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Eye tracking and artificial intelligence for competency assessment in engineering education: a review

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In recent years, eye-tracking (ET) methods have gained an increasing interest in STEM education research. When applied to engineering education, ET is particularly relevant for understanding some aspects of student behavior, especially student competency, and its assessment. However, from the instructor's perspective, little is known about how ET can be used to provide new insights into, and ease the process of, instructor assessment. Traditionally, engineering education is assessed through time-consuming and labor-extensive screening of their materials and learning outcomes. With regard to this, and coupled with, for instance, the subjective open-ended dimensions of engineering design, assessing competency has shown some limitations. To address such issues, alternative technologies such as artificial intelligence (AI), which has the potential to massively predict and repeat instructors' tasks with higher accuracy, have been suggested. To date, little is known about the effects of combining AI and ET (AIET) techniques to gain new insights into the instructor's perspective. We conducted a Review of engineering education over the last decade (2013–2022) to study the latest research focusing on this combination to improve engineering assessment. The Review was conducted in four databases (Web of Science, IEEE Xplore, EBSCOhost, and Google Scholar) and included specific terms associated with the topic of AIET in engineering education. The research identified two types of AIET applications that mostly focus on student learning: (1) eye-tracking devices that rely on AI to enhance the gaze-tracking process (improvement of technology), and (2) the use of AI to analyze, predict, and assess eye-tracking analytics (application of technology). We ended the Review by discussing future perspectives and potential contributions to the assessment of engineering learning.

KEYWORDS

eye tracking, artificial intelligence, competency, assessment, engineering education

1. Introduction

Eye tracking has been integrated into many applications, such as human-computer interaction, marketing, medicine, and engineering (e.g., assistive driving, software, and user interfaces). Recent studies revealed that eye tracking (ET) and artificial intelligence (AI), including machine (ML) and deep learning (DL), have been combined to assess human behavior (e.g., Tien et al., 2014). However, although extensive studies have focused on the application of AI techniques to eye-tracking data in some STEM disciplines, little is known about how this could be used in engineering design educational settings to facilitate instructors' assessment of the design learning of their students, especially design competency.

1.1. Competency assessment in engineering education

1.1.1. Competency-based engineering education

The development of student competencies has become a central issue in complex fields, such as engineering education. With regard to competencies, various terminologies are used to describe a learner expertise in a situation and their ability to solve complex engineering problems; for instance, competence (pl. competences), competency (pl. competencies), capability, and so on, are generally used. The debate about terminology is still ongoing. In this paper, we refer to both "competence," i.e., the general term, and "competency," i.e., the components of a competence as holistic constructs, with the focus on "competency" as the ability to integrate knowledge, skills, and attitudes (KSAs; Le Deist and Winterton, 2005) and their underlying constituents (cognitive, conative, affective, motivational, volitional, social, etc.; e.g., Shavelson, 2013; Blömeke et al., 2015) simultaneously (van Merriënboer and Kirschner, 2017). From an instructional design perspective, learning, which is also the acquisition of skills and competencies, has integrative goals in which KSAs are developed concurrently to acquire complex skills and professional competencies (Frerejean et al., 2019). This approach is interesting and may help avoid core issues in instructional engineering design, such as compartmentalization, which involves the teaching of KSAs separately, hindering competency acquisition and transfer in complex engineering learning. Therefore, as suggested by Spencer (1997), competency assessment (we discuss this further in the next section) determines the extent to which a learner has competencies. Competency is assumed to be multidimensional (Blömeke et al., 2015) and discipline-specific (Zlatkin-Troitschanskaia and Pant, 2016). Competencies can be learned through training and practice. Siddique et al. (2012) noted two levels of competencies in professional fields: (1) field-specific task competencies, and (2) meta-competencies as generalized skill sets. Le Deist and Winterton (2005) argued that a multi-dimensional framework of "competence" necessarily involved conceptual (cognitive and meta-competence) and operational (functional and social competence, including attitude and behavior) competencies. They assumed competence is composed of four dimensions of competencies: cognitive dimension (knowledge), functional dimension (skills), social (behavior and attitudes), and meta-competence (Le Deist and Winterton, 2005). Engineers argue that these dimensions also apply to engineering education. With the emerging complexity involved in designing engineering systems, tackling complexity is a new requirement. As such, Hadgraft and Kolmos (2020) proposed that three basic competencies should be incorporated into engineering courses: complexity, system thinking, and interdisciplinarity. Therefore, we argue that competency and competency assessment should be described by a more holistic framework that is appropriate to learning and instruction in complex engineering education.

1.1.2. Challenges of assessing student competencies in engineering education

Instructors' assessment of students' engineering competencies is a critical topic that has been addressed for decades in the engineering education literature. Despite this, assessment of engineering learning suffers from several issues, such as a lack of consistency. It is still highly subjective, labor-intensive, and time-consuming. The COVID-19 pandemic has exacerbated these issues as many engineering instructions shifted from face-to-face to online or remote instructions using online platforms, thus increasing teacher workloads, cognitive loads, etc. More critically, engineering assessment suffers from an integrative approach to engineering competencies and competency assessment even with the use of advanced techniques, such as AI and other computing technologies (e.g., Khan et al., 2023). Most technologies used to assess engineering student competencies usually focus on some aspects of an engineering competence and not on a systemic holistic approach to competency.

1.2. Eye-tracking technologies: a brief history in scientific research

Several papers have reviewed the history of eye-tracking research (e.g., Wade and Tatler, 2005; Płużyczka, 2018). Płużyczka (2018) identified three developmental phases in the first 100 years of eye tracking as a research approach: the first phase of eye-tracking research dates back to the late 1870s with Javal's studies on understanding and assessing the reading process. At that time, the eye-tracking approach was optical-mechanical and invasive. The second era of eye-tracking research originated with film recordings in the 1920s. The third phase started in the mid-1970s and refers to two main phenomena related to the development of psychology (the establishment of a theoretical and methodological basis for cognitive psychology) and technology (the use of computer, television, and electronic techniques to detect and locate the eye). Motivated by the rapid development of eye-tracking and computer processing technologies, Płużyczka (2018) also suggested that another phase led to contemporary eye-tracking research that took place in the 1990s.

Eye tracking permits the assessment of an individual's visual attention, yielding a rich source of information on where, when, how long, and in which sequence certain information in space or about space is looked at (Kiefer et al., 2017). Different eye-tracking techniques have been referenced. For instance, Duchowski and Duchowski (2007) identified four categories of eye movement measurement methodologies: electro-oculography (EOG), scleral contact lens/search coil, photo-oculography (POG) or video-oculography (VOG), and video-based combined pupil and corneal reflection (p. 51). Li et al. (2021) also provided a similar overview. Among other techniques, they cited the earliest manual observations followed by new techniques, such as electrooculography, video and photographic, corneal reflection, and micro-electromechanical systems, and those based on machine and deep learning. For each method, they examined the benefits and limitations. They argued that CNN-based approaches offer better recognition performance and robustness; however, they require large amounts of data, complex parameter adjustments, and an understanding of black box characteristics, and involve high costs.

1.3. AI and ET to assess engineering

Artificial intelligence and computer vision (CV) have advanced significantly and rapidly over the past decade due to highly effective deep learning models, such as the CNN variants (Szegedy et al., 2015; He et al., 2016; Huang et al., 2017) and vision transformers (Dosovitskiy et al., 2020), and the availability of large high-quality datasets and powerful GPUs for training such large models. As a result of these advances in AI and CV, eye-tracking technology has reached a level of reliability sufficient for wider adoption, such as for evaluating student attention via their eye-gaze on the study materials taught. More specifically, this application has the benefit of being able to measure multiple spectrums of student attention. For example, such technology can measure whether the student is focusing more generally on the class or specifically on certain parts of the lecture material. Adding on the dimension of time, one can also measure the amount of time students spend on different parts of the course content and when their attention starts to drift.

