

IoT based Personalized Online Learning Systems (Systematic Mapping Study)*

Edlir Spaho¹ and Betim Çiço²

¹ Epoka University
Tirana, Vore 1032, Albania
espaho@epoka.edu.al

² Faculty of Architecture and Engineering
Tirana, Vore 1032, Albania
bcico@epoka.edu.al

Abstract. The Internet of Things (IoT) has found a wide application in different domains. One domain in which IoT has considerable impact is in Education. In this context, IoT plays an important role in obtaining information about the environment and actors in which the educational processes take place. This paper presents a systematic review of the literature identifying how IoT is integrated in Education to enhance personalization of online learning processes. To achieve this, we conducted an extensive mapping study analyzing the different techniques and methods used to integrate IoT in Education with particular focus on Personalized Online Learning (POL). Our mapping study involved screening of more than 6400 research and academic articles, from which 65 papers were identified as having implemented experimental or solution-based research involving IoT. From preliminary results we determined that the use of IoT in Education to implement POL is in its early stages. This study highlights the possible gaps in implementing IoT in POL and suggests future work opportunities for researchers, educators, and practitioners.

Keywords: Personalized Online Learning, Internet of Things, Systematic Mapping Study.

1. Introduction

The number of objects connected to the internet has increased at an unprecedented rate, turning the concept of the Internet of Things (IoT) into a reality [4]. IoT is becoming more pervasive and it is used in several domains like healthcare, transportation, manufacturing, agriculture, commerce, and energy [75]. In addition to the aforementioned domains, IoT has also been implemented successfully in education domain where it has not only changed the traditional learning and teaching practices, but has brought changes to the infrastructure and teaching methodology of educational institutions [33]. Three main stakeholders that deliver services when IoT is implemented in education are instructors, students, and administrative staff [39].

Different authors have concluded that integration of IoT in education is shifting the structure of educational systems [52], [71]. With its ability to collect vast amounts of

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data, IoT can be a powerful technology in developing smart campus models. IoT provides enhanced learning tools, Personalized Learning (PL) experiences and smart education delivery [33], [59]. Use of IoT in education spans the e-learning ecosystem, provides new research opportunities, boosts engagement in learning and e-learning processes, and increases creativity and collaboration through its hyper-connectivity properties [1]. IoT is being integrated into education to enable PL experiences through smart classrooms equipped with sensors, cameras, beacons, and wearable devices. These technologies collect data on student behavior, learning preferences, and performance, allowing for dynamic adjustments to lesson pace and difficulty based on individual learning styles and real-time performance. [5], [100].

Despite increasing interest and acknowledgment of its potential advantages, the incorporation of IoT into Personalized Online Learning (POL) is still insufficiently under-explored. Existing literature predominantly focuses on distinct facets of integrating IoT into POL, with limited comprehensive studies addressing this intersection. A systematic mapping study within this domain is necessary to identify key trends, gaps, and future research directions. This study fills that gap by conducting a systematic literature review of how IoT technologies are being integrated into existing POL systems, enhancing the adaptability and effectiveness of learning environments.

The primary objective of this systematic mapping study is to investigate the current state of research on the integration of IoT into POL systems. To achieve this, we address the following key research question:

- How can IoT be effectively integrated into existing POL systems?

This study encompasses peer-reviewed journal and conference articles published within the last six years, specifically focusing on the integration of IoT technologies into POL systems. Articles that exclusively address IoT or POL, without examining their intersection, have been mostly omitted from the scope of this research. To systematically map the existing body of research, we adhered to a widely recognized protocol commonly used in engineering studies [68]. This approach ensures a rigorous, methodical, reliable, and reproducible process, incorporating a comprehensive literature search, selection of relevant studies based on predefined inclusion and exclusion criteria, as well as structured data extraction and synthesis. This study provides significant contributions to both academic literature and practical applications by exploring the integration of IoT in POL environments. Main contributions of the work include:

- Scoping of the research which use IoT within POL and identifying IoT integration technologies, methods, models and tools;
- Identifying the volume and nature of existing research within this field;
- Mapping the publication frequency trends over time in IoT-enabled POL;
- Assessing the current implementation and utilization of IoT in POL systems;
- Evaluating the application of IoT to personalize online learning across different educational levels;
- Highlighting research gaps in the implementation of IoT to personalize or adapt online learning to enable guidance for future studies.

The structure of the study is outlined below. Section 2 presents the research background. In Section 3, we describe the systematic mapping approach implemented for paper selection. Section 4 provides an analysis of the results and addresses the research

question (RQ). Finally, Section 5 concludes the study and outlines potential areas for future research. After this study-based review, we present the background of our research.

2. Research Background

Personalized Online Learning (POL) is an educational methodology that uses electronic and distance learning, computer algorithms, and artificial intelligence to adapt online learning services like content, path, exercises, and feedback to recommend appropriate educational content. The use of emerging technologies, such as the Internet of Things (IoT) in education bridges the gap between the physical and virtual worlds by integrating physical objects and environments with virtual platforms, making the learning process more interactive and immersive [41], [26], [81], [98], [95].

We define the Internet of Things (IoT) in education as an emerging technology that enhances POL by integrating data from learner physical environment, socio-psychological and behavioral attributes during their interactions with existing PL frameworks. IoT integration in education improves student health and safety monitoring, attendance tracking, and facilitates ubiquitous learning. It enhances learning by boosting retention, accelerating progress, fostering critical thinking, and enabling dynamic communication between students and teachers [50], [10].

Integrating IoT into Learning Management Systems (LMS) enhances flexibility, supports self-directed learning, enriches teaching and learning experiences, optimizes assessments, and promotes collaboration among stakeholders [54]. Integration of IoT in e-learning has significant impact on student efficiency, learning experience and educational productivity. It also offers high levels of flexibility, accessibility, adaptability, and scalability [71]. IoT can also be used to create more significant learning spaces by engaging physical objects in learner environment with digitally association within a particular learning subject [35]. It is assumed that IoT has tremendous potential in education, particularly with the implementation of the "hypersituation" concept, which amplifies the information generated by multiple sources in real-time, thereby providing contextualized learning framework supported by the surrounding environment [59]. With the application of big data analytics, Adaptive Learning Environments (ALEs) can be significantly reshaped, reducing the risk of failure for online learning professionals and online learners [45].

IoT, Cloud Computing, and Learning Analytics (LA) enable personalized, interactive learning by replacing rigid curricula with data-driven, customizable approaches. These technologies provide insights into student and teacher behaviors, and supporting evidence-based decision-making in education. Although still in its infancy, analyzing behavioral patterns via IoT data shows promise for creating decision support systems tailored to the individual learner [58].

This study considers the possible methods, technologies, processes, and set of practices used in integrating IoT properties, technologies, protocols, and frameworks into personalized or adaptive online learning systems. Additionally, the study examines systematic reviews in IoT in education and future trends of IoT in education literature with a special focus on POL systems.

2.1. Existing systematic reviews in IoT in Education to Personalize Online Learning

Use of IoT in the Education domain with a special focus on POL is in its early stages. Sneesl et al. (2022) conducted a systematic review concerning the theoretical framework of the adoption of IoT technology related to smart campus adaptation [78]. Laksmi et al. (2022) carried out a systematic review with a focus on the IoT platform's use in educational processes especially in teaching and learning processes [46]. A state-of-the-art review on integrating Industrial Revolution 4.0 and IoT in academia to identify the factors that affect the level of motivation toward the integration of these technologies was performed by Butt et al. (2020) [15]. Asad et al. (2022) executed a review study on sophisticated insights regarding the impact of IoT-based smart laboratories on student academic performance in higher education in terms of conceptual and practical implementations [7]. Adi et al. (2020) conducted a critical review on how IoT-generated data are processed for Machine Learning (ML) analysis and current challenges in furthering intelligent solutions in the IoT environment with a proposed framework for ML and knowledge discovery for IoT to integrate adaptive learning techniques locally, at the edge, through a fog or in the cloud [3]. Chen et al. (2021) carried out a comprehensive review to understand the past, present, and future academic structure, major research topics, and contributors in smart learning research [17].

2.2. Use of IoT in Education to Personalize Online Learning

The use of wearable devices like smartwatches, fitness trackers, and biometric sensors is growing in education [9]. Schools and universities use these tools to collect data on student behavior, physiological responses, and health metrics [2]. This data personalizes learning by detecting focus loss and adjusting lessons or monitoring biometrics like heart rate and movement for learning insights [19]. In addition, IoT devices and LA provide data on student behavior and learning preferences, enabling PL plans to better achieve individual goals [101].

IoT in Education has proved to be effective in improving teaching and learning activities by analyzing the impact of physical environmental properties such as temperature, noise pollution and CO_2 level on student attention, and in observing student reactions to lectures with the use of sensing and monitoring technologies which provide real-time feedback [8], [9], [79].

Adaptive learning platforms use data analytics and ML algorithms to personalize online learning by analyzing IoT-collected data to identify where students are struggling and provide additional support or resources as needed [30]. In addition these platforms can use sensors to monitor learner responses and adjust content or pace accordingly [80]. Of note, Yakoubovsky and Sarian (2021) combine IoT and Electroencephalography (EEG) device to monitor student brain activities to assess student levels of engagement to provide a better POL experience [94].

