PERSONALIZATION COMPONENTS AND ALGORITHMS IN IOT BASED PERSONALIZING ONLINE LEARNING SYSTEMS (A SYSTEMATIC REVIEW)

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ABSTRACT

The integration of Internet of Things (IoT) technologies into Personalized Online Learning (POL) systems has revolutionized educational paradigms, enabling the delivery of individualized and dynamic learning experiences. This paper offers a comprehensive exploration of IoT-based POL systems, synthesizing findings from existing research to highlight main personalization components and algorithms. These systems leverage IoT data—such as learner profiles, environmental contexts and physiological responses—combined with adaptive learning algorithms to tailor content and create responsive learning environments that address individual learner needs. Key algorithms, including learning analytics, machine learning and deep learning, are analyzed for their roles in enabling adaptive learning pathways and context-aware personalization. By synthesizing 65 primary studies, this paper identifies both current advancements and research gaps, providing actionable insights and future directions for enhancing online learning personalization. The findings demonstrate that IoT-enhanced POL systems hold significant potential to transform education by accurately classifying learners, adapting to diverse needs and creating effective, dynamic learning experiences. Recommendations for researchers, educators and developers are offered to further the adoption and optimization of IoT-driven personalized learning solutions.

Keywords: personalization components, machine learning algorithms, personalized online learning, systematic review, internet of things

1. INTRODUCTION

Online learning systems have gained significant traction in modern education, offering flexibility, accessibility and scalability. One of the most transformative developments in this domain is the shift towards personalized learning, where systems adapt to the individual needs and learning preferences of students. Personalization in online learning enhances engagement, retention and academic performance by tailoring content, pace and feedback mechanisms supporting a more effective and efficient learning process, to dynamically respond to student needs and behaviors (Jando *et al*., 2017).

The Internet of Things (IoT), characterized by interconnected devices capable of collecting and exchanging data, is emerging as a key enabler of personalized learning environments and playing an increasingly vital role in this transformation. IoT enables the collection of real-time data through sensors, wearables and other smart devices embedded in the learning environment. These devices can monitor learner behavior, physiological responses, environmental conditions and interactions with learning materials (Al-Emran *et al.*, 2020).

The integration of IoT into education has transformed learning environments, enabling Personalized Online Learning (POL) through the use of real-time data from interconnected devices (Yao, 2017). IoT-driven systems, such as context-aware ubiquitous learning environments and sensor-based feedback mechanisms, provide dynamic educational experiences tailored to individual needs. In personalized online learning, IoT incorporates wearable devices, mobile platforms and environmental sensors, all of which generate data streams that adaptive learning algorithms process to enhance student engagement and performance. IoT-enabled personalized learning integrates different data sources, including learners' preferences and profile, wearable biosensors, environmental sensors, facial recognition and contextual inputs, as personalization component approaches to tailor educational experiences (Shapsough and Zualkernan 2020).

Machine Learning (ML) algorithms play a vital role in processing the large volumes of heterogeneous data generated by IoT devices in educational contexts (Adi *et al*., 2020). Algorithms such as reinforcement learning, deep learning and classification methods, enable the development of adaptive learning paths and personalized content delivery by analyzing learner behavior, biological and physiological responses and contextual factors. ML techniques are increasingly being used to classify learners, recommend content and assess cognitive and emotional states, thereby improving the personalization and efficacy of IoT-based learning systems (Camacho *et al*., 2020).

The primary objective of this systematic review is to identify, categorize and analyze the existing personalization components and machine learning (ML) algorithms employed in IoT-based POL systems. By reviewing current literature, this study aims to provide a comprehensive framework for understanding the key personalization components and the main ML techniques utilized to process these components in order to create personalized learning experiences. Additionally, the review will explore the challenges, such as device and data heterogeneity, data privacy and algorithmic bias, associated with integrating ML into IoT-enabled learning environments.

While IoT holds immense potential for improving personalized learning, effectively integrating these technologies into learning environments presents significant challenges. The inherent complexity of IoT-based systems—comprising numerous interconnected devices, real-time data processing and adaptive learning pathways—demands advanced design and implementation strategies. Notably, there is a lack of comprehensive reviews that explore how IoT is used to support personalization in online learning, particularly regarding the learning components and algorithms that enable such personalization. Existing literature is fragmented, often focusing on IoT in education or personalized learning separately. However, there is limited systematic exploration of the intersection of these fields and how IoT technologies can be utilized to achieve meaningful personalization in learning environments (Al-Emran *et al*., 2020; Hlioui *et al*., 2016). Furthermore, while algorithms and learner models are central to personalization, the specific components that enable it —such as real real-time feedback, context-aware sensors and adaptive content delivery—remain underexplored in the current body of research (Mavroudi *et al*., 2019).

Thus, there is a pressing need for a systematic review that explores ML algorithms used within IoT-based personalized or adaptive online learning systems. Such a review is crucial to identifying trends, challenges and research gaps, while providing a detailed examination of the computational techniques used to process personalization factors to adapt learning experiences in IoT-driven POL systems.

This review aims to offer valuable insights for researchers, educators and technology developers seeking to enhance the design and implementation of POL systems leveraging IoT. By doing so, it contributes to the expanding body of literature in this interdisciplinary field.

The primary objectives of this study are as follows: i) to provide a comprehensive overview of the personalization components used in IoT-based online learning systems, such as learner's profile and environmental context; ii) to review the algorithms that underpin POL within IoT environments, including ML, rule-based and hybrid approaches; iii) to identify key trends, challenges, and gaps in the literature regarding the integration of IoT based personalization components in POL; and iv) to offer insights into future research directions that could advance the personalization of learning through IoT technologies.

To achieve these objectives, the study seeks to answer the following research question:

- **What are the primary personalization components used in IoT-based POL systems?**
- **What are the primary ML algorithms employed to achieve personalization in IoT-based POL systems?**

Our findings indicate that learner's learning style, prior knowledge, location, preferences, and emotions are the most commonly used personalization components. Furthermore, 32% of selected studies use different learning analytic to process and analyze personalization data, whereas the second most commonly used approach of 28% is the combination of different algorithms to provide personalization services in IoT based POL systems, meanwhile cryptographic techniques are utilized to enhance security of IoT-based POL systems and not as personalization tool.

The paper is structured as follows: Section 2 discusses IoT-based POL systems, emphasizing the role of IoT in education and its potential for enhancing personalization. Section 3 focuses on the systematic review research methodology. Section 4 represent the results of the study by identifying ML algorithms utilized in these systems and providing a comparative analysis of different techniques. Finally, Section 5 presents conclusions and future directions, highlighting opportunities for further research and advancements in this field. Following literature review, we aim to present the background of our research.

