Usage of Attention in Adaptation of Intelligent Systems

A systematic literature review

Marie Louise Grundfør[1]
Supervisors: Bernd Dudzik, Vandana Agarval
[1]EEMCS, Delft University of Technology, The Netherlands

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Name of the student: Marie Louise Grundfør
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Abstract

With an increased demand for personalized systems, adaptive systems can support its users by recognizing their cognitive state, and adapt different elements to improve the user's mental state. With a literature survey, the following question has been answered: how do intelligent systems acquire and use information related to user attention? The answer was found by following the PRISMA guidelines [1], using the identification flowchart, to ensure reproducibility of the identification and screening of the papers, in addition to applying consistent criteria to which articles could be included in the review. This process resulted in 74 papers that fit the criteria. The results showed a large variety in the sensor input, modeling, objectives and domain, while the adaptation strategies could be summarized by five categories: UI change, feedback timing, automation level, difficulty adjustment and behavioral feedback. Combinations of categories were also present. UI changes and feedback timing were the most popular categories, especially from 2015 onward. Difficulty adjustments were surprisingly rarely utilized, especially in articles focused on education, possibly because the adaptation requires additional complexity to be added to the system. Challenges described in the literature were mainly focused on short term improvements, instead of long term issues.

1 Introduction

Intelligent systems are increasingly prevalent in everyday life, supporting tasks that range from personalized recommendations to adaptive user interfaces. Their effectiveness depends on the capacity to model, interpret, and respond to individual users, not only by capturing long-term preferences, but also by sensing and adapting to dynamic cognitive states such as attention.

It is well established that diminished attention, or commonly referred to as a lack of focus, can significantly impair human task performance. As a result, modeling user attention has become a compelling objective for adaptive systems. By accurately estimating attention levels, such systems may enhance user effectiveness through timely interventions, such as stimulating engagement, modulating task difficulty, or mitigating risks in safety-critical scenarios.

In recent years, the integration of attention into adaptive and intelligent systems has emerged as a rapidly expanding area of research. This growth has been driven by advances in both sensing technologies and the increasing sophistication of adaptive systems. However, the pace of development has made it increasingly difficult to maintain a clear understanding of how attention is currently being utilized, what methods are most prevalent, and which challenges or research gaps remain. In order to address these gaps, a literature review was chosen to systematically analyze the role of attention in adaptive systems. Specifically, it examines how human attention is sensed and adapted to, identifies recurring patterns and approaches, and provides a structured overview of the current research landscape to clarify future directions and opportunities.

1.1 Background

Adaptive systems function through a continuous feedback loop. They gather various bio-signals associated with attention, such as eye movements, EEG patterns, or reaction times. These inputs are then processed, classified, and interpreted within context. Based on this analysis, the system adjusts its behavior to respond to the user. These adaptations, in turn, affect the user's behavior, which feeds back into the system for further refinement. This ongoing exchange creates a dynamic and responsive interaction cycle. A simplified illustration of this loop, based on the version from [2], is shown in Figure 1.

Attention is defined as "a state in which cognitive resources are focused on certain aspects of the environment rather than on others." [3] While often regarded as a cognitive process, attention also involves affective components—emotions that influence what individuals notice and how they react to stimuli. Anderson [4] distinguishes between voluntary and involuntary attention, noting that both are often shaped by perceived threats and rewards.

Although this study focuses primarily on the cognitive dimensions of attention, its emotional aspects remain relevant. Emotional states can modulate attentional focus and responsiveness, which in turn has implications for how adaptive systems interpret and respond to user behavior.

The integration of cognitive and affective aspects of attention is important in designing adaptive intelligent systems. Such systems adjust their responses based not only on where a user's attention is directed but also on their emotional state. For instance, in high-stress settings like military operations, adaptive technologies can prioritize and modify information delivery based on attentional and emotional signals, thereby improve safety, performance, and knowledge retention. [5] Given the limited capacity of human attention [3], attention-aware systems are also valuable in educational contexts. By tailoring content to a learner's attentional state, these systems can support engagement and reduce cognitive overload. [6]

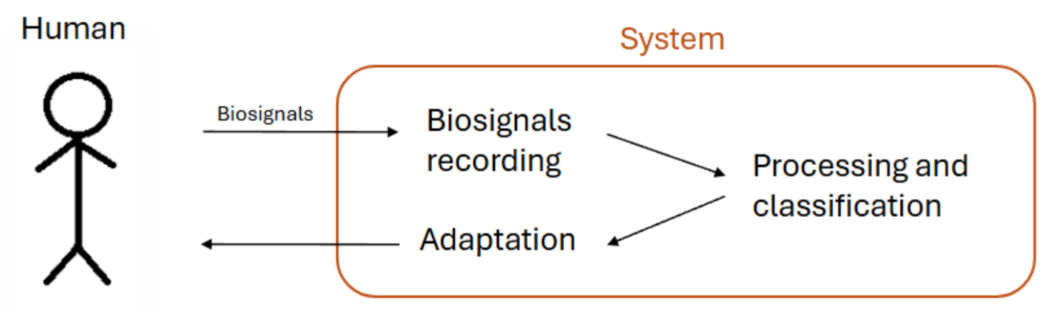

Figure 1: An adaptive system loop, simplified version of illustration presented in [2]

