Surveying the Usage of Learning-Related Information in Adaptation for Intelligent Systems

A Systematic Literature Review

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Abstract

This paper is a systematic literature review (SLR) investigating how intelligent systems leverage learning-related information to adapt their behaviour. This paper is done according to PRISMA guidelines, which ensures reproducibility. For this review, we analysed 58 papers published after 2023. The review focused on types of inputs, system objectives, and application domains. The systems in this survey adapt their behaviour based on various inputs, such as facial expression, gestures, eye gaze, and user preferences. These systems enhance the learning experience by increasing user engagement and motivation. Many of these papers target the education domain, such as STEM, but there are also papers focused on motor skills training or cognitive training. Time constraints limited the scope of the review, particularly in identifying long-term trends. But the result can be a solid base for future research into adaptive learning and training platforms.

1 Introduction

Artificial intelligence (AI) has become an everyday occurrence in people's lives. It ranges from systems that can recommend your next favourite show to personalised healthcare applications. With the increased interest in personalised content came the need for human-centred AI (HCAI) that understands personal nuances and adapts to each individual. One way to make the experience unique to the individual is to create an application attuned to their cognitive-affective processes. In this case, a cognitive-affective process is the interaction between feeling and thinking and how it influences one's behaviour. Some examples are memory, attention, motivation, reasoning, and learning.

This study focuses on learning and how intelligent systems leverage it in their adaptation. Learning is a person's ability to acquire new information and change their behaviour over time, based on said information. This ability is not limited to acquiring academic knowledge; it also includes training and the development of skills. In the context of adaptive systems, proposed models aid in learning and teaching by identifying the user's state and adapting the output based on it. This paper will call the state that influences the system's adaptation a learning state. This state can be determined by emotions, context, user behaviour, EEG signals, learning style, or other inputs showing the user is engaged in the learning process [1]. Some existing applications can identify the user's learning state and adapt the content accordingly. For example, intelligent tutoring systems [2] that monitor the user's engagement during a session and adjust the study material automatically, adaptive learning tools [3], and other personalised teaching technologies.

Even though the need for adaptive systems in education has become more obvious, over the years, the focus has been on identifying these learning states based on the different factors that determine them. There is a lack of understanding of how learning states are used in real-life adaptive applications. Literature reviews have been done on this topic, but they do not cover the full scope of learning. One of the papers relevant reviews analyses pedagogical tools [4] that mainly focus on user preferences. Also, this paper only includes academic settings for learning, thus omitting training. Another study discusses technologies that aid language learning [5], but it omits systems that provide help in other areas of learning. This paper is meant to cover this gap and analyse all the adaptive systems that make use of learning states, including systems that aid training. The full inclusion and exclusion criteria will be discussed in section 2.1.

The scope of this survey is defined by introducing a research question and seven additional sub-questions (SQ), which are shown in Table 1.

Main research question:

How do intelligent systems use learning-related information to adapt their behaviour?

Sub-question	Motivation
SQ1: *What forms of information related to learning states has HCAI research used to adapt intelligent systems?*	Multiple types of inputs can denote a learning state
SQ2: *For what objectives has this information been used?*	Looking at abjectives might enable future research to consider different uses
SQ3a: *How has this information been used?*	There is no universal design for an adaptive system. Knowing how the systems leverage the input information could lead to a better understanding of these platforms.
SQ3b: *Are there any trends or patterns observable in this usage?*	Any observed pattern regarding system adaptation
SQ4: *In which application domains is this information used?*	It is relevant to understand if the scope of this research is more suited for a certain domain
SQ5a: *What challenges exist in recent developments?*	This might give an insight into the current state of the art for this type of system
SQ5b: *Are there any trends or patterns observable concerning these aspects?*	Possible challenges might help with future developments.

Table 1: Sub-question that will help answer the main question and their motivation

The paper is constructed as follows: Chapter 2 details the methodology used for this review. Chapter 3 shows the analysis results. Chapter 4 discusses the reproducibility of this survey. The results are discussed in Chapter 5, considering the limitations of this research. Chapter 6 presents the conclusion and future works.

