Author(s): Mertala, Pekka; Fagerlund, Janne; Calderon, Oscar

Title: Finnish 5th and 6th grade students' pre-instructional conceptions of artificial intelligence (AI) and their implications for AI literacy education

Year: 2022

Version: Published version

Computers and Education: Artificial Intelligence 3 (2022) 100095

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.sciencedirect.com/journal/computers-and-education-artificial-intelligence

Finnish 5th and 6th grade students' pre-instructional conceptions of artificial intelligence (AI) and their implications for AI literacy education

Pekka Mertala [a,*], Janne Fagerlund [b], Oscar Calderon [b]

[a] Department of Teacher Education, University of Jyväskylä, Alvar Aallon katu 9, 40014, Jyväskylä, Finland
[b] Finnish Institute for Educational Research, University of Jyväskylä, Alvar Aallon katu 9, 40014, Jyväskylä, Finland

ARTICLE INFO

Keywords:
Artificial intelligence
AI literacy
Conceptions
Students
Primary education

ABSTRACT

In the present paper, we report the findings of a qualitative survey study of 195 Finnish 5th and 6th grade students' pre-instructional conceptions of artificial intelligence (AI). An exploration of these initial conceptions provides insight into students' preliminary understanding of the topic and informs curriculum designers and teachers about misconceptions that might jeopardize student learning. The findings suggest that students' initial conceptions of AI are varied and often uninformed. For instance, references to the role of data in training AI applications were practically nonexistent. Instead, AI was often described as an anthropomorphic technology that possesses cognitive qualities equivalent to those of humans—a conception that notably resembles how AI is portrayed in the media. As a pedagogical implication, our findings suggest that it would be valuable to "demystify" AI by exploring its technical principles (i.e., the role of data) of the "human-like" AI solutions students encounter in their everyday lives.

1. Introduction

Artificial intelligence (AI) has a pervasive role in various fields of human life (Pelau et al., 2021), including education (Carvalho et al., 2022; Williamson & Eynon, 2020). In the educational sphere, roughly two partly overlapping branches of research and practice can be distinguished: teaching *with* AI and teaching *about* AI. The first branch conceives AI as a tool for education, and it can take such concrete forms as predictive and personalized learning analytics and automatic facial detection (e.g., Andrejevic & Selwyn, 2020; Leaton Gray, 2020; Raffaghelli et al., 2022; Southgate et al., 2019). The latter branch approaches AI as the substance of education, a target of learning (e.g., Carvalho et al., 2022;Kim et al., 2021; Kreinsen & Schulz, 2021, October; Ng et al., 2022; Su et al., 2022; Su & Zhong, 2022; Touretzky et al., 2019; Vartiainen et al., 2020) often referred to as AI literacy (e.g., Jandrić, 2019; Long & Magerko, 2020, April; Long & Magerko, 2020).

One common objective in various AI literacy frameworks is to help children to form accurate conceptions of AI (e.g., Kreinsen & Schulz, 2021, October; Long & Magerko, 2020; Su et al., 2022). The influential "Big Ideas" in AI -framework (Touretzky et al., 2019), for instance, states that students should learn to understand that in AI applications "computers perceive the world using sensors [...] [and] can learn from the data" (Touretzky et al., 2019, p. 9797). Put differently. AI literacy education should provide children a conception that AI is (often) a sensory technology, which uses data (sometimes collected via sensors) to improve its functionality.

Research shows that children develop their own conceptions of abstract digital technologies like the Internet, code, and ubiquitous computing before their formal introduction in (pre)school (e.g., Edwards et al., 2018; Eskelä-Haapanen & Kiili, 2019; Mertala, 2019, 2020; Wennås Brante & Walldén, 2021). This stands for AI as well (Kreinsen & Schultz, 2021; Ottenbreit-Leftwich et al., 2021). Thus, AI literacy education needs to acknowledge children's AI-related preconceptions because exploration of the initial conceptions provides insight about students' initial understanding of the topic as well as informs curriculum designers and teachers about misconceptions that might jeopardize their learning: If students have a misconception prior to learning a subject, this may prevent them from learning the new subject properly, thereby leading to new misconceptions (Biber et al., 2013) —a notion acknowledged in AI literacy frameworks as well (Kreinsen & Schulz, 2021).