1.2 Related works

Several existing surveys explore topics that intersect with the focus of this work. Notably, the recent survey by Dritsas et al. [7] demonstrates significant overlap. They offer a comprehensive review of multimodal interaction and interfaces, covering a broad range of input modalities such as gaze, brain-computer interfaces (BCIs), and touch. In addition to input types, they address various aspects of multimodal systems, including communication, interaction, challenges, applications, and future directions. This survey builds on their work by narrowing the scope to focus specifically on adaptive systems that utilize attention as a key input signal. As such, it includes a broad spectrum of both implicit and explicit input modalities—provided they reflect or convey human attentional states. In doing so, this survey offers a more targeted perspective on the role of attention within adaptive intelligent systems.

Another related work is the survey by [8], which concentrates on user state recognition through eye-based input using machine learning techniques. This survey extends this focus by considering a wider range of recognition technologies beyond eye-tracking. It also encompasses adaptive systems more broadly, without restricting them to machine learning-based approaches, thereby including rule-based and hybrid systems as well.

1.3 Research question

The research question covered in this survey is: *How do intelligent systems acquire and use information related to the cognitive-affective process (of users) of attention*? To answer this question, the research question has been split into multiple sub-questions.

RQ 1 What forms of information related to this type of process has HCAI research used for adaptation of intelligent systems?

RQ 2 For what objectives has this information been used?

RQ 3a How has this information been used?

RQ 3b Are there any trends or patterns observable in this usage?

RQ 4 In which application domains?

RQ 5a Are there any trends or patterns observable with respect to these aspects?

RQ 5b What challenges and trends exist in recent developments?

2 Method

To address the research questions, a literature survey was conducted following the methodology outlined by Boland et al. [9], supplemented by the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines. [1] The process described by Boland et al. involves developing a protocol, screening titles and abstracts, selecting full-text articles, extracting data, and ultimately analyzing and synthesizing the findings. PRISMA was chosen as the reporting framework to ensure transparency and reproducibility throughout the review process.

2.1 Protocol

The initial step in the protocol involved identifying the core concepts, which were derived from key themes and focal points in the research questions. These concepts needed to be broad enough to capture all relevant literature while still constraining the results in a systematic and focused manner. The final core concepts selected were *attention*, representing the target cognitive-affective state, *adaptive systems*, referring to the specific class of systems under investigation, and *user*, to ensure the results cover specifically human attention and involved user interaction within the adaptive systems. Related and synonymous terms for each core concept were also gathered to support the development of the search query used to retrieve relevant literature. An overview of the core concepts and associated terms is presented in Table 1.

user	adaptive systems	attention
person human student learner	dynamic systems personalized systems adaptive interfaces	(in)attentiveness focus eye-movement tracking gaze mind-wandering absent-minded

Table 1: Overview of concepts used in the queries.

After deciding on the core concepts, the concepts and terms were applied to different databases: Scopus[1], IEEE Xplore[2] and Web of Science[3]. They were chosen because they have a large library of different publications, and cover a broad area of literature within the computer science field. These databases were also accessible through the TU Delft Library[4], which was convenient considering the limited time frame of this survey.

2.2 Search criteria

To identify papers relevant to this literature review, specific criteria were established to ensure consistency in inclusion and exclusion decisions. Notably, no strict inclusion criteria were applied. Instead, any paper not excluded based on predefined exclusion criteria was considered potentially relevant for addressing the research question. The exclusion criteria define the core concepts more carefully, and allows the screening process to be consistent and transparent. Table 2 shows an overview over the exclusion criteria that was used.

Exclusion Criterion	**Reason**
Papers released after 26.05.2025	Only papers that were released at the time of the survey have been considered.
Not in English	Only papers written in English were considered for the sake of consistency.
Surveys and reviews	The papers considered should be able to answer the research questions, and look at attention applied to systems.
Not about human attention as input	The paper needs to be about an adaptive system that uses directly or indirectly human attention as an input.
The system is not an adaptive computer system	This survey is specifically about adaptive computer systems, and the system described therefore needs to have an adaptation loop similar to Figure 1.

Table 2: Exclusion criteria.

2.3 Identification and screening

The PRISMA flowchart [1] was used to guide the identification and screening of relevant papers. Identification was carried out by executing the predefined search queries in each

[1]Scopus: https://www.scopus.com
[2]IEEE Xplore: https://xplorestaging.ieee.org
[3]Web of Science: https://www.webofscience.com
[4]TU Delft Library: https://www.tudelft.nl/en/library

selected database. The resulting records were then exported to EndNote 21[5], where they were organized into groups based on their source database. Each stage of the PRISMA process was assigned a dedicated group in EndNote to maintain a clear overview of the workflow.