In terms of the instructor-side, the integration of eye tracking and AI has various benefits for the assessment of engineering design education. Similar to the application of eye tracking and AI with students, these technologies can generally be used to measure which part of a student assignment an instructor focuses more on and the amount of time they spend on different parts of an assignment. In addition, we see the following potential cases for the use of eye tracking and AI:

- Studying the effectiveness of assessment criterions. Alongside a marking rubric, eye tracking and AI can be used to find a correlation between different assessment criteria and specific parts of a submitted assignment. For example, we can compare the criteria in a marking rubric that an instructor is looking at and the corresponding parts of an assignment they look at next. Pairs of these marking criteria and assignment segments can then be used for correlation studies.
- Streamlining instructor assessment workload. With explainable AI (XAI) techniques, a system can highlight portions of the student assignments that an instructor should focus on based on the different criteria. Such a model can be trained on past data of instructor assessment and student assignments, alongside the captured eye-tracking data. This model can then be transferred and fine-tuned to other assignments.
- Detecting discrepancies between instructor assessments. Different instructors may have varying standards or interpretations of engineering assessments, e.g., between newer and more experience instructors. Eye tracking and AI can be used to determine whether there are any differences between instructors in terms of the parts of the student assignments they focus on, how much time they spend on each portion, and, most importantly, any significant differences in the assigned grades for each criteria.

2. Purpose and research questions

This study aims to understand research trends in the use of AIET to assess engineering student competencies. The overall research questions (RQs) are as follows:

- RQ1: What are the current research trends (or categories) in AI- and ET-based competency assessment in engineering education over the last decade?
- RQ2: What are the most salient competency dimensions and labels to which we attribute studies related to assessing engineering education?

3. Methods

3.1. Data collection

We reviewed the literature and collected papers from the following four databases: Web of Science (WoS), IEEE Xplore (IX), Academic Search Complete (ASC), and Computers and Applied Sciences Complete (CASC) hosted by EBSCO and Google Scholar (GS). The Review was conducted with research published in the last decade, i.e., from 2013 to 2022. Focusing on title, abstracts, and keywords, we used a general equation including terms used in the topic of eye tracking and artificial intelligence in engineering education research, such as Title-Abs-Key[("eye-track*" OR "eye-gaze" OR "eye movement") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("assess* OR evaluat* OR measur* OR test* OR screen*) AND ("competenc*" OR "skills" OR "knowledge" OR "attitudes") AND ("engineering design" OR "engineering education")]. The review process, which comprised three steps, namely identification, screening, and eligibility, is summarized below and in the flow diagram (Figure 1):

1. Identification: an initial record of $N = 89$ studies were identified by searching the databases: EBSCOhost (19 studies), WoS (24 studies), IX (26 studies), and GS (20 studies).
2. Screening: after duplicates were removed, records were screened based on the relevance of titles and abstracts.
3. Eligibility: peer-reviewed studies written in English and related to engineering education, competency assessment, and higher education were selected.
4. Finally, $N = 76$ studies were retained in this Review.

All references collected from the databases were imported into Rayyan, an intelligent platform for systematic review, to help in the review process. Data were then manually categorized (according to labels that fit in the dimensional aspects of a student's competency as defined earlier) and exported in an editable format containing three variables: title, abstract, dimension, and corresponding labels. In addition, the generated format contained the following criteria: relevance to assessing EE (yes/no), higher education (yes/no), tested with instructors or students (yes/no), methodology used (type of assessment), competency dimensions (cognitive, functional, social, and meta), contributions, and limitations (Figure 2).

3.2. Data analysis

Qualitative and quantitative methods were used to analyze the data. Following the collection, we first performed a qualitative analysis (i.e., thematic analysis), manually categorizing and labeling the focus of each paper according to the competency dimensions. This helped

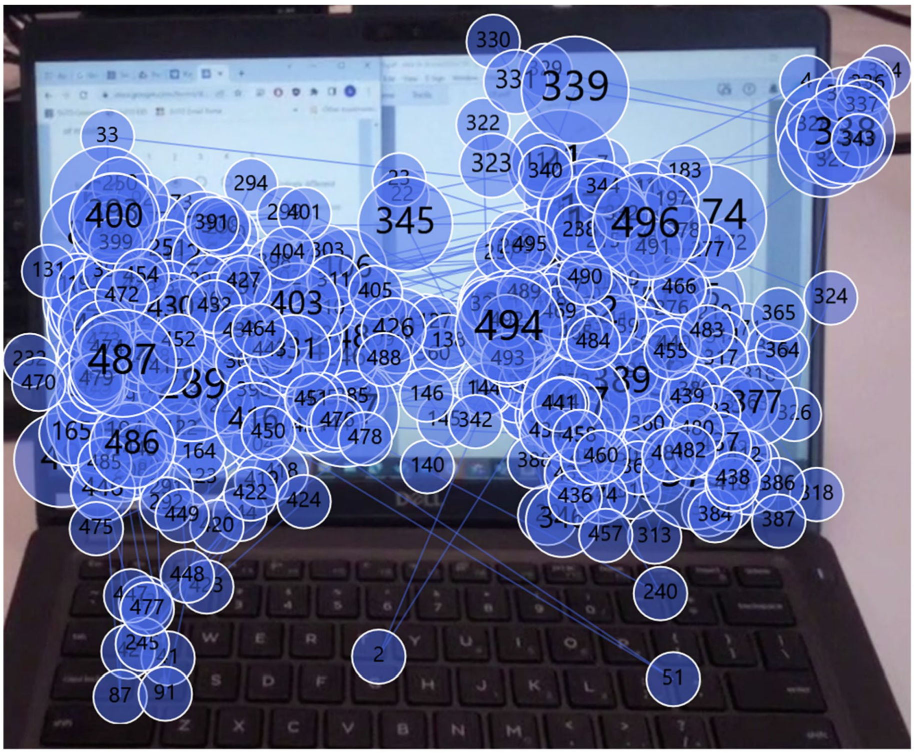

FIGURE 1
Instructor on-screen assessment of student design creativity. This pilot experiment (one person involved) used Tobii glasses 2 (issues related to the use of this specific tool are not discussed here). The instructor followed a rubric (left side of the screen) comprising a set of criteria to assess creativity in students' design solutions (right side of the computer screen). The results of this study are not reported in this paper.

to identify the types of AIET. Based on this corpus, we then furthered the Review with a lexicometry analysis with IRaMuTEQ 0.7 alpha 2 (Ratinaud, 2009) and RStudio 2021.09.1 + 372 for macOS. IRaMuTEQ is an R interface for multidimensional analysis of texts and questionnaires. It offers different types of analysis, such as lexicometry, statistical methods (specificity calculation, factor analysis, or classification), textual data visualization (usually called word cloud), or term network analysis (called similarity analysis).

We conducted a clustering based on the Reinert's method (Reinert, 1990). This method includes a hierarchical classification, profiles, and correspondence analyses. To obtain the co-occurrence graphs, we then conducted a similarities analysis that used the graph theory also called network analysis to analyze trends within the reported data. Finally, we also used thematic analysis to organize the reported data into categories for the assessment types, titles of clusters, and types of AIET.

4. Results

4.1. Categories of artificial intelligence and eye tracking

Our first research question attempts to explore current research trends in AIET-based assessment in engineering education. Typically, and based on the manual thematic analysis, two relatively dependent types of AIET research categories can be identified with regard to assessment: (1) eye-tracking devices that use AI and sub-domains to improve the process of tracking (improving the technology), and (2) the use of AI to analyze and predict the eye-tracking data analytics related to student learning (the application of the technology). The first typology generally consists of combining AI and sub-domains, such as machine learning (ML) and deep learning (DL) with ET. As opposed to traditional tracking approaches that often estimate the location of visual cues, researchers developing this orientation attempt to improve the tracking process; for instance, favoring detection over tracking. Reported results from this approach detail the performance and accuracy of detection. This is receiving increasing attention. Conversely, although the second typology also utilizes AI to predict and detect behaviors, it mainly focuses on assessing and providing insights into learner behaviors afterwards based on recorded eye-tracking data. Collected data can be reinjected into the learning system afterwards to support the learners and/or educators.

Usually there are more practical applications to educational assessment. With regard to these typologies, a multimodal approach integrating ET and several signals, such as EEG (e.g., Wu et al., 2021), fNIRS (Shi et al., 2020), and skin conductance (e.g., Muldner and Burleson, 2015), is also referenced (Table 1).

