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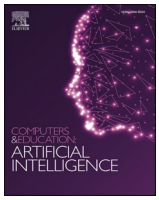

Myths, mis- and preconceptions of artificial intelligence: A review of the literature

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ABSTRACT

Artificial Intelligence (AI) is prevalent in nearly every aspect of our lives. However, recent studies have found a significant amount of confusion and misunderstanding surrounding AI. To develop effective educational programs in the field of AI, it is vital to examine and understand learners' pre- and misconceptions as well as myths about AI. This study examined a corpus of 591 studies. 25 relevant studies were identified by applying the following eligibility criteria: English-written original empirical research on education and AI and reporting AI conceptions in a formal learning context. The review found studies from six continents, with the majority conducted in Europe and North America. The studies predominantly focus on the school and university levels. Findings reveal a range of preconceptions, misconceptions, and myths about AI, such as: Learners often have limited understanding of AI on a technical level. They tend to attribute human-like characteristics or attributes to AI systems and may have narrow views of AI's scope, capabilities, and limitations. The review also shows that learners often have binary and unspecific views about the threats, dangers, and benefits of AI. Effective educational programs are key to empower learners' understanding of AI, thus helping them make informed decisions about the integration of AI in our society, rather than being swayed by misinformation and unnecessary fear. This review may help inform the development of more effective teaching and outreach strategies in AI education.

1. Introduction

The field of artificial intelligence (AI) has seen significant progress in recent years, with advancements in many fields like machine learning and natural language processing leading to the development of increasingly sophisticated AI systems (Jiang, Li, Luo, Yin, & Kaynak, 2022; Latif et al., 2023). While AI is rushing into our lives and workplaces, there is still a significant amount of confusion, misunderstandings and uncertainty surrounding AI (Oh et al., 2017). There is confusion about technical terms concerning AI (Lindner & Berges, 2020), the misunderstanding to conceptualize AI as embodied (Kreinsen & Schulz, 2021) and uncertainty like unspecific fear as well as hope towards AI (Antonenko & Abramowitz, 2022).

Given the increasing importance of AI in our society, it is crucial that the general public has a basic understanding of the capabilities and limitations of AI, as well as the ethical implications of its use. Exploring these myths, mis- and preconceptions about AI among learners can provide valuable insights into their prior understanding of the field and help develop effective learning programmes. Although there is some research on how learners conceptualize AI (e.g. Antonenko & Abramowitz, 2022; Chounta, Bardone, Raudsep, & Pedaste, 2022; Lindner & Berges, 2020; Lindner & Romeike, 2019; Teng et al., 2022), it is still considered to be in the early stages of development (Mertala, Fagerlund, & Calderon, 2022). This literature review synthesizes myths, mis- and preconceptions about AI among learners, with the goal of informing the development of more effective teaching and outreach strategies in the field. Under the term 'learners' we summarize individuals engaged in a formal process of learning, like students from schools and universities as well as participants of professional developments.

The objectives of this review are 1) to identify and consolidate common mis- and preconceptions about AI among learners, 2) cluster them into themes under a framework, and 3) identify possible research gaps in the literature. To identify these potential research gaps it will be important to see which groups of learners are already covered quite

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satisfactorily by existing studies and which groups might be not represented yet.

The review is guided by the questions.

1. Which group of learners are already covered by existing studies; which groups might be not represented?
2. What are some common myths, misconceptions, and preconceptions that appear in the literature?

To obtain a comprehensive, qualitative understanding without limiting our perspective we searched for any empirically reported myth or pre- or misconception about AI among learners. We define the terms pre- or misconception in line with Özdemir and Clark (2007) as phenomenological primitives, facts, facets, narratives, concepts, and mental models at various stages of development and sophistication and enhance it with the understanding of myths in AI as an understanding of beliefs and cultural implications about AI. To improve readability throughout this paper we will substitute the term 'pre- or misconception and myths about AI' with 'conceptions of AI'.

2. Framework

While educational programs in the field of AI are gaining popularity among instructors, researchers and in curricula (Su, Zhong, & Ng, 2022), most learners did not have the opportunity to participate in any formal AI courses (for university students: Hornberger et al. (in prep.)). However, AI has been a topic in the news and popular media for decades, and learners have likely encountered it in various contexts (Leufer, 2020). Research has shown that conceptions of AI are heavily influenced by the way AI is represented in the media and the language used to describe it (Chao, Hsu, Liu, & Cheng, 2021; Kerr, Barry, & Kelleher, 2020; Zhai & Krajcik, 2022). Especially the concepts of embodied or general AI have a long-standing tradition in media and the movies (e.g. The Terminator Series; I, Robot). This can lead to the development of naive mental models prior to the development of formal knowledge in that area (Taber, 2014). Learners' existing beliefs and knowledge about AI likely guide the interpretation of new information they encounter. This process can sometimes lead to or perpetuate misconceptions (Gooding & Metz, 2011), as learners' prior knowledge and believes may not align with the true nature of AI. Driven by the diversity of prior knowledge, believes and ideas acquired through informal learning, one central model of learning in AI education is conceptual change. Conceptual change means the commitment to a new conception about a principle or a phenomenon, and the abandoning of an old one (White & Gunstone, 1989). In recent discussions, the term "conceptual change" has been replaced with "conceptual reconstruction", recognizing that current conceptions frequently don't require complete abandonment but instead are more likely to evolve progressively toward formal knowledge (Potvin, 2022). It builds on the precise and comprehensive knowledge of learners pre- and misconceptions and believes (cf. Özdemir & Clark, 2007). Therefore, understanding of the pre- and misconceptions as well as believes and myths about AI among learners is crucial. Deeper understanding of popular conceptions about AI could help educators and researchers in the field develop more effective teaching and outreach strategies. These teaching strategies could eventually support learners to gain a more accurate and nuanced understanding of AI based on their prior conceptions.