2. RESEARCH BACKGROUND

Personalization in online learning systems refers to the ability of a learning platform to adapt content, instructional methods, and feedback to meet individual learner needs. Personal Online Learning (POL) has increasingly been recognized as a powerful approach to improve learner engagement and academic outcomes. POL aims to deliver customized learning experiences that adapt to individual learner preferences, behaviors, and cognitive needs. The primary focus of POL systems is to use data-driven algorithms and technologies to dynamically modify learning paths, instructional strategies and content to suit each learner's specific requirements. Traditional online learning platforms have relied on static learner profiles, prior academic performance and self-reported preferences to personalize content delivery. Early personalization methods were largely rule-based, with limited flexibility to adapt to the evolving needs of learners during the learning process (Jando *et al*., 2017). However, with advancements in artificial intelligence (AI) and machine learning (ML), adaptive learning systems have emerged, enabling more dynamic and responsive personalization. These systems leverage learning analytics, user interaction data, and assessment outcomes to refine content relevance and the effectiveness of learning materials (Tang and Wang 2018; Kulbach *et al*., 2020).

Despite these advancements, the scope of personalization in early systems was confined to data that learners generated through digital interactions, such as clicks, quizzes and time spent on specific tasks. This approach overlooked critical contextual factors—such as the learner's physical environment, emotional state, and engagement levels—that influence the learning experience (Bernacki *et al*., 2021). The introduction of IoT technologies in POL systems addresses this gap by offering a broader and more nuanced dataset. IoT provides real-time insights into how learners engage with content within both physical and digital environments. Over the past few decades, POL systems have evolved, with the integration of the Internet of Things (IoT) introducing new dimensions to personalization. IoT enables real-time data collection from learners' physical, cognitive, and emotional environments (Adi *et al*., 2020). By leveraging a combination of environmental, physiological, and behavioral data, IoT enhances learning outcomes.

IoT sensors can track factors such as temperature, lighting, and noise levels to optimize the learning environment for each student fostering better focus and engagement (Mohana *et al*., 2023; Yau and Hristova 2018). This layer of contextual awareness enhances traditional e-learning, enabling learning systems to adjust content based on environmental variables and learner interactions (Ciolacu, *et al*., 2019). Personalization remains a key objective of modern online learning systems, with IoT playing a central role in delivering tailored educational experiences (Jando *et al*., 2017).

The integration of IoT data into ML algorithms is essential for developing adaptive learning systems that personalize the educational experience. IoT devices generate vast amounts of data, which are processed by ML models to make real-time predictions about the learner's needs. These models include reinforcement learning, neural networks, and clustering techniques, all of which help classify learners, recommend resources, and adjust learning content dynamically based on environmental and physiological feedback (Kim *et al*., 2019).

In summary, the integration of IoT with ML facilitates the creation of intelligent systems that can anticipate and adapt to learner needs, thereby improving the overall efficacy of POL environments. Building on this background of IoT integration in POL systems, this paper will now address the research methodology used in this study.

3. METHODOLOGY

The objective of this study is to identify what are the personalization components and Machine Learning (ML) algorithms in IoT-based POL models. The primary focus is on the intersection of personalization components and ML Algorithms employed to process these components' data within IoT based POL systems. To achieve a comprehensive overview of the area, we conducted an extensive review of IoT in education papers that address POL methods, techniques, models and frameworks.

Various systematic review study guidelines can be used for such review, including those proposed by Littell (2006), Kitchenham and Charters, (2007), and Kitchenham (2004). However, the systematic mapping study guidelines by Petersen *et al*., (2015) were selected for this study as they consolidate the best practices suggested by other researchers. According to Petersen *et al*., (2015), a systematic mapping review process begins with formulating research questions (RQs). The subsequent steps involve screening the papers based on their titles, abstracts and keywords metadata, followed by a full content to answer the RQs. The systematic mapping process used in this study is depicted in Figure 1.

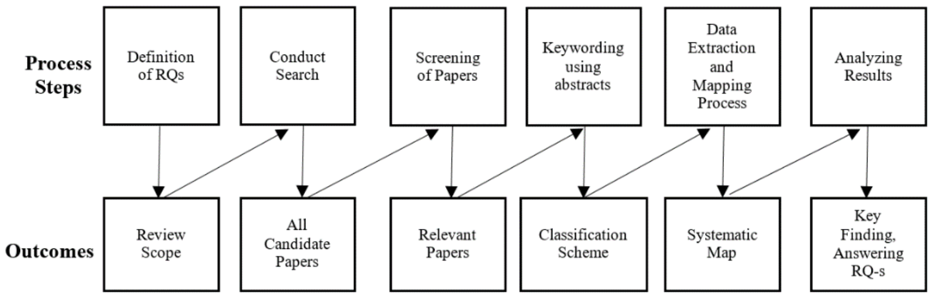

Fig. 3: The systematic review process (Petersen et al., 2015).

Based on the study's motivation and objectives (Section 1), the following research questions (RQs) were proposed to guide the search and selection process:

RQ1: What are the primary personalization components used in IoT-based POL systems?

RQ2: What are the primary ML algorithms employed to achieve personalization in IoT-based POL systems?

The first step in conducting a systematic review was identifying the search string for publications. To derive keywords and formulate the search string from research questions, we applied the PICO (Population, Intervention, Comparison, and Outcomes) criteria developed by Petersen *et al.*, (2008). These criteria are defined in Table 1.

Table 1: PICO of the study

Population	Primary studies which integrate IoT in POL systems (both theoretical and empirical studies).
Intervention	Personalization Components and ML Algorithms utilized to process these components in IoT based POL systems.
Comparison	Comparing different ML Algorithms employed to process Personalization Components in IoT based POL systems.
Outcome	Evaluation of Personalization Components and ML Algorithms utilized to process these components in IoT based POL systems.

To explore how IoT is integrated in POL systems in primary studies, we formulated a search string designed to capture the combination of IoT and POL systems. The three main concepts of the search string— ‘‘Internet of Things’’, ‘‘Personalized” and “Online Learning’’— we derived from research questions. Our basic string was (**Internet of Things AND Personalized AND Online Learning**). To broaden the scope of our research, we reviewed the literature to identify synonyms or interchangeably used terms for these primary concepts. Using the Boolean operator AND, we combined the main concepts, while the OR operator was employed to include synonyms or interchangeable terms for each concept.

For our research, we implemented the search string in ACM and IEEEXplore digital libraries, as well as in the Education Resources Information Center (ERIC) and Springer Link databases. We selected ERIC was selected as one of the primary education research and information databases, while ACM, IEEEXplore digital libraries and Springer Link database were chosen as key sources for engineering-related articles. To capture the latest trends, we limited the research between January 2017 and December 2023, as the integration of IoT in Education for personalizing online learning is an emerging field. Based on the research methodology outlined in this section, the subsequent section presents our findings, focusing on the ML Algorithms employed in IoT based POL systems.

Table 2. Criteria used for including and excluding research studies

Inclusion Criteria	**Exclusion Criteria**
- 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 literatures	- Duplicate papers from the same study in different databases. - Mention of IoT is tangential with different scopes not directly related to Personalized Online Learning - Publications not written in English - Publications not directly related to our topic - Full-text is inaccessible - Books and gray literature

Papers were selected based on the research questions and the inclusion and exclusion criteria outlined in this mapping study (see Table 2). The screening process included reviewing titles, abstracts, and keywords identified through the search string. A total of 6,441 papers published between 2017 and 2023 were retrieved through database searches, with the majority sourced from the SpringerLink digital library.