The first step involved the removal of duplicate entries. This was initially performed using EndNote's automatic duplicate detection, followed by a manual review to remove any remaining duplicates that were not identified automatically. The subsequent step was the screening phase, in which titles and abstracts were assessed against predefined exclusion criteria. Papers that met one or more exclusion criteria were removed, and the reason for exclusion was documented.

Articles that passed the initial screening were then retrieved. EndNote's automated retrieval function was used where possible, and remaining articles were located and downloaded manually. In the final screening step, the full-text versions of the retrieved papers were reviewed using the same exclusion criteria. As before, all exclusions were documented with justifications.

2.4 Data extraction

Each paper was investigated, and data related to each research question was documented in a Microsoft Excel[6] sheet. The following information from each paper was noted in regards to the research questions:

- What does the system sense?
- What does the system model?
- What is the objective?
- What is the outcome?
- What are the related domains?
- Are there any recent developments or challenges?

Additionally, the year, country, a short system description, input type and target user group was documented at the same time. This way, papers could easily be grouped together for analysis on broader patterns.

3 Results

To answer the research questions, the results of the search and extraction is presented. The extraction results have been separated into tables and charts covering the different research questions. The full extraction table can be found here (external link).

[5]EndNote: https://web.endnote.com
[6]Microsoft Excel: https://www.microsoft.com/microsoft-365/excel

3.1 Search results

Using the final developed query for each database, which can be found in Appendix A, a total of 724 papers were recorded, where 180 duplicates were removed. The screening process started with 544 papers. A total of 312 papers were excluded in this first round of screening.

Due to time restraints, 16 papers could not be retrieved for analysis and were therefore excluded. After retrieval, 214 full length papers could be screened. Based on the full length screening, a further 145 papers were excluded.

This resulted in 74 papers that could be used for the data extraction step. A visual overview over the search results and reasons for exclusions can be seen in the flowchart in Figure 2.

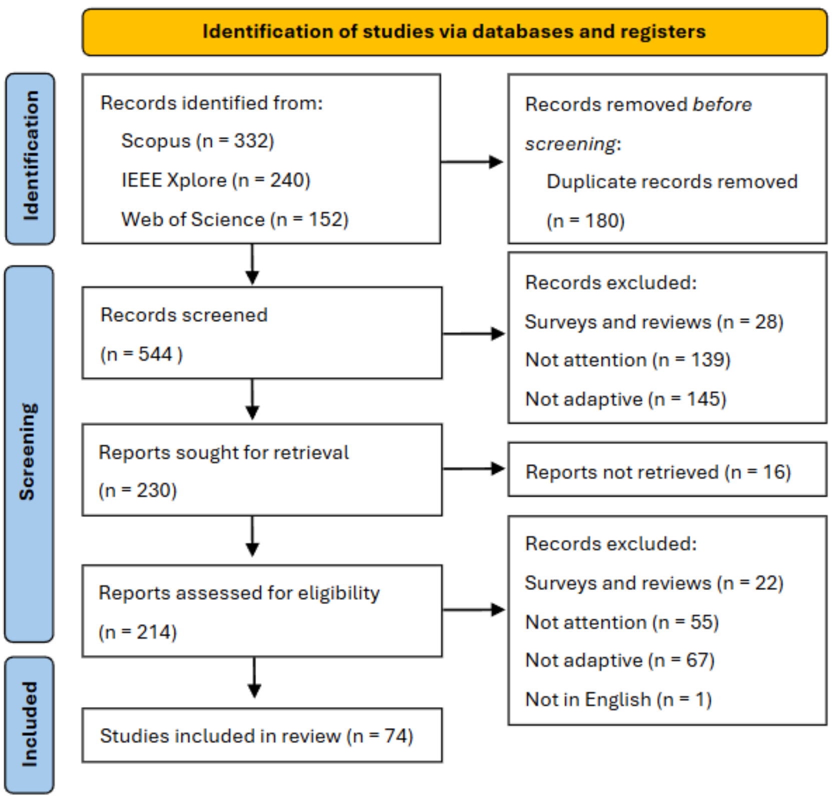

Figure 2: The PRISMA flowchart, adapted from [1].

3.2 Information used for adaptation

Various input modalities were used to capture user attention, with many studies employing multiple types simultaneously. The majority of papers (45 out of 74) utilized eye-gaze tracking to monitor where users directed their visual attention during system interaction. Another frequently used input was brain-computer interfaces (BCI), which, when employed, were often the sole input method for the system.