Additionally, exploring the myths, mis- and preconceptions about AI among learners can provide valuable insights into the general public's understanding of the field. Given the increasing importance of AI in our society, it is crucial that the general public has a basic understanding of the capabilities and limitations of AI, as well as the ethical implications of its use (Ng, Leung, Chu, & Qiao, 2021).

Often myths and pre- and misconceptions in the field of AI are reported in gray literature like tech articles or reports lacking empirical foundation (e.g.: Google, 2022; Liang, 2021; VK, 2022). It remains uncertain whether these myths, preconceptions, and misconceptions actually exist. This study provides an overview of common myths and pre- and misconceptions about AI and consolidates them empirically. Overall, this study of myths, mis- and preconceptions about AI among learners has the potential to provide valuable insights into their understanding of the field, and can inform the development of more effective teaching and outreach strategies in the field of AI.

There are alternative terms and labels to describe the naive mental models held by learners prior to the development of formal knowledge in an area (Taber, 2014). The terms *preconceptions* and *misconceptions* are commonly invoked in discussions around conceptual change, though no universal definition of these terms is agreed upon across disciplines (Chi & Roscoe, 2002). *Misconceptions* are used to describe a flawed mental model held by learners, which conflicts with commonly accepted scientific consensus (Clement 1993; Sanger & Greenbowe 1997; Smith et al. 1994). While the term of misconceptions may have a negative connotation, alternative terms are *preconception* or *naive knowledge structures*, which include, but are not limited to phenomenological primitives, facts, facets, narratives, concepts, and mental models at various stages of development and sophistication (Özdemir & Clark, 2007) without a negative bias. Preconceptions are generally loosely held beliefs that, though incorrect, are easily replaced with instruction, whereas misconceptions are more difficult to repair (Chi & Roscoe, 2002). By contrast, when discussing AI in popular scientific articles (e.g. www.aimyths.org from Leufer, Steinbrück, & Liptakova, 2020), news articles (e.g. Forbes, 2022) and articles in the scientific discipline of computer science itself (Emmert-Streib, Yli-Harja, & Dehmer, 2020) as well as the social sciences (e.g. Atkinson, 2016) the term of *myths* in AI rather than the term pre- or misconceptions resonates widely. Myths are not true or false and focus more on the beliefs and cultural aspects than knowledge (Natale & Ballatore, 2020).

3. Method

3.1. Search procedure

The aim of this review is to get a broad, qualitative overview of any empirically reported conceptions about AI among learners. In order to maintain a comprehensive perspective, the original corpus consisted of not just peer-reviewed papers but also conference proceedings and institutional reports.

The systematic review presented in this paper was planned, conducted, and reported according to the PRISMA 2020 statement (Page et al., 2020). The PRISMA 2020 statement comprises a 27-item checklist guiding the introduction, methods, results and discussion sections of a literature review.

For the database search, we selected databases representing different disciplines related to education, psychology and computer science. These included the Education Resource Centre (ERIC, www.eric.org) by the US Department of Education for the field of educational sciences, the Web of Science by Thomson Reuters in all fields but limited to the topic of 'Education & Educational Research' and the IEEE Xplore as academic database in the field of engineering and computer science.

Search terms for IEEE Xplore were "artificial intelligence" AND "students" AND "misconceptions", "artificial intelligence" AND "students" AND "preconceptions" and "artificial intelligence" AND "students" AND "myths".

The term "students" was omitted for the search of the ERIC and the Web of Science database because of their a priori focus (ERIC) on the field of educational research or by limiting the search to the topic of 'Education & Educational Research' (Web of Science).

To broaden the view on possible conceptions about AI the sample was augmented by searches conducted by Google Scholar as Google Scholar is considered to be important sources of gray literature, conference proceedings and institutional reports (Haddaway, Collins, Coughlin, & Kirk, 2015). Therefore, although Google Scholar has its

limitations and should not be used as the only source for systematic reviews, it seemed to be apt for the purposes of this qualitative and explorative review.

Search terms for Google Scholar were identical to the search terms of IEEE Xplore. We limited the included results for every single search with Google Scholar to 150.

In the database search of IEEE Xplore and the search on Google Scholar we included the term 'students' to focus on educational studies and persons who are somehow engaged in a learning process as it was not possible to limit the search to a specific field. Using the by far not so prominent term of 'learners' would have cropped results too vigorous to achieve the goal of a broad review.

We did not omit studies e.g. reporting misconceptions among teachers from this qualitative literature review. Therefore, in this article we use the broader term of 'learners'. The search was conducted on 13th and 14th of December 2022. Over all databases as well as the augmenting Google Scholar searches 591 records were identified.

3.3. Eligibility criteria

We first reduced redundant articles. All duplicates of articles were removed. This led to the reduction of the corpus by 24 records. To identify the most relevant literature, we then identified a set of eligibility criteria.

a) Written in English
b) Original, empirical research
c) Scope relates to education and artificial intelligence
d) Report on any conceptions about AI
e) study conducted in context of a formal learning process or institution (like school or university)

Based on the criteria, we screened the titles of the articles, and removed any articles with obviously no connection to myths, pre- and misconceptions about AI (in total 260 of 426). We then read the abstracts of the 163 articles and further excluded 136 articles that do not meet all five criteria. Five of the remaining articles could not be retrieved and were excluded from the review, which resulted in 25 articles to be reviewed. The process is visualized in the flowchart shown in Fig. 1.