4.2. Engineering competencies and dimensions

We view competency as the integration of student skills, knowledge, and attitudes and their underlying constituents

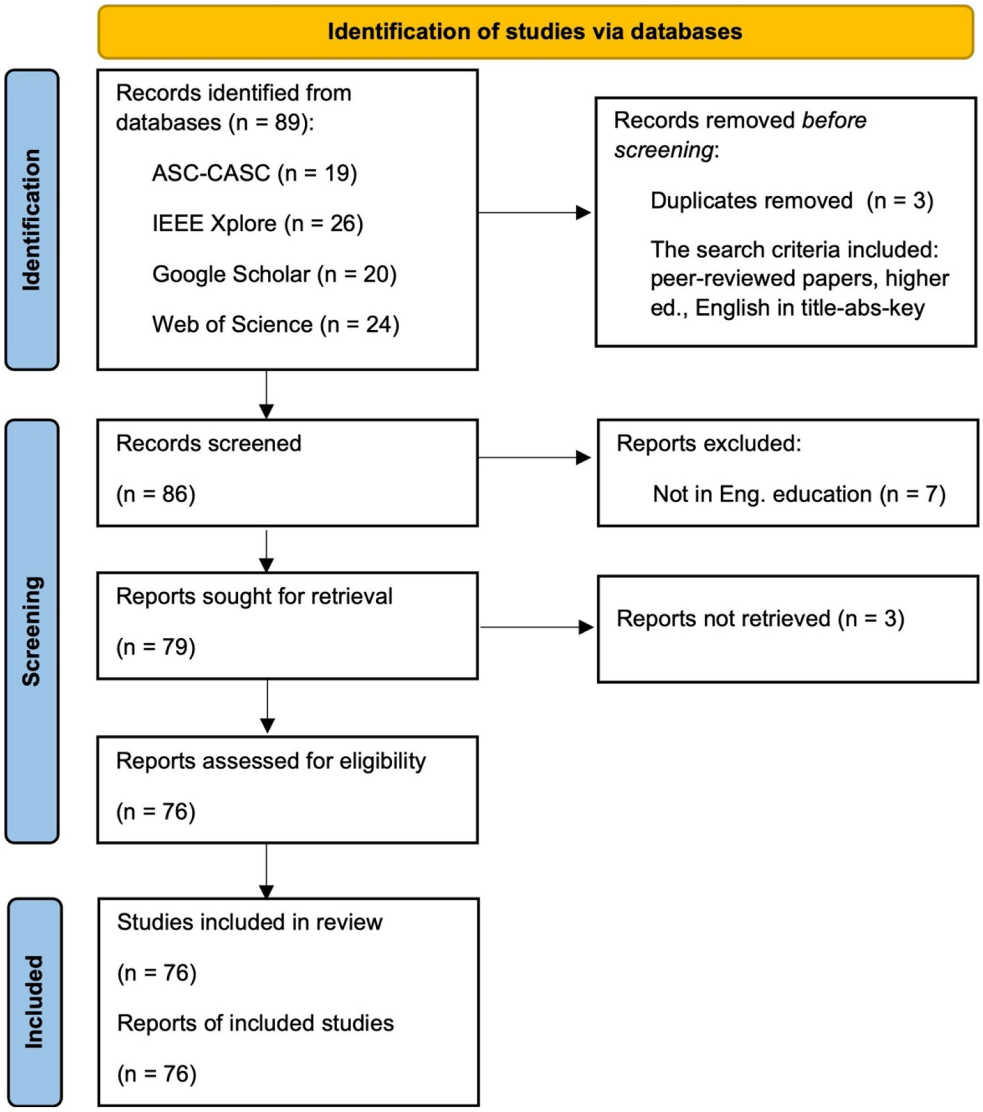

FIGURE 2
Flow diagram.

simultaneously, hence highlighting different learning dimensions as defined earlier. There is no meaningful skill acquisition without suitable connections to these defined dimensions. Consequently, the competency acquisition is analyzed in terms of these dimensions, namely cognitive, functional, social, and meta. Among these dimensions, the assessment of the cognitive dimension of engineering student expertise seems to be the primary focus of AIET applications (*cf.* Table 2).

Moreover, our results showed an overview of learners' mental state assessments, including cognitive, affective, and social levels of learners' competencies. Although the visual and cognitive competency dimension was a particular focus, studies are lacking when it comes to students' design expertise and its assessment by instructors. The reported studies examined the issues of addressing an aspect of student competency; however, they still lack focus on a holistic approach of competency assessment with competency being the integration of KSAs. Additionally, we manually analyzed references to highlight the types of assessment included in studies (see Table 3). The lexicometry analysis ran a hierarchical top-down classification that helped to identify four classes (or clusters) within the reported data (see Table 4). Class 1 (28.1% of the data), which we named "Eye-tracking method," grouped terms related to gaze, achieve, feature, and eye, which were used to track and assess visual patterns. This class is correlated with Class 2 (13.9%) comprising the "AI functional approach" used to track and assess learners' mental states and behaviors through the eye-tracking analytics. Such behaviors are described in Class 3 (22.1%), which we named "Mental state and behavioral assessment." This class included terminology associated with the assessed aspect/behavior, such as cognitive, perceptual, awareness, stress, mental, and competency. Finally, we identify Class 4 (35.9%), which addressed "Instructional approach and student learning" as it included terms such as "student," "learning," and "team."

In addition to this classification, we ran a correspondence analysis (CA) that showed the visual relationships of the identified clusters (*cf.* Figure 3). We analyzed the CA based on the first two

TABLE 1 Typologies of AI and ET.

Dimensions	Focuses	Examples	References
Using AI to improve the tracking technology	Tracking the reading progression: line detection vs. line tracking	Although traditional eye trackers provide an estimation of the eye-gaze points and their location every few milliseconds (not sufficient to quantify reading progression), this approach uses a Kalman filter and hidden Markov model to detect read lines accurately. The estimated eye-tracking point improved line detection accuracy by 27.1% relative to line tracking.	Bottos and Balasingam (2020)
Using AI to analyze and predict the eye-tracking data	Prediction of the difficulty level of spatial visualization problems	The use of machine learning to study (1) the differences in eye movement between different difficulty levels of the problem and (2) the possibility of predicting the difficulty level from eye-tracking data. The model generated an average accuracy of 87.60% for tracking data seen by the classifier, and 72.87% for unseen data.	Li et al. (2020)

TABLE 2 Cognitive, functional, social and meta aspects of competency assessment.

Dimension	Categories (% Freq.)	References
Cognitive (64.7%)	Spatial visualization, design behaviors (3.2%)	Muldner and Burleson (2015), Dogan et al. (2018), Li et al. (2020), and Mehta et al. (2020)
	Measuring cognitive loads (9.7%)	Bozkir et al. (2019) and Amadori et al. (2021)
	Attention (25.8%), concentration, and engagement (1.6%)	Meza et al. (2017), Guo and Barmaki (2020), Bharadva (2021), Chakraborty et al. (2021), Su et al. (2021), Khosravi et al. (2022), Renawi et al. (2022), and Singh and Modi (2022)
	Cognitive vigilance and awareness (16.1%)	Farha et al. (2021) and Lili et al. (2021)
	Comprehension, retention (6.5%), and perception of behavior (3.2%)	Das and Hasan (2014) and Hijazi et al. (2021)
Functional (17.7%)	Reading skills, speaking proficiency (1.6%)	Bottos and Balasingam (2020) and Tamim et al. (2021)
	Classification of learning (1.6%)	Pritalia et al. (2020)
	Recognition of creativity skills (6.5%)	Muldner and Burleson (2015)
	Navigation (3.2%), traceability (1.6%), and decision making (1.6%)	Ahrens (2020) and Lili et al. (2021)
Social (14.5%)	Affective and emotion recognition (9.7%)	Aracena et al. (2015) and Meza et al. (2017)
	Interpersonal skills (e.g., teamwork, communication; 4.8%)	Amri et al. (2017), Chen (2021), and Lili et al. (2021)
Meta (3.2%)	Intention to cheat (1.6%)	Singh and Das (2022)

TABLE 3 Types of assessment.

