furthermore, with the help of physiological computing, m-learning applications can start perceiving the learner's preferences to provide accurate information effectively. The field has the potential to bring students a tailored information source, which will fulfill their specific needs and improve their learning outcomes.

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