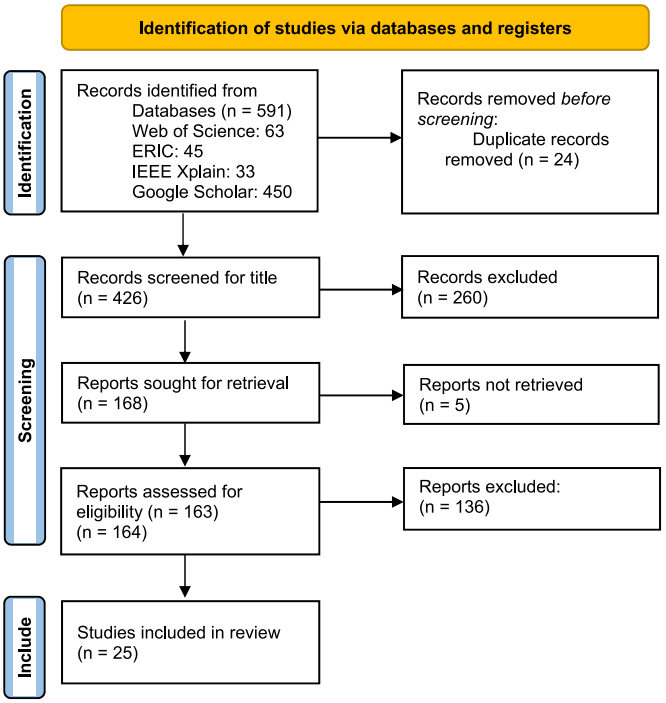

Fig. 1. Prisma flowchart.

3.3. Identifying AI conceptions via content analysis

All articles included in the analysis were reviewed by experts in AI education with respect to the reported conceptions. Descriptions of the items (individual myths, mis- or preconceptions) mentioned in the studies were identified and extracted. This was done by highlighting relevant texts in the results of the reviewed paper and saved for further processing in a table document. We then further employed qualitative content analysis to analyze the highlighted texts (Mayring, 2021). This involved paraphrasing (deleting text components that do not fit the content focus), splitting into separate conceptions if necessary, and generalization (generalizing the conceptions to the desired abstraction level, e.g. omitting references to the sample group). This led to 110 conceptions (items) which could be identified. An example of analysis is illustrated in Table 1.

3.4. Clustering the conceptions into categories and themes

As our data basis we used the items gained from the content analysis (see section 3.3). For pooling the conceptions (items) into categories and the categories into themes, we followed a structured process containing three steps:

Identifying the Conceptions. First, we read through the items multiple times to become familiar with the content and identify recurring themes, ideas, or patterns. After this, we started to identify relationships and connections between the different items. This process, called axial coding (Cliff & Melissa, 2017), created categories based on the patterns and relationships observed in the data. Using the axial coding, we identified categories that are closely related or overlap in meaning and merged them into a single, more comprehensive category. Therefore we defined an algorithm: We iterated through each of the 110 items. The first item created an initial category. We checked if the next item was similar to any existing category by comparing it with all existing categories. If the item was found to be similar to a category, it was included in that category. The check for similarity was always guided by the heuristics of internal homogeneity (maximizing cohesive validity with

Table 1
Example of the process of qualitative content analysis (Mayring, 2021) on reviewed papers.

Original finding	Paraphrasing	Splitting	Generalization
"Medical students were unsure if AI would particularly affect their specialty of choice (31.7% agree, 35.1% disagree), but agreed that they will need to understand AI throughout their career (68.3% agree; 104 strongly agree, 212 agree) and that they would use applications of AI during their careers (72.9% agree; 110 strongly agree, 223 agree)." (Pucchio et al., 2022, p. 4, p. 4)	Medical students agreed that they will need to understand AI throughout their career and that they would use applications of AI during their careers.	Medical students agreed that they will need to understand AI throughout their career Medical students agreed that they would use applications of AI during their careers	thinking of the need to understand AI in their careers AI will be essential and commonly used in medicine

clear similarity among all content within a category) and external homogeneity (establishing discriminant validity with clear differentiation between the content of two different categories) (Kelle & Kluge, 2010). If the category name needed revision after adding the item, we updated the category name accordingly. For example the category 'General limited knowledge of AI or some specifics (methods, algorithms, terms, features)' was augmented to 'General limited *or inaccurate* knowledge of AI or some specifics (methods, algorithms, terms, features)' after adding the item 'Not knowing what AI is or having an inaccurate understanding of AI' (Teng et al., 2022). The iteration continued to check all remaining categories for similarity. If the item was not similar to any of the existing categories, a new category was created using the item. This new category would then be added to the list of categories with the item included in the new category. This process was repeated for all items in the list, ensuring that each item was assigned to a category based on its similarity with other items. The algorithm for categorization of the items into the categories is described in the flowchart in Fig. 2.

At last, we reassessed the categories to ensure that each category was accurately coded with the updated category name and made minor changes in their names as well as their descriptions. This procedure finally led to 43 categories.

Identifying the Themes. We conducted a second pooling to consolidate categories into themes. This process was similar to the categorization method previously depicted in Fig. 2, except that we used categories to generate themes instead of items to generate the categories of conceptions.

This procedure resulted in eight overarching themes. The second pooling was done to organize the 43 diverse categories into thematic structures and make sense of the findings. For an illustration of the relationship between items, categories and themes, please refer to Fig. 3 as an example. This is the foundation for determining if overarching themes can be derived from the identified categories.