Types	Studies	Example of tasks
Formative assessment	Guo and Barmaki (2020), Su et al. (2021) and Tamim et al. (2021)	Automatic assessment of team performance during collaborative tasks
Summative assessment	Bottos and Balasingam (2020), Bozkir et al. (2019), Ahrens (2020), and Hijazi et al. (2021)	iReview, an intelligent tool used to evaluate code reviews
Self-assessment	Khosravi et al. (2022)	Learners can use the eye tracker for attention guidance
Peer-assessment	Chen (2021)	TeamDNA, used to measure the communication aspect of teamwork. It provides objective and non-interruptive measurements, observer-based measures with team process-based analyses, and sensor-based measures with non-intrusive measurements

factors, which were quite representative of the data samples (factor 1, 40.81%; factor 2, 32.19%). Results highlighted that Clusters 1 and 2 were well correlated, suggesting the relevance of the association of eye tracking and AI. However, these two clusters were in opposition, i.e., negatively correlated with Cluster 3 about mental states and behavior assessment on axis 2 (vertical), and with Cluster 4 about instructional approaches on axis 1. From these results, we identified the most well represented words of each cluster (see Table 4; "gaze" in cluster 1: $\chi^2 = 33.78$, $p < 0.0001$; "network" in cluster 2: $\chi^2 = 258.56$, $p < 0.0001$; "cognitive" in cluster 3: $\chi^2 = 51.41$, $p < 0.0001$; and "student" in cluster 4: $\chi^2 = 88.44$, $p < 0.0001$). This analysis confirmed the three clusters, namely the classes described above.

To obtain the co-occurrence graphs, we then performed a similarities analysis that used the graph theory also called network analysis to analyze trends in the literature. This analysis displayed the overall connection and grouping of terms used in the reported papers based on the co-occurrence scores of words (*cf.* Figures 4–6).

TABLE 4 Significancy table (terms per class).

Clusters: name	Most significant terms per cluster*	Chi-square χ^2 (*p*-value)	Term sources (or correlated with)
Cluster 1: "Eye-tracking approach"	Gaze	33.78 (<0.0001)	-
	Achieve	33.35 (<0.0001)	
28.07%	Feature	28.86 (<0.0001)	
	Eye	23.52 (<0.0001)	
Cluster 2: "AI functional approach"	Network	258.56 (<0.0001)	Keywords ($\chi^2 = 4.84$; $p = 0.02778$)
	Neural	224.43 (<0.0001)	
13.94%	Convolutional	95.26 (<0.0001)	
	Emotion	64.55 (<0.0001)	
Cluster 3: "Mental state and behavior assessment"	Cognitive	51.41 (<0.0001)	-
	Drive	33.72 (<0.0001)	
22.12%	Perceptual	28.59 (<0.0001)	
	Awareness	26.59 (<0.0001)	
Cluster 4: "Instructional approach and student learning"	Student	88.44 (<0.0001)	Abstract (NS***; $p = 0.10722$)
	Learn	42.66 (<0.0001)	
35.85%	Team	35.4 (<0.0001)	
	Online	29.67 (<0.0001)	

*Due to the limitation of table dimension, only the first four significant terms are provided. **The terms "assessment" and "assess" were situated in the cluster 3 list, with $\chi^2 = 16.17$ (<0.0001) and 15.96 (<0.0001). ***NS, not significant.

Whereas Figure 4 highlights grouping words from the reported literature (title, abstract, and keyword), Figure 6 shows the relationships between those three variables and our defined dimensions (cognitive, functional, social, and meta) and the labels defined in Table 2.

Regarding competency assessment in engineering education, we particularly focused on the feature "assess*" and analyzed (1) trends (Figure 7), (2) keyword-in-context (Table 5). With regard to research trends, Figure 7 (top), which depicts the absolute occurrence of the feature "assess*" across years, shows a clear trend of increasing interest in assessment with technologies, such as AI and ET, whereas Figure 7 (bottom) outlines the relative occurrence of "assess*" in comparison with all other features. Examples of citations in abstracts mentioning the purpose of analysis are provided in Table 4.

4.3. Application scenarios and model accuracy

Artificial intelligence and eye tracking has been applied in several engineering contexts with different focuses. A summary is provided in Table 6. We noticed applications in the classroom but also in lab practice, simulation training, and industry. However, despite the relevance, research is lacking on how models can help assess competency in a broader way involving the dimensions discussed earlier.

To understand the relevance of these AIET applications, we identified studies on the accuracy of developed models that integrate AI and ET to support engineering assessment broadly speaking, i.e., of and for/as learning with regard to the engineering literature (see Table 7). A relatively good average accuracy of 79.76% was found with an estimation range from 12% to 99.43%.

5. Discussion

This paper reviews the engineering literature to identify research focusing on AI and ET to support the assessment of competency in engineering education. Our study revealed that combining eye tracking and AI to assess engineering student competencies is receiving increasing attention. The association seems to be well supported, especially with the development of advanced technologies, such as AI. The Review highlights the main types of AIET, which are discussed below.

5.1. Two types of AIET in engineering competency assessment

Overall, two types of AIET focuses were reported: (1) an eye-tracking device that uses AI to improve the process of visual tracking itself, and (2) the use of AI to analyze, predict, and assess the eye tracking analytics.

5.1.1. AIET to improve the process of visual tracking

Most studies reported in this Review use this first approach to improve current eye-tracking technologies. For instance, in recent years, the prediction of eye movement scanpath can be divided into two categories: prediction models that hand-design features and powerful mathematical knowledge, and methods that intuitively obtain the sequence of eye fixes from the bottom-up salinity map and other useful indications (Han et al., 2021). With the advances of machine and deep learning, the study of computational eye-movement models has been mainly based on neural network learning models (e.g., Wang et al., 2021). For instance, in the