2.3. Challenges of integrating IoT in Educations

Integration of IoT and data mining in e-learning brings challenges and opportunities to educational institutions and students [52]. Some of the challenges identified by Alfoudari

et al. (2021) in their study were lack of engagement, interactivity and personalization of external factors, learning attitudes and teaching methods [5]; whereas some of the challenges addressed by Ennouamani and Mahani (2017) were finding the most influential characteristics of e-learners and proper integration of adaptive learning platforms modules [30]. Privacy and security are commonly identified challenges by authors. In addition, the size and heterogeneity of data that need to be handled were identified by Arishi and Mavaluru (2018). Ghallabi et al. (2020) highlighted challenges related to the high costs of sensors, the battery life of IoT devices, wireless coverage, adaptation of m-learning, and AR. Meanwhile, Kassab et al. (2020) identified scalability and humanization as key issues [39], [52]. In addition to identified challenges, typical responsibilities of students and teachers are fundamentally changed in IoT-based e-learning settings and there is an imminent need for innovative teaching methods to enable integration of IoT in education [71], [10]. E-learning entities and platforms have faced criticism due to completion rates, costs, employment, and career readiness, but integration of new technologies and IoT applications can help improve e-learning platforms to overcome these challenges [92]. Considering this background in the use of IoT and POL, this paper will address implemented research methodology.

3. Research Methodology

3.1. Motivation for conducting the systematic literature mapping

The objective of this study is to identify to what extent and how IoT is implemented into existing POL models. Its specific focus is on the intersection between IoT and POL, exploring this intersection on how IoT is implemented in POL. To achieve a complete overview of the area, we reviewed IoT in Education papers that address POL methods, techniques and frameworks identified in Section 2.1.

There are different reviews and mapping studies regarding POL or IoT as described in Section 2.1. Chweya and Ibrahim (2021) investigated implementation of IoT in learning institutes and concluded there was a lack of studies in respect to models and methodologies used to implement IoT in Education [20]. In their systematic literature review, Kassab et al. (2020) stated there were few, if any, consolidated and coherent reviews implementing IoT in education [39]. In addition, within the last decade there has been no systematic map addressing common ways of implementing IoT in POL. Our mapping study allows researchers and stakeholders to make informed decisions regarding implementation of IoT in online learning by taking into consideration present and future challenges and requirements.

3.2. Systematic mapping study

There are different guidelines that can be implemented to conduct systematic mapping; [42], [67], [43], however, Petersen et al. (2015), consolidated the best practices suggested by other researchers, which enabled a clearer structure for understanding the types of research reports and results that have been published by categorizing papers [68]. The process begins by formulating research questions (RQs) with the next steps involve screening papers based on their title, abstract, and keyword metadata specific to the RQs. The primary goal of a systematic mapping study is to identify the gaps in the research area being investigated. The conducted systematic mapping process is represented in Figure 1.

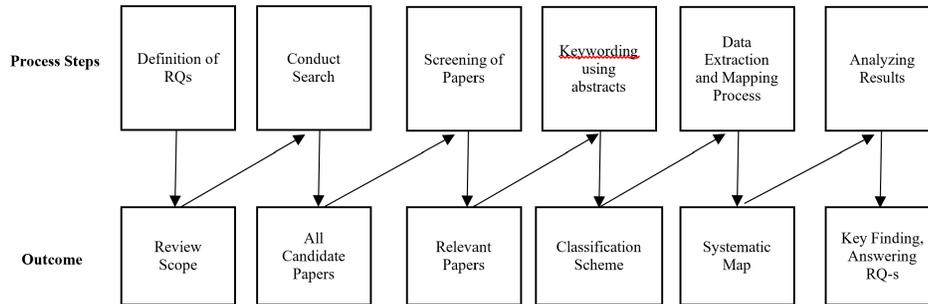


Fig. 1. The systematic mapping process [68]

3.2.1 Definition of RQs

Based on study motivation and objectives (Section 3.1), we proposed the following RQ to guide the search and selection process:

R.Q.1: How can IoT be integrated within existing Personalized Online Learning systems? The research question is composed of seven sub-questions (listed in Table 1) to analyze different aspects of integration of IoT in POL.

Table 1. R.Q.1. sub-questions

RQ.	Research Sub-question
RQ1.1	What are potential techniques used to integrate IoT in existing POL systems?
RQ1.2	What are the POL models or strategies that may be added or enhanced by using IoT?
RQ1.3	What are the POL system input components or parameters that may be added or enhanced by using IoT?
RQ1.4	What are the tools or methods used to measure POL components or parameters?
RQ1.5	What are the POL algorithms that may be added or enhanced by using IoT?
RQ1.6	What are the IoT tools that may be used in POL?
RQ1.7	Which research approaches are used in academic literature related to the integration of IoT into POL and what contribution has been achieved?

3.2.2 Conducting the search

Identifying the search string of publications was the first step in conducting a systematic research process. To identify keywords and formulate search string from research questions we followed PICO (Population, Intervention, Comparison and Outcomes) criteria developed by Petersen et al. (2015) [68]. These criteria are defined in Table 2.

To explore how IoT is integrated in POL systems in primary studies we formulated a search string that reveals combination of IoT and POL systems. On this study we extracted information on different aspects of IoT integration to POL systems. The extracted information consisted of IoT integration techniques (RQ1.1), IoT POL models (RQ1.2) and personalization components (RQ1.3). In addition, tools or methods for measuring person-

alization components (RQ1.4), algorithms used to process data providing personalization services (RQ1.5), and IoT tools used (RQ1.6), are also extracted.

Table 2. PICO of the study

Dimension	Description
Population	Primary studies which integrate IoT in POL systems (both theoretical and empirical studies).
Intervention	Techniques, models, components, algorithms, and tools used to integrate IoT in POL systems.
Comparison	Comparing different techniques, models, components, algorithms and tools used to integrate IoT in POL systems.
Outcome	Evaluation of collected empirical studies which integrate IoT in POL systems.

The details of generating keywords and classification scheme are described in Section 3.2.4.

There are three main concepts of the search string "Internet of Things", "Personalized", and "Online Learning" derived from research questions. Our basic string was "Internet of Things" AND "Personalized" AND "Online Learning". To extend the scope of research we conducted a literature investigation for synonyms and interchangeable terms which identified main concepts. Various terms related to the "Internet of Things" have been used by different authors, standardization bodies, alliances, projects, and industries, often with similar or different meanings. Main terms extracted from literature for the first concept are: Internet of Everything, Machine to Machine, Cloud of Things, Web of Things, and Network of Things. Regarding the second concept, we identified Adaptive, Individualized, Tailored, Customized, Context-aware and Learner-centric keywords. Meanwhile, for the third concept, we retrieved e-Learning, Elearning, Distance Learning, Virtual Learning, Web-Based Learning, Electronic Learning, Digital Learning, Distance Education, Computer-Supported Learning and Internet-Based Learning terms [39], [30], [20], [47], [103], [36]. To construct the full string, we used AND Boolean operator to combine main concepts and OR Boolean operator to express synonyms or interchangeable terms of main concepts. The constructed full search string was ("IoT" OR "Internet of Things" OR "IoE" OR "Internet of Everything" OR "Industry 4.0" OR "Web of Things" OR "WoT" OR "Machine to Machine" OR "M2M" OR "CoT" OR "Cloud of Things" OR "NoT" OR "Network of Things") AND ("Personalized" OR "Adapted" OR "Individualized" OR "Tailored" OR "Customized" OR "Context-aware" OR "Learner-centric") AND ("Online Learning" OR "Distance Learning" OR "Distance Education" OR "e-learning" OR "Elearning" OR "Electronic Learning" OR "Virtual Learning" OR "Digital Learning" OR "Computer-Supported Learning" OR "Internet-Based Learning").

Various systematic literature reviews regarding IoT or POL used several options for electronic library and database selection such as ACM Digital Library, IEEE Xplore, Education Resources Information Center (ERIC), Scopus, Springer Link, Web of Science, Science Direct, and DBLP bibliography. To conduct our research, we implemented the search string in ACM and IEEE Xplore digital libraries and on Education Resources Information Center (ERIC) and Springer Link databases. We selected ERIC as the main education research and information databases, while ACM, IEEE Xplore digital libraries

and Springer Link database as main sources for engineering related articles. To determine latest trends we limited the research from January 2017 to March 2023. Detailed results of implementation of search string and results are show in Table 3.

Table 3. Number of unique studies and search strings (Time interval: 2017 - 2023)

Source	Basic string	Full String	Invalid Resources	Duplicates within Search Strings	Duplicates between Databases	Library Total
ACM	305	165	79	13	23	355
ERIC	8	898	7	0	0	899
IEEEExplore	38	150	1	9	0	178
Springer Link	2363	2514	1	565	4	4307
Total	2714	3727	88	587	27	5739

3.2.3 Screening of paper

Based on the RQ and Inclusion and Exclusion criteria of this mapping study, the most relevant papers were identified during the screening process. Based on study title, abstract and keywords, we included or excluded each study found within the search string. From the database search, we identified a total of 6441 papers published during 2017 – 2023 time span. Most of the publications are in the Springer Link digital database.

Phase 1 involved the automatic removal of 88 invalid sources, such as workshop programs, keynotes, book covers, speeches, retracted articles, PhD theses and unpublished works. Furthermore, with the help of spreadsheet software we automatically removed 614 duplicate papers. For Phase 2, we relied on 5739 remained references.