Even though the importance of paying attention to (pre)conceptions people have about AI is widely recognized and accepted (e.g., Kreinsen & Schulz, 2021; Long & Magerko, 2020; Vartiainen et al., 2021) specific

* Corresponding author.
E-mail addresses: pekka.o.mertala@jyu.fi (P. Mertala), janne.fagerlund@jyu.fi (J. Fagerlund), Oscar.e.calderon@jyu.fi (O. Calderon).

https://doi.org/10.1016/j.caeai.2022.100095
Received 7 May 2022; Received in revised form 30 August 2022; Accepted 30 August 2022
Available online 6 September 2022

research on peoples' conceptions of AI is still in an emerging stage. Most of the related research has focused on attitudes toward AI (e.g., Bao et al., 2022; Dang & Liu, 2021; Gonzalez et al., 2022; Li & Sung, 2021; Maier et al., 2019; Selwyn et al., 2020; Zhang & Dafoe, 2020, February) and the few existing conception-themed studies have concentrated on adults (e.g., Cave et al., 2019; Chao et al., 2021; Kerr et al., 2020; Sulmont et al., 2019; Zhang & Dafoe, 2020). Children's initial conceptions of AI has been touched upon only in short conference proceedings with small samples (N = 10–12 in qualitative studies; N = 60 in quantitative studies) and no data excerpts that would shed light on children's rationales (Kreinsen & Schulz, 2021, October; Kreinsen & Schultz, 2021; Ottenbreit-Leftwhich et al., 2021). To conclude, to design a relevant curriculum, more knowledge about children's initial conceptions of AI is needed.

The present paper contributes to filling this gap in knowledge by reporting the findings of a qualitative survey study that investigated 195 Finnish 5th and 6th grade students' (12–13-year-old) pre-instructional conceptions of AI. Drawing on Marton's (1981) classical work, we approach conceptions as categories of description of the world, where conceptions refer to (often linguistic) descriptions of how things and phenomena appear to us. The research questions that have guided our project are: What kind conceptions 5th and 6th graders have about.

- AI as a technology?
- where AI is used?; and
- why AI is used?

The article is structured as follows. First, the different definitions of AI are discussed, followed by a section that presents the previous research on peoples' conceptions of AI. Then, the methods of the current study are described, followed by the findings, discussion, and concluding remarks.

2. Background

2.1. Definitions of AI

Kurzweil (1990) defined AI as the art of creating machines that perform functions that require intelligence when performed by people. Although the definition dates back more than three decades, it still provides a fruitful starting point for defining AI. First, it suggests that AI is not intelligent per se but capable of successfully conducting tasks that are considered intelligent. One example is image recognition, in which a machine learning-based AI "learns" how to sort images by "training" with an appropriate dataset (Tedre et al., 2021). However, although AI may be able to distinguish the image of a table from that of a whale, it does not understand what tables or whales are. Second, by highlighting the role of machines in mimicking intelligence, the definition emphasizes that AI is digital: "AI cannot be done with a pencil and piece of paper, hence, a computer is always required" (Emmert-Streib et al., 2020, n.p).

Even within these limits, AI has remained a "fuzzy concept" with no one universally accepted definition (Emmert-Streib et al., 2020; Kaplan & Haenlein, 2019). One reason is that AI challenges human conception, as it violates category boundaries typical of human thinking: AI is both an actor and an artifact, and it makes decisions that can be qualified as ethical without AI being a conscious and moral being (Laakasuo et al., 2020). As a result, AI may represent the emergence of a new ontological category (see also Severson & Carlson, 2010). Another (not mutually exclusive) reason for the conceptual fluidity is that AI—as a technology and phenomenon—locates in the intersection of science, economy, and policy, and each of these domains approaches AI from a different viewpoint and with varying aspirations (Parviainen, 2021). Put differently, researchers speak differently about AI than politicians, and both groups differ from those of the representatives of technology companies (Parviainen, 2021; Slotte Dufva & Mertala, 2021).[1] To make sense of this ambiguity, Kaplan and Haenlein (2019) proposed that it would be beneficial to conceptualize AI through its evolutionary stages, the core principles and differences of which are summarized in Table 1.