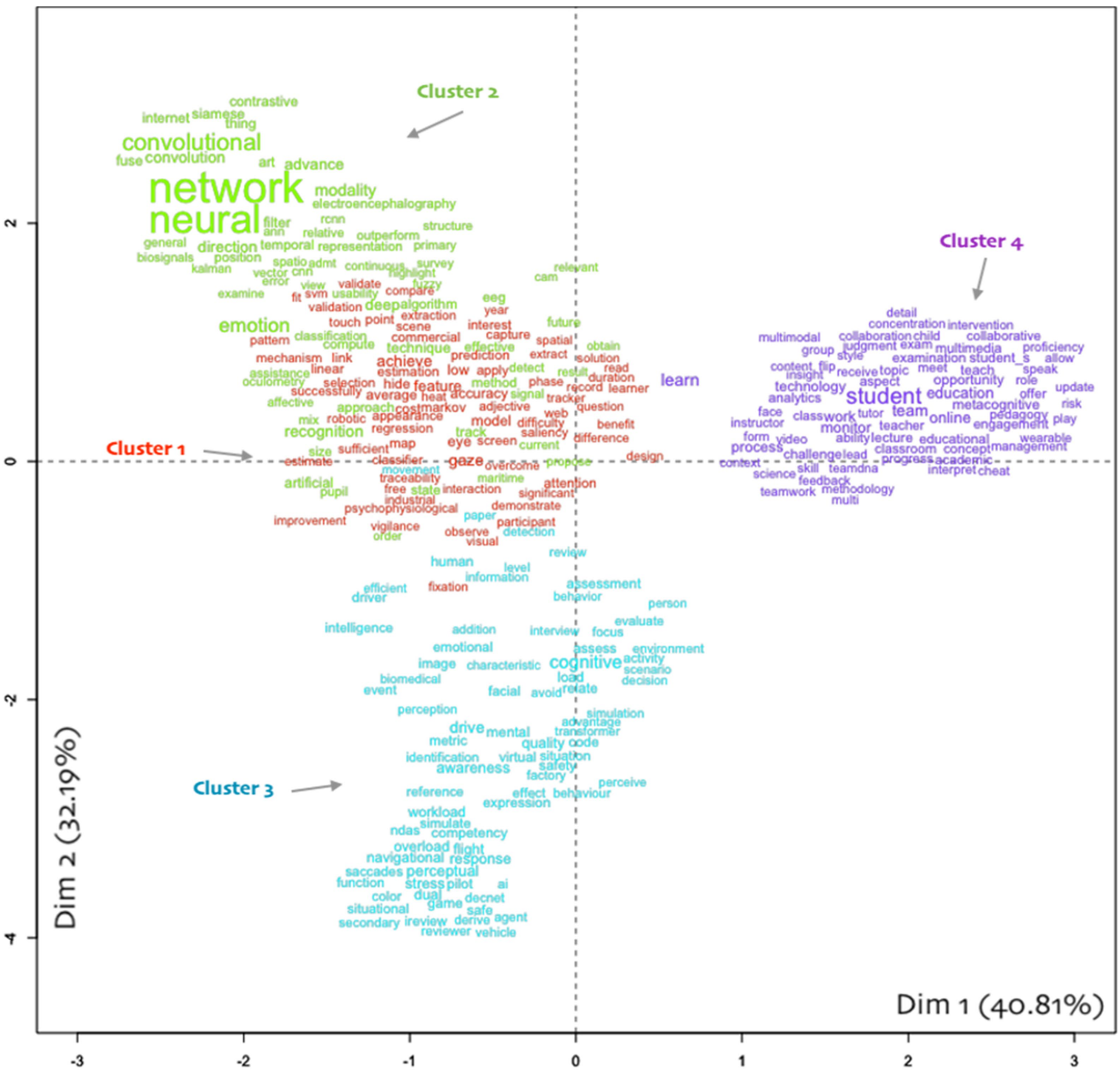

FIGURE 3
Correspondence analysis with factor 1 (40.81%) and factor 2 (32.19%).

context of robotic cars, Saha et al. (2018) proposed a CNN architecture that estimates the direction of vision from detected eyes and surpasses the latest results from the Eye-Chimera database. According to Rafee et al. (2022), previous eye-movement approaches focused on classifying eye movements into two categories: saccades and non-saccades. A limitation of these approaches is that they confuse fixations and smooth tracking by placing them in the non-saccadic category (Rafee et al., 2022). They proposed a low-cost optical motion analysis system with CCN technology and Kalman filters for estimating and analyzing the position of the eyes.

5.1.2. AIET to analyze and predict learners' behaviors

With this approach, engineering assessments in the age of AI take a new shift and offer diverse possibilities (Swiecki et al., 2022), especially with the increase of online education platforms and environments (Peng et al., 2022). As such, research suggests that machine learning technologies can provide better detection than current state-of-the-art event detection algorithms and achieve manual encoding performance (Zemblys et al., 2018). When applied in engineering education, AIET-based approaches have the potential to provide automatic and non-intrusive assessment (Meza et al., 2017; Ahrens, 2020; Chen, 2021), higher accuracy (Hijazi et al., 2021), complex dynamic scenes such as video-based data (Guo et al., 2022), and a less consuming process. For instance, Hijazi et al. (2021) used iReview, an intelligent tool for evaluating code review quality using biometric measures gathered from code reviewers (often called biofeedback).

Costescu et al. (2019) combined GP3 Eye Tracker with OGAMA to identify learners at risk of developing attention problems. They were able to accurately assess visual attention skills, interpret data, and predict reading abilities. Ahrens (2020) tracked how software

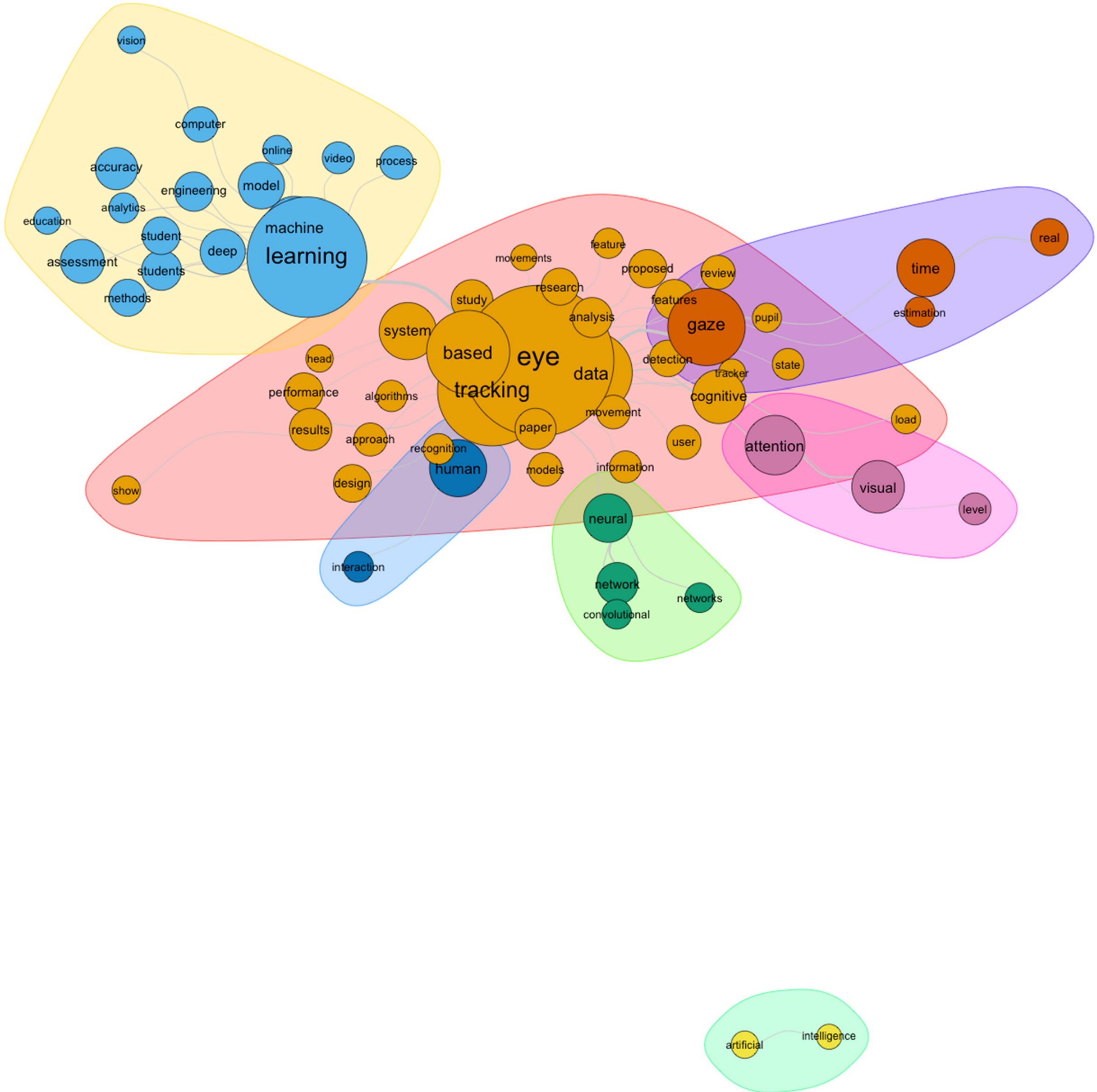

FIGURE 4
Graph of similarity of the whole corpus (title-abstract-keywords).

engineers navigate and interact with documents. By analyzing their areas of focus and gaze recordings, the author developed an algorithm to identify trace links between artifacts from these data. He finally concluded that eye tracking and interaction data are automatic and non-intrusive, allowing automatic recording without manual effort. This approach has interesting applications and perspectives for engineering design, namely the assessment of student visual parameters and algorithm replication for mass assessment, fairness and accuracy (objectivity, overload, and increased perception), understanding student learning behaviors, etc.

Moreover, as reported in our Review, AI and subsets for eye-tracking studies appear to be effective, as an average accuracy of approximately 80% was found for applications in engineering education, including in-class, VR, laboratory, and industrial settings.

5.2. Dimensions in engineering competency assessment of/for learning

With regard to our second research question, different dimensions of student learning have been analyzed. A somewhat unsurprising result was the prevalence of assessing student cognitive state, as eye tracking indeed relates to learners' visual cues. As such, multiple studies can be found within the pertinent literature over the last few decades focusing on the assessment of cognitive states (e.g., Hayes et al., 2011) and visual cognition and perception (e.g., Gegenfurtner et al., 2013; Rayner et al., 2014). However, taken together and considering the sample size ($N = 76$ papers) reported over the last decade, this Review revealed that few studies in the field of engineering education have focused on AI- and eye-tracking-based assessment of student learning.