In Phase 2, we applied additional filtering, based on the inclusion and exclusion criteria, Table 4, to titles and keywords, producing 2510 references, and then we manually excluded 2405 articles based on titles and then based on abstracts, as recommended by [47] resulting on 96 candidate studies.

In the last Phase, after full text reading of candidate studies we excluded 31 papers as not totally related to our systematic mapping study, resulting in 65 accepted studies. The number of included and excluded papers for each Phase is presented in Figure 2.

3.2.4 Keywording using abstracts and classification scheme generation

The goal of keywording in the context of systematic mapping studies, according to [67], is to facilitate the classification and organization of research papers. This process, which involves identifying key terms from abstracts, creates a structured overview of a research area. This systematic approach aids in categorizing the studies, making it easier to identify trends, research gaps, and the distribution of research efforts across different topics within the field.

To classify the papers, we followed the process documented in Fig 3, as proposed by [41], who rated classification schemes based on the basis of a set of quality attributes: **Scheme Definition:** The taxonomy/classification is created on the basis of an exhaustive

Table 4. Criteria used for including and excluding research studies

Inclusion Criteria	Exclusion Criteria
<ul style="list-style-type: none"> - Included content of IoT that investigates Educational perspectives to Personalize Online Learning i.e., methods, frameworks and use cases; - Published between January 2017 and March 2023; - Written in English with full-text available; - Peer-reviewed journal and conference literature; 	<ul style="list-style-type: none"> - Duplicate papers from the same study in different databases. - Mention of IoT is tangential with different scopes not directly related to POL; - Publications not written in English; - Publications not directly related to our topic; - Full-text is inaccessible; - Books and gray literature;

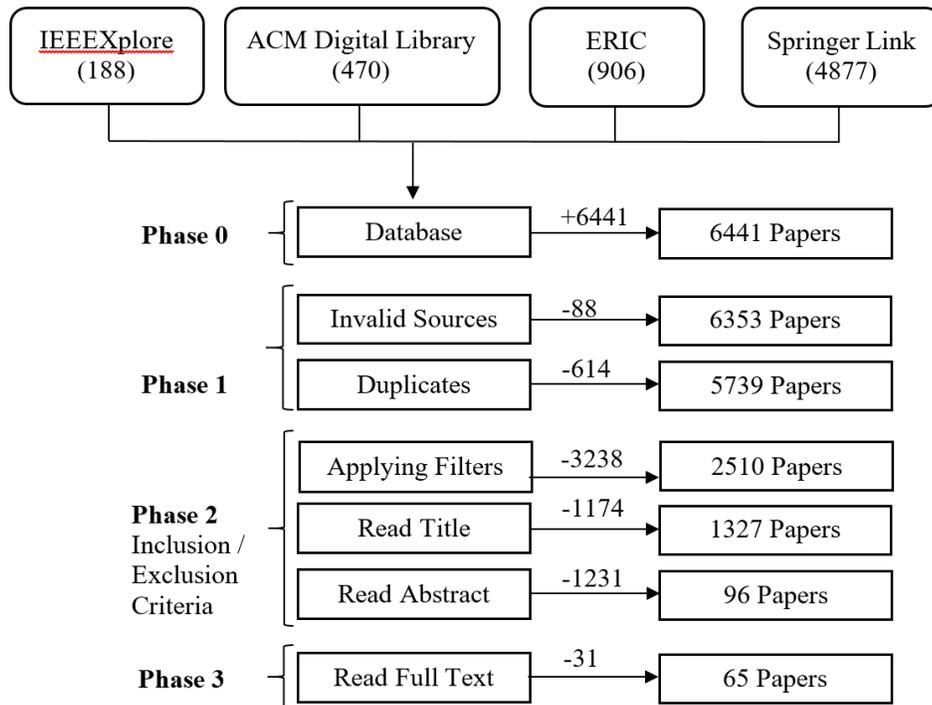


Fig. 2. Selection of primary studies [68]

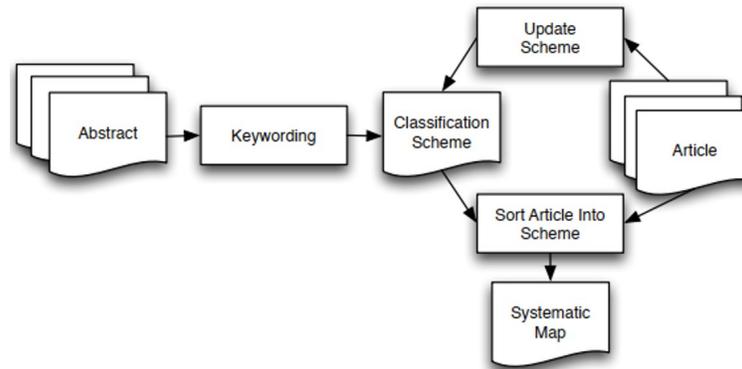


Fig. 3. Classification Scheme Generation Process [41]

analysis of existing literature in the field.

Scheme Terminology: The taxonomy uses terms that are used in existing literature.

Orthogonality: There are clear boundaries between categories which makes it easy to classify.

Complete: No categories are missing, allowing existing articles to be classified.

Accepted: The community accepts and knows the classification/taxonomy.

In Figure 4 we represent the classification scheme where all facets are derived from the existing literature on the subject, as well as the results of our own study. To build the classification scheme we conducted the following steps as described in [67]:

Step 1: Reviewing the abstracts and keywords of primary studies identified the main concepts for these studies. When abstracts were not sufficient, the introduction and conclusion sections of the papers were also analyzed. Extracted keywords are strictly related to the RQ to classify and map papers accordingly.

Step 2: Combining together the set of keywords and concepts from different papers, determined the categories representative of the research area of the relevant primary studies. Additionally, these categories were refined and updated to accommodate new data.

Step 3: Categories formed by final set of clustered keywords are classified into higher hierarchical levels to develop a high level of understanding about the nature and contribution of selected primary studies. The following section presents key findings of the systematic mapping study, offering insights that directly reflect our objectives. To outline the results, we followed the structure and layout of a systematic mapping study conducted by Cico et al. [21].

4. Results

As indicated above, our main research questions was: “How can IoT be integrated within existing POL systems?”. From an initial sample of 6441 papers, 65 primary relevant studies were selected for answering RQs. In order to analyze the main dimensions of research question, seven other sub-questions were included (e.g. R.Q.1), with the results allowing for each article to be classified into categories pertinent to specific sub-questions.

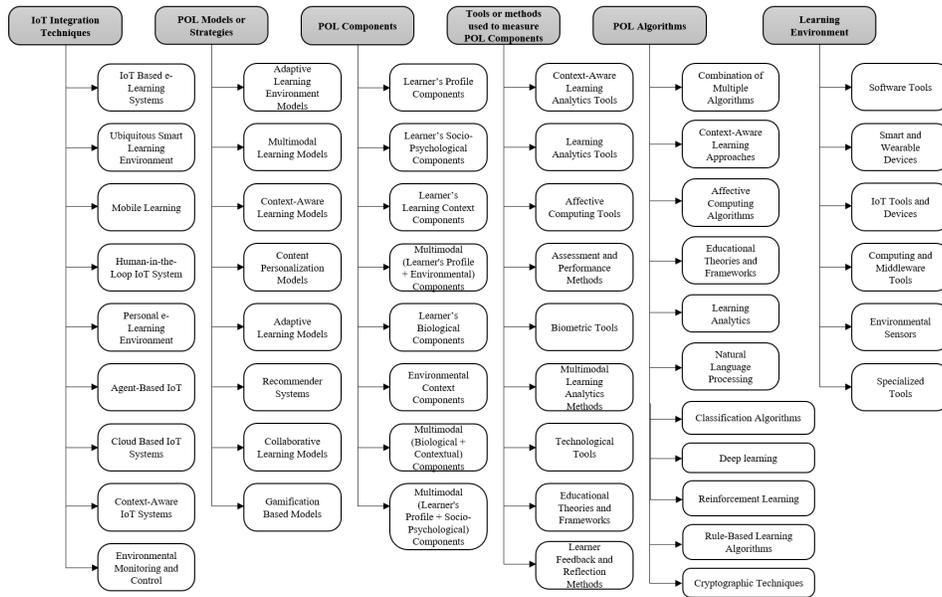


Fig. 4. Classification scheme derived from keywording using abstracts

4.1. Descriptive analysis of results

This section presents a comprehensive descriptive analysis of the selected studies focusing on distribution of articles over years and the databases where they were retrieved from.

Table 5 presents the distribution of publications from January 2017 to March 2023 and their dissemination across different digital databases and libraries.

Table 5. Distribution of selected studies over years and digital libraries or databases

Publication Year	Number of Publications	Percentage	ACM	ERIC	IEEE	Springerlink
2017	8	12%	3	5	0	0
2018	8	12%	0	3	1	4
2019	15	23%	2	6	4	3
2020	11	17%	1	6	1	3
2021	10	15%	2	4	2	2
2022	8	12%	2	3	1	2
2023	5	8%	0	1	1	3

The integration of IoT into POL systems is an interdisciplinary field between information technology and education. ERIC database contains scholarly articles related to education and the integration of different technologies into education to improve the quality of learning. Given this context, it makes sense that nearly half of the primary studies,

specifically 43% of the total, are found in it. The Springer link digital database is the second most utilized source, with 17 publications, representing 26% of the total. In addition, 69% of selected studies were journal articles and 31% of were published in conference proceedings.