Of these three stages, only the first one—narrow AI—is currently a real and achievable one (Fjelland, 2020). Common examples of narrow AI are voice-activated digital assistants, such as Alexa and Siri, which perceive auditory information by using sensors (Touretzky et al., 2019) and can perform simple tasks, including retrieving information from the internet (Kaplan & Haenlein, 2019). General AI and super AI are conceptualizations currently situated in the realm of science fiction instead of reality. However, in peoples' conceptions the lines between facts and fantasy often overlap as illustrated in the following section.

2.2. Peoples' conceptions of AI

Research on peoples' conceptions of AI[2] suggest that the current reality of narrow AI and the speculative promises of general and super AI sometimes mix. For instance, students in Kreinsen and Schultz's (2021) study described AI as having feelings. They also conceptualized AI as the brain of robots, suggesting that AI is comparable to the human brain (see also Emmert-Streib et al., 2020; Szczuka et al., 2022). Kreinsen and Schultz's (2021) findings provide twofold cues about the nature of AI conceptions. First, paralleling AI with human emotions and cognition implies an anthropomorphic conception of AI (Cave et al., 2018; Salles et al., 2020). Anthropomorphism refers to the attribution of distinctively human-like feelings, mental states, or behavioral characteristics to inanimate objects[3] (Airenti, 2015; Epley et al., 2007). Second,

Table 1
Stages of AI (Kaplan & Haenlein, 2019).

Narrow AI	General AI	Super AI
Applies AI only to specific areas. Unable to autonomously solve problems in other areas. Can outperform/equal humans in a specific area.	Applies AI to several areas. Able to autonomously solve problems in other areas. Can outperform/equal humans in several areas.	Applies AI to any area Able to solve problems in other areas instantaneously. Outperforms humans in all areas.

[1] There is, of course, variation within the domains as well.

[2] Informed selection was done while choosing the main body of the background-literature. For example, in majority of AI-attitude research, the respondents are given a-priori definitions or examples of the kind of AI they are asked to evaluate (e.g., Bao et al., 2022; Dang & Liu, 2021; Schepman & Rodway, 2020). Thus, these studies do not report attitudes that are based on the participants initial conceptions but ones that are "primed" with examples given by the researchers. This tendency is well illustrated in Selwyn et al. (2020, p. 9), who reported that "we found 43% of the respondents, who initially considered themselves 'opposed' to the development of AI, to shift subsequently to either a 'neutral' or 'supportive' stance once having engaged with all the survey questions." Thus, such research was not included in the review. There are also few studies that have focused on children's interactions with or explanations about AI-enabled technologies (e.g., Druga et al., 2017; 2018, 2019; Lovato & Piper, 2015; Vartiainen et al., 2020, 2021). Druga et al. (2017), for instance, asked children to reason how a (AI-enabled) robot can navigate through a maze. However, since the actual term AI was not used when discussing these technologies with children, it is highly speculative whether the children were talking specifically about AI due the opaque nature of these technologies (Long & Magerko, 2020). Thus, we decided not to include these studies in the review.

[3] … as well as to animals, and in general to natural phenomena and supernatural entities (Airenti, 2015; Epley et al., 2007).

paralleling AI with the human brain provides hints about the conceptions of how AI functions, as it suggests that AI works similarly to the brain (Emmert-Streib et al., 2020).

Further, according to Kreinsen and Schultz (2021), the functionality of AI was often attributed to the storage and retrieval of pre-programmed and personalized data. These conceptions remind us of the ones about computers as "omniscient databases" identified in previous research (Rücker & Pinkwart, 2016). Such conceptions are inaccurate and are likely the result of spontaneous observations instead of intentional teaching. In the Vygotsky (1987) tradition, these are called everyday concepts that arise either from hands-on experiences or via other sources (see also, Edwards et al., 2018; Mertala, 2019). Students in Kreinsen and Schultz (2021) stated that AI manifests itself in everyday life in the form of cookies in web browsers, and voice assistants in smartphones –all examples that are representative of the everyday digital realm in Western contexts (see also Edwards et al., 2018). Take Finland, the context of the present study, for example. Almost all households have an internet connection (Official Statistics of Finland, 2021). Smartphones are the most common device used online by 10–14-year-old children, and the most common online activities in the age group are gaming, social media, and information retrieval (Merikivi et al., 2016). Finnish schools are also well digitalized: the vast majority of schools have wireless internet connections, and the student-device ratio is 4:1 for tablets and 7:1 for laptop computers (Tanhua-Piiroinen et al., 2019).