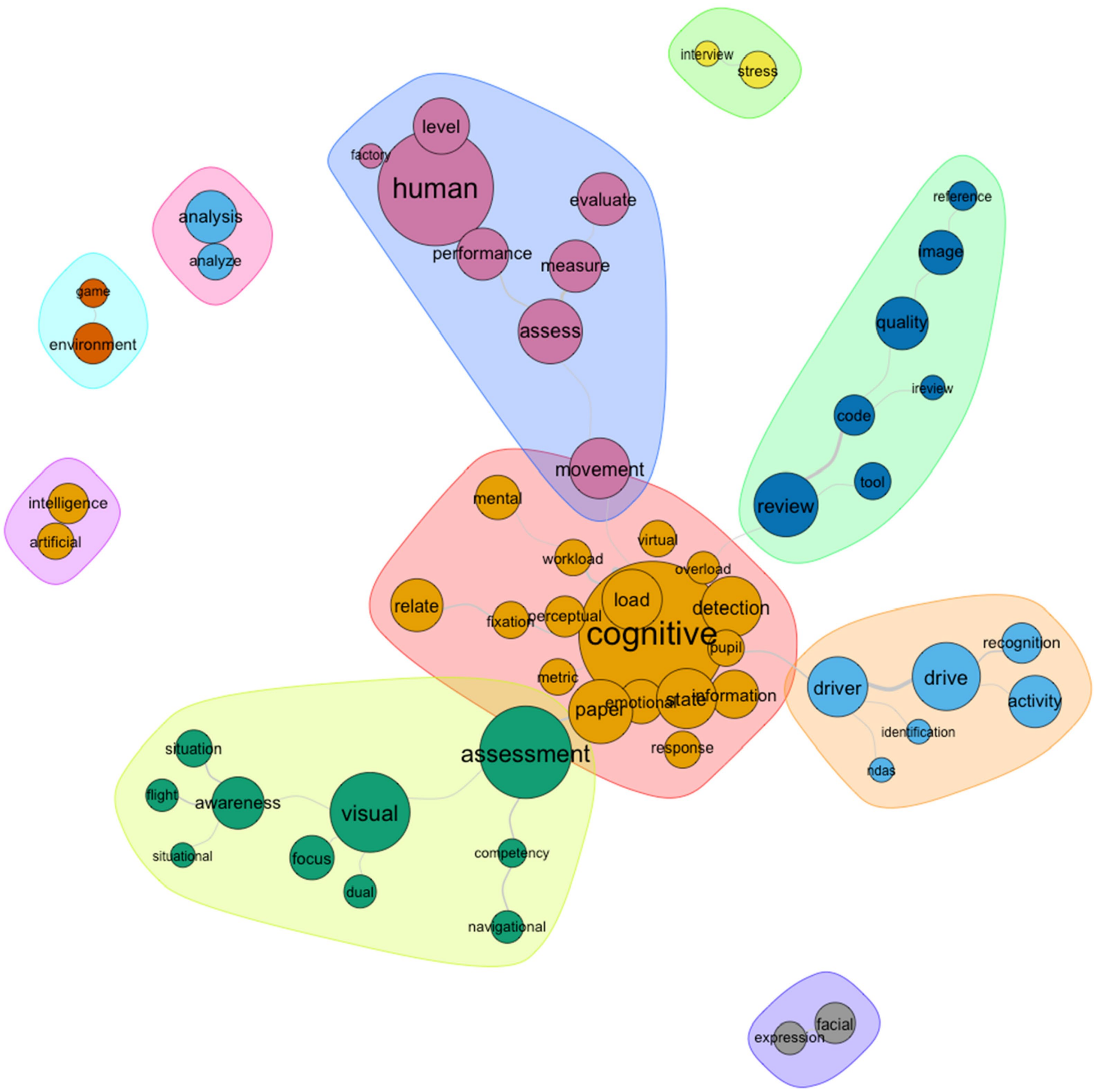

FIGURE 5
Cluster graph of "assessment" ($\chi^2 = 16.17$; $p < 0.0001$) and "assess" ($\chi^2 = 15.96$; $p < 0.0001$).

Although the expected finding was that papers would essentially focus on the visual and cognitive aspects of student learning and competencies, this study also shows an interest in the literature that focuses on other components, such as functional (skills) and social (attitudes) aspects of student learning. Indeed, it is assumed that eye tracking is essentially used as a tool for examining cognitive processes (Beesley et al., 2019). However, references for the meta competency aspect are seriously lacking. Several reasons may explain this repartition. First, it is true that early studies in this area focused primarily on obtaining insights into learners' visual patterns and therefore attempted to describe visual dynamics when learners look at the material in different environments and formats. Over the last decade, the focus has shifted to computational perspectives to visual attention modeling (e.g., Borji and Itti, 2012), driven by a digital transformation with the advances of attention computing, AI, machine learning, and cloud computing. Since 2013, and a bit later in 2016, as shown in Figure 7 (top), there has been a rapid rise of eye-tracking and AI-based assessments in research, especially when the field of AI becomes more accessible to cognitivists, psychologists, and engineering educational researchers. For instance, motivated by the complexity of contemporary visual materials and scenes, attention mechanism was associated with computer vision to imitate the human visual system (Guo et al., 2022). Moreover, this shift can be analyzed following the AI breakthroughs over the decade (2015: Russakovsky et al., 2015: OpenAI co-founded in 2015: deep learning models…). For instance, in January, 2023, the MIT Review published their 22nd 10 breakthrough technologies 2023 annual list (MIT Technology Review, 2023), recognizing key technological advances in many fields, such as AI. This list ranked "AI that makes images" in second position, justifying the growing interest visual computing has in contemporary research.