4.2. Answering Research Questions

In the next section we provide the results of research questions and each research sub-question by clustering and analyzing them according to main classification categories.

4.2.1 What are potential techniques used to integrate IoT in existing POL systems?

To answer this question, we created the “IoT Integration Techniques” classification categories of the selected studies, as shown in Table 6. From summarized results we can

Table 6. Number of papers according to used IoT Integration Technique

IoT Integration Technique	Number of Studies	Percentage
IoT Based e-Learning Systems	12	18%
Ubiquitous Smart Learning Environment	11	17%
Mobile Learning	10	15%
Human-in-the-Loop IoT System	9	14%
Personal e-Learning Environment	9	14%
Agent-Based IoT	6	9%
cloud-based IoT Systems	3	5%
Context-Aware IoT Systems	3	5%
Environmental Monitoring and Control	2	3%

observe that about 35% of the papers have as main focus IoT Based e-Learning Systems and the creation of Ubiquitous Smart Learning Environment.

The most commonly used IoT integration technique into POL is the development of **IoT Based e-Learning Systems** that focus on delivering personalized or adaptive learning experiences by leveraging IoT technologies. These systems are used to recommend appropriate content to learners using multimedia recommendation schemes powered by IoT [41]. They combine content-based information with collaborative user preferences [25] and utilize ML algorithms to analyze IoT collected data [3] to provide personalized recommendations. In addition, IoT based tools for emotion detection adapt learning paths based on facial expressions [40], [80], while sensor-driven activities enable hands-on, environment-specific learning experiences [62]. Additionally, deep learning and multi-classification algorithms personalize content by classifying students based on their learning data [86]. IoT technologies further enable real-time data mining to analyze student engagement [31] and support smart laboratories that foster interaction and creativity in learning environments [7]. Lastly, an innovative IoT system categorizes students by learning styles (visual, auditory, kinesthetic) using fingerprint analysis, while tracking their academic performance [74].

The second most commonly used IoT integration technique, nearly 17% of selected papers, is the creation of **Ubiquitous Smart Learning Environment** (USLE). Several educational strategies and technologies are used in designing USLE, such as Augmented Reality (AR), Virtual Reality (VR) [51], [89], [88], [65], [38], ubiquitous computing and learning [53], [76], PL spaces [102], and an ambient and pervasive PL ecosystem [12] to create a comprehensive and immersive learning experience. Ubiquitous Computing, Mobile Computing, and IoT are integrated to develop learning scenarios for middle school education, although without detailed IoT-based personalization techniques [53]. The VIL-LAGE project explored the use of virtual environments, chatbots, and time machines to enhance the immersion of language learners and personalize experience through interactive digital artifacts [88]. AR techniques are employed in Personalized Learning (PL), allowing interaction with paper-based learning sheets that are enhanced by AR. This supports the content with online resources, such as YouTube videos [89]. Authors in [65] focused on the use of virtual laboratories as a complement to traditional laboratories for teaching chemistry concepts. A novel generic architecture for context-aware ubiquitous learning systems, based on the IoT computing paradigm, is implemented using common IoT edge devices. Four variants of the architecture are presented, each based on different protocols [76]. Authors in [102] used IoT devices to create and measure the effectiveness of PL space in the educational metaverse. Meanwhile, [13] focused on the implementation and testing of an IoT Dataflow system in classroom settings, primarily to enhance K-12 science education through hands-on experiments. Furthermore, authors in [51] experimented on advanced techniques like 3D presentations using AR, VR, smart assessments, digital libraries, and cloud integration for effective data management in educational frameworks. Additionally, game-based systems and educational data mining were employed to provide customized experiences with AR and VR to enhance content delivery and retention [12].

Mobile Learning (m-learning) techniques use mobile devices mainly to extract the context where the learning takes place [83], [96], [60], [48], [22] and as a learning device tool [64], [14], [56], [85], [66]. In context-aware m-learning systems authors used Global Positioning System (GPS) and other mobile phone embedded sensors to provide adaptive learning content based on the learner location and environmental conditions [96], [48], [83] and to adapt the learning path in mobile and ubiquitous learning environment [60]. Authors in [64] outlined a m-learning framework specifically tailored for low-income economies, emphasizing the importance of aligning theoretical approaches with practical m-learning strategies in resource-constrained environments. Additionally, authors in [14] proposed an adaptive m-learning environment that adjusts educational content and strategies to fit the learner cognitive, behavioral, emotional, psychological, and sociological profiles. Meanwhile, advanced technologies like wearable devices and smart glasses are explored by [85] to enhance interactivity, assessment, and POL experiences. Moreover, embedded biosensors (noninvasive, low-cost, and distraction-free) used in smartphones and smartwatches are investigated by [22] to implement the adaptivity within the Education 4.0 processes.

Human-in-the-loop IoT systems incorporate human feedback and interactions into the decision-making process of POL. These systems are explored in [82], where wearable EEG devices are used to infer a learner cognitive state and detect changes in learning performance. In [28], a Reinforcement Learning (RL)-based framework is proposed to

adapt IoT applications according to human variability, utilizing RL to account for dynamic learning behaviors. Additionally, an Intelligent Music Selection System is introduced by [18], utilizing wearable sensing devices to measure Heart Rate Variability (HRV) and predict user emotions. This enables automatic song recommendations based on physiological responses. Meanwhile, authors in [27] propose a Domain-Specific Modeling Language (DSML) designed to integrate IoT data sources and model human emotions to personalize online learning experiences based on emotional states. Lastly, authors in [77], used smart glasses and Raspberry Pi to explore real-time student behavioral analysis through facial recognition algorithms, meanwhile, authors in [63] assessed the feasibility of wearable physiological sensing technologies such as Electro-Dermal Activity (EDA), Photoplethysmography (PPG), and Skin Temperature (ST) to measure student engagement levels.

Personal e-Learning Environment mainly consists on personalized recommendation systems [72], [26], [11], [99] and on adaptive e-learning environments [90], [91], [55]. These systems encompass a variety of approaches to enhance e-learning experiences. These include course recommendations tailored to a learner profile and preferences [66], the use of collaborative and content-based filtering techniques to adapt learning materials to individual student needs [11], Technique Feature Analysis (TFA) for recommending personalized word-learning tasks [99], and a learning path recommendation system that generates PL paths for e-learners, based on learning styles, knowledge levels, and learning goals [26].

Adaptive e-learning environments integrate a variety of innovative methods. Authors in [90] discussed the adaptation of the e-learning environment based on the learner personality and emotional state. Meanwhile, [91] focused on the use of apps that adapt to the learner specific situation and needs. Additionally, a dynamic and student-controlled learning space is achieved by integrating Personal Learning Environments with LMS through a service-based framework, as outlined in [55]. In addition, a system that combines Explainable AI and Internet of Behavior technologies to assess student behavior and personalize learning materials is developed by [29].

Agent-based IoT integration techniques commonly incorporate Educational Chatbots (ECs) to deliver POL services. In [44], authors developed an EC focused primarily to support project-based learning and examined its impact on learning outcomes. Meanwhile, in [24], an EC was designed to respond to student queries by detecting questions using Natural Language Processing techniques and domain ontologies. Additionally, virtual assistants in the educational sector, developed with Google Dialogflow as described by [73], concentrate on abstracting knowledge and generating responses. This functionality facilitates effective interactions by analyzing course materials and managing entities and intents. Lastly, intelligent agents are employed by [84] to track student knowledge states by analyzing their interactions to recommend personalized content.

Cloud-Based IoT Systems include a conceptual framework proposed by [69] to enhance analytical thinking and support PL by adapting to individual learner needs through problem-solving and cloud-based resources. Additionally, an approach to integrate personalization parameters as a collection of web services uploaded to cloud databases to model the learner is proposed by [32].

In **Context-Aware IoT Systems**, contextual parameters such as location, noise level, and time of day are used by [97] to build user profiles for selecting PL materials. Ad-

ditionally, the impact of environmental variables like temperature, humidity, air quality, light, and sound on attention, motivation, and attitudes is assessed through a prototype and a Perception of Academic Achievement questionnaire [8].

IoT integration in POL enables adaptive and context-aware learning experiences through IoT-based e-learning systems, USLEs, and m-learning. VR, AR, and context-aware systems enhance immersion and personalization. Meanwhile, cloud-based ECs and intelligent agents promote improved interaction and adaptive content delivery.

Key Findings:

- IoT-Based Personalized Learning Systems integrate IoT and ML algorithms to classify students based on their learning data in order to provide adaptive learning paths or content based on individual needs and preferences;
- Ubiquitous Smart Learning Environments integrate IoT, mobile computing, augmented and virtual reality to create immersive learning experiences;
- Mobile and Context-Aware IoT Systems use mobile devices and wearable technologies to provide adaptive learning content based on learner context and preferences.

4.2.2 What are the POL models that may be added or enhanced by using IoT?

In the realm of educational technology, various models and strategies enhance learning experience through personalization and adaptability, as shown in Table 7. Adaptive Learning Environments and Multimodal Learning Models are among the most commonly identified models in POL systems.