Input	Literature
Eye-gaze	[10] [11] [12] [13] [14] [15] [16] [17] [18] [19] [20] [21] [22] [23] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44] [45] [46] [47] [48] [49] [50] [51] [52] [53] [54]
BCI	[16] [20] [23] [55] [56] [57] [58] [59] [60] [61] [62] [63] [64]
Body movement	[15] [18] [21] [25] [28] [29] [30] [46] [48] [65] [66] [67] [68] [69]
Body measures	[11] [20] [36] [70] [71] [72] [73] [74] [75]
Actions	[15] [17] [19] [26] [44] [45] [70] [72] [73] [74] [76] [77] [78] [79]
Speech	[11] [45] [49]
Mouse	[16] [21] [27] [31] [44] [46] [51] [80] [81]
Keyboard	[21] [46] [51] [80]
Questionnaires	[57] [71] [78]
External	[45] [69] [70] [79] [82]
Unclear	[83]

Table 3: Sensor input and related literature, simplified from Table 8

A few studies stood out for not relying on direct physiological recordings. For example, [80] modeled user attention using mouse and keyboard activity, while [81] inferred understanding and attention through mouse movements and latency data. Similarly, [82] estimated users' mental workload indirectly using vehicle data (e.g., GPS and vehicle parameters) influenced by the driver's actions, rather than monitoring the user directly.

In terms of application, the most common use of input data (43 papers) was to model user attention, mental workload, or cognitive state. However, no strong correlation was observed between specific input types and the particular aspects of attention being modeled.

A summary of the input types used is provided in Table 3, with a more detailed breakdown available in Table 8 in Appendix B. The corresponding modeling purposes are outlined in Table 4.

Model	Literature
Attention	[13] [20] [29] [34] [37] [39] [47] [48] [49] [56] [58] [60] [61] [63] [68] [79]
(Cognitive) Workload	[19] [21] [23] [36] [54] [55] [57] [64] [70] [73] [74] [82]
(Cognitive) Mental state	[21] [24] [26] [28] [50] [52] [55] [57] [65] [72] [73] [76] [77] [78] [80]
Gaze and focus	[10] [20] [27] [32] [35] [40] [41] [44]
Performance	[10] [36] [45] [62] [67] [76]
Emotions	[11] [23] [65] [71] [75]
Knowledge / Understanding	[11] [33] [43] [81]
Behavior	[12] [16] [45] [46] [80]
Learning	[30] [56] [68]
Engagement	[15] [42] [57] [61] [62] [75]
Satisfaction	[18] [75]
Memory	[35] [71] [73]
Intention	[31] [38] [53] [59]
Unclear	[14] [17] [22] [25] [51] [69] [83]

Table 4: Modeling from sensor inputs

3.3 Objectives of the literature

The literature presents a wide range of objectives, many of which are described with considerable detail. For the purposes of this study, these objectives have been generalized into broader, more presentable categories. The most common goals were improving user performance and providing support or guidance, with 11 papers falling into each of these categories. Additionally, many studies focused on influencing or managing mental workload. 5 papers did not state their goals clearly enough to be placed in a category.

A few studies had notably distinct objectives. For example, [29] aimed to reduce bandwidth consumption in cloud streaming by leveraging user gaze data and an attention model. Similarly, [34] sought to create a narrative experience, also through the use of gaze data and attention modeling.

Objectives		**Literature**
Workload	Prevention Reduction Optimizing	[17] [54] [55] [82] [19] [36] [37] [50] [65] [74] [76] [77] [78] [45]
Concentration	Maintaining Recapture	[36] [51] [73] [80] [65] [79]
Performance	General improvement Skill estimation	[11] [13] [21] [33] [42] [44] [56] [61] [62] [68] [76] [11]
Action	Efficiency improvement	[16] [22] [37] [41] [58]
Safety	Road Flight	[12] [52] [69] [70] [74] [83] [20]
Engagement	Improvement	[42] [56] [67]
Provide	Personalized learning Communication Alternative approaches Information	[57] [81] [40] [60] [25] [47] [49] [38]
Training	Gaze sharing / following Gaze in robots / systems	[10] [59] [66]
Improvement	Well-being Usability	[14] [53] [72] [23] [32]
Support / Guidance		[14] [15] [27] [28] [30] [31] [43] [48] [63] [64] [71]
Reduce	Bandwidth consumption	[29]
Create	Narrative Interface	[34] [35] [75]
Unclear		[18] [24] [26] [39] [46]

Table 5: Objectives of the input

3.4 Information usage

The collected data was primarily applied in five distinct ways: by changing the user interface (UI), adapting the feedback timing, change of the automation levels, adaptive difficulty adjustments and providing behavioral feedback. Several studies also combined up to two of these adaptation strategies. A detailed overview of how each paper was categorized can be found in Table 6.

The distribution of these usage types over time is illustrated in Figure 3. The study by [59] was deliberately excluded from the figure, as the adaptation method described was ambiguous and could not be reliably classified. From 2015 onward, there is an increase in the number of publications, particularly those employing UI changes and adaptive feedback timing. Notably, none of the papers published prior to 2015 employed adaptive difficulty adjustment.