We verified the identified conceptions and their assignment to different categories and themes through an expert rating. Three experts from the areas of education, psychology and computer science assigned the conceptions with the categories as well as the themes. The expert rating revealed a close similarity of two categories ('Anthropomorphization of AI systems' and 'Conception that AI systems are humanoid or mimicking humans'). This led to the merge of these two categories into one ('Anthropomorphization of AI systems, such as the perception that they are humanoid or mimic human behavior'). Hence, the final number

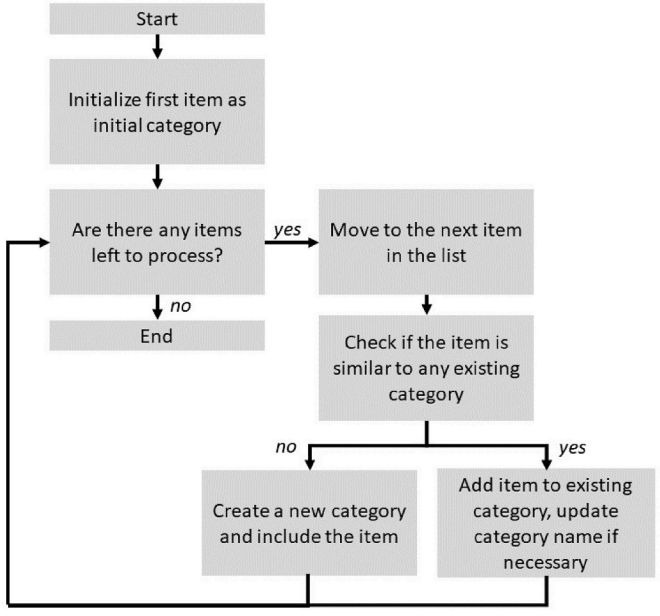

Fig. 2. Flowchart of the categorization process.

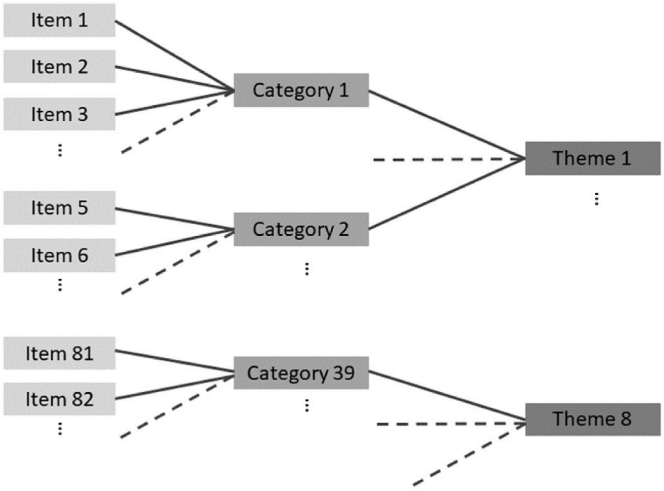

Fig. 3. Schematic representation of the relationship between items, categories, and themes.

of categories is 42. The theme 'Impact on society and industry' was slightly redefined by adding the term 'healthcare' and now is labeled as 'Impact on society, healthcare and industry'.

The interrater agreement for the three raters was calculated using Fleiss Kappa (Fleiss, 1981). For the categories interrater agreement of $\kappa = .83$ was achieved, for the themes $\kappa = .86$ can be reported. Both interrater agreements can therefore be described as "almost perfect" ($\kappa > 0.81$) (Landis & Koch, 1977).

3.5. Other information sought from the reviewed studies

Besides the conceptions we retrieved descriptive variables from the studies. These variables retrieved from the studies are the country(ies) of study, the reported sample size, and the educational institution where the study was conducted.

4. Results

4.1. Descriptive findings of the literature

We found that studies in this review were conducted in various regions including North America, Europe, Asia, South America, Africa, Oceania, and the Middle East (see Fig. 4). Most studies were (partly) conducted in Europe (15 countries mentioned) followed by North

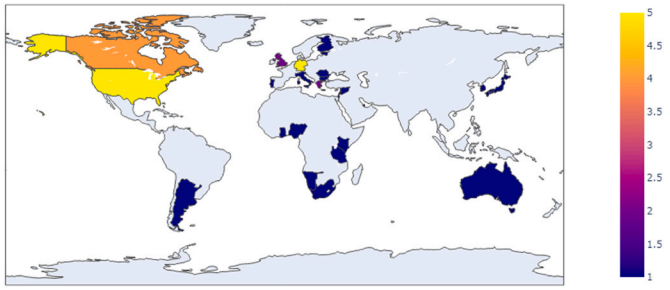

Fig. 4. Countries of origin of the studies included in the review by number of contributions (number of studies in brackets): North America: USA (5), Canada (3). Europe: Germany (5), Greece (2), UK (2), Finland (1), Bulgaria (1), Italy (1), Romania (1), Portugal (1), Estonia (1). Asia without the Middle East: South Korea (1), Japan (1). South America: Argentina (1x) Africa: Nigeria (1), Ghana (1), Tanzania (1), Kenya (1), South Africa (1), Namibia (1). Oceania: Australia (1). Middle East: Israel (1), Qatar (1), Lebanon (1), Syria (1). Many of the reviewed studies involve multiple countries.

America (eight studies mentioned). There were individual studies in Asian, Middle Eastern, and African countries. South America and Oceania are each mentioned with one study. Many of the reviewed studies involve multiple countries.

The studies included in this review have a diverse group of participants, ranging from elementary school students (eight studies) to university students (eight studies), and the latter were with a focus on medical science (six studies) and informatics (one study). There are also eight studies focused on teachers and two studies with participants from other or unspecified backgrounds. One study focuses on students as well as teachers, therefore mentioned twice.

The studies under review had a wide range of sample sizes, varying from 6 to 2167 participants. The median sample size is 81, the mean sample size is 245.

4.2. Themes of conceptions on AI

In this section, we present the conceptions of AI in eight themes entailing each a table that lists its categories, references, and a brief description for each category.

It is important to acknowledge the variety of phenomenological primitives, facts, facets, narratives, concepts, and mental models at various stages of development and sophistication (Özdemir & Clark, 2007) as well as myths described in this review. The notions are not consistently erroneous or simplistic, necessitating a comprehensive conceptual shift. Some of these ideas exhibit an advanced understanding of AI literacy (e.g. Long & Magerko, 2020).