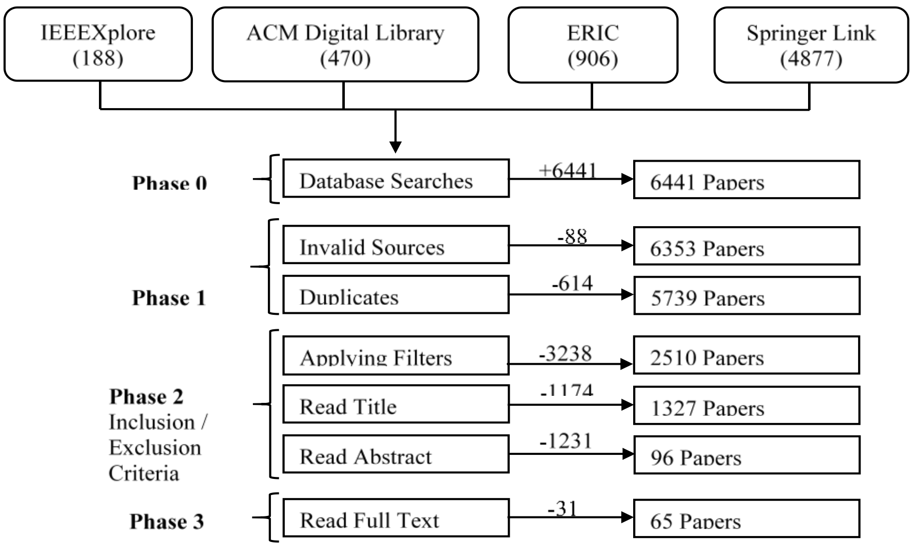

Fig.4. Selection of primary studies (Petersen et al., 2008).

Phase 1 involved the automatic removal of 88 invalid sources not intended for citation, such as workshop programs, keynotes, book covers, speeches, retracted articles, PhD theses, and unpublished works. Additionally, 614 duplicate papers were automatically removed using spreadsheet software, leaving a total of 5739 references.

Phase 2 applied further filtering based on the inclusion and exclusion criteria (see Table 4). First, titles and keywords were screened, reducing the number of studies to 2510. Next, abstracts were evaluated following the recommendations of Petersen *et al.*, (2008), resulting in 96 candidate studies.

In the final phase, following a full text reading of candidate studies, 31 papers were excluded as they were not entirely relevant to our systematic mapping study. This left a total of 65 accepted studies. Figure 2 illustrates the number of included and excluded papers for each phase.

4. RESULTS AND DISCUSSIONS

From an initial sample of over than 6400 papers, 65 primary studies were identified as relevant for answering the research questions. The results of the systematic review study are presented as follows:

4.1. Personalization Components in IoT based POL Systems

The integration of IoT into POL systems enables the incorporation of various personalization components, each contributing to a more adaptive and learner-centric experience. The systematic review analysis identified three primary categories of personalization components in IoT-enabled learning systems:

- Learner’s profile (77%): Includes elements such as learning style, prior knowledge, preferences, and emotional state.
- Contextual adaptation (40%); Focuses on environmental factors like location, time, and physical conditions.
- Pedagogical strategies (14%): Involves dynamic instructional methods tailored to individual learning goals.

Figure 3 provides a visual representation of the distribution of these personalization components across the analyzed studies.

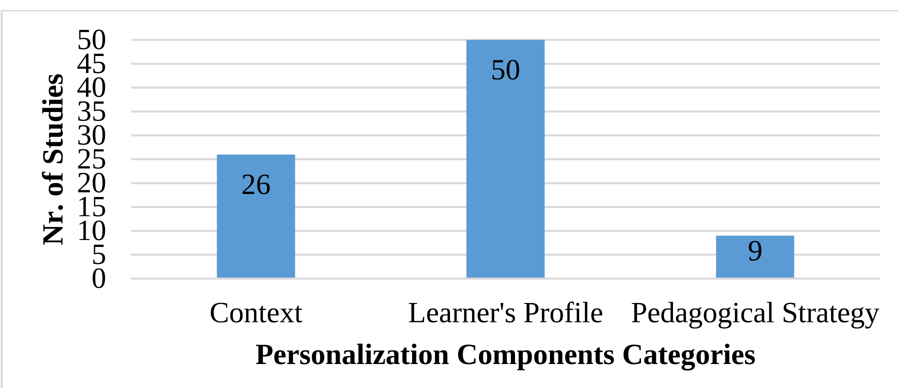

Fig. 5: Personalization components categories.

The learner profile emerges as the dominant category of personalization components for providing POL services. It offers a comprehensive, multi-dimensional framework that integrates psychological, academic, pedagogical, sociological, biological, cognitive, and demographic factors. The contextual awareness category encompasses components such as Environmental, Technological and Socio-Psychological Context components, enabling learning environments to dynamically adapt based on situational data. Meanwhile, pedagogical strategies focus on refining teaching and learning approaches to align with personalized needs. Table 2 provides detailed summary results of personalization categories, their subcategories, number of studies utilizing each subcategory components, and their percentage over the total of selected studies

Table 3: Personalization components categories and sub categories

Components Category	**Components Sub Category**	**No. of Studies**	**Percentage**
Learner's Profile	Psychological Profile	23	35%
Learner's Profile	Academic Performance	20	31%
Learner's Profile	Pedagogical Profile	19	29%
Learner's Profile	Sociological Profile	17	26%
Learner's Profile	Biological Components	10	15%
Learner's Profile	Cognitive Ability	8	12%
Learner's Profile	Demography	3	5%
Context-Awareness	Environmental Context	14	22%
Context-Awareness	Technological Context	10	15%
Context-Awareness	Special Context	4	6%
Context-Awareness	Socio-Psychological Context	2	3%
Pedagogies	Pedagogical Strategy	9	14%

Among these, in IoT based POL systems the psychological profile stands out the main factor for constructing an effective learner profile. Table 4 provides a summary personalization component exploited to build the psychological profile of the learner that are implemented by two or more selected studies.

Table 4: Psychological Profile Main Personalization Components

Personalization Component	No. of Studies	Percentage	References
emotions	7	11%	Perry and Edwards, 2019; Bourekkache and Kazar, 2020; Zhao *et al.*, 2022; Fatahi, 2019; Dwivedi *et al.*, 2018; Mesquita et al., 2016; Shrestha and Furqan, 2020
engagement	3	5%	Asad *et al.*, 2024; Ciolacu, Binder and Popp, 2019; Yakoubovsky and Sarian, 2021
motivation	3	5%	Farhan et al., 2018; Elmalaki, 2021; Ghallabi *et al.*, 2020
interests	2	3%	Benhamdi *et al.*, 2017; Whalley *et al.*, 2020
learning goals	2	3%	Dwivedi *et al.*, 2018; Ma and Li, 2021
personality	2	3%	Fatahi, 2019; Prihar *et al.*, 2022
attention	2	3%	Camacho *et al.*, 2020; Ciolacu, Binder and Popp, 2019
needs	2	3%	Prihar *et al.*, 2022; Yakoubovsky and Sarian, 2021

Personalized learning systems employ methods like MBTI personality typing and emotional desirability to create tailored environments. These systems incorporate motivational elements— such as encouraging messages, energetic music and animations— to enhance engagement (Fatahi 2019). Emotional states, including happiness, sadness, anger and fear, are monitored alongside stress management techniques to optimize learning paths. Tools like FLVCAS dynamically adapt content to reduce anxiety and support participation (Elmalaki 2021; Asad *et al.*, 2024; Perry and Edwards 2019).