Information usage	Literature
UI change (UI)	[12] [13] [16] [18] [21] [22] [23] [24] [25] [26] [29] [30] [31] [32] [33] [34] [35] [37] [40] [41] [48] [50] [52] [53] [54] [58] [68] [72] [75]
Feedback timing (FT)	[11] [19] [20] [28] [36] [38] [42] [43] [56] [60] [61] [62] [70] [71] [73] [80] [81] [82] [83]
Automation level (AL)	[39] [45] [63] [66] [69] [76] [77]
Difficulty adjustment (DA)	[57]
Behavioral feedback (BF)	[46] [47] [49]
UI + FT	[14] [17] [27] [44] [51] [55] [64] [74] [78] [79]
UI + DA	[65]
FT + DA	[15] [67]
DA + BF	[10]
Unclear	[59]

Table 6: Usage of information

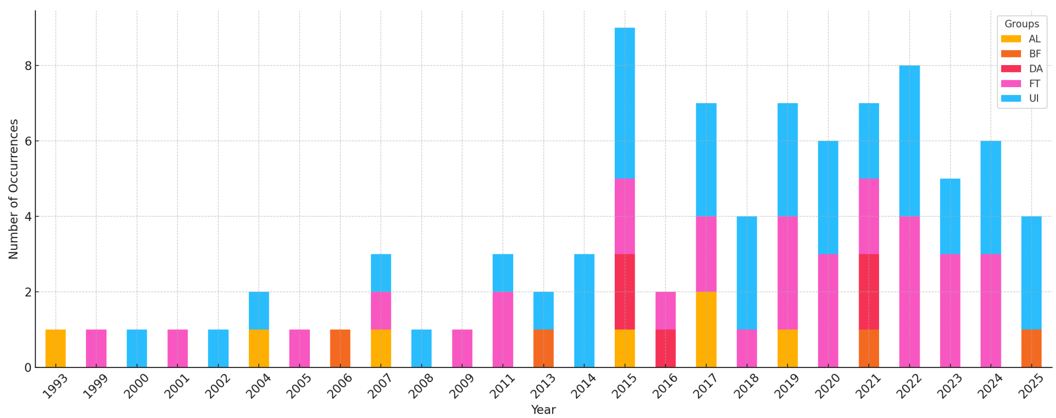

Figure 3: Distribution of usage groups per year.

3.5 Application domains

The data extraction revealed a range of application domains. The education sector accounted for the largest portion, consisting of nearly 23% (17 out of 74) of the studies. This category includes research on adaptive learning platforms, educational environments, and tutor support systems. An overview of the identified domains is presented in Table 7.

Many robotics-related papers were excluded during the screening phase, as they did not incorporate human attention in their adaptation mechanisms. Notably, [66] was the only study in the robotics domain that remained. Additionally, [64] was the sole paper focused on music, standing out from the more function-oriented categories. 6 papers did not clearly specify a domain based on the available information. Furthermore, [59] lacked both a clearly defined adaptation strategy and an identifiable application domain.

3.6 Trends and patterns in recent development

To identify trends and patterns in recent developments, the distribution of input types over time is illustrated in Figure 4. A gradual increase in the use of eye-gaze tracking technology can be observed, with notable upticks beginning in 2011 and again in 2019. Although [76] noted that eye-gaze tracking technology existed as early as 1993, they opted for an

Domain	Sub-domain	Literature
Task	Management Improvement Performance	[36] [50] [77] [78] [17] [51] [13] [23] [58]
Education		[10] [11] [15] [30] [42] [43] [44] [56] [57] [60] [61] [62] [65] [68] [76] [79] [81]
Accessibility		[16] [22] [25] [32] [33] [35] [41] [47] [48] [49]
Driving	Safety	[12] [39] [52] [69] [70] [74] [82] [83]
Video games		[28] [29] [46] [49]
Well-being	Improvement	[14] [21] [63] [72]
Aviation		[20] [24] [37] [45]
Productivity	Improvement	[55] [73] [80]
Behavioral adjustment		[10] [75]
Navigation	Assistance	[19] [54]
Rehabilitation		[67] [71]
Travel		[27] [31]
Robots		[66]
Art		[34]
Music		[64]
No apparent domain		[18] [26] [38] [40] [53] [59]

Table 7: System domains and related literature

alternative method to assess user state due to challenges in processing the data, specifically the individual variability and the sheer volume of data.

In [32], the authors reported accuracy issues with eye-tracking equipment and relied on a commercially available device for their user study. By contrast, more recent studies such as [40], which employed a newer version of the same brand of eye-tracker, and [47], which used a different approach based on camera images and a large dataset, reported no problems related to eye-tracking. This suggests improvements in eye-tracking technology and data processing capabilities over time.

The use of brain-computer interfaces (BCIs) has been sporadic since 2011. However, no significant changes in methodology or application are evident. For example, EEG-based approaches were used in both [23] and [58], with comparable purposes and techniques across the years.