The closed nature of contemporary technologies makes it difficult to distinguish which applications are AI-based and which are not (Long & Magerko, 2020). For example, only under 30% of adults (N = 2000) in Zhang and Dafoe's (2020, February) study correctly assessed that YouTube's recommendation system or Google Translate uses AI. Due to the opaqueness of digital technology, peoples' AI-conceptions may be rooted in experiences other than first-hand experiences. Adults and children have named self-driving cars and autonomous robots the forms of AI they are the most aware of, even when they have not had first-hand experiences with these technologies (Kerr et al., 2020; Kreinsen & Schultz, 2021). Further, children see AI as possessing more threats than positive possibilities and thus have a cautious attitude toward AI (Kreinsen & Schultz, 2021). Similarly, 45% of the respondents (N = 1078) in Cave et al.'s (2020) study were concerned about machine uprising where AI enables computers to become more powerful than humans. According to Liang and Lee (2017), 26% of respondents (N = 1541) expressed fear toward AI and autonomous robots. However, 54% of the respondents in Cave et al. (2020) ranked increased ease of life as a likely future scenario to impact them personally during their lifetime, which signals a positive stance toward AI (see also Chao et al., 2021; Zhang & Dafoe, 2020, February). Similarly, 63.5% of Australian adults (N = 2019) reported positive attitudes toward AI (Selwyn et al., 2020).

There is also emerging evidence that peoples' conceptions of AI are shaped by public representations of AI and verbal descriptions surrounding it (Bao et al., 2022; Cave et al., 2019; Chao et al., 2021; Kerr et al., 2020; Liang & Lee, 2017; Sulmont et al., 2019). In public discussions, the lines between the different stages of AI are blurred (Slotte Dufva & Mertala, 2021). In media texts, narrow AI is often described as an active and intentional agent who "does things" and "has aspirations" (Barassi, 2020; Jokela, 2018; Slotte Dufva & Mertala, 2021). News media has reported that Google's AlphaGo AI has *defeated* its opponents in the game of Go, *quitted* the game at the top, *retired*, and *taken actions* to cure diseases (Barassi, 2020; Jokela, 2018). Another illustrative example is the robot Sophia by Hanson Robotics (n.d.). On Hanson Robotics' website where Sophia "introduces" herself by using a first-person noun and "describes" how she "*dream[s]* of that future, wherein AI and humans *live* and work together in friendship" (Hanson Robotics n.d., italics added). Sophia was even granted citizenship in Saudi Arabia in 2017 (Parviainen, 2021). Overall, representations of anthropomorphic or super AI have a long tradition in Western media. Steven Spielberg's movie A.I. – Artificial Intelligence introduced David, a childlike android capable of loving. More recently, Marvel Comics portrayed the superhero and supervillain AI machines J.A.R.V.I.S., Vision, and Ultron in their highly influential cinematic universe. Films such as *2001: A Space Odyssey*, *Terminator 2: Judgment Day*, and *I, Robot* have popularized the idea of super AI by portraying AI as a sentient machine that aims to overcome or control humans. Additionally, the relative news media coverage of threats of humans losing control of AI tripled in volume from the 1980s to the 2010s (Fast & Horvitz, 2017; see also Brokensha, 2020; Obozintsev, 2018).