The Theme ***'Confusion and constrictive conceptions of AI at a technical level'*** (Table 2) includes misunderstandings and confusion about the definitions and concepts of AI such as machine learning, neural networks, and deep learning.

The Theme ***'Anthropomorphization and embodied AI'*** (Table 3) entails conceptions which refer to the tendency to attribute human-like characteristics or attributes to AI systems. The conceptualization of AI as embodied arises from the idea of AI systems being embodied in physical form, such as robots with arms, legs, and the ability to exhibit human-like behaviors and responses.

Conceptions in the theme ***'Understanding of the scope, capabilities and limitations of AI and its future potential and development'*** (Table 4) reflect a narrow view of AI and its potential applications with focus on robotics and sensors as well as digital assistants, especially recommender systems. Other conceptions relate to the future potential and development of AI, including the idea that it is a technology that is an upcoming trend in its infancy and is constantly improving and evolving.

Conceptions which relate to the potential dangers posed by AI and unspecific fears connected to AI are grouped into the theme ***'Threats, dangers and benefits of AI'*** (Table 5). Many learners tend to view AI with binary, simultaneous attitudes of fear and hope; they show a more nuanced understanding. Generally, these views remain rather unspecific.

Conceptions in the theme ***'Autonomy of AI'*** (Table 6) suggest that people may have the belief that AI systems are fully autonomous technologies that can function and develop without the need for human intervention.

The theme ***'Impact on society, healthcare and industry'*** (Table 7) entails conceptions about how AI will affect various industries and fields, and the potential impact on daily lives and society as a whole.

Conceptions pooled in the theme ***'Role of AI in education and careers'*** (Table 8) show a range of attitudes towards learning with and about AI, from hopeful optimism to skepticism and uncertainty.

Overall, conceptions of the theme ***'Inclusiveness, bias and trust'*** (Table 9) show a range of attitudes towards the cost and objectivity of AI, from skepticism about its accessibility and impartiality to confidence in its capabilities. All these conceptions can be only found by one paper. They are theoretically derived and empirically tested.

Table 2
Identified categories in the theme 'confusion and constrictive conceptions of AI at a technical level'.

Category	Reference(s)	Brief description of the category
Limited understanding of how a robot functions	Ellis, Lauer, Silva, and Nina (2007)	This conception does not entirely focusses on AI, it encompasses a lack of awareness of the software, algorithms, and hardware that make up a robot and how they interact to produce the desired outcome.
Inability to describe or distinguish technical terms related to AI such as machine learning, neural networks, and deep learning	Antonenko & Abramowitz, 2022; Lindner & Berges, 2020; Pucchio et al., 2022; Teng et al., 2022	Having these knowledge gaps might be hindering one's ability to effectively engage with discussions and decision-making related to AI.
General limited or inaccurate knowledge of AI or some specifics (methods, algorithms, terms, features)	Antonenko & Abramowitz, 2022; Chounta et al., 2022; Lindner & Berges, 2020; Lindner & Romeike, 2019; Teng et al., 2022	Having limited or inaccurate knowledge of AI is hindering the effective use of AI and the understanding of potential impacts on society.
AI algorithms make mistakes	Antonenko and Abramowitz (2022)	It is important to understand that AI systems are not perfect and can sometimes produce incorrect results, especially when working with complex or novel problems, limited data, or when there are biases in the training data.
AI is considered technically complex and unpredictable in terms of its results	Lindner and Berges (2020)	While AI systems can be complex, with many interrelated components and algorithms, they are designed and programmed by humans and can be made to operate in a transparent and explainable manner. At the same time, the results of AI systems can be influenced by the data and algorithms used in their development, as well as by the conditions under which they are used.
Definition of AI focused on programming and robotics	Evangelista, Blesio, and Benatti (2018)	This narrow definition can lead to misunderstandings about the nature and capabilities of AI, as well as to misconceptions about the ways in which AI systems can be used to solve problems and make decisions. Understanding the full range of AI is crucial for effectively utilizing AI and for understanding its potential impacts on society.
Rudimentary conceptions of machine learning	Evangelista et al., 2018; Sanusi, Oyelere, & Omidiora, 2022	As learners may not have a deep understanding of the mathematical foundations of machine learning or the technical details of how these algorithms are implemented and optimized they might be able to understand the overall concept and can engage in basic discussions about the potential applications of AI and machine learning.

(*continued on next page*)

Table 2 (*continued*)

Category	Reference(s)	Brief description of the category
Very limited understanding of AI research methods	Pucchio et al. (2022)	This conception can lead to difficulties in evaluating the quality and reliability of AI research findings, as well as in making informed decisions about the use and development of AI technology. Having this conception might be not as problematic for learners on a basic level as for learners in the field of computer science.

4.3. Most frequent conceptions on AI

In our review of AI literature, we encountered numerous conceptions on AI that were repeatedly discussed in different papers. The following summarizes the most frequent conceptions found about AI (four findings or more). Firstly, we discovered that many learners struggle to describe or differentiate between technical terms associated with AI such as machine learning, neural networks, and deep learning (four studies). Additionally, they possess a limited or incorrect understanding of AI and its various components in general (five studies). This limited knowledge of AI seems to lead often to a narrow focus on specific applications of AI, such as robotics, digital assistants, and recommender systems (five studies) and the anthropomorphization of AI systems (five studies). Furthermore, our findings indicate a growing concern about AI causing unemployment and job loss, as well as negative views on its potential impact on human life and society in general (6 studies). However, there seems to be a lack of belief that their own profession as physicians, radiologists or teachers will be replaced by AI (five studies).