Engagement is tracked through behavioral observations, facial recognition, and IoT-enabled data analysis, enabling adaptive content delivery (Camacho *et al.*, 2020; Ma and Li 2021). Interactive platforms, such as IoT-based labs and collaborative discussions, promote active participation and teamwork. Additionally, real-time attention monitoring, powered by reinforcement learning, ensures sustained engagement (Bourekkache and Kazar, 2020; Wang, 2017; Farhan *et al.*, 2018).

Cognitive and immersive strategies utilize virtual environments and arts-based methods, such as reflective mosaics, to create interactive and emotionally engaging experiences. These approaches incorporate stress management and creativity, sustaining learners' interest while aligning with their individual goals (Asad *et al*., 2024; Perry and Edwards, 2019; Kaisar and Chowdhury, 2020).

Learners' interests and preferences paly a vital role in guiding personalized recommendations and collaborative environments. These strategies ensure that tasks align with individual goals, enhancing engagement and effectiveness. Reinforcement learning frameworks promote fairness and inclusivity by adapting to group variability and accommodating diverse learning needs (Dwivedi *et al*., 2018; Fatahi 2019; Zhao *et al*., 2022; Yakoubovsky and Sarian 2021). Intention inference techniques dynamically adjust content to meet learners' immediate needs, showcasing the potential of IoT-based systems to deliver dynamic, inclusive, and effective educational experiences (Asad *et al*., 2024; Shrestha and Furqan 2020).

The second most commonly used factor to build the learner's profile in IoT based POL systems is learner's academic performance. Table 5 summarizes the most commonly used personalization components for extracting learner's academic performance data. Among these, prior knowledge and domain-specific skills constitute the primary components for constructing a comprehensive academic profile.

Table 5: Academic Performance Main Personalization Components

Personalization Component	**No. of Studies**	**Percentage**	**References**
knowledge and skill level	7	11%	Yau and Hristova, 2018; Zhao *et al.*, 2022; Ghallabi *et al.*, 2020; Dwivedi *et al.*, 2018; Benhamdi *et al.*, 2017; Whalley *et al.*, 2020; Reyes *et al.*, 2019
performance	3	5%	Elkobaisi and Al Machot, 2022; Ciolacu, Binder, Svasta, *et al.*, 2019; Yakoubovsky and Sarian, 2021
interaction	3	5%	Yau and Hristova, 2018; Guo and Wang, 2021; Farhan *et al.*, 2018
progress	3	5%	Rawat and Dwivedi, 2019; Shapsough and Zualkernan, 2020; Zou and Xie, 2018
completed game stages	2	3%	Asad *et al.*, 2024; Saxena *et al.*, 2019

The development of learner modeling profiles in IoT-based POL systems heavily relies on modeling techniques that assess prior knowledge and categorize learners into various skill levels, such as beginner, intermediate, or advanced. These categorizations help tailor learning materials to meet individual needs effectively (Yao, 2017; Shapsough and Zualkernan, 2020; Ghallabi *et al*., 2020; Embarak, 2022). Frameworks evaluating proficiency and performance further refine recommendations for personalized content, ensuring alignment with the learner's evolving capabilities (Yau and Hristova, 2018; Rawat and Dwivedi 2019).

Progress tracking is another critical aspect enabled by IoT systems, which monitor metrics like completed assignments, interaction frequency messages exchanged, and time spent on specific tasks. This data helps identify learner progress and areas for targeted interventions (Yao, 2017; Ciolacu *et al.*, 2019; Shapsough and Zualkernan, 2020; Zhao *et al.*, 2022). Gamified elements, such as tracking progress through game stages, are integrated to maintain learner motivation and assess skill application in practical contexts, offering tailored challenges to promote growth (Guo and Wang, 2021).

Interaction frameworks foster collaboration and engagement within IoT-enabled learning environments. These systems utilize real-time dashboards to provide feedback on learner behaviors, facilitating adaptive learning paths and increased involvement (Yao, 2017; Farhan *et al.*, 2018; Saxena *et al.*, 2019). Additionally, historical data on courses previously taken ensures personalized content delivery, avoiding redundancy and building on prior learning (Rawat and Dwivedi, 2019).

Level of study is a vital academic performance factor integrated into adaptive systems, aligning content complexity with learners' academic stages and foundational knowledge (Dwivedi *et al*., 2018). The inclusion of prior knowledge, skill levels, progress metrics, and interactive elements collectively supports personalized education models within IoT-based POL systems.

Lastly, learner's learning style, stands out as the most utilized personalization component, according to Table 6, emphasizing its role in constructing comprehensive learner profiles. This component aligns instructional approaches with individual preferences, making it a cornerstone of effective IoT-based personalization in education.

Table 3: Pedagogical Profile Main Personalization Components

Personalization Component	**No. of Studies**	**Percentage**	**References**
learning style	10	15%	Shapsough and Zualkernan, 2020; Tortorella and Graf, 2017; Trifa *et al.*, 2019; Zhao *et al.*, 2022; Ciolacu, Binder, Svasta, *et al.*, 2019; Prihar *et al.*, 2022; Dwivedi *et al.*, 2018; Bourekkache and Kazar, 2020; Elmalaki, 2021; Soui *et al.*, 2022
preferences	7	11%	Shapsough and Zualkernan, 2020; Yao, 2017; Zhao *et al.*, 2022; Benhamdi *et al.*, 2017; Zou and Xie, 2018; Mesquita *et al.*, 2016; Yakoubovsky and Sarian, 2021
language preferences	2	3%	Yau and Hristova, 2018; Ghallabi *et al.*, 2020

Personalized Learning Environments (PLEs) leverage to adapt to individual learners' unique styles and preferences. By integrating contextual data gathered from sensors, these systems enhance content delivery to align with learner's unique needs. This adaptability extends to media preferences, enabling the presentation of content in text, video, or other formats that resonate with individual profiles. Such personalization approaches significantly improve engagement and comprehension, creating a more effective learning experience (Tortorella and Graf 2017; Dwivedi *et al.*, 2018; Bourekkache and Kazar, 2020).

Language preferences are another critical component of PLEs. These systems allow learners to access educational content in their preferred language, such as French or English, ensuring inclusivity and comfort in the learning process. Real-time adjustments to environments and strategies, guided by preferences and historical data, further enhance the learning experience. This dynamic personalization fosters a deeper connection between learners and their educational material (Yau and Hristova 2018; Benhamdi *et al.*, 2017; Ghallabi et al., 2020).

Adaptation to learning speeds and patterns is a hallmark of PLEs. These systems tailor content delivery rates to match each learner's pace, reducing cognitive overload and facilitating better understanding. By analyzing learning patterns, adaptive pathways are crafted to meet the specific needs of each individual. This personalized pacing ensures learners can progress confidently while maximizing their educational outcomes (Trifa *et al.*, 2019; Zhao *et al.*, 2022).