3. The present study

3.1. Data and participants

This study aims to learn about primary school students' pre-instructional conceptions of AI through a qualitative survey. The data were collected from 195 Finnish 5th and 6th graders from 10 different classes via an online survey in April and May 2021. An invitational letter to participate openly and voluntarily by having students respond to an online questionnaire was sent to 5th and 6th grade teachers via e-mail through a network of municipal school ICT (information and communication technologies) coordinators in a medium-sized municipality in Central Finland. Finland provides a rich context for empirical research on AI-conceptions. There is a widespread political ambition "to make Finland a forerunner in the age of artificial intelligence" (Ministry of Economic Affairs and Employment, 2019, p. 924) and free educational material have been provided to adults (Elements of AI, n.d) and -more recently-to children (Uudet lukutaidot, 2022) to teach them about the rudiments of AI. Additionally, AI is a common theme in Finnish news media (Jokela, 2018; Slotte Dufva & Mertala, 2021).

The network covered all schools in the municipality (35 schools), providing a satisfactory initial number of recipient teachers (estimation: 135). Participants were initially sought from only one municipality due to the requirement of obtaining a separate research permit for each municipality, effectively shaping the sampling method as convenience sampling (Patton, 2014). Ten teachers, representing roughly 215 students (based on the municipal average; see Ministry of Education and Culture, n.d.), expressed interest in participating. As a requital for the time and effort invested in our study, the classes were provided with open web-based instructional material about the technical and ethical aspects of AI after the students had completed the survey.[4] The lesson plan also served as an incentive for participating in the study.

Our research motive was exploratory, and we aimed to study the variety of the students' conceptions—not whether there would be different conception profiles linked with some background variables, such as gender, socio-economic background, and school success. Thus, no personal data or sensitive information was collected. However, the students were asked about their interest in and (self-evaluated) knowledge regarding AI and digital technologies in general. Among the responding students, 66.8% reported that they were interested in digital technology, and 47.8% indicated that they knew the subject well. With AI, the equivalent numbers were 35.5% (interested) and 19.5% (knows the subject well). In total, 11.6% of the students had participated in an ICT-themed club, either as a hobby or as an optional subject in school. The most common examples were coding and gaming clubs. AI was not mentioned as a substance. The students were also asked what digital applications they used for schoolwork and leisure. Common examples of software used for schoolwork were platforms such as Microsoft Office 365 and Google Classroom, student administration and communication software "Wilma", and online learning platform "ViLLE." Typical examples of leisure-time software were different digital games (i.e., Minecraft, Fortnite, HayDay), social media applications (i.e., Instagram, Snapchat, TikTok, WhatsApp), and streaming services (i.e., YouTube,

[4] Link to the material was removed to ensure the anonymity of the authors.

Netflix, Spotify).

The data used in the present paper consisted of the responses to five open questions, which inquired about the students' conceptions of AI (see Table 2). In the questionnaire instructions, we emphasized (and instructed the teachers who were conducting the questionnaires) that the questionnaire should be completed alone, that it was not an exam or a test, and that there were no right or wrong answers. To avoid the priming effect identified in previous research (see Selwyn et al., 2020), we avoided value-laden expressions and statements. The open questions were posed in the questionnaire as follows (translated from Finnish into English):

The study followed the practices of ethical research (Finnish National Board of Research Integrity [TENK], 2019) and current legislation on information privacy and data protection (GDPR.EU, 2022). An initial research permit was attained from the educational administration office of the municipality, and a school-specific permit to participate was required from the principals of the participating schools prior to data collection. To ensure the participants' anonymity, we did not gather the names of the schools, classes, or the students. Since no identifiable information was collected, consent from the students' legal guardians was not required [TENK, 2019]. A data management plan was devised and upheld to store the data securely and maintain its integrity.

3.2. Analysis

The abductive method, in which deductive and inductive reasoning are practiced in parallel (Dey, 2003; Suddaby, 2006), was used. Unlike in deductive analysis, in the abductive method, the role of the theory is not tested by the data. Instead, theory and previous research are treated as "threads" (Grönfors, 2011), which can provide working categories for the initial analyses but are a subject to be refined via data-driven interpretations (Mertala, 2020). The main theoretical threads in this study were the stages of AI (Kaplan & Haenlein, 2019), "Big Ideas" in AI (Touretzky et al., 2019) Vygotskian-based idea of everyday concepts (Edwards et al., 2018; Mertala, 2019), existing research on people's conceptions of AI (Cave et al., 2019; Kreinsen & Schultz, 2021; Zhang and Dafoe, 2020), and the public representations of AI (e.g., Brokensha, 2020; Cave & Dihal, 2019; Chuan et al., 2019; Fast & Horvitz, 2017; Jokela, 2018; Obozintsev, 2018; Slotte Dufva & Mertala, 2021).