5. Discussion

This study found that the studies published were with significant diversity in terms of territories, participants, and sample sizes. The western countries such as the US, Germany conducted more studies compared to countries in other regions. This might be due to economic resources and broad academic infrastructure in western countries as well as language barriers as we focussed solely on research published in English. Findings from studies conducted in Europe and North America may not necessarily apply to other regions due to these differences in economic and academic infrastructure as well as cultural and social contexts. As a result, the generalizability of the findings of the reported studies (and therefore this review) to other regions might be limited, leading to less effective interventions and strategies for addressing AI misconceptions globally.

We also found that four different groups of learners were under investigation: elementary students and high school students, university students with a huge focus on medical students and (soon to be) teachers. This is a very limited sample of learners. The focus on students might stem from a desire to understand the conceptions that arise during the formative years of education. By targeting conceptions at this stage, researchers hope to better inform and improve educational practices, curricula, and materials to encounter misconceptions and promote a more accurate understanding of AI in future generations. To the best of our knowledge, there are currently no existing studies with samples covering professions affected by AI advances. These include fields such as law, management, journalism, social sciences, arts, music, philosophy, and natural sciences, among others. This might indicate that there is an assumption that certain professions, such as medicine and education, are more directly impacted by AI advancements, and therefore get more attention. This could bias researchers toward focusing on these groups, even though AI is affecting a wide range of fields. The findings call for studies to broaden the sample to verify prominent conceptions as well as to possibly identify conceptions not described yet.

Table 3
Identified Categories in the Theme 'Anthropomorphization and embodied AI'.

Category	Reference(s)	Brief description of the category
Anthropomorphization of AI systems, such as the perception that they are humanoid or mimic human behavior	Antonenko & Abramowitz, 2022; Evangelista et al., 2018; Lindner & Berges, 2020; Mertala et al., 2022; Oh et al., 2017	Anthropomorphization can result in a misleading understanding that AI systems can perform tasks that they are not capable of, or can understand and respond to human behavior in the same way that a human would. This conception may also influence how people interact with and perceive AI, even leading to ethical concerns.
Belief that AI works like the human brain	Antonenko & Abramowitz, 2022; Ellis et al., 2007; Lindner & Berges, 2020	This conception can lead to incorrect assumptions about the way AI processes and stores information. Understanding the differences between AI and the human brain is important for effectively evaluating the potential and limitations of AI technology.
Conceptualization of AI as embodied (e.g., robots with arms, legs, and feelings)	Kreinsen and Schulz (2021)	While some AI systems may be embodied, many AI technologies, such as machine learning algorithms or natural language processing systems, are not physically embodied and exist only in software. Not knowing the different forms that AI can take and the ways in which AI systems interact with the world can lead to a limited conceptualization of AI.
AI is nothing like the human brain and does not solve problems the way humans can	Antonenko and Abramowitz (2022)	While AI systems do operate differently from the human brain, they are capable of solving problems and making decisions that are beyond the capabilities of humans in some areas. At the same time, AI systems also have limitations and may not be able to perform certain tasks that are easy for humans, such as understanding context and recognizing emotions. Understanding these differences is key for AI literacy.

The studies found eight themes of misconceptions of AI. Specifically, the findings show that there is limited technical understanding about AI among learners, including confusions about definitions and concepts such as machine learning, neural networks, and deep learning. Learners also may not be able to distinguish between technical terms related to AI. This might be a result from getting most of the ideas, often only it's 'buzzwords' about AI, from the media (Lindner & Romeike, 2019; Sulmont, Patitsas, & Cooperstock, 2019) which is not backed by a basic understanding.

The tendency to attribute human-like characteristics or attributes to AI systems and the conceptualization of AI as embodied might originate

Table 4
Identified Categories in the Theme 'Understanding of the Scope, Capabilities and Limitations of AI and its future Potential and Development'.

Category	Reference(s)	Brief description of the category
Mixed views on the convenience and abilities, like creativity, of AI	Antonenko & Abramowitz, 2022; Oh et al., 2017	Learners with mixed views on AI likely understand the potential benefits and limitations of AI, but are uncertain about the full extent of its abilities and the impact it will have on society. This nuanced perspective is a central aspect of AI literacy, as it encourages critical thinking and balanced assessments of the role of AI.
Focus on specific applications of AI such as robotics, digital assistants or recommender systems	Clark, 2021; Evangelista et al., 2018; Kreinsen & Schulz, 2021; Marrone, Taddeo, & Hill, 2022; Ottenbreit-Leftwich et al., 2021	Learners who have a limited or focused understanding of AI based solely on their exposure to specific applications, such as robotics, digital assistants, or recommender systems may have a narrow view of AI and its capabilities. They may not fully appreciate its broader impact on society. For example, someone who only has experience with AI-powered digital assistants may not understand the implications of AI in areas such as privacy or ethics. This type of conception might hinder individuals from critically examining the role of AI in society.
Conceptualization of AI as a sensory technology that uses sensors to acquire information from its surroundings	Mertala et al. (2022)	Learners have an understanding that AI is primarily a sensory technology that collects information from its surroundings through the use of sensors. This limited view of AI may lead to misunderstandings about the nature and capabilities of AI, and eventually cause learners to underestimate the potential impact of AI.
AI viewed as a novel and mysterious problem space	Greenwald, Leitner, and Wang (2021)	These learners might be somehow fascinated by the complexity of AI and its potential to solve difficult problems, but may also have misconceptions about its capabilities and the potential consequences of its use.
AI cannot be creative or match human creativity	Antonenko & Abramowitz, 2022; Marrone et al., 2022	Learners who hold this conception may see AI mainly as a tool for automating repetitive tasks, but not as a capable source of creative output. They may not fully appreciate the potential of AI in areas such as art, music, or writing, and therefore might not understand the role of AI in shaping our cultural landscape.

Table 5
Identified categories in the theme 'threats, dangers and benefits of AI'.