The sociological aspects of learners are also addressed through personalized systems. By analyzing behavioral patterns and social interactions, PLEs create environments that reflect individual social and educational contexts. Collaborative efforts, such as group projects and forum interactions, are optimized to enhance teamwork and foster a sense of community. These sociological insights ensure that the learning environment supports both individual and group dynamics effectively (Yao, 2017; Bourekkache and Kazar 2020; Guo and Wang, 2021).

Finally, immersive virtual environments enhance learner engagement by fostering collaboration and interaction in tailored educational setups. These environments provide opportunities for learners to engage with peers and systems in meaningful ways, promoting active participation and personalized educational outcomes. By integrating these diverse personalization components, PLEs offer adaptive, inclusive, and engaging learning experiences that cater to the needs of all learners (Wang *et al.*, 2017; Rawat and Dwivedi 2019; Adi *et al.*, 2020).

Table 4: Sociological Profile Main Personalization Components

Personalization Component	**No. of Studies**	**Percentage**	**References**
behavioral	6	9%	Bourekkache and Kazar, 2020; Zhao *et al.*, 2022; Yao, 2017; Q. Wang *et al.*, 2022; Adi *et al.*, 2020; Guo and Wang, 2021
interactions	6	9%	Trifa *et al.*, 2019; Phunaploy *et al.*, 2021; Ma and Li, 2021; Kim *et al.*, 2019; Elkobaisi and Al Machot, 2022; Prihar *et al.*, 2022
sociological profile	2	3%	Bourekkache and Kazar, 2020; Zhao *et al.*, 2022
collaboration patterns	2	3%	Kim *et al.*, 2019; Guo and Wang, 2021

Social cues, such as emotional responses and non-verbal interactions, play a pivotal role in IoT-based Personalized Online Learning (POL) systems by enabling real-time adaptation of learning environments.

These systems dynamically respond to learners' emotional states, creating a responsive educational setting that supports engagement and well-being (Elkobaisi and Al Machot, 2022). By incorporating these cues, IoT systems ensure that learners feel understood and catered to, fostering a more immersive and effective learning experience. The integration of social environments as a core component of learning design enhances the personalization of educational outcomes. Social modeling connects physical, technological, and pedagogical elements, creating a cohesive framework for adaptive learning experiences. By mapping horizontal and vertical social networks, these systems account for peer and hierarchical relationships, tailoring learning pathways to reflect the dynamics of the learner's social interactions (Mavroudi *et al*., 2019; Guo and Wang 2021). To refine personalization further, IoT systems track social indicators like volunteering and leadership within collaborative settings. These insights are used to evaluate learners' roles and contributions, enabling the design of role-specific educational interventions. By acknowledging individual social dynamics, these systems not only enhance teamwork but also foster personal development, ensuring a well-rounded learning experience (Wang *et al*., 2017).

Beyond social dynamics, IoT-based POL systems leverage biosensors to incorporate learners' biological features as personalization components. These systems analyze biometric data, such as heart rate, stress levels, and physical activity, to adapt content delivery and learning strategies. This biological dimension adds depth to personalization, ensuring that learners' physical states are considered alongside their cognitive and social needs, creating a holistic learning environment. Table 8 highlights the most commonly used biological features in IoT-based POL systems, showcasing their role in enhancing personalization within the education domain. By integrating these diverse components—social, emotional, and biological—IoT systems create adaptive, learner-centric environments that cater to individual preferences, capabilities, and contexts, driving effective and meaningful educational outcomes.

Table 5: Main Biological Personalization Components

Personalization Component	**No. of Studies**	**Percentage**	**References**
heart rate	3	**5%**	Adi *et al*., 2020; Mylonas *et al*., 2023; Shrestha and Furqan, 2020

eye tracking	3	**5%**	Guo and Wang, 2021; Betts *et al.*, 2020; Shrestha and Furqan, 2020
fingerprint patterns	2	**3%**	Ciolacu, Binder, Svasta, *et al.*, 2019; Soui *et al.*, 2022
blood pressure	2	**3%**	Mylonas *et al.*, 2023; Tsai *et al.*, 2018
physical activity, steps	2	**3%**	Shapsough and Zualkernan, 2020; Adi *et al.*, 2020

IoT-based systems employ innovative approaches to enhance personalized learning environments by integrating physiological data, creating a deeper understanding of learner engagement and needs. For instance, monitoring learners' heart rates provides insights into their engagement levels, allowing the system to dynamically adapt the learning environment. This real-time adaptation ensures learners remain in an optimal cognitive state, with task difficulty adjusted based on physiological responses to maintain focus and minimize cognitive overload (Adi *et al*., 2020; Shrestha and Furqan 2020; Mylonas *et al*., 2023). Eye-tracking technology further personalizes learning by analyzing gaze patterns and focal points. By identifying areas of interest or difficulty, these systems deliver targeted teaching materials and offer interactive feedback, enhancing engagement and retention. This dynamic interaction between learners and content helps to create immersive educational experiences tailored to individual needs (Shrestha and Furqan 2020; Guo and Wang 2021; Betts *et al*., 2020).

Fingerprint analysis, combined with Visual, Auditory, and Kinesthetic (VAK) learning styles, allows IoT systems to categorize learners based on their unique preferences. This biometric approach aligns content delivery with individual learning styles, ensuring that each learner receives material in the most effective format for their needs. Such alignment promotes deeper understanding and satisfaction in the learning process (Ciolacu *et al*., 2019; Soui *et a*l., 2022). Blood pressure monitoring offers additional insights into learners' stress levels, highlighting the physiological impact of learning environments on performance. By incorporating this data, IoT systems can adjust teaching strategies to promote well-being, reduce stress, and maintain learner focus. This holistic approach not only supports cognitive engagement but also addresses the emotional and physical aspects of learning (Tsai *et al*., 2018; Mylonas *et al*., 2023).

IoT-based systems further enhance personalized learning by incorporating data from physical activity, such as step counts, to assess learners' overall activity levels. This data not only helps monitor physical health but also offers insights into how physical activity impacts cognitive performance. By tracking activity, these systems encourage healthy habits that can complement educational engagement, fostering a balanced approach to learning (Adi *et al*., 2020; Shapsough and Zualkernan, 2020). Electro-dermal activity (EDA), another important physiological metric, is analyzed to detect emotional responses. By monitoring skin conductivity, which fluctuates with changes in emotional arousal, IoT systems can gauge learners' emotional states in real time. This data allows for the dynamic adaptation of learning content, ensuring that materials are presented when learners are emotionally ready, thereby optimizing emotional engagement and improving their readiness to absorb new information (Tsai *et al*., 2018).

Facial recognition is implemented to observe and evaluate student behaviors, such as expressions and attentiveness, which are then used to refine teaching methods and engagement strategies (Soui *et al*., 2022). Additionally, learners' memory span is measured using specific tests to tailor learning resources effectively, ensuring materials align with the individual's cognitive capacity and enhance retention (Benhamdi *et al*., 2017).

Cognitive abilities, states, and needs are utilized as personalization components in IoT based POL systems to adapt to individual learners' needs and preferences. For instance, mobile and adaptive learning applications utilize multimedia tools and interactive processes to create tailored experiences, ensuring content aligns with learners' cognitive profiles and engagement levels (Bourekkache and Kazar, 2020). Similarly, chatbots utilize natural language processing and learning ontologies to infer learners' intentions, dynamically adapting the pace and content delivery to their unique abilities and preferences (Clarizia *et al*., 2018). Furthermore, wearable biosensors further enhance personalization by monitoring cognitive load and subjective well-being, enabling systems to adjust dynamically (Ciolacu *et al*., 2019).