2 Methodology

This chapter details how a systematic literature review (SLR) that follows the PRISMA [6] guidelines is conducted. In an SLR, a search protocol needs to be created before analysing the selected papers. This protocol includes creating the search query, selecting, and reviewing the results. Section 2.1 details the first part of this protocol, which is defining the eligibility criteria for a paper to be included in the survey. Then, section 2.2 identifies the key concepts used to create the query. Section 2.3 shows the second part of the protocol, where the search results are filtered based on eligibility, and the relevant papers are selected. Section 2.4 details how the data was extracted, and Section 2.5 gives an overview of the search results.

2.1 Eligibility Criteria

A paper can be included or excluded from the review based on some criteria. In this review, the following criteria were defined:

Inclusion Criteria

- The paper introduces an adaptive system. Papers that describe a system that adapts its behaviour based on user input. *(The scope of this paper)*
- The system uses learning state information. Systems that leverage the learning process by interpreting emotions, behaviours, gestures, EEG signal, learning styles, and other learning-specific indicators. *(The scope of this paper)*
- The paper is from the Computer Science or Engineering field. *(This survey is focused on papers that design an adaptive systems)*

Exclusion Criteria

- The paper is not written in English
- The paper is not published in an article of a conference
- The paper only describes a way to identify learning states. Papers that describe systems that can determine whether a user is learning or not.
- The paper models a user's learning state. *(This excludes systems that are not adaptive)*
- The paper does not mention the use of learning-related information; it only describes how the system may adapt its behaviour. Papers that do not explicitly mention learning. *(This excludes papers that do not leverage learning-related information)*
- The paper is a literature review or a survey. *(Including reviews would prevent accurate data extraction)*

2.2 Search Strategy

In this research, we are looking for papers describing an adaptive system that uses inputs depicting learning states. To create the query, four key concepts were identified: ***adaptive system***, ***user modelling***, ***learning***, and ***education***. These concepts were expanded into broader and narrower terms that were used in different iterations of the search query. Additionally, to the key concepts, we added the term ***review*** to filter out other literature reviews and surveys. The terms will be searched in the title, abstract, and keywords. Table 1 shows an overview of the terms used in the final query.

Adaptive System

Under this term, we included multiple dedicated systems such as adaptive learning, personalised learning, personalised system, individual, dynamic system, and personalised tools. Considering the learning component of this survey, we also included terms like intelligent tutoring systems, educational tools, and e-learning systems.

User Modelling

This concept was included to ensure that the described systems are focused on user interaction. Terms like user, participant, student, teacher, trainee, person, and child describe it.

Learning

This is the most crucial concept besides the adaptive system. Under this term, we included all the terms that can depict a learning state, such as emotion, boredom, frustration, motivation, attention, anxiety, engagement, eye movement, body movement, and concentration.

Education

We introduced this concept to narrow the search to adaptive systems that aid in the learning process. The following terms were included: tutor, educator, teaching, classroom, and pedagogy. Additionally, by using terms like training and coaching, we ensured that the learning scope included developing skills.

Keyword Category	Search Terms
adaptive system	adapt*, dynamic*
user modelling	user*, student*, participant*, teacher child*
learning	learn* affect, learn* state, emotion*, bored, anxiety, frustration, concentrat*
education	educat*, tutor*, train*, coach*, e-learn*
review	review, survey, compar*

Table 2: Search keyword categories and associated terms

2.3 Selection process

The papers for the review were collected in June 2025, from three databases: Scopus[1], Web of Science[2], and IEEE Xplore[3]. The initial search returned 5401 papers. The original amount of paper was not feasible because the proposed survey was conducted in nine weeks. A time-based feasibility criterion was introduced to resolve this issue. After only selecting papers published after 2023, the total amount was 1751. Furthermore, after filtering out the duplicates, the set used for the next step comprised 1587 papers.

After selecting the initial group of papers, they were assessed based on the eligibility criteria and manually filtered on title and abstract. If it is clear from the title that a paper is unsuitable for this review, it is excluded. Otherwise, the abstract is checked. The paper is excluded if the abstract indicates that it does not meet the eligibility criteria.