Category	Reference(s)	Brief description of the category
Negative views (risk and threats) of AI's impact on humans and society	Eagle, Lander, & Hall, 2021; Ghotbi, Ho, & Mantello, 2022; Joshi, Rambola, & Churi, 2021; Lopes, 2022; Mertala et al., 2022; Oh et al., 2017	Learners may be concerned about the unintended consequences of AI, such as biased decision-making or the erosion of human agency. This type of conception can lead to a one-sided view of AI, and may cause individuals to underestimate its potential benefits and to overstate the risks and threats associated with its use.
Lack of trust in AI due to absence of human qualities such as emotions and affect	Nazaretsky, Cukurova, and Alexandron (2022)	Learners who hold this view may see AI as being impersonal, uncaring, or lacking in empathy. This may cause individuals to reject or be skeptical of AI-powered technologies and systems.
Unspecific fears about AI	Antonenko & Abramowitz, 2022; Lindner & Berges, 2020	Learners who hold this abstract fear may be concerned about the potential consequences of AI, but may struggle to articulate or identify specific risks or threats associated with its use. Individuals therefore could be skeptical of or even reject AI-powered technologies and systems without fully understanding their potential benefits and risks.

from encounters from media like famous movies like 'The Terminator' (Cave et al., 2018). While, from a perspective to foster AI literacy, human-like characteristics or attributes to AI systems should be avoided, programmers and designers often strive to create AI systems that possess strong anthropomorphic features, behavior, and interaction to gain higher acceptance from humans towards these AI systems (Pelau, Dabija, & Ene, 2021). Unfortunately, this has resulted in misleading conceptions.

Concerning the perceived threats and dangers as well as possible benefits and potential, many learners tend to view AI somewhat binary, beneficial and dangerous simultaneously. Studies show that learners with a lower degree have a more negative outlook on AI. Learners with a higher degree have a more positive or a mixed view on threads and potential (Marrone et al., 2022). More generally, different demographic groups often seem to exhibit vastly differing levels of trust towards AI (Richardson, Prioleau, Alikhademi, & Gilbert, 2020, pp. 489–496).

There is a recognition that AI is present in daily life and AI leads to a general, somewhat unspecific, social change. Views on the overall impact of AI on society are not uniform. Some have concerns about the

Table 6
Identified categories in the theme 'autonomy of AI'.

Category	Reference(s)	Brief description of the category
Conceptualization of AI as an autonomous technology that can conduct tasks without human input	Antonenko & Abramowitz, 2022; Mertala et al., 2022	Learners who hold this view may believe that AI systems have the ability to make decisions and carry out actions on their own, without the need for human intervention, similar to the perception that AI systems can independently change and extend their program code. This conception can lead, as the conception mentioned before, to a misunderstanding of the nature of AI systems, as well as the role of human decision-makers in their development and use.
AI cannot learn or function independently of humans	Antonenko and Abramowitz (2022)	This conception is the opposite of the conception described before.

Table 7
Identified categories in the theme 'impact on society, healthcare and industry'.

Category	Reference(s)	Brief description of the category
No Believe that (they) humans like physicians, radiologists, teachers would be replaced	Antonenko & Abramowitz, 2022; Clark, 2021; Gong et al., 2019; Lopes, 2022; Pucchio et al., 2022	Learners who hold this view may believe that their specific job or profession is immune to automation, or that AI systems are not capable of performing the tasks that they perform. Learners might have a false sense of security and a lack of preparedness for the future of work in the age of AI.
Expectation that AI will be essential and commonly used to improve medicine in the future	Doumat, Daher, Ghanem, & Khater, 2022; Pucchio et al., 2022; Swed et al., 2022	This conception describes the conception that AI will revolutionize the field of medicine by enabling more accurate diagnoses, personalized treatment plans, and improved patient outcomes. This can lead to a positive outlook on the potential of AI to improve healthcare, but also may lead to unrealistic expectations and a lack of understanding of the limitations and challenges associated with using AI in medicine.
AI is present in our daily lives	Lindner & Berges, 2020; Mertala et al., 2022	Learners who hold this view might acknowledge AI as ubiquitous and constantly surrounding them.
AI is useful and makes things easier for people	Joshi et al., 2021; Mertala et al., 2022	This very broad and unspecific conception may lead to seeing AI as a technology that can automate routine tasks, provide personalized recommendations, and solve problems more efficiently than humans. It might be connected with a positive outlook on the potential of AI to improve quality of life, but also may entail a lack of understanding of the limitations and challenges associated with using AI.
Concern of inability to follow and control the advancement of AI	Oh et al. (2017)	Learners who hold this view may feel that the rapid advancements in AI are outpacing their ability to understand and keep up with it, leading to feelings of unease and uncertainty about the future. This type of conception can stem from a lack of understanding about AI and eventually may lead to fear or mistrust of AI technology.
AI leads to a general social change, although this impact is often not specific	Lindner and Berges (2020)	Learners have the conception that AI has the potential to revolutionize the way we live, work, and interact with each other, but may not be able to articulate exactly how or why this will occur. While it shows a general awareness of AI and its growing presence in various aspects of life it also

(*continued on next page*)

impact of AI on employment and the overall impact on society, as well as anxiety about its use in specific industries. Opposing this, there is the belief that almost no humans like physicians, radiologists, teachers would be replaced by AI – interestingly the learners spare only the profession they are studying (Nazaretsky et al., 2022; Pucchio et al., 2022). The participants see the impact of AI on employment as a whole but think their jobs won't be affected in a negative way by this transformation. This conception might be caused by a self-protection mechanism. If they would acknowledge their own profession is challenged by the advancements of AI they would have to seriously reconsider their profession of choice. However, learners think that AI can also be useful, especially in healthcare, and have optimism towards the impact of AI on society.