Electroencephalography (EEG) data is integrated into IoT-enabled e-learning systems to extract brain activity data to provide insights into cognitive states and supports the development of context-aware learning experiences that align with individual learners' needs (Soni, 2019). Language development needs are addressed by designing scenario-based interactive environments for young learners. These systems allow educators to personalize content and interaction patterns, fostering effective language acquisition and cognitive growth through tailored activities (Cheng *et al*., 2020).

Personal capabilities are integrated through federated recommender systems, which adapt global models to local data, ensuring that personalized outcomes cater to the diversity in user behavior and preferences. This approach balances individual needs with broader learning objectives, creating a more effective and tailored educational environment (Wang *et al*., 2017).

A primary demographic personalization component used to build the user profile is the learner's age, which is used to adapt educational content to suit the developmental and cognitive capabilities of learners. For instance, fairness-aware IoT systems consider age-related variability when tailoring interactions and learning materials, ensuring inclusivity and equitable access for users of different age groups (Elmalaki 2021). Additionally, active personal learning environments utilize age data to enhance the relevance and engagement of content delivered through virtual tutors and smart devices, creating experiences tailored to individual learner profiles (Whalley *et al*., 2020). Personal details, including different demographic data, are integrated into IoT based POL model to plan personalized learning activities, ensuring the delivery of relevant and effective learning experiences (Zhao *et al*., 2022).

One of the most significant benefits of integrating IoT into existing POL systems is the incorporation of the user's interaction context. By integrating and processing the contextual data, these systems achieve personalization by considering its influence and tailoring personalization services accordingly. The primary contexts integrated are environmental and technological contexts, ensuring that personalized services adapt dynamically to the user's specific environmental conditions and technologies they are using. Table 9 lists main environmental personalization components used in IoT based POL systems.

Learners' location is integrated into personalized learning systems using IoT sensors and GPS technology, allowing systems to adapt content based on real-time geo-positional data. For instance, systems can provide relevant learning materials and feedback tailored to the learner's immediate environment. Time as a contextual factor enhances personalization by adapting learning content to the learner's schedule and preferences, ensuring optimal engagement periods (Yao 2017; Yau and Hristova 2018; Shapsough and Zualkernan 2020; Elkobaisi and Al Machot 2022).

Environmental factors such as noise levels, temperature, and air quality are monitored using IoT-enabled devices to provide optimal learning conditions. Noise levels are used to adjust content delivery to suit quieter or noisier settings, while temperature and air quality metrics support physical comfort and cognitive performance. Current environmental conditions, including humidity and light, are analyzed to create adaptive learning spaces that meet individual learner preferences and improve focus (Yau and Hristova 2018; Asad *et al*., 2024; Aydin and Göktaş 2023).

Table 6: Main Environmental Context Personalization Components

Personalization Component	**No. of Studies**	**Percentage**	**References**
location	7	11%	Shapsough and Zualkernan, 2020; Yao, 2017; Yau and Hristova, 2018; Chen *et al*., 2019; Elkobaisi and Al Machot, 2022; Reyes *et al*., 2019; Whalley *et al*., 2020
time	5	8%	Yau and Hristova, 2018; Chen *et al*., 2019; Elkobaisi and Al Machot, 2022; Reyes *et al*., 2019; Whalley *et al*., 2020
noise level	3	5%	Yau and Hristova, 2018; Aydin and Göktaş, 2023; Saxena *et al*., 2019
temperature	2	3%	Aydin and Göktaş, 2023; Taherisadr et al., 2024
air quality	2	3%	Kumar, 2021; Aydin and Göktaş, 2023

Environment preferences are incorporated into IoT-enabled systems to create flexible learning environments. These systems adjust content delivery and interaction methods based on learner-specific environmental and technological settings. Flexible learning environments support diverse needs, accommodating both structured and exploratory learning approaches in different physical and virtual spaces (Mavroudi *et al*., 2019; Bondaryk *et al*., 2021).

Advanced environmental personalization includes olfactory factors, such as the introduction of rosemary scents, which have been shown to enhance memory and concentration during learning tasks. Weather conditions and other external factors are also integrated into personalized systems to adjust learning experiences dynamically. Technological and physical environments are mapped to align with pedagogical goals, ensuring that both infrastructure and content delivery are optimized for learner success (Mavroudi *et al.*, 2019; Elkobaisi and Al Machot, 2022; Aydin and Göktaş, 2023).

Regarding the technological context, cameras are used within IoT systems to facilitate real-time data capture and analysis, enabling personalized educational experiences by monitoring learner behaviors and interactions (Saxena *et al.*, 2019). Device accessibility is enhanced through personalized cloud frameworks, allowing students to integrate their personal devices seamlessly into the learning environment, thereby increasing participation and tailoring educational activities to their preferences (Mitra and Gupta 2020). Device usage is monitored and analyzed using IoT technologies to adapt learning experiences based on how and when students interact with their devices, ensuring content delivery aligns with their usage patterns (Elkobaisi and Al Machot 2022).

The educational environment is adapted through the use of virtual assistants, which provide structured, interactive, engaging, and accessible learning experiences tailored to individual needs (Reyes *et al.*, 2019). QR code detection is employed in IoT-enabled environments to identify points of interest, enabling systems to deliver relevant teaching materials dynamically based on learner focus and interaction (Betts et al., 2020).

IoT-based Personalized Online Learning (POL) systems integrate simulations within virtual laboratories, allowing learners to explore complex concepts through personalized and interactive methods. These simulations cater to various learning styles, leveraging multimedia elements to transform abstract topics into engaging educational experiences (Kim *et al.*, 2019; Penn and Ramnarain 2019). Moreover, mobile devices act as versatile tools within these systems, supporting active, student-centered learning through personalized content and feedback (Whalley *et al.*, 2020).

Virtual tutors, powered by smart technologies, play a pivotal role in providing one-to-one guidance. These systems utilize contextual bandits to analyze user interactions and dynamically adapt learning paths, ensuring the delivery of relevant materials tailored to individual needs (Spyrou and Vretos, 2018). Immersive environments measure general and spatial presence using tools like the Igroup Presence Questionnaire (IPQ) to enhance learners' engagement and realism. By creating environments that evoke physical and emotional immersion, these systems significantly improve educational outcomes (Wang *et al*., 2017)

Contextual bandits within IoT-based personalized learning systems dynamically adapt learning paths by analyzing user interactions and feedback, leveraging real-time data to optimize educational outcomes. This ensures the presentation of the most relevant learning materials or tasks, aligned with individual needs and preferences (Spyrou and Vretos 2018).

Low-level multi-domain context is integrated into end-user development frameworks to enhance personalization. By collecting detailed data from user interactions and incorporating semantic reasoning, the system identifies hidden connections and delivers highly relevant recommendations, improving the learning experience (Corno *et al*., 2019).