After the title and abstract filtering, 95 papers were found suitable for the study. If the full text for the documents can be retrieved, they go into the next filtering step, where the full text is assessed. If, from reading the paper, it is clear that it does not fit the study requirements, the paper is excluded; otherwise, relevant data is extracted and included in the results.

[1] `https://www.scopus.com`
[2] `https://www.webofscience.com/`
[3] `https://ieeexplore.ieee.org`

2.4 Data extraction and synthesis

We need to decide what data to extract to properly assess the papers' content and ensure that the research questions are answered. Table 3 shows the data extracted from each paper and how this relates to the sub-questions.

Information	SQs
What type of system is described?	
What type of input does the system have?	1
What does the system measure?	1
How is the input interpreted?	1
How does the system adapt?	2
What is the motivation for building the system?	3a
For which domain was the system created?	4
What kind of challenges does the system face?	5a

Table 3: Extracted data

Depending on the extracted data, the papers are grouped for analysis and for identifying relevant patterns, which could answer SQ3b and SQ5b.

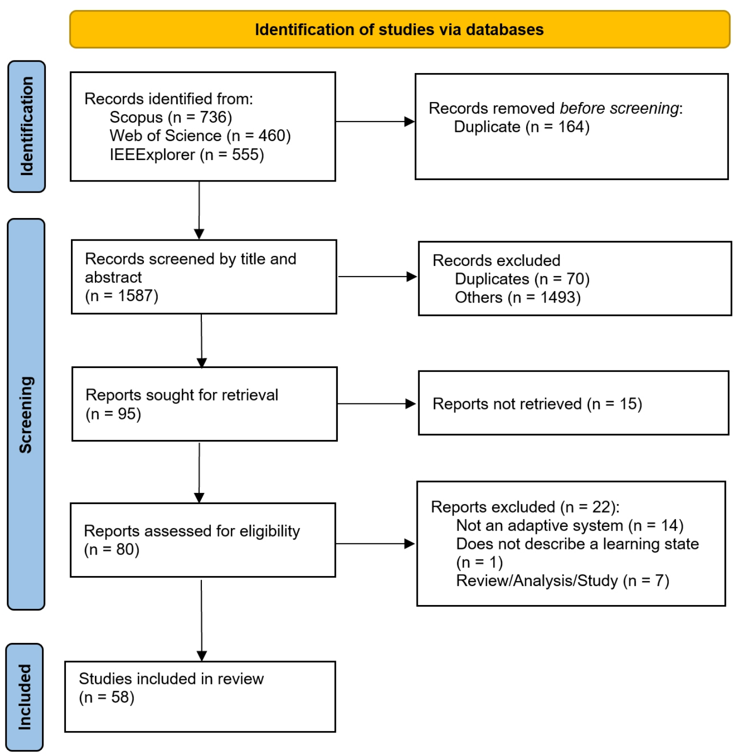

Figure 1: Adapted PRISMA diagram

2.5 Search results

The overview of the search results is presented in Figure 1, which was created by adapting the standard PRISMA diagram [6]. After applying the search protocol with the feasibility and eligibility criteria, the review included 58 papers.

3 Results

This section shows the results compiled after extracting data from 58 papers. Section 3.1 presents an overview of the types of inputs the systems accept. Section 3.2 shows the different system types and why a system is included in its group. Section 3.3 gives an overview of the domains for which these systems were developed. Sections 3.4 and 3.5 discuss objectives and challenges, respectively.

3.1 Input types

The analysed system responds to four types of inputs: audio, biosignals, text, and video. These inputs are often combined to give a more accurate reading of the learning state. These inputs are interpreted differently depending on what the system tries to achieve. The majority of the systems use **video** inputs. These systems measure facial expressions ([7], [8]), which are mapped to relevant emotions like frustration, confusion, or boredom. In some cases, eye gaze is detected and used to determine the reading comprehension [9]. Additionally, some systems focused on skills training trace gestures ([10], [11]). **Audio** inputs are used for systems with dialogue functions [12], but also for recording speech patterns for language learning [13]. **Text** inputs are mostly questionnaires used to asses the initial state of the user ([14], [15]), or direct feedback given by the user after completing a task [8]. When dealing with **bosignals**, systems predominantly use EEG signals to determine the user's engagement [16]. One unique paper measures the blood oxygen saturation when the user performs physical activities [17]. Table 4 shows how the systems are grouped in input categories.