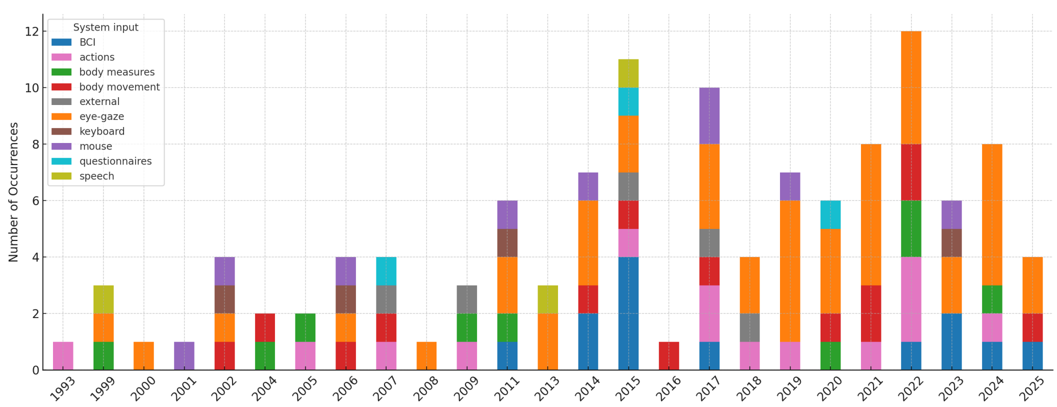

Figure 4: Distribution of type of input per year.

3.7 Challenges in the long term

During the data extraction process, few papers addressed long-term challenges. Most studies concentrated on immediate progress and short-term goals specific to their individual research goals, making it difficult to categorize overarching long-term issues. Nonetheless, a few relevant challenges were identified. For example, [55], which utilized a BCI with functional near-infrared spectroscopy (fNIRS, an alternative to EEG) to filter notifications and information, highlighted the limitation of relying on specialized, non-portable hardware. As a result, they identified the development of portable solutions compatible with commercial devices as a key next step. Similarly, [31] discussed the constraint of conducting their user study on a desktop computer, despite the intended use of their adaptive map system being on mobile platforms.

4 Responsible Research

Ethical considerations related to conducting a literature survey on cognitive-affective adaptive systems must be acknowledged. These are discussed in the following sections.

4.1 Reproducibility and replicability

A key aspect of a structured literature survey is ensuring its reproducibility and replicability. To support this, each step of the methodology has been described as clearly as possible, with particular commitment to the PRISMA guidelines [1], which are specifically designed to promote transparency and reproducibility in systematic reviews. Additional effort was made to document reasons for paper exclusion earlier in the process than typically required by PRISMA, providing greater clarity on the decision-making throughout the review.

The complete search queries are available in Appendix A, and the exclusion criteria are outlined in Table 2. By applying these elements to the same databases, it should be possible to reproduce the exact set of results, even at a later point in time.

4.2 Selection bias

During the screening process, there is a risk of selection bias, or "cherry-picking." This can occur when a paper does not clearly meet the exclusion criteria, or when relevant information is obscured within the text, which is an issue that becomes more pronounced when screening a large number of papers simultaneously. To reduce this risk, the exclusion criteria were designed to be as clear, objective, and defensible as possible, minimizing ambiguity and helping to prevent papers from falling into a gray area between inclusion and exclusion. Nevertheless, it is important to recognize that personal bias may still influence the screening process, as it is not possible to eliminate such bias entirely.

5 Discussion

The results indicate that eye-gaze tracking is the most commonly used input method for capturing user attention. However, brain-computer interfaces (BCIs) also remain relatively prevalent compared to other input types. What distinguishes BCIs is the stability in their usage over time—remaining consistent since 2011—while eye-gaze tracking has seen a noticeable rise, particularly from 2019 onward. Several factors may explain this trend. One possibility is that BCIs may be less compatible with adaptive systems, prompting more recent studies to explore alternative methods for attention detection. For example, EEG signals are highly sensitive to user movement. As highlighted in [56], this sensitivity posed a limitation during their user testing, where participants were instructed to minimize movement as a workaround. Another factor could be limited access to BCI equipment. [59] notes that EEG is becoming more consumer-friendly but does not clarify whether it is widely accessible.

A noteworthy observation is the relatively infrequent use of adaptive difficulty adjustment as an adaptation technique. Among the 17 papers categorized in the education domain, only four employed this approach. Although these studies do not explicitly discuss the challenges involved in implementing difficulty adjustments, one might presume that such systems are more complex and resource-intensive to develop compared to alternatives like feedback, suggestions, or hints. Furthermore, the added complexity may not lead to significant improvements in learning outcomes, potentially discouraging broader use.