Socio-cultural and socio-economic contexts are also integrated into personalized learning systems to enhance inclusivity and relevance. For instance, IoT-enabled frameworks employ customized digital content delivery to accommodate diverse socio-cultural backgrounds, enabling students to access tailored educational materials at any time (Mahapatra *et al*., 2021).

IoT-based POL systems continue advancing through innovative pedagogical approaches that integrate new instructional strategies, real-time feedback mechanisms, decentralized learning environments, and immersive technologies. Feedback mechanisms are essential components, providing real-time monitoring and support for student activities. Teachers can observe student performance and offer immediate feedback to enhance engagement and address learning challenges effectively (Bondaryk *et al*., 2021). Additionally, content recommendation systems use feedback data to refine learning materials, ensuring alignment with individual learner preferences and progress (Kim *et al*., 2019). Interactive feedback systems, combined with tailored teaching material design, enable real-time adaptation of content to match learners' needs and interests, enhancing the overall educational experience (Betts *et al*., 2020).

Arts-based instructional strategies personalize education by addressing both social-emotional and cognitive outcomes, thus making online learning environments more interactive and humanized (Perry and Edwards 2019). Learning strategies incorporate intelligent systems that analyze learner behavior and adapt teaching methods accordingly, ensuring that instructional techniques align with individual learning goals and cognitive abilities (Ma and Li 2021). One-to-few educational relationships, facilitated through virtual tutors, provide focused guidance and create a more personalized and supportive learning environment for small groups of students (Chen and Zhang 2022). Practical learning is promoted through IoT-based systems that facilitate hands-on activities and real-world applications of knowledge, enabling learners to gain deeper insights and apply concepts effectively (Farhan *et al.*, 2018). Student-driven approaches encourage learners to take control of their educational journey by conducting experiments, sharing insights, and exploring materials at their own pace (Bondaryk *et al.*, 2021).

Decentralized learning environments leverage personal cloud frameworks, allowing learners to access, store, and manage educational resources securely and independently. This approach supports self-paced learning while maintaining privacy and adaptability to individual preferences (Mitra and Gupta, 2020).

The subjective experience of realism in virtual environments is another key component of these systems. Immersive technologies assess learners' sense of presence and engagement, adapting the environment to provide a more authentic and impactful educational experience (Wang *et al.*, 2017).

This section emphasizes the integration of diverse personalization components—behavioral, social, cognitive, physiological, demographic, environmental, and technological—into IoT-based POL systems, creating adaptive, responsive, and learner-centered educational experiences. By incorporating advanced tools and strategies, including biometric technologies, contextual and immersive personalization techniques, these systems enhance engagement, accessibility, adaptability, and inclusivity, based on learner's profile and context, fostering dynamic educational environments.

The next section will describe the machine learning algorithms used to process the data generated by personalization components described in this section to achieve more effective and real time personalization.

4.2. Machine Learning Algorithms in IoT based POL Systems

In IoT-based POL systems, machine learning (ML) algorithms play a pivotal role in processing the data streams generated by IoT devices. These devices, including wearables, sensors, and mobile platforms, generate real-time data about learners' interactions, physiological states and environmental conditions. The most frequently employed approaches to process data generated by IoT-based POL systems, as shown in Table 10, are Learning Analytics (LA) and the Combination of Multiple Algorithms.

Table 7: Algorithms used in IoT based POL Systems

POL Algorithm	Number of Studies	Percentage
Learning Analytics (LA)	21	32%
Combination of Multiple Algorithms	18	28%
Not specified	5	8%
Natural Language Processing (NLP)	4	6%
Classification Algorithms	3	5%
Deep Learning	3	5%
Rule Based Algorithms	3	5%
Computer Vision	2	3%
Machine-to-Machine (M2M) Interaction Algorithms	2	3%
Reinforcement learning (RL)	2	3%
Affective Computing Algorithms	1	2%
Cryptographic Techniques	1	2%

In IoT based POL systems, the main Learning Analytics approaches include Learning Analytics Tools, Affective Computing, Context-Aware Learning and Educational Theories and Frameworks. Learning Analytics Tools include techniques such as Feature Analysis (TFA) for generating personalized learning tasks (Zou and Xie 2018), integration of VAK (Visual, Auditory Kinesthetic) learning style model, Pattern Recognition Algorithm, and fingerprint analysis and assigns personalized educational content based on learner’s learning styles (Saxena *et al.*, 2019). Educational Data Mining (EDM) is also used as a method for processing, analyzing, and adjusting personalization components within smart learning systems (Betts et al., 2020).

Affective Computing tools include Photoplethysmography (PPG) signals, which monitor learners' heart rate, during the learning process to assess their engagement and emotional states in meta-verse educational environment (Zhao *et al.*, 2022). The Emotion Recognition Modeling Tool that can recognize, interpret and process human emotions in the context of

Active and Assisted Living (AAL) environments (Elkobaisi and Al Machot 2022) or standardized questionnaire like Myers-Briggs Type Indicator (MBTI) and Ortony, Clore and Collins (OCC) Model for personality and emotion modeling (Fatahi 2019).

Context-Aware Learning include Intelligent Personalized Context-Aware Learning Algorithms (Yao 2017; Louhab *et al.*, 2019), Adaptive Sensor-Based Learning Algorithm (Tortorella and Graf 2017) and Multisensory Learning Environment Assessment (Mohana *et al.*, 2023) to adjust learning experiences based on physical environmental conditions such as temperature, humidity, air quality and other environmental factors that can influence students' attention, motivation and academic achievement.

The second most commonly used approach for processing data in IoT-based POL systems is the combination of multiple algorithms. This approach is implemented in recommender systems where techniques such as Clustering (K-Means Clustering Algorithm), Classification (Instance-Based Classifier, IBC), and Collaborative Filtering are applied to personalize learning experiences by recommending courses in e-learning environments (Rawat and Dwivedi 2019). Additionally, methods like the Variable Length Genetic Algorithm (VLGA), Collaborative Filtering, Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) are combined to recommend personalized learning paths (Dwivedi *et al.*, 2018). Collaborative and Content-Based Filtering, along with Clustering and Multidimensional Similarity Evaluation, are used to recommend personalized learning materials (Benhamdi *et al.*, 2017).

In IoT based POL systems, one commonly used approach involving the combination of multiple algorithms is affective computing, where these algorithms are integrated to analyze learners’ socio-psychological attributes to provide POL services. For example, Attention-Scoring Model (ASM), Behavioral Analysis, Clustering, and Reinforcement Learning Algorithms are used to measure student attention during video lectures by analyzing facial and eye movements, as well as to analyze online student behaviors, such as interaction patterns, attention levels, and engagement with learning materials (Farhan *et al.*, 2018). In addition, OpenCV, the Keras CNN model, and the TensorFlow API are sued to provide adaptive learning based on emotional and physiological data, such as facial emotion detection, eye-gaze tracking, and heartbeat monitoring (Kassab and Mazzara, 2020).

Furthermore, the combination of multiple algorithms is utilized to provide Multimodal Learning Analytics where Classification Algorithms like J48 and OneR algorithms and Rule-Based Algorithm like PART are combined to provide Focused on a novel engagement classification system (Camacho *et al*., 2020). Additionally, Genetic Algorithm, combined with Multi-classification algorithms like Bayes, C4.5, SVM are used to generate high-level context information based on low-level multi-domain context (Jia *et al*., 2017).