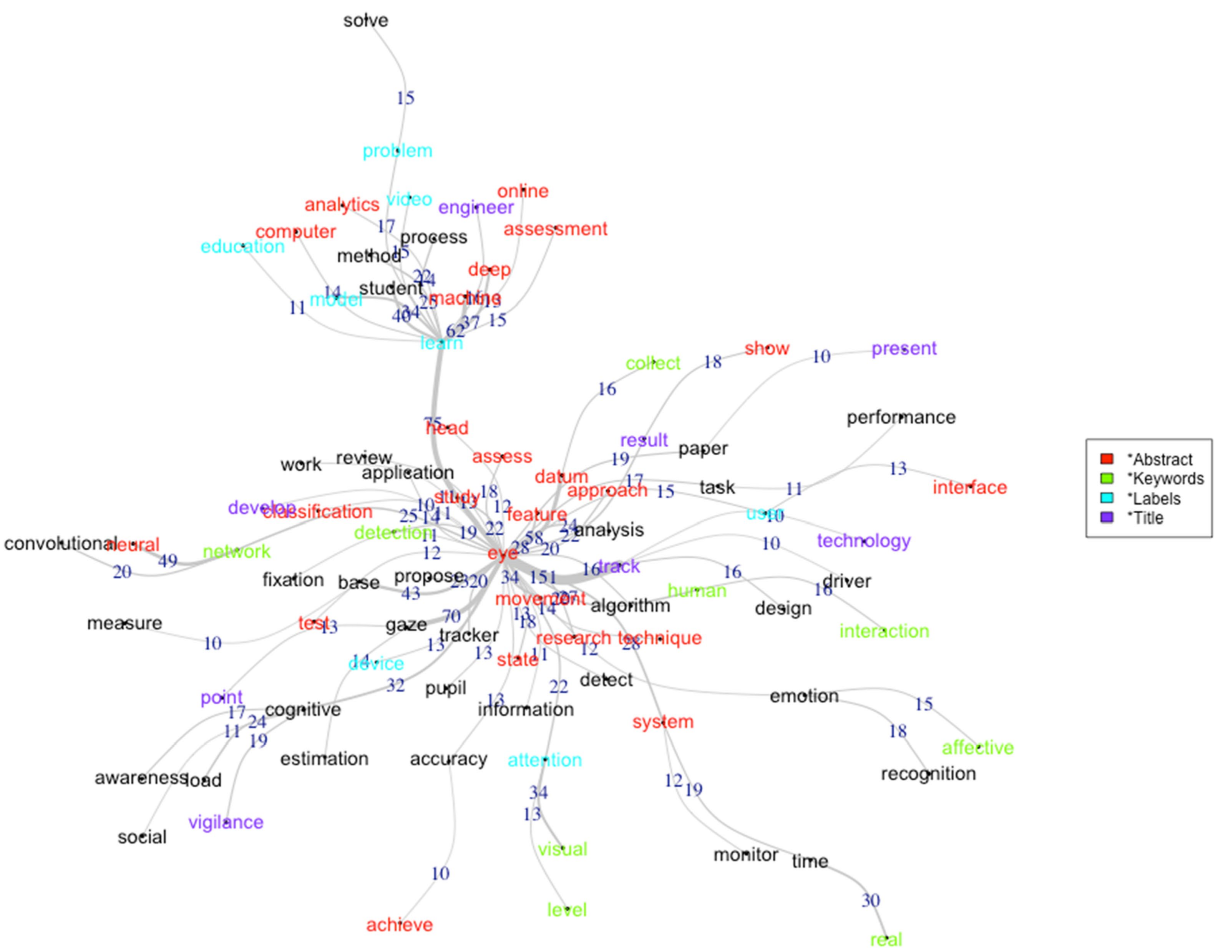

FIGURE 6
Graph of similarity of the corpus (tit-abs-key) with defined labels (addresses RQ2).

Shao et al. (2022) identified three waves of climax in AI advancements: in the early 60s, the second climax, and the third wave of AI, which according to LeCun et al. (2015) started with the era of deep learning, highly fostered developments and progress in society. As such, ImageNet was released in 2012, which in 2015 helped companies such as Microsoft and Google develop machines that could defeat humans in image recognition challenges. ImageNet was foundational to the advances of computer vison research (including recognition and visual computing).

We also reported the following different forms of assessments in engineering education: assessment of learning, i.e., as a summative evaluation (e.g., Bottos and Balasingam, 2020; Hijazi et al., 2021), formative assessment, i.e., assessment for learning, including feedback (e.g., Su et al., 2021; Tamim et al., 2021), self-assessment (Khosravi et al., 2022), and peer-assessment (Chen, 2021). In fact, engineering tasks are becoming increasingly complex. Therefore, current engineering instructions apply several assessments to better map student learning and their abilities, especially in active pedagogies such as project-based learning (PBL). This is reported by Ndiaye and Blessing (2023), who analyzed engineering instructors' course review reports and highlighted several combinations of assessment (e.g., summative: 2D project, exam, review, and prototype evaluation; formative: quizzes, problem sets, and homework assignment; peer assessment: peer review…). Providing an effective competency assessment for learning, especially feedback, to all students in such complex fields is challenging and time-consuming. Therefore, as there is a strong association between AI and ET, researchers have been exploring alternative solutions within this synergy. As such, Su et al. (2021) used video to analyze student concentration. They proposed a non-intrusive computer vision system based on deep learning to monitor students' concentration by extracting and inferring high-level visual signals of behavior, including facial expressions, gestures, and activities. A similar approach was used by Bottos and Balasingam (2020), who tracked reading progression using eye-gaze measurements and Hidden Markov models. With regard to team collaboration assessment, Guo and Barmaki (2020) used an automated tool based on gaze points and joint visual attention information from computer vision to assess team collaboration and cooperation.

5.3. Challenges of AIET

Despite the importance, AIET-based engineering assessment has some limitations. First, it suffers from a systematic and integrative approach of competency and competency assessment. Khan et al.

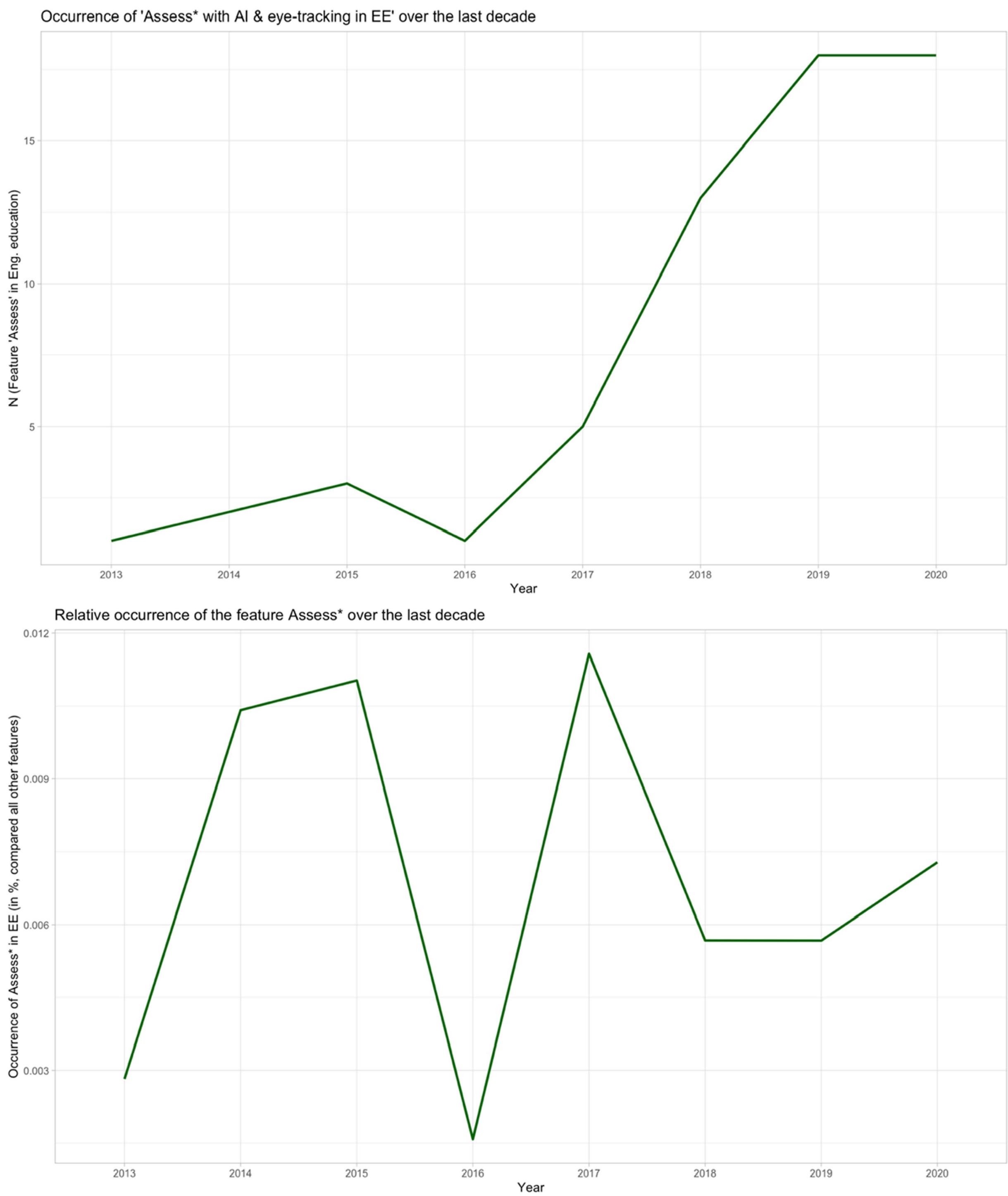

FIGURE 7
Absolute and relative occurrence of the feature "assess*" in the context of AIET.

(2023) reviewed the literature and identified a similar result for AI-based competency assessment in engineering design education. Indeed, competency, especially the measurement of student expertise, is viewed differently among researchers. There is ongoing debate about terminology within the literature (e.g., Le Deist and Winterton, 2005; Blömeke et al., 2015).

A second key challenge is the technique that is used to evaluate student learning. There are different eye-tracking methods and tools and they do not use the same tracking approach, hence not allowing tracking of the same behaviors. Consequently, further investigation is needed to achieve an appropriate network construction, followed by more efficient training to avoid common failures, such as over-training (e.g., Morozkin et al., 2017).

Other critical issues can be highlighted. AIET technologies are often too expensive and time-consuming (e.g., analysis of manual gaze data and data interpretation) to be implemented in

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TABLE 5 Keyword-in-context (with 10 examples of a match).