Another interesting finding is the wide range of application domains covered in the literature, including some that are initially unexpected. The link between attention and domains such as education and driving is intuitive. In educational contexts, sustained attention is often considered essential for effective learning, while in driver safety, attentiveness is crucial for quick reactions and situational awareness. What stands out, however, is the notable number of adaptive systems designed for motor-impaired individuals and the elderly. Upon closer inspection, this is understandable given the promise of eye-gaze technology as an alternative to traditional input devices like the mouse and keyboard. For instance, [22] developed a gaze-controlled virtual keyboard with an adaptive layout based on common typing patterns, and [49] proposed a system that maps gaze to mouse and keyboard inputs. By lowering the fine motor skill requirements associated with conventional input devices, such technologies can greatly enhance accessibility for elderly or disabled users, potentially improving their independence, quality of life, and social inclusion. [35]

6 Conclusions and Future Work

This survey successfully addressed the central research question: how intelligent systems acquire and use information related to cognitive-affective processes of attention. The findings reveal a broad range of input modalities used to record user attention, with eye-gaze tracking, brain-computer interfaces (BCI), and head or facial recordings emerging as the most commonly employed methods. While no consistent relationship was found between input type and the specific modeling approach, most studies focused on modeling user attention, mental workload, and cognitive state—concepts that are closely interrelated.

The objectives of the reviewed studies were similarly diverse. However, enhancing user performance, providing support and guidance, and managing cognitive workload emerged as the most frequent goals. Other common goals included improving road safety and task efficiency.

Adaptation in these systems typically occurred through personalized user interface (UI) changes or adjustments to the timing of feedback, with several studies combining both strategies. In contrast, automation level adjustments, adaptive difficulty, and behavioral feedback were used less frequently. Since 2015, the use of UI changes and adaptive feedback timing has notably increased and remained prevalent. Notably, no studies published before 2015 utilized difficulty adjustment techniques.

In terms of application domains, the reviewed literature was again highly varied. The three most prominent domains were education, accessibility, and driver safety. The amount of education-focused articles is unsurprising, given the strong link between attention and learning. The prominence of accessibility-focused applications, while initially unexpected, is understandable in light of the potential for eye-gaze technology to serve as an alternative to traditional input devices, which is particularly beneficial for elderly and disabled users.

Looking at trends in technological adoption, eye-gaze tracking has seen increased use beginning in 2011, with another rise in 2019. Over time, studies have demonstrated growing confidence in this technology, evolving from concerns about data processing and variability to successfully using gaze as a standalone input method, such as controlling a mouse cursor. BCI, while consistently present, has not experienced similar growth. This is likely due to ongoing practical challenges in usability and movement sensitivity, which is unfavorable in a commercial system.

Long-term challenges were rarely addressed across the literature. Most papers focused on short-term system improvements and current performance, making it difficult to identify patterns or trends related to future obstacles or development needs.

For future research, deeper investigation into the modeling of attention, especially within the specific context of adaptive systems, could offer valuable insights, building on initial efforts such as those presented in [7]. Additionally, a systematic review evaluating which adaptation strategies achieved their intended outcomes, and which did not, would be highly beneficial for guiding the design and development of future adaptive systems.

Appendix

A Full Queries Used

A.1 Scopus

TITLE-ABS-KEY (("user* attention" OR "visual attention" OR "involuntary attention" OR "subject attention" OR "attenti* level" OR "level of attention" OR "human attention" OR "attenti* state" OR attentive* OR "user focus" OR "visual focus" OR "eye movement track*" OR "eye-movement track*" OR "mind-wander*" OR "mind wander*" OR gaze OR "mental state" OR "cognitive engage*" OR inattention OR inattentive* OR distract* OR "absent-minded" OR "absent minded" OR daydream* OR "day dream*")

OR (attention W/2 (user OR student OR learner OR person OR human)))

AND TITLE-ABS-KEY ("adaptive system*" OR "system adapt*" OR "personalized system*" OR "personalised system*" OR "adaptive interface" OR "adaptive UI")

AND TITLE-ABS-KEY (user OR student OR learner OR person OR human)

A.2 IEEE Xplore

((("All Metadata":"user* attention" OR "All Metadata":"visual attention" OR "All Metadata":"involuntary attention" OR "All Metadata":"subject attention" OR "All Metadata": "attenti* level" OR "All Metadata":"level of attention" OR "All Metadata":"human attention" OR "All Metadata": "attenti* state" OR "All Metadata":"attentive*" OR "All Metadata":"user focus" OR "All Metadata":"visual focus" OR "All Metadata":"eye movement track*" OR "All Metadata":"eye-movement track*" OR "All Metadata":"mind-wander" OR "All Metadata":"mind wander" OR "All Metadata":"mind-wandering" OR "All Metadata":"mind wandering" OR "All Metadata":"gaze" OR "All Metadata":"mental state" OR "All Metadata":"mental states" OR "All Metadata":"cognitive engage*" OR "All Metadata":"inattention" OR "All Metadata":"inattentive*" OR "All Metadata":"distract*" OR "All Metadata":"absent-minded" OR "All Metadata":"absent minded" OR "All Metadata": "daydream" OR "All Metadata":"day dream" OR "All Metadata":"daydreaming" OR "All Metadata":"day dreaming" OR ("All Metadata":"attention" NEAR/2 ("All Metadata":"user" OR "All Metadata":"users" OR "All Metadata":"student" OR "All Metadata":"learner" OR "All Metadata":"person" OR "All Metadata":"human")))