In IoT based POL systems, Natural Language Processing (NLP) is utilized for creating immersive virtual learning environments through tools like chatbots and time machines. Some of the algorithms used are Latent Dirichlet Allocation (LDA) (Clarizia *et al*., 2018), BERT (Bidirectional Encoder Representations from Transformers) (Almada *et al*., 2023). Additionally, tools like OpenSimulator (Wang *et al*., 2017) and Google Dialogflow (Reyes *et al*., 2019) are also employed to facilitate personalized learning experiences.

The most frequently employed classification algorithms include decision trees (C4.5, J48), K-nearest neighbors (KNN), and support vector machines (SVM), each serving different purposes in classification and prediction tasks. The support Vector Machine (SVM) Algorithm is utilized to analyze learners' traces by effectively modeling and classifying them to provide POL services in a cloud computing environment (Ghallabi *et al*., 2020). The Random Forest algorithm is used for activity recognition based on heart rate monitoring with smartwatch sensors (Ciolacu *et al*., 2019). In addition, Heart rate variability (HRV) is analyzed with Decision Tree algorithms to create two classifiers: one predicts the user's happiness level and the other predicts how active or energetic they feel (Chiu and Ko 2017).

Another key approach in adaptive learning involves Deep Learning, specifically Convolutional Neural Network and Graph Neural Network (GNN), which are used to analyze and predict complex patterns from real-time IoT data. These algorithms allow systems to respond to learners' cognitive and emotional states, providing feedback that optimizes the educational experience on a personalized level (Kim *et al*., 2019; Guo and Wang 2021).

Rule-based learning algorithms utilize IF-THEN Rules and Learning to rank algorithms to create scenario-based interactive learning environments (Cheng *et al*., 2020; Corno *et al*., 2019). **Reinforcement learning (RL)** algorithms, such as multi-armed bandits and Q-learning, are widely used to dynamically adjust learning paths by continuously updating the system's understanding of the learner's needs (Elmalaki 2021).

Computer Vision Algorithms employ facial landmark detection algorithm to locate specific areas of the face, which are then used to create a graph for facial expression analysis to infer student emotion and engagement (Spyrou and Vretos 2018). Machine-to-Machine (M2M) interaction algorithms facilitate autonomous communication between IoT devices, such as temperature sensors and air conditioners, to create a smart learning environment by adjusting conditions based on real-time data (Soni 2019).

Most of the analyzed studies implement a multimodal approach, integrating different personalization components to provide tailored services. Classification algorithms are generally used to classify students' prior knowledge, emotions, engagement, and stress level, while clustering algorithms are employed to group students based on their interactions and behavioral patterns.

5. DISCUSSIONS

The integration of IoT technologies in POL systems (POL) presents transformative opportunities to enhance education by creating adaptive, context-aware, and learner-centric environments. However, critical challenges persist that demand comprehensive evaluation and strategic solutions.

One notable advancement is the leveraging of diverse personalization components—such as learner profiles, environmental contexts, and physiological data—to dynamically tailor educational experiences. The prevalence of IoT devices enables the real-time collection of data, significantly expanding the dimensions of personalization. For instance, integrating psychological profiles and contextual data into POL systems enhances learner engagement and motivation. Nevertheless, reliance on extensive data introduces concerns regarding data heterogeneity and privacy. While cryptographic techniques, anonymization, and edge processing offer a degree of security, their implementation in IoT-based POL systems remains underexplored.

The integration of AI in IoT-based POL systems requires strict adherence to legal and ethical frameworks. The European Union (EU) categorizes the use of AI in education as a high-risk endeavor, prohibiting the classification of learners using biometric data, including facial recognition, due to potential misuse. To comply with regulations such as the General Data Protection Regulation (GDPR), any biometric data used in machine learning processes must be securely stored and processed within protected environments, ensuring it is not transferred outside these confines. Moreover, data collection, storage, and processing must prioritize transparency and privacy, aligning with GDPR principles to safeguard learner information while fostering innovation in personalized education.

Machine learning algorithms, such as learning analytics and combined methodologies, have proven instrumental in processing IoT-generated data. The systematic use of algorithms like deep learning, classification models, and natural language processing ensures personalized recommendations, adaptive content delivery, and robust learner classification. Despite these advancements, issues such as algorithmic bias and the complexity of integrating heterogeneous datasets remain. Addressing these challenges is crucial to ensuring equitable and effective personalization outcomes.

Environmental and technological contexts integrated via IoT also offer innovative avenues for adaptive learning. Environmental factors like noise levels, temperature, and air quality can influence cognitive performance and engagement. However, current implementations often lack comprehensive frameworks to dynamically integrate these physical variables. Similarly, technological factors such as device compatibility and accessibility are pivotal in ensuring inclusive and seamless learning experiences. Yet, scalability and infrastructure limitations restrict their broader adoption.

6. CONCLUSIONS AND FUTURE WORK

This systematic review has provided a detailed overview of the personalization components and ML algorithms used in IoT-based online learning systems by synthesizing data from 65 primary studies. It highlights the transformative role of IoT and ML in advancing POL systems to create dynamic, adaptive, and learner-centered experiences. The most commonly used components for personalization in IoT-based POL systems include learners' learning styles, prior knowledge and skill levels, locations, preferences, and emotions. Additionally, learners' psychological profiles are widely integrated into these systems.

The study reveals that Learning Analytics (LA) and combinations of multiple algorithms are the most frequently implemented approaches. These techniques enable the processing of diverse data streams, facilitating personalized learning paths, adaptive content delivery, and real-time feedback. While effective, challenges such as data heterogeneity, scalability, ethical concerns, and privacy issues remain significant barriers to broader implementation. Addressing these challenges is crucial to unlocking the full potential of IoT-based POL systems in diverse educational settings.

The integration of IoT into POL systems introduces sophisticated algorithms that significantly enhance the personalization of the learning experience. A critical examination of the algorithms reveals their distinct roles in delivering tailored learning paths and adaptive content. 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 contexts.

Future research should focus on the integration of IoT in multimodal learning analytics and on the personalization of physical environmental factors like classroom temperature and lighting, which remain under-researched areas. These components have significant potential to influence learner engagement and performance, presenting a promising direction for further study.

Additionally, exploring potential relationships between keywords (features) in the selected articles could provide valuable insights into the availability and existence of research that combines multiple identified features.

Some pressing challenges related to IoT-based POL systems also require the immediate attention of researchers. These include data overload and processing challenges, ethical and privacy concerns, and issues related to scalability and infrastructure. Addressing these issues will not only enhance the functionality of POL systems but also ensure their ethical and effective application in real-world educational settings.

Finally, the design of adaptive learning models that continuously update and recalibrate personalization strategies is an essential direction for future research. These models must dynamically respond to evolving learner profiles and contexts, ensuring that IoT-enabled systems remain relevant and effective in addressing the diverse and changing needs of learners. By focusing on these areas, future research can significantly advance the capabilities of IoT-based POL systems, fostering more inclusive, adaptive, and learner-centric educational solutions.

This study lays the groundwork for continued research into the dynamic integration of IoT and ML, offering the potential to revolutionize POL by making it more adaptive, responsive, and learner-centric.

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