Table 7. Number of papers according to used POL Models or Strategies

POL Models or Strategies	Number of Studies	Percentage
Adaptive Learning Environment Models	14	22%
Multimodal Learning Models	13	20%
Context-Aware Learning Models	11	17%
Content Personalization Models	8	12%
Adaptive Learning Models	7	11%
Recommender Systems	6	9%
Collaborative Learning Models	3	5%
Gamification Based Models	3	5%

Adaptive Learning Environment Models includes PL spaces that are cognitive load-aware, particularly in the context of the metaverse [102], as well as dynamically adjustable and student-controlled learning environments [55]. Learning paths are personalized through recommendation systems [26], and further optimized using models that sequence learning objects and automatically construct course structures [60]. Additionally, authors in [91] introduced the concept of an educational ecosystem, where technology and pedagogy fill specific niches, supported by applications and delivered through PLEs. Authors in [56] suggested creating a personalized cloud environment for m-learning to

make education more accessible. Additionally, an empirical study conducted by [90] explored the impact of adaptive e-learning environments based on learner personality and emotion.

Multimodal Learning Models integrate multiple aspects simultaneously to deliver an enhanced, personalized, and adaptive learning experience. These models utilize Multimodal LA to assess and classify student engagement in e-learning environments [16], [31], enabling adaptive learning scenarios [80] and automatically recommending songs based on the user physiological responses [18]. Additionally, wearable devices are used in [82] to monitor and adjust to the learner cognitive state in real-time by adapting content delivery according to the learner engagement and understanding levels. In [94], authors incorporated Digital Dynamic Modulation, which modulates video content with brain-stimulating frequencies to improve cognitive functions, such as attention and memory retention. Furthermore, an immersive learning model is implemented by [57] using multi-sensory effects such as olfactory cues, vibrations, and airflow to enhance the overall learning experience.

Context-Aware Learning Models can use learner socio-cultural and socio-economic contexts to support PL experiences [64]. These models can enhance the Felder-Silverman Learning Style Model (FSLM) by incorporating context-awareness, gathered from sensor data, into each component of the FSLM framework [83]. Additionally, they can provide personalized, context-aware recommendations using GPS technology [96]. These models can increase learner attention and motivation by integrating data from environmental sensors into existing POL algorithms or systems [8]. Furthermore, they can utilize low-level multi-domain context data to generate high-level contextual information [37].

Content Personalization Models adapt learning materials based on various factors, including the learner environmental context and knowledge level [97], as well as learner environmental context and behavioral analytics [3]. These models may also personalize content according to the learner characteristics, preferences, background, behaviors, and learning style [14]. Additionally, educational content can be tailored into a structured chatbot format [73], or recommendations can be personalized using knowledge tracing techniques [84].

Adaptive Learning Models dynamically adjust learning materials and experiences to address the unique needs, abilities, and preferences of individual learners. An experiment on adaptive learning through learner profiling in a cloud-based approach is conducted by [32]. A problem-solving-based PL model, emphasizing PL through problem posing to deliver tailored content and resources, is implemented by [69]. The authors in [89] explored a blended learning strategy that combines AR-based and online-based content delivery to adapt to individual learning speeds and preferences. Additionally, an adaptive teaching model, where instructors modify class activities based on student feedback, is proposed by [51].

Several **recommendation techniques** are identified from selected studies to provide tailored educational resources including online courses recommendations [66] news and related multimedia recommendations [41], learning resources recommendations [79], collaborative and content-based filtering recommendations [87], and social recommendations [34]. A unique hybrid and semantic recommendation system that combines content-based information with collaborative user preferences is proposed by [25].

Collaborative Learning Models explore ECs to facilitate project-based learning, where they provide personalized feedback, simulate peer interactions, and enhance reflection and metacognition [44]. Furthermore, the Student - Instructor - Technology Environment model is employed by [66], focusing on the interaction between these elements to enhance collaborative e-learning experiences.

Gamification Based Models focus on increasing student engagement and personalization through game-like elements. For instance, the GAIA Challenge game adapts the learning experience by progressively revealing new sections of the game map as student complete different stages, offering a PL trajectory [62]. Additionally, the integration of gamified elements like badges and biofeedback methods are implemented by [22] to boost student motivation and support academic success.

Key Findings:

- Adaptive Learning Models play a central role in personalized education by dynamically adjusting learning materials and experiences to meet individual learner needs, abilities, and preferences;
- Multimodal Learning Models provide a highly adaptive learning experience by integrating multiple forms of inputs and LA to adapt content, enhancing engagement and cognitive performance;
- Context-aware learning models enhance existing personalized or adaptive online learning frameworks by integrating environmental, socio-cultural, and socio-psychological data through sensor-based inputs.

POL models include ALEs, primarily used to create dynamic, user-controlled PL spaces or cloud-based PLEs. Multi-modal learning models integrate multiple aspects simultaneously, delivering an enhanced, personalized, and adaptive learning experience. Context-aware learning models are utilized to improve existing POL models by integrating contextual data or to develop new context-driven POL models. Content personalization models adapt content based on the learner's profile and environmental context. Recommendation-based POL systems suggest courses or learning resources to enhance POL services. Additionally, models such as Collaborative Learning and Gamification foster engagement and provide tailored resources through dynamic, interactive, and game-based approaches.

4.2.3 What are the POL system components or parameters that may be added or enhanced by using IoT?

POL systems integrate various components to adapt to individual learner needs and preferences. As depicted from Table 8, the integration of different types of components is the most commonly implemented approach in the selected studies to provide POL services.

Nearly 40% of studies offer personalization services by either focusing solely on the **learner profile** or by combining it with environmental or socio-psychological components. The main elements used to construct the learner profile include prior knowledge, learning style, and learning preferences. Additional factors considered are the learner personality, emotions, cognitive state, intentions, and stress levels. Demographic information such as age, academic major, and academic performance is also incorporated. Further-

Table 8. Number of papers according to used POL Components

POL Components	Number of Studies	Percentage
Learner Profile Components	18	28%
Learner Socio-Psychological Components	12	18%
Learner Learning Context Components	11	17%
Multimodal (Learner Profile + Environmental) Components	11	17%
Learner Biological Components	5	8%
Environmental Context Components	3	5%
Multimodal (Learner Profile + Socio-Psychological) Components	3	5%
Multimodal (Biological + Contextual) Components	2	3%

more, the learner profile includes data on the learner activities and performance, as well as intra-human, inter-human, and multi-human variabilities.

The subsequent most frequently utilized personalization elements are **Learner Socio-Psychological Components**. The main socio-psychological components used in POL are the learner behavioral patterns [16], [14], [29], combined with user emotions [90], [18], [27] and other factors such as learner motivation and engagement [16], learning styles, and cognitive load [14]. Additionally, anxiety levels in virtual learning [38], immersive tendencies [88], social relationships [34], affective interactions [44], intention inference [24], and engagement [63] are considered to provide POL experiences.

Learner Learning Context Components are utilized to extract the learner context, enabling the delivery of POL services. High-level context information is derived from low-level, multi-domain data sources [37]. In the m-learning framework [64], sociocultural and socioeconomic factors are also considered to tailor learning experiences. In addition, **Environmental Context Components**, such as the learner location [96], temperature, humidity, light [8], noise level, and time of day [97], along with graphical elements like layout and background texture [49], are utilized to create an optimal learning environment. These components foster immersive, collaborative, and PL experiences.

Learner Biological Components are critical elements used to build and enhance POL systems. These components primarily include physiological signals such as heart rate, brain waves, galvanic skin response, and visual attention metrics. For instance, the heart rate signal [102], [23], [80], [40], captured through PPG (Photoplethysmogram) sensors or smartwatches, is utilized to gauge learner emotional engagement and cognitive levels. Brain waves, monitored via EEG [23], provide real-time feedback on learner brain activity. Galvanic skin response along with heart rate [94], aids in detecting emotions with high accuracy, thereby allowing the system to adapt to the learner emotional state. Visual attention metrics, such as the number of faces, eye count, and eye status [102], combined with affective state monitoring, including indicators like frustration or engagement [80], collectively facilitate the development of ALEs. By tailoring content and interactions to align with each learner's physiological and emotional states, these systems aim to enhance overall educational outcomes.

POL systems utilize various components to tailor educational experiences to individual learners. These components include learner profiles, which comprise prior knowledge, learning styles, preferences, emotions, and demographic data, along with socio-psychological factors such as behavioral patterns, motivation, engagement, and emotional states. Additionally, biological signals like heart rate and brain waves, combined with environmental factors such as location, noise levels, and lighting, further enhance personalization by creating adaptive and immersive learning environments. Collectively, these elements enable POL systems to deliver responsive and customized learning experiences that cater to the diverse needs of learners.

Key Findings:

- Learner Profile components play a crucial role in providing POL services;
- Integration of IoT into existing POL systems incorporates biological and environmental context components;
- Integration of IoT into existing POL systems increase significance of Multimodal components.