AND ("All Metadata":"adaptive system" OR "All Metadata":"adaptive systems" OR "All Metadata":"system adapt*" OR "All Metadata":"personalized system" OR "All Metadata":"personalized systems" OR "All Metadata":"personalised system" OR "All Metadata":"personalised systems" OR "All Metadata":"adaptive interface" OR "All Metadata": "adaptive interfaces" OR "All Metadata":"adaptive UI")

AND ("All Metadata":"user" OR "All Metadata":"users" OR "All Metadata":"student" OR "All Metadata":"students" OR "All Metadata":"learner" OR "All Metadata":"learners" OR "All Metadata":"person" OR "All Metadata":"persons" OR "All Metadata":"human" OR "All Metadata":"humans")))

A.3 Web of Science

TS=(("user* attention" OR "visual attention" OR "involuntary attention" OR "subject attention" OR "attenti* level" OR "level of attention" OR "human attention" OR "attenti* state" OR attentive* OR "user focus" OR "visual focus" OR "eye movement track*" OR "eye-movement track*" OR "mind-wander*" OR "mind wander*" OR gaze OR "mental state" OR "cognitive engage*" OR inattention OR inattentive* OR distract* OR "absent-minded" OR "absent minded" OR daydream* OR "day dream*") OR (attention NEAR/2 (user OR student OR learner OR person OR human)))

AND TS=("adaptive system*" OR "system adapt*" OR "personalized system*" OR "personalised system*" OR "adaptive interface" OR "adaptive UI")

AND TS=(user OR student OR learner OR person OR human)

B Full Tables

Input		Literature
Eye-gaze	Fixation	[10] [11] [12] [17] [19] [29] [35] [38] [42] [48] [49] [50] [53] [54]
	Blink rate	[11] [19] [50] [54]
	Pupil diameter	[11] [19] [35] [36] [42] [48] [50] [53] [54]
	Saccades	[12]
	EOG	[41]
	Angle	[53]
	Unspecified	[13] [14] [15] [16] [18] [20] [21] [22] [23] [24] [25] [26] [27] [28] [30] [31] [32] [33] [34] [37] [39] [40] [43] [44] [45] [46] [47] [51] [52]
BCI	EEG	[20] [23] [56] [57] [58] [59] [60] [61] [62]
	fNIRS	[55] [64]
	Unspecified	[16] [63]
Physical condition		[70] [73]
Heart rate		[11] [20] [36] [71] [74] [75]
Head and face movement		[15] [18] [21] [28] [29] [30] [46] [48] [65] [66] [68] [69]
Arm and hand movement		[18] [21] [25] [46] [67]
Blood pressure		[20] [75]
Skin conductance		[20] [36] [75]
Nasal temperature		[72]
Behavior		[17] [26] [45] [70] [72] [73] [79]
Task performance		[15] [19] [26] [45] [74] [76] [77] [78]
Responsiveness		[15] [44] [78]
Speech		[11] [45] [49]
Mouse		[16] [21] [27] [31] [44] [46] [51] [80] [81]
Keyboard		[21] [46] [51] [80]
Questionnaires		[57] [71] [78]
External	Environment	[45] [70] [79]
	Vehicle status	[69] [82]
Unclear		[83]

Table 8: Sensor input and related literature

C Usage of AI

ChatGPT has been used to facilitate the writing process of this document.

Example prompt 1: In Overleaf, I want to add a link to an external website at the bottom of the page, and have a little reference in the text. It should look like this: Text^1, and then at the bottom of the page: ^1 Here is link: url. How can I do that?

Answer: To add a small reference in the text like Text[1] and place a clickable URL at the bottom of the page in Overleaf (LaTeX), you can use the \footnote{} command along with \href{} from the hyperref package. Here's how to do it:

Minimalist Example:

\{article}
\usepackage{hyperref} Enables clickable links
\begin{document}
This is some example text\footnote {Here is the link: \href{https://example.com}
{https://example.com}} with a footnote.
\end{document}

Explanation:

- \footnote{...} creates a numbered footnote at the bottom of the page.
- Inside the footnote, \href{URL}{text} makes the URL clickable.
- The superscript number is automatically handled by \footnote.

You can also change the text of the link (instead of showing the raw URL):
\footnote{For more info, see \href{https://example.com}{this website}.}

Let me know if you want to style the footnote marker differently (e.g., using symbols instead of numbers).

Example prompt 2: Can you rephrase this? "There are ethical aspects regarding a literature survey about cognitive-affective adaptive systems that need to be addressed. This is covered in the following sections."

Answer: Certainly! Here's a more polished version of your sentence: Ethical considerations related to conducting a literature survey on cognitive-affective adaptive systems must be acknowledged. These are discussed in the following sections.

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