Table 2
Open questions and their justification.

Questions	Justification
Describe what you think artificial intelligence means.	Provides information about how students understand AI either as a technology or as a concept (Long & Magerko, 2020). We chose to use the term "means" instead of "is" as previous research suggests that children may find it difficult to answer what an abstract concept/technology strictly "is" (Wennås Brante & Walldén, 2021). Thus, we reasoned that "means" would be a more inclusive and open-ended term.
Describe where you think artificial intelligence is or what it is used for.	Provides information about students' conceptions about the practical applications of AI and the contexts it is used (Kreinsen & Schultz, 2021; Long & Magerko, 2020)
Describe how you think artificial intelligence works.	Provides information about students' (mis) conceptions about the technological/ mathematical principles behind AI (e.g. Emmert-Streib et al., 2020; Long & Magerko, 2020; Vartiainen et al., 2021).
Describe why you think artificial intelligence is used.	Provides information about students' (mis) conceptions of the motives behind the use (and development) of AI (Emmert-Streib et al., 2020).
Name any words, things, or objects that you think are related to artificial intelligence	Provides possibility for free-association, which does not require students' to formulate full sentences.

The data were processed through the plagiarism detection software Turnitin to detect that the answers were not copy-pasted from the Internet. As a result, one student's response was excluded, as it was copied from Wikipedia. The data were then organized and coded using the qualitative analysis software Atlas.ti. The actual analysis process was iterative, drawn from the tradition of constant comparison (Boeije, 2002; Fram, 2013)—a common feature of the abductive analysis method (Dey, 2003; Suddaby, 2006). The different phases of the analysis process are explained in more detail in Table 3, and the types of comparisons are outlined in Table 4.

Table 5 provides an example of the codes and the logic used during the analysis process. More data extracts are provided in the Findings section to improve the transparency of the study. On a related note, as our research motive and strategy were exploratory and interpretative (see Biesta, 2010), we opted not to report the exact frequencies of different codes and categories to avoid evaluating the different themes based on their incidence. Numbers are a powerful form of representation, and therefore they should be used with caution—not for the sake of conventionality (see also Sandelowski, 2001). Themes or categories with the highest frequencies are typically considered the main ones. However, the occurrence of a certain conception does not necessarily infer its strength: one conception may be common in data but superficial and easily changed, whereas the other may be less prevalent but more stable. When applicable, we use descriptive terms such as "most, "many", and "few" to inform the reader about the quantitative relations between different categories (see also Sandelowski, 2001).

4. Findings

"AIs are in phones, web browsers, cars, and so on — AI is a coded helper for people and it is coded to do something from words, for example, if a camera or a sensor is connected to a computer where it [AI] is it can make a command from a movement, for example" (Student 117).

The extract above summarizes many of the main themes included in the ways in which the participants conceptualized AI with regard to our three research questions: 1) What kind of technology is AI? 2) Where is AI? and 3) Why is AI used. The student described AI as programmed (coded) technology that uses sensors to capture and process information from its surroundings, such as the motions it detects. The student also commented that AI can be found in common everyday technologies, such as smartphones and internet browsers. Lastly, the student noted

Table 3
Phases of the abductive analysis process in this study.

Phase	Description
1	At the first phase, each of the authors independently familiarized with the data (Säljö, 1997) by reading the students' answers and making notes. Observations and interpretations were then discussed in joint meetings.
2	Author 1 created an initial coding manual. The manual combined the theoretical threads discussed above as well as the observations and inductive interpretations made individually and discussed in Phase 1.
3	Author 3 did the preliminary coding for the data and marked ambiguous parts with a code "unclear." The comment function of Atlas.ti was used to inform the other researchers about new inductively-derived ideas and interpretations. Author 1 and Author 2 separately went through the data, checked Author 3's coding and comments, and left their own suggestions by using the comment function.
4	The results of the first coding round were discussed together with the whole research team. The topics included, for instance, how different codes relate (hierarchically) and interlap with each other (Han & Ellis, 2019). All uncertainties were discussed throughout (Tight, 2016), and new literature was reviewed based on the inductive interpretations. At this point, some of the codes were refined, for instance, by combining codes under a more abstract category.
5	Authors 1, 2, and 3 went through the data, respectively and refined the coding done in the first round of coding.
6	The results of the second coding round were discussed together, and there was a joint agreement that no new codes were needed.