Concerning the inclusiveness, bias and trust of AI learners seem to have heterogeneous conceptions (AI is biased vs. AI can be 100% objective). These conceptions were described by one paper and are theoretically derived but empirically tested. Other studies seem not to put focus on investigating conceptions in this field which might be allocated in ethics of AI.

There is an awareness that AI will be important in the future and that having a basic understanding of it is crucial. However, this awareness is accompanied by a feeling of being unprepared for this new technology. Additionally, there is some concern that AI is too complex to understand. This might be due to the belief that AI is for computer scientists and other professionals only (Sulmont et al., 2019). Despite this, there is generally a positive attitude towards AI education as a tool.

6. Conclusion and limitations

Especially in the last two years research on pre- and misconceptions of AI is getting more attention all around the globe. Some conceptions about AI seem described in various studies with different foci, samples and methods (qualitative and quantitative). We tried to allocate the identified conceptions to overarching themes. The high interrater agreement for the attribution of the conceptions to the categories and themes might be an indicator for a first, yet tentative, framework for classification of conceptions. The strong agreement among raters in assigning conceptions to categories and themes may be a first, albeit preliminary, approval of our inductively derived framework for classifying conceptions.

Besides being a central aspect in many AI literacy frameworks (e. g. Long & Magerko, 2020; Michaeli, Romeike, & Seegerer, 2022)

Table 7 (*continued*)

Category	Reference(s)	Brief description of the category
		reveals a lack of in-depth understanding of AI.
Limited knowledge and skepticism about how AI could be used in practice at work	Chounta et al., 2022; Clark, 2021; Pucchio et al., 2022	Learners who hold this view may have limited knowledge of how it can be used to improve work processes and outcomes. They may question the potential benefits of AI and be skeptical about how it could be integrated into the workplace. It might originate from a lack of exposure to AI in the workplace, limited understanding or a general skepticism towards new technology.
AI holds optimism and promise for individual fields or society	Antonenko & Abramowitz, 2022; Teng et al., 2022	These learners believe that AI has the ability to solve complex problems and improve outcomes, and that it can be used to create new products, services, and opportunities. This conception might come with limited awareness of possible threats and dangers of AI.

Table 8
Identified categories in the theme 'role of AI in education and careers'.

Category	Reference(s)	Brief description of the category
Feeling unprepared and thinking of the need to use and understand AI in their careers	Pucchio et al., 2022; Teng et al., 2022	These learners may feel unprepared or ill-equipped to handle AI, and believe that they must take steps to gain an understanding of it in order to remain competitive in the job market.
High motivation and positive attitude towards AI as tool for learning	Polak, Schiavo, and Zancanaro (2022)	Some learners, in this case teachers, might tend to have a proactive mindset and may be willing to invest time and effort to understand AI and its applications.
Anyone can understand how AI works	Antonenko and Abramowitz (2022)	This conception, while encouraging from the perspective of an educator, might entail a lack of recognition of the complexity and technical nature of AI, and an overestimation of the ease of learning and understanding AI systems and algorithms.

conceptions about inclusiveness, bias and trust of AI did not appear in any study but one. Either conceptions in the general field of ethics may be not very common or this field wasn't a focus in the reviewed studies. More research about conceptions of AI in the field of learners would help to make sense out of the findings.

This exploratory review showed that there is a variety of pre- and misconceptions and myths about AI among learners. This calls for educational efforts across all professions to achieve real AI literacy among learners and promote a deeper understanding of the technology and its potential applications. Through education, learners can gain a deeper understanding of the technology and its capabilities, as well as the potential social and economic implications of its use. This knowledge empowers them to make informed decisions about the integration of AI in our society, rather than being swayed by misinformation and fear.

Table 9
Identified categories in the theme 'inclusiveness, bias and trust'.

Category	Reference(s)	Brief description of the category
AI is expensive and only for huge corporates	Antonenko and Abramowitz (2022)	
AI is infallible and can be 100% objective	Antonenko and Abramowitz (2022)	This belief is misguided, as AI systems are only as objective as the data they are trained on, the algorithms they use, and the ways in which they are used in practice. Understanding the ways in which AI systems can be designed and developed to minimize bias and error is critical for effectively utilizing AI technology and for ensuring that it is used in a responsible and ethical manner.
AI is always biased	Antonenko and Abramowitz (2022)	This refers to the conception that all AI systems are inherently biased, which is true as AI systems perpetuate and amplify existing biases in the data they are trained on.

Promoting AI literacy may help to ensure that the technology is developed and used in ways that are beneficial to society as a whole.

One limitation of this study is the complementary use of Google Scholar as an additional source of records for our review. As Google Scholar is not a scientific database but a scientific search engine, replication of results might be limited. We argue that using Google Scholar as an additional source might provide a more holistic picture of this emerging research field.

Another point of discussion might be the definition of our search terms. An alternative search term instead of "students" might be "learners". We have chosen the term of "students" besides being narrower because it seems the term mostly referred to in educational sciences: The database ERIC reports 76 000 results for the term "learners" while reporting around 452 000 results (around 6x more) for the term "students".

The allocation of the single items to categories and overarching themes is our first approach to sorting the very heterogeneous conceptions found in the reviewed studies. While there are other category systems published we decided to inductively derive categories and themes. The process of pooling the items into categories and themes depends on parameters like the given emphasis on coherence and precision as well as the selected initial item constituting the first category and therefore might lead to (slightly) different outcomes depending on the persons conducting the pooling. Although first quality checks are encouraging, alternative classifications may be more suitable. As these themes arose from an exploratory search they are open to further development like identification of themes not described yet or the split of themes as more studies about conceptions of AI are published.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT (GPT-3.5) in order to improve readability and language of single sentences as some authors are not native English speakers. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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