Input type	No. of papers	Papers
Text	35	[7], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [8], [35], [36], [37], [38], [13], [14], [39], [15], [40], [41], [42], [43], [44], [45], [46], [47]
Video	31	[7], [18], [19], [12], [48], [49], [25], [26], [50], [17], [51], [34], [52], [8], [35], [53], [38], [14], [54], [55], [9], [39], [15], [41], [56], [10], [57], [58], [59], [60], [11]
Audio	16	[18], [12], [49], [26], [17], [51], [35], [53], [13], [9], [39], [40], [56], [57], [58], [60]
Biosignal	8	[12], [49], [61], [62], [17], [34], [16], [55]

Table 4: Input types

3.2 System types

The system types are diverse, but predominantly, the papers describe **e-learning platforms**. This category encompasses systems that combine multiple functions, such as recommender systems, feedback loops, and real-time content changes ([52], [8], [39], [60]). **Recommender systems** can also operate independently. In these cases, the systems are less complex and have only one function. For example, break recommendations ([63], [46]) or learning path suggestions ([43], [45]). Similar to recommender systems are **chatbots**, which can give feedback and suggestions in a dialogue form. Another major category is **serious games**, which are platforms with a game-based approach to displaying the content. They usually adapt the difficulty ([10], [55]) or the game path ([22], [29]) to suit the user's knowledge level and progress. Similar to the serious games are the **Extender Reality (XR) environments**, which immerse the user in a game-like simulation. These systems usually train a skill. For example, [51] helps with training medical skills, and [56] and [58] let the user practice their public speaking skills in a safe environment that helps reduce anxiety. Additionally, some systems serve as **assistive tools** for people with cognitive or physical impairments, such as hard-of-hearing people [11]. Other systems that have an assistive function are **robots**. They can act as companions and help improve cognitive functions in children [57] and the elderly [12]. Table 5 shows how the systems are grouped by type.

System type	No. of papers	Papers
E-learning platforms	17	[7], [20], [48], [25], [62], [28], [31], [52], [8], [16], [13], [14], [9], [39], [15], [60], [11]
Serious games	10	[22], [29], [32], [33], [37], [54], [55], [44], [10], [47]
XR environments	9	[49], [61], [51], [34], [35], [64], [56], [58], [59]
Recommender systems	7	[63], [18], [19], [21], [43], [45], [46]
Assistive tools	4	[23], [50], [40], [17]
Robots	3	[12], [53], [57]
Chatbots	3	[30], [36], [38]
Others	5	[24], [26], [27], [41], [42]

Table 5: Types of systems

3.3 Domain distribution

The papers included in the review described systems for a range of educational and training domains. However, the majority did not specify the subject area, implying they are suited for multiple disciplines. Some systems defining their subject area were created with **STEM education** in mind. The subjects range from mathematics [20] to programming ([23], [24], [36]). These systems provide feedback and try to enhance the learning outcome and engagement. Another significant group focuses on **language learning**, using audio and text inputs, and adapts to the user's progress and knowledge. **Alternative education** systems include platforms focusing on non-traditional learning contexts. They focus on users who need additional support, such as students with Inattentive Attention Deficit Hyperactivity Disorder [25]. The training-focused systems were split into two groups. **Skills training** platforms that help with motor skills, such as assembly work [59] and other physical activities, and **social and cognitive training** platforms provide tools for improving behaviours [10], and emotion regulation [40]. Table 6 shows how the systems are grouped by their application domain.