4.2.4 What are the tools or methods used to measure POL components or parameters?

Integration of IoT into existing POL systems enable incorporation of contextual components generated by IoT sensors data. The main category of the tools or methods used to measure POL components or parameters, as shown in Table 9, are **Context-Aware Learning Analytics Tools**. These tools include IoT Edge Devices equipped with various sensors to represent the state of physical things and their context in ubiquitous learning environments [76] and to adapt and measure learning components based on the learner physical context and environmental conditions [48]. Additionally, contextual mapping techniques

Table 9. Tools or methods used to measure POL Components

Tools or methods to measure POL Components	Number of Studies	Percentage
Context-Aware Learning Analytics Tools	12	18%
Learning Analytics Tools	10	15%
Affective Computing Tools	9	14%
Assessment and Performance Methods	8	12%
Biometric Tools	6	9%
Multimodal Learning Analytics Methods	6	9%
Technological Tools	6	9%
Educational Theories and Frameworks	4	6%
learner Feedback and Reflection Methods	4	6%

are employed to measure and adjust learning paths according to the learner context, while a context-aware mechanism, integrates GPS, QR code interfaces, and learning logs to adapt the content [60], [96]. Furthermore, ML approaches are used to develop a context

fusion model, inferring multi-domain context information from various IoT sensors [37], and to process data intelligently [3]. In addition, personalized m-Learning applications are used as context-aware measurement tools to provide POL services [83], [97].

Learning Analytics Tools and ML techniques, are employed to track and analyze learner engagement using wearable devices [16]. Additionally, TFA is used for personalized word-learning tasks, grounded in a comprehensive word learning theory [99]. Graph Neural Network (GNN) methods are implemented to encode user and item feature spaces for social recommendations, addressing correlations between user preferences and item features [34]. In another approach combination of metadata analysis (views, likes, comments) and readability assessments (Coleman-Liau index, Flesch-Kincaid grade level), along with the use of scoring mechanisms (time, popularity, difficulty) are used to measure and personalize online learning content [41].

The primary **Affective Computing Tools** used to understand and respond to learner behavior, personality, and emotional states include biometric-based tools such as Facial Recognition Algorithms and Raspberry Pi Cameras [77], Facial Emotion Detection using Webcams and Emotion Detection APIs [40], Emotion Recognition and Usability Assessment Tools [27], and Eye-Tracking Measurement Method [85]. Additionally, IoT devices including cameras, microphones, and inertia sensors [80] are employed to capture and analyze the learner affective state by tracking facial expressions, eye-gaze, heart-beat, and speech cues. Another commonly used approach involves questionnaires, such as the Myers-Briggs Type Indicator (MBTI) model for personality and the Ortony, Clore and Collins (OCC) model for emotion modeling [90], as well as the Immersive Tendencies Questionnaire, Igroup Presence Questionnaire [88], and the Attention-Scoring Model (ASM) [31]. These tools help to better understand and respond to learner affective states, enhancing the personalization and effectiveness of POL systems.

Assessment and Performance Methods primarily rely on data-driven performance evaluation and interaction analysis, utilizing data mining techniques [51] and ML algorithms [79], [70]. In addition, performance-based and observational assessment methods [7], along with pre- and post-tests [65], [22], are commonly employed. Qualitative methods to measure engagement metrics include student reflections, feedback, and interaction analysis [66].

The primary **Biometric Tools** and methods utilized in measuring components of POL systems include HRV for Physiological Data Analytics [102], [18], [23], EEG for Neuropsychological and Cognitive Measurement [82], [94], and the combination of EDA, PPG and ST as tools for engagement measurement [63].

Multimodal Learning Analytics Methods encompass a mixed-methods evaluation approach that integrates both quantitative and qualitative techniques. These methods assess various facets of student learning, including engagement, interactions, perceptions of learning, motivational beliefs, creative self-efficacy, and perceptions of teamwork to measure the impact of PL interventions [64], [44]. Behavioral and performance-based measurement methods assess learner performance using a variety of approaches, including tests, monitoring of engagement levels, tracking of progress, and interactions with IoT-enabled devices [13], [14]. Additionally, learner profiling and cognitive assessment tools include questionnaires that capture learner preferences, interests, domain-specific knowledge, and the Recall Serial Information test used to measure learner memory capacity [11].

Various **Technological Tools** are exploited to measure components of POL. Main tools include secure access and authentication mechanisms, such as the Zero Knowledge Proof system to ensure personalized and safe access to educational resources [61]. In addition, Human-Computer Interaction is evaluated through authoring system for creating PL scenarios, particularly in the context of using robots and IoT-based toys for language learning [93]. Lastly, a service-based framework links PLEs with LMS [55], while federated learning metrics and models like MAML and REPTILE ensure user privacy [87].

Educational Theories and Frameworks Methods employ standardized questionnaires such as the VAK (Visual, Auditory, Kinesthetic) Theory [74], Bloom's Four Agents of Change [12], and the National Survey of Student Engagement [91]. These tools are used to assess student learning styles and to analyze individuals, processes, data, and devices. This comprehensive evaluation supports the creation of PL experiences within the context of IoT.

Learner Feedback and Reflection Methods are essential for understanding and enhancing the PL experience by collecting data on student perceptions, attitudes, self-efficacy, and emotional states. These tools include the Perceptions of Academic Achievement Questionnaire [8], which measures student attention, motivation, attitudes, and perceptions of academic achievement in relation to physical classroom variables. The Foreign Language Virtual Classroom Anxiety Scale (FLVCAS) [38] is used to quantitatively assess anxiety levels in virtual language classrooms. Additionally, Quality of Experience questionnaire [57] evaluates PL components, while another questionnaire measure the impact of PL supports, learner self-evaluation perceptions, and their self-perceived progress [89].

A variety of tools and methods are utilized to measure POL components. Context-Aware LA Tools, such as IoT edge devices and sensors, adapt learning environments based on learner physical context and environmental conditions. Affective states are measured using biometric tools such as HRV, EEG, and emotion detection systems, alongside questionnaires that capture learner preferences and emotional responses. Educational theories and feedback tools further enhance PL experiences by enabling detailed learner profiling and improving system effectiveness.

Key Findings:

- Context-Aware LA Tools including IoT edge devices equipped with sensors, are frequently used to adapt and measure POL components by tracking the learner physical context and environmental conditions in real-time, providing data-driven personalization;
- Biometric Tools, such as Heart Rate Variability, Electroencephalography, and facial emotion detection systems, are commonly used to monitor learners' emotional and physiological states, improving the responsiveness of POL environments to individual needs.

4.2.5 What are the POL algorithms that may be added or enhanced by using IoT?

There are various approaches and algorithms used when integrating IoT into POL systems to deliver PL services. The most common approach, identified from selected primary studies as shown in Table 10, involves **combining multiple ML algorithms**.

Table 10. Algorithms used in POL Systems

POL Algorithms	Number of Studies	Percentage
Combination of Multiple Algorithms	18	28%
Context-Aware Learning Approaches	10	15%
Affective Computing Algorithms	9	14%
Educational Theories and Frameworks	8	12%
Learning Analytics	6	9%
Natural Language Processing	5	8%
Classification Algorithms	2	3%
Deep Learning	2	3%
Reinforcement Learning	2	3%
Rule-Based Learning Algorithms	2	3%
Cryptographic Techniques	1	2%

Classification algorithms, including C4.5, the J48 algorithm, and instance-based classifiers, combined with rule-based methods such as OneR, PART, are employed to classify and analyze student engagement levels. K-means clustering, alongside collaborative filtering techniques and genetic algorithms are utilized to personalize learning experiences by leveraging learner data, behavioral patterns, and individual preferences [72], [16], [37]. The combination of Variable Length Genetic Algorithm, Collaborative Filtering Methods, Ant Colony Optimization and Particle Swarm Optimization are used to generate and recommend PL path [26], [60]. Furthermore, collaborative and content-based filtering algorithms are used to provide PL materials [11]. ML models, such as Dynamic Key-Value Memory Networks and their augmented versions [84], trace student knowledge states and predict performance. ASM and behavioral analysis algorithms measure student engagement during video lectures by analyzing facial and eye movements, contributing to personalized engagement metrics [31], meanwhile RL, Rule Based Learning, and Deep Spatio-Temporal Convolutional LSTMs model dynamically adjust learning content based on cognitive states inferred from EEG data [82]. Furthermore, multi-armed bandit algorithms and decision trees [70] recommend the most effective support to students.

Context-Aware Learning Approaches employ an algorithmic approach in which data from sensors and IoT devices is processed to deliver personalized educational content based on real-time environmental data and user input. Adaptive sensor-based learning algorithms adjust m-learning content based on both predefined learning style models and real-time inputs from physical sensors [83], [96]. Context-aware user profiling focuses on creating personalized user profiles by incorporating context factors to recommend relevant learning objects [97], [48]. IoT technology is also employed to adapt learning experiences according to physical classroom conditions [8]. Furthermore, PhET simulation laboratories, combined with Inquiry-Based Learning and the Technological Pedagogical Content Knowledge framework, are used as interventions in virtual laboratories [65].

In **Affective Computing Algorithms**, emotional and physiological data are utilized through techniques such as facial landmark detection, eye-gaze tracking, and heartbeat monitoring, combined with data aggregation methods to tailor the learning experience to the learner emotional and physiological state [77], [40], [80]. The MBTI model is used to assess learner personality, while the OCC model is applied for emotion modeling, and

the Desirability Level Prediction model helps predict student desirability levels [90]. Affective learning assessments focus on measuring emotional components, such as foreign language anxiety, using tools such as FLVCAS [38]. In addition, PPG signal analysis, LA, and Cognitive Load Measurement, assess emotional engagement in educational metaverse environments [102]. The Wilcoxon signed-rank test is employed as a statistical tool to analyze differences in engagement levels based on physiological metrics [63].