[text7, 299] was developed to	| assess |	Vigilance levels
[text11, 128] neurophysiological approach to		Workers' stress
[text14, 216] data are used to		The workers' ergonomic performance
[text39, 15] tracking data to		Cognitive vigilance levels
[text40, 134] to measure and		Navigational competence
[text41, 60] data allows to		The cognitive load
[text43, 50] in order to		Virtual agent's eye
[text51, 73] we proposed to		The visualization environment
[text52, 185] are used to		The reviewer's comprehension
[text53, 85] able to accurately		Their visual attention

TABLE 6 Application scenarios.

Scenarios	Task focus	Application/Testing	References
Classroom learning	Student attention and engagement: use of ordinary web cam-based and computer vision algorithms to estimate (individually and in groups) and display student attention levels through easy color-coded charts for the instructor to take the necessary action during the lecture.	Classroom-based	Renawi et al. (2022)
	Self-directed learning environment: development of a low-cost webcam-based eye tracking solution combined with machine learning algorithms. The model implemented to a 4-min engineering lecture can achieve similar accuracy compared with the head-worn tracker.	Classroom-based: third year engineering students	Khosravi et al. (2022)
	Class insight, a student monitoring system: development of a machine learning-based monitoring system that allows teachers to submit an assessment to students in a completely paperless way. The system tracks students' faces and eyes during reading and updates the progress immediately, hence helping instructors to monitor tasks in real time.	Classroom-based	Tamim et al. (2021)
Simulation training: situational awareness	Flight simulation: a situation awareness (SA) assessment method based on an AI neural network (NN) and integrating visual cues and flight control is developed and resulted in 96% accuracy of the SA classification of the NN model to the experimental data set.	Simulated flight training experiments for flight cadets	Jiang et al. (2022)
	Navigational competency: development of an AI-based competency assessment tool for safe navigation (AICATSAN) for various behaviors, such as situational awareness, decision making, teamwork, and communication and influencing skills.	Maritime navigational safety	Lili et al. (2021)
Lab practice	Human-machine interaction: characterization performed on two types of eye tracking devices to support the development of cognitive human-machine systems.	Laboratory	Lim et al. (2019)
VR/AR settings	Cognitive load assessment: proposition of an autonomous, privacy- preserving, and attention-based cognitive load recognition system for drivers under critical conditions based on driving data collected from a previously simulated VR driving environment. Multiple classifiers were trained to help assess the driver's cognitive load. Integrating the visual ET data into the VR configurations improves the accuracy (>80%) to predict user cognitive load.	User interface	Bozkir et al. (2019)
Other industry settings	Software traceability: development of an algorithm aiming to track how software engineers interact with documents and record eye connections between these documents.	Document interaction in industry	Ahrens (2020)

classroom practice. Therefore, the development of low-cost approaches can be a better and more inclusive approach for engineering learning and instructions. Finally, the assessment of the student (behavior, mental state, etc.) often tends to replace the assessment of student learning (outcomes). It is not clear how studies clarify this difference.

6. Conclusion

This Review provides important insights into AI- and eye-tracking-based competency assessment in engineering education. With regard to our first research question (RQ1), this Review revealed that research trends have taken two orientations over the last decade.

TABLE 7 Accuracy of AI and ET in engineering assessment.

References	Topic	Accuracy (%)
Jiang et al. (2022)	Awareness in flight simulation	96
Wu et al. (2021)	Emotion classification on ET and EEG fused signals employing deep gradient neural networks	88.1
Li et al. (2021)	Predicting the level of difficulty in spatial visualization problems	87.6
Xin et al. (2021)	Detecting the difficulty of the task	91.8
Shi et al. (2020)	A neurophysiological approach to assess training outcomes under stress: a VR experiment	80.38
Bottos and Balasingam (2020)	Tracking the progression of reading using eye-gaze point measurements and hidden Markov models	27.1
Bharadva (2021)	An ML approach to detect student online engagement	88.9
Singh and Modi (2022)	A camera-based eye gaze tracking system to analyze visual attention using deep learning	84
Chen (2021)	Automatic measurement of teamwork processes	75
Farha et al. (2021)	Assessment of cognitive vigilance levels	76.8
Bozkir et al. (2019)	Autonomous and real-time assessment of cognitive load using ET in a VR setup	80
Pritalia et al. (2020)	Classification of learning approaches in multimedia learning using ET and ML	71
Hijazi et al. (2021)	A code evaluation tool using biofeedback (iReview)	87
Chakraborty et al. (2021)	A human-robot system estimating the visual focus of the attention level	99.43
Singh et al. (2018)	Guiding the selection of software inspectors	94
Bautista and Naval (2021)	CLRGaze: representations of eye movement signals	97.3
Gite et al. (2021)	ADMT: driver motion tracking system	12
Aunsri and Rattarom (2022)	Eye-based features for head-free gaze estimation using web cameras	97.71

We showed that research generally discussed that (1) eye-tracking devices developed intrinsically with AI to enhance the gaze-tracking process (improvement of techniques), and/or (2) AI can be used to analyze, predict, and assess eye-tracking analytics (application domain). With regard to RQ2, i.e., the salient competency dimensions and labels attributed to assessing engineering education, the main finding is that visual cognitive aspects of learner competency are a primary focus. Hence, despite growing interest in advanced technologies, such as AI, attention computing, and eye-tracking, it is shown that student competency and underlying components are assessed in a fragmented way, i.e., not in a systematic and integrative approach to engineering competency and holistic assessment. Assessing engineering student expertise with AIET is essentially limited to visual aspects, and there is a lack of references and understanding about how it can be extended to more complex engineering learning. Therefore, we argue that such limitations can be situated in the technology itself, which relies on the eye (hence visual cognition and perception only) as a portal to an individual brain to understand human behavior. In addition, there is not yet a common understanding of expertise and competency. Terminologies vary depending on the subject domain.

This Review presents some limitations. Although the debate about competency or competence is still ongoing within the literature, we focus on engineering competency in terms of dimensions to analyze what is being effectively assessed. However, as preliminary research, an approach may need to be extended to other underlying engineering fields and explore different possible components in student competency acquisition. This needs to be better clarified with regard to existing frameworks. Additionally, as for every review, we only used well known terms; however, many terminologies are being used to describe eye-tracking techniques and studies (eye or gaze tracking, eye movements, visual tracking, etc.), including the variation in the syntax of the words (e.g., eye tracking or eye tracking or eye tracking) and competency (competence, ability, etc.). AI also suffers from this variation (e.g., machine learning, deep learning, NLP, etc.). Not all these terms were used, thus reducing the search.

This Review is probably one of the first to discuss trends in research on the assessment of engineering education with AIET technologies. Multiple relevant perspectives are possible. For engineering education, it is important to investigate in-depth how AIET can support complex learning and instruction. AIET may open new opportunities to better assess learning inclusively and efficiently, assuming that relevant assessment frameworks of the content to be assessed are well defined and situated. It is necessary to examine the combination of holistic approaches to assess complex engineering skills. As such, this Review may have several implications for the integration of AIET in engineering education. It may open new research perspectives on the.

AIET-based assessment of student learning, which will be worth investigating. This is a key area to be explored in-depth further.

Future research can focus on exploring multimodal approaches to better capture less-represented dimensions of engineering student competencies, helping to mitigate existing assessment shortcomings. One of the main issues is mapping student abilities and their engagement holistically during their learning with different assessments methods. Therefore, an increasing interest lies in associating different inclusive fine-grained techniques, such as electrical (EEG), physiological (heart-rate variability, galvanic skin resistance, and eye tracking), neurophysiological (fMRI) signals, and other traditional assessments (e.g., self-reported surveys, quizzes, peer-assessment, etc.), to improve assessment accuracy and efficiency. For instance, Wu et al. (2021) developed a deep-gradient neural network for the classification of multimodal signals (EEG and ET). Their model predicted emotions with 81.10% accuracy during an experiment with eight emotion event stimuli. Similar studies exploring learning and assessment are needed to gain holistic insights into student learning, instructions, and assessments.

Author contributions

YN and KL made a substantial, direct, and intellectual contribution to the work. LB reviewed and provided general comments on the work. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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