Domain	**No. of papers**	**Papers**
Education	23	[63], [18], [?], [21], [22], [26], [62], [30], [52], [8], [16], [53], [38], [14], [64], [39], [41], [42], [43], [44], [45], [46], [47]
Skill training	9	[61], [50], [17], [51], [54], [55], [56], [58], [59]
STEM education	8	[7], [20], [23], [24], [29], [32], [33], [36]
Language learning	8	[49], [27], [28], [31], [37], [13], [9]
Social and cognitive training	5	[12], [34], [40], [10], [57]
Alternative education	5	[25], [15], [60], [11], [48]

Table 6: Domains distribution

3.4 Objectives

The overall objective of these systems is to enhance the learning experience. The systems present different approaches to achieve this and have smaller objectives. A significant part of the environment's aim is to improve engagement and motivation in students ([19], [22], [30], [33], [47]), while giving a personalised experience and addressing individual needs. Other focuses are reducing anxiety in high-stress situations ([56], [13]), or simulating realistic routines [10]. Another objective is to mimic face-to-face teaching in situations where it is crucial to the development of the user ([16], [50]). While most systems are education-focused, one unique system aims to support gait rehabilitation [61] by creating a game-like environment where the user has to collect several batteries.

3.5 Observed challenges

Most studies do not explicitly discuss the challenges of the system, and in the cases where the limitations are acknowledged, they are addressed briefly. A pattern for the systems that report their limitations is the narrow range of emotions that the system identifies ([14], [55], [20]). For example, some systems only classify emotion into positive and negative, overlooking the human behaviour nuances. Also, some papers consider the domain to be a limitation and argue that the developed platforms could benefit from more flexibility and adaptability in multiple subjects ([24], [14]). Other systems fail to account for cultural backgrounds [13] and gender differences [22]. Additionally, some papers mention that their system could benefit from a broader range of sensors ([53], [60]), or more complex interactions mapping [7].

4 Discussion

There are multiple factors that influenced the results of this review. One of the most essential points is the limited timeframe. This research was conducted over nine weeks, which directly facilitated the introduction of several feasibility constraints. One such constraint is the reduced period during which the papers were collected. This limited the answer for SQ5b, regarding trends and patterns. Even though multiple patterns were observed, we cannot safely deduce whether time influences them. The final selection of papers may not fully represent the full range of available literature on the topic. Additionally, the full text could not be retrieved for some of the selected papers due to this time constraint. However, despite the set limitation, the study still captured enough relevant information to answer all the proposed sub-questions.

The results show that most adaptive systems leverage emotions in their adaptation, using different techniques to identify emotional states specific to learning. Most emotion-focused platforms use video inputs to determine the user's state ([52], [53]), but some outliers deduce these states from audio [60] or text-based inputs [30]. The emotional states that were used the most were confusion, frustration, engagement, and boredom. In some cases, these emotions were classified as negative and positive states ([38], [15]). Another observation regarding the input type is that most systems use multimodal inputs (combination of audio, biosignals, text and video) to increase their accuracy when classifying states. For example, [8] uses facial expression and the user's feedback to identify their emotional state. Not emotionally aware systems use gestures or the user's knowledge and experience to influence the system's adaptation.

Additionally, it is important to note how these systems approach adaptation. Some systems adapt in real-time ([7], [49], [51], [59], [11]), adjusting the content [38] or the difficulty of the task [34]. Other systems adapt cyclically; they wait until the user finishes the current task, then use feedback and other collected data to adapt for the next task [22].

Another observation is that all the systems aim to provide personalised solutions for learning and training, which was expected given the research's learning-focused scope. Because many systems do not explicitly mention the subject they are built for, we can assume they have the potential for flexibility and adaptation over various educational domains. Across this range, most systems aim to enhance the learning (or training) experience and offer individual actions for each user. And even the more unique systems, such as medical training [51] and gait rehabilitation [61], can identify the user's needs and adapt for each personal instance.

Additionally, most systems that aim to train motor skills are XR environments or serious games. This correlation can be attributed to the fact that it is easier to learn a skill when there is an appropriate environment to practice. A good example is [56], where users can freely practice public speaking. The platform allows them to choose the audience type and the room size. Additionally, they get real-time feedback on their performance, which can help correct mistakes.