The **Educational Theories and Frameworks** applied in POL emphasize pedagogical strategies to enhance PL through conceptual approaches rather than specific algorithms. These include Social Constructivism and Flow Theory for m-learning personalization, fostering interaction and engagement [64], and Blended Learning, which integrates m-learning to offer self-directed learning at learner pace [64], [66]. Additionally, Instructional Scaffolding and Project-Based Learning help learners grasp complex concepts in Ubiquitous Computing environments [53]. Problem-Based Learning in Cloud Learning Environments further tailors learning experiences by leveraging cloud technologies for flexible and collaborative learning [69]. Finally, Arts-Based Learning strategies, such as Poetweet and Reflective Mosaic, enhance interaction and social presence in m-learning environments [66].

Learning Analytics plays a crucial role in POL by utilizing various algorithms and models to improve educational outcomes and adapt learning processes. An IoT-based system categorizes students based on their learning styles using the VAK theory and fingerprint analysis, assigning personalized educational content tailored to these styles [74]. Furthermore, LA and educational data mining are employed to create pervasive and adaptive learning ecosystems that personalize learning experiences [12], [7]. In addition, ML-enhanced LA integrates models such as Random Forest for activity recognition and predictive analytics to enhance personalized and adaptive learning processes [23].

Natural Language Processing (NLP) algorithms are commonly utilized in the development of ECs within POL systems. Bidirectional Encoder Representations from Transformers model is used to build proactive chatbot framework [6]. Additionally, the integration of 3D virtual worlds, such as OpenSimulator, enhances immersion and presence in language learning environments. These virtual environments utilize tools like chatbots and "time machines" to create engaging, context-rich learning experiences [88]. Furthermore, Latent Dirichlet Allocation is utilized to process user queries and map learning object metadata into a structured ontology, contributing to a more PL environment [24]. Lastly, NLP algorithms [79] process feedback from instructors and students to optimize the educational framework by analyzing course outcomes.

Classification Algorithms such as the Support Vector Machine algorithm is used for learner modeling by analyzing learner traces in Cloud Computing environment [32]. Additionally, decision tree methods are used to create classifiers that predict user emotional states and activity levels based on HRV, to provide PL experiences based on learner physiological responses [18].

Deep Learning algorithms are used to provide POL by leveraging various neural network models and federated learning techniques. For instance, a deep GNN-based Social Recommendation framework encodes user and item feature spaces into graph networks for personalized recommendations in IoT scenarios. This framework uses matrix factorization in conjunction with encoded graph spaces to infer missing rating values, which is crucial for delivering PL experiences [34]. Similarly, Convolutional Neural Networks

combined with attention networks are employed to enhance the personalization of content based on learner interactions [41].

Reinforcement Learning (RL) frameworks, including hierarchical RL, utilize a Governor RL agent based on a Markov Decision Process to adjust parameters in IoT applications by addressing human variability [28]. Alongside RL, data mining techniques are employed to analyze student learning behaviors and preferences to recommend learning strategies and content [86].

In **Rule-Based Learning Algorithms** RecRules combines content-based and collaborative filtering using semantic reasoning to personalize recommendations [25], while ECs use rule-based, retrieval-based, and generative models for adaptive content delivery and interaction design [44]. In addition, **Cryptographic Techniques** like Hadamard Matrix-based Zero Knowledge Proof System implements authentication secure access roles, which is critical to protect PLEs [61].

These ML algorithms collectively contribute to the personalization of online learning by accurately classifying learners, generating adaptive learning paths, managing human variability, and providing tailored recommendations and interactions. Each algorithm addresses specific aspects of learner behavior and preferences, creating a more adaptive and effective learning environment.

Key Findings:

- The combination of traditional ML algorithms, such as C4.5, J48, and Genetic Algorithms, with IoT-generated data demonstrates the ability to create individualized learning experiences based on learner engagement, preferences, and environmental context;
- ML algorithms like Support Vector Machine, K-Means Clustering, and graph neural networks are employed to analyze learner profiles, classify data, and offer personalized recommendations;
- The reliance on predefined rules and classification parameters can limit the flexibility needed for truly dynamic and real-time personalization;
- The combination of rule-based algorithms with clustering techniques like K-Means can be seen as an effective strategy for handling large-scale data.

4.2.6 What are the IoT tools that may be used in POL?

The integration of IoT tools in POL systems utilizes a variety of protocols, devices, and sensors, Table 11, to enhance the learning experience.

Software Based IoT Tools typically include Chatbots, Virtual Immersive Learning Tools, and Intelligent Agent-based Tools. These tools integrate a range of software technologies to enhance learning personalization and optimize educational processes. Examples of software-based tools include Google Dialogflow, combined with Google Sheets, Python, and JavaScript scripts automates data manipulation processes [73]. Additionally, Textit, a no-code platform for chatbot development, is employed to design and deploy chatbots through messaging platforms such as Telegram [44]. Furthermore, conversational workflows are managed using tools such as Context Dimension Trees and Petri Nets, to develop highly interactive and adaptive chatbot systems [24]. Virtual Immersive Learning Tools, such as PhET Simulations, are utilized in virtual chemistry labs to facilitate

Table 11. IoT tools integrated into POL Systems

IoT Tools	Number of Studies	Percentage
Software Tools	23	35%
Smart and Wearable Devices	17	26%
IoT Tools and Devices	10	15%
Computing and Middle-ware Tools	6	9%
Environmental Sensors	5	8%
Specialized Tools	4	6%

conceptual understanding [65]. In addition, CloudSim, an IoT-based simulator, supports learner modeling in cloud environments, offering flexibility in the delivery of educational content [32].

Furthermore, **Tools** such as Microsoft Cognitive Services-API1, Google Cloud Vision-API2, CLMtrackr3, ADOxxR are utilized for recognizing emotions [27], meanwhile a video camera, Visual C Programming Language and Computer Vision Library are used to measure engagement levels by analyzing video data [31]. Lastly, Audacity Software, JavaScript Templates, LEDs, Sensors, Actuators, and Educational Micro-controllers are used as IoT Educational Tools for creating Ubiquitous Computing, Mobile Computing, and IoT learning scenarios [53].

IoT-enabled Personal Smart Devices based platforms focus on utilizing mobile devices both as IoT tools and learning tools. These devices, embedded with sensors such as accelerometers, proximity sensors, ambient light sensors, and GPS, are used to create ubiquitous learning environments [60], to build context-aware mechanisms [96], and to optimize content delivery based on the learner environment and device capabilities [48]. Additionally, these devices play a significant role in the development of m-learning frameworks [64], [83], [66].

Wearable devices have become integral components of modern IoT-based personalized e-learning environments. These devices include the Mio® Alpha heart rate sport watch, used for emotion prediction [18], and devices such as Google Glass, Oculus Rift, Apple Watch, and Android Wear to provide seamless and PL experience [56]. Other examples include the MKB0805 Dynamic PPG Heart Rate and Blood Pressure Module, as well as Oculus Quest 2 Glasses used to assess learner emotional engagement and cognitive levels [102]. Additionally, wearable devices equipped with NFC readers, often worn on the wrist, are used to track learner progress and assess motivation [16]. Smart Glasses, featuring both outward- and inward-facing cameras, accurately determine visual focal points, enabling the tracking of learner attention and interests [85]. Moreover, Empatica™ E4 device is used measure EDA, PPG, and ST to capture physiological responses to infer engagement levels [63].

IoT data collection and networking tools in personalized e-learning environments encompass a variety of innovative technologies and devices designed together to process and analyze real-world data. Key communication technologies such as Zigbee, Bluetooth, Wireless Sensor Networks, Cloud Computing services, and Internet facilitate connectivity between environmental sensors (e.g., sensor nodes, RFID, GPS) and edge computing tools [61], [7]. Data sources include real-world IoT datasets like Epinions, Yelp, and Flixster [34]. In addition, tools such as Raspberry Pi, RFID, Smart Boards, Biometric Scanners,

Electronic Whiteboard Screens, and Bluetooth Beacons facilitate comprehensive data collection [77], [12].

IoT Prototyping and Development Devices include tools that facilitate the creation and testing of IoT-based e-learning environments. Devices like Raspberry Pi with different sensors, Arduino Uno Board, and Mobile Devices combined with platforms such as Node-RED, GrovePi sensors, and IoT Lab Kits form the basis for IoT-based e-learning environments prototyping [41], [62], [74], [57].

Environmental sensors and tools play a crucial role in enhancing POL by creating context-aware ALEs that respond to physical conditions. An IoT-based system integrates temperature, humidity, air quality, light, and sound sensors to collect environmental data in order to enhance personalization of learning environments [8]. Another application uses GPS to capture location context and deliver personalized and location-based learning content [97]. Furthermore, the dataset titled "Sensor Signal Dataset for Exploring Context Recognition of Mobile Devices" which includes environmental sensors data is utilized to demonstrate the use of mobile device sensors as critical IoT tools for context-aware learning environments [37].

Middle-ware Tools contribute in developing PLEs by integrating IoT with Cloud Technologies [91] LMS such as Moodle [55]. Additionally, middle-ware facilitates data collection and interaction within the educational framework [51]. Edge computing tools facilitate the deployment of Deep Spatio-Temporal Convolutional LSTM models on edge-based prototypes for processing EEG signals to recognize human emotions [82]. Additionally, edge devices such as black globe thermometers and skin temperature monitors are used to assess human thermal comfort [28].