5 Responsible Research

We presented the methodology and the process to ensure this review can be reproduced. The methodology was described using the PRISMA guidelines, and the necessary information was included. We detailed the approach for the search protocol and the retrieved results (as of June 2025). Additionally, we included an explanation of the search terms and eligibility and feasibility criteria. The number of papers at every stage of this research was reported, as well as the search queries used to retrieve the papers (Appendix A)

It is also important to note that this research was conducted by a Computer Science student with no significant background in psychology. This fact might lead to mistakes during the selection and filtering process. However, we tried to combat this using standard practices and clear criteria for including papers.

Additionally, Grammarly[4] was used for grammar checks and rephrasing to ensure the text was clear and error-free. By reviewing every suggestion the tool made, the meaning, nuances, and academic tone of the text were preserved.

6 Conclusions and Future Work

This study conducted a systematic literature review to investigate how adaptive systems use learning-related information. We focused on the input types, system types, objectives, motivations, and application domains. We followed the PRISMA guideline to ensure the review is reproducible and transparent.

According to the methodology, the first step was to develop the search protocol for collecting relevant papers. We identified and defined the four core terms: adaptive system, user modelling, learning, and education. These concepts were expanded into relevant terms that were later used to create the search query. The search was conducted over Scopus, IEEE Xplorer, and Web of Science. Due to the timeframe of this research, we introduce feasibility constraints, limiting the review to papers published after 2023. The final search and filtering resulted in 58 papers that were analysed.

The results show that most systems using learning-related data were designed for education or training. In the educational context, most systems do not specify a particular domain, thus indicating that these systems can be flexible and adapted to a wide range of topics. In comparison, training systems focused on improving motor skills use XR environments or serious games to create an interactive learning environment. Also, the results show that most papers use multimodal inputs, such as text, audio, video and biosignals to classify the users' states accurately.

This review can be a basis for additional work on the topic. Further research can be done by removing the feasibility constraints and analysing a larger set of papers. Additionally, including experts with backgrounds in education or psychology could enhance the data interpretation when analysing the implications of the systems

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A Full queries for database search

A.1 Scopus

(TITLE-ABS-KEY ("learn* affect" OR "learn* state" OR "emotion*" OR "bored" OR "anxiety" OR "frustration" OR "concentrat*") AND TITLE-ABS-KEY ("adapt*" OR "dynamic*") AND TITLE-ABS-KEY ("educat*" OR "tutor*" OR "train*" OR "coach*" OR "e-learn*") AND TITLE-ABS-KEY ("user*" OR "student*" OR "participant*" OR "teacher" OR "child*") AND NOT TITLE-ABS-KEY ("review" OR "survey" OR "compar*")) AND PUBYEAR > 2022 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SUBJAREA , "COMP"))

A.2 IEEE Xplorer

("All Metadata":"learn* affect" OR "All Metadata":"learn* state" OR "All Metadata":"emotion*" OR "All Metadata":"bored" OR "All Metadata":"anxiety" OR "All Metadata":"frustration" OR "All Metadata":"concentrat*") AND ("All Metadata":"adapt*" OR "All Metadata":"dynamic*") AND ("All Metadata":"educat*" OR "All Metadata":"tutor*" OR "All Metadata":"train*" OR "All Metadata":"coach*" OR "All Metadata":"e-learn*") AND ("All Metadata":"user*" OR "All Metadata":"student*" OR "All Metadata":"participant*" OR "All Metadata":"teacher" OR "All Metadata":"child*") NOT ("All Metadata":"review" OR "All Metadata":"survey" OR "All Metadata":"compar*")

A.3 Web of Science

(((((TS=(learn* affect OR learn* state OR emotion* OR bored OR anxiety OR frustration OR concentrat*)) AND TS=(adaptive system OR dynamic system)) AND TS=(educat* OR tutor* OR e-learn* OR train* OR coach*)) AND TS=(user* OR student* OR participant* OR teacher OR child*)) NOT TS=(review OR survey OR compar*))