The integration of IoT tools into POL systems enhances educational experiences through a variety of protocols, devices, and sensors. Software-based tools such as chatbots, virtual immersive learning tools, and intelligent agents optimize personalization by using different platforms. In addition, wearable devices such as smartwatches and smart glasses monitor physiological responses to assess learner engagement. Environmental sensors and edge computing tools further personalize learning by adapting to physical conditions. Lastly, middle-ware tools seamlessly integrate IoT with cloud technologies and LMS to optimize data collection and interaction within the learning framework.

Key Findings:

- IoT Software Tools like chatbots, immersive virtual tools, and intelligent agents enhance POL by automating processes and providing personalized interactions;
- Wearable and environmental devices along with sensors for temperature, light, and sound, monitor learner physiological and environmental data to personalize learning experiences;
- Tools like Raspberry Pi, Arduino, and cloud technologies facilitate real-time data collection and creation of adaptive learning environments.

4.2.7 Which research approaches are used in academic literature related to the integration of IoT into POL and what contribution has been achieved?

Table 12 presents the research contribution types and their distribution related to the integration of IoT in POL. Among the various types of contributions, papers proposing

frameworks or methods are the most prevalent, accounting for 68% of selected papers. These papers introduce innovative IoT and AI-based systems that use wearable sen-

Table 12. Number of publication by contribution type

Contribution Type	Number of Studies	Percentage
Framework/methods	44	68%
Tool	11	17%
Model	7	11%
Guidelines	2	3%
Lesson learned	1	2%

sors and biosensors, to personalize and enhance educational experiences. Extracted main frameworks include IoT for Education 4.0 [23], ERUDITE [82], and APPLE [91], which utilize tools like smartwatches and EEG signals to track emotions. Additionally, FaiR-IoT framework addressed human variability in order to provide adaptive, sustainable, and learner-centered education [28].

Another collection of research papers introduces various educational **tools** to enhance learning experiences. These tools include an iOS application for personalized course content based on learning styles, WIoTED system for improving student engagement through wearable IoT devices, and an authoring system for robots and IoT-based toys to support EFL teaching [83], [96], [93]. Highlighted other tools include an intelligent music selection system based on HRV, an IoT-based system for supervising online English teaching through intelligent face perception, and a personalized NIE content recommendation system [18], [41], [77].

The collection of papers under the **Model** contribution type introduces various innovative models to enhance educational experiences. Extracted main models include the Customized X-Learning Environment model, which integrates multiple learning elements and technologies to create a student-centered virtual education environment [55]. PrivRec and DP-PrivRec, privacy-preserving federated learning-based recommender systems, models are also highlighted [87]. Additionally, a ML-based context fusion model infer high-level context information from low-level multi-domain IoT data [37]. Moreover, Decision Tree Thompson Sampling is introduced as a novel model for PL within the Automatic Personalized Learning Service framework [70].

Table 13 presents the results of the study based on the research types of the selected papers. The majority of primary studies (66%) focus on **proposing solutions**, most of which aim to develop and test new approaches that have not yet been fully evaluated in real-world practical scenarios. These solution-oriented papers introduce various frameworks and systems. Highlighted main solutions include an m-learning framework designed for resource-constrained environments [64], a Cloud of Things-based online education framework [61], a Personalized Context-Aware Recommendation learning system [96], and an IoT-based educational systems [93]. Other solutions include an IoT-based personalized Newspaper in Education content recommendation system [41], an IoT-based interaction framework combined with an attention-scoring algorithm [31], and an adaptive learning models utilizing ML to track student knowledge states [84]. Experimental results and

empirical studies validate the effectiveness of these solutions, demonstrating improved learning outcomes, and increased user satisfaction across diverse educational contexts.

Table 13. Number of publication by research type

Research Type	Number of Studies	Percentage
Solution research	43	66%
Evaluation research	18	28%
Validation research	3	5%
Experience paper	1	2%

Evaluation research is the second most common research type implemented in IoT-based POL, comprising 23% of selected studies, and focuses on assessing the effectiveness and performance of various educational technologies and interventions in real-life settings. These studies span over multiple aspects, including context-aware ubiquitous learning systems [76], adaptive e-learning systems based on personality and emotion [64], and a PL through an iOS application that improves student comprehension [61]. IoT technology impact on student attention and motivation through physical variables [8], the influence of virtual classrooms on foreign language anxiety [38], and vocational student self-efficacy and attitudes toward m-learning [90] have also been evaluated. Lastly, the Personalized Learning Space in the Educational Metaverse [83] using physiological and cognitive metrics, and IoT-enabled smart labs to assess their impact on academic performance [7] are also highlighted.

The rest of papers falls into different categories emphasising different experiences and validations of IoT-based POL systems [62], [82], [94].

Key Findings:

- Research contributions of integrating IoT into POL primarily focus on developing different frameworks and methods;
- Solution-based studies dominate the integration of IoT into POL, though often not yet tested extensively in real-world environments;
- Evaluation research studies assesses real-life effectiveness of IoT-based POL systems across various educational technologies.

5. Conclusions and Future Works

This paper conducted a systematic mapping study exploring the integration of IoT technologies in POL, and identified the current landscape, limitations, and potential research gaps. We systematically considered various dimensions of IoT integration within existing POL systems, providing a comprehensive understanding of techniques, models, components, tools, and algorithms involved.

Our analysis reveals that 35% of the reviewed studies integrate IoT to create ubiquitous smart learning and IoT based e-learning systems, however as few as 3% of studies

used IoT to integrate and control environmental parameters into POL systems. Furthermore, 40% of these studies highlight learner profile as a primary factor in personalizing educational experiences where IoT is expressly used to extract socio-psychological, and biological context. Additionally, 42% of the studies utilized LA and a combination of multiple algorithms to process data and delivered tailored online learning services. 66% of selected studies focused on solution research, while 63% of the latter selection were solution proposals, frameworks or methods.

Use of IoT in education is shifting the structure of educational system by bringing changes to educational institutions infrastructure, and involving innovative teaching methodologies and learning practices. Typical responsibilities of students and teachers are fundamentally changed in IoT-based e-learning settings and there is an imminent need for innovative teaching/learning methods to enable integration of IoT in education.

The use IoT in POL bridges the gap between the physical and virtual worlds and significantly reshapes ALEs. The integration of IoT in personalizing environmental factors, intelligent tutoring systems, and reinforcement learning algorithms remain under-explored, additionally, there is a lack of utilizing IoT to seamlessly integrate the adaptation of physical and virtual learning environments.

Additional analysis of psychological and behavioral patterns through IoT data holds great promise for the development of decision support systems that cater to the unique needs of individual learners. In addition, challenges of privacy, security, and personalization of external factors, proper integration of adaptive learning platform modules, and heterogeneity of data need to be handled in IoT-based POL systems.

Based on our findings we conclude that integration of IoT into existing POL systems increases personalization and enhances academic outcomes. Furthermore, we also conclude that there is a need for new pedagogical approaches, personalization models, and standardizations to accommodate IoT innovations in Education. Lastly, our study shows that there is a lack of longitudinal studies examining the long-term impacts of IoT-enhanced learning environments on educational outcomes.

These findings offer valuable insights for educators, policymakers, and technology developers to enhance the design and implementation of PLEs.

Our future study will propose a solution framework that seamlessly integrates biological, psychological, and environmental components into existing POL systems. In addition, the impact of these components on educational outcomes will be assessed.

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Edlir Spaho is a seasoned computer engineer with extensive experience in education management and IT services. Based in Tirana, Albania, he serves as an assistant lecturer at "Bedër" University College and "Epoka" University, where he teaches a range of courses, including C++ Programming, Artificial Intelligence, Data Mining, and Internet of Things (IoT) Fundamentals. With a Master of Science in Computer Engineering from "Epoka" University and ongoing PhD studies focused on developing a personalized e-learning algorithm leveraging IoT, Edlir combines technical expertise in programming and AI with a deep commitment to advancing educational technology. His professional background also includes roles in IT management, curriculum development, and authoring educational materials. He has received several awards, including recognition at the Balkan Olympiad of Informatics. Beyond teaching, he is passionate about research and innovation in personalized and adaptive learning systems.

Betim Çiço is a full professor in the Computer Engineering Department at Epoka University. His current research interests include high-performance computing, digital design, methodologies and tools, e-learning, and FPGA applications in nuclear electronics, among others. He received his Diploma Engineer degree in Electrical and Electronic Engineering from the Polytechnic University of Tirana, Albania (PUT), and his PhD in Nuclear Electronics from the Institute of Nuclear Physics (INP, Research Institute), Tirana, Albania, in 1983. He served as a scientific researcher at the INP from 1972 to 1998 (Head of the Nuclear Electronic Department) and as a part-time professor at PUT. Since 1998, he has been a full professor at PUT (until 2012, Head of Computer Engineering Department), South East European University in Tetovo, Macedonia (Dean of Faculty of Contemporary Sciences and Technology, 2 years), and at Epoka University in Tirana since 2016. He participated as a partner in many European Scientific Activities, like FP5, FP6, FP7, and Horizon 2020. He is also a member of many program committees and stirring committees (ACM, IEEE, Springer Fergal) and on the editorial board of journals.

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