Table 4
Phases of the analysis process.

Type of comparison	Example	Phases
Comparison between theory and data	The initial coding manual which was used as the basis for the first round of coding was grounded on theoretical threads identified from previous research.	2, 5
Comparison between data and theory	Data-driven interpretations led to a review of additional literature to seek whether previous research has identified similar themes as well (e.g., anthropomorphic conceptions of AI).	4
Comparison within data	Comparing and contrasting different codes and categories with each other to understand how relate and overlap with each other (Han & Ellis, 2019)	4
Comparison between the researchers' interpretations	Following the principles of investigator triangulation—the use of two or more researchers to provide multiple observations (Carter et al., 2014) and minimize researcher bias (Tight, 2016)—the data was screened and coded by the whole research team, and the decisions were validated via joint discussions.	1, 3–6

that AI helps people. In what follows, more in-depth accounts of all three research questions are provided in their own subsections, each of which follows a similar logic: a figure summarizing the main themes is provided, followed by a more detailed written account.

4.1. Students' conceptions of the kind of technology AI is

In this section, we present findings regarding the students' conceptions of what kind of technology AI is (see Fig. 1). First, many students conceptualized AI as a **sensory technology** that uses sensors to acquire information from its surroundings. In some cases, the actual term "sensor" was used, as the following excerpts illustrate: "AI works so that many sensors and programmings are used" (Student 18); "It [AI] works with electricity and sensors" (Student 168).

However, more commonly, the presence of sensors was addressed in an implicit manner by referring to the device's ability to capture and process auditory, visual, or spatial information. Sometimes, the presence of sensors was discussed in an abstract manner, with no references to particular devices or software. Instead, as the following extract exemplifies, AI was simply argued to perceive different kinds of information from its surroundings: It [AI] perceives shapes and blocks (Student 107).

In other cases, the presence of sensors was expressed by mentioning specific devices or software and their ability to react to information. Voice commands and voice assistants, such as Siri and Alexa, were common examples of AI with auditory sensors. AI can also be an assistant found on phones, for example, Siri is found on Apple's devices (Student 157); for example, if you say 'open YouTube' to your phone, it opens it (Student 19). Voice assistants also served as an example of what we classified as **obedient technology**, that is, technology that takes commands from the human user. As an obedient technology, AI does not "choose" the tasks it takes care of but does what it is told (as in the case of Siri) or instructed by using some other medium, such as gestures or typed commands.

As the following excerpts illustrate, another prevalent theme was the conceptualization of AI as an **autonomous technology** that conducts tasks with no real-time input from humans (i.e., remote control; Turja, 2021).

> A robot can do things independently. (Student 64)
>
> AI makes decisions by itself. (Student 128)
>
> For example, in games, AI does things independently. (Student 16)

In some cases, the conception of AI as an autonomous technology

Table 5
Coding of a sample data excerpt.

Data extract	Code	Interpretation(s)	Approach
There are many kinds of artificial intelligence. For example, Apple's phones have artificial intelligence called Siri, which answers people's questions when it hears a question for which it can provide an answer (Student 87).[a]	Narrow AI	The student says that there are many kinds of AIs and notes that Siri's capabilities for providing answers are limited: it cannot answer all questions.	Deductive (Stages of AI; Kaplan & Haenlein, 2019)
	Everyday technology	The student explains that AI, namely Siri, can be found from a mobile phone.	Deductive (Everyday concept, e.g., Edwards et al., 2018)
	Media/application	The student notes that AI can take form as a mobile application	Deductive (Everyday concept, e.g., Edwards et al., 2018)
	Sensory technology (explicit)	The student explains that Siri "can hear" the user's voice, which refers to comprehension that AI can be combined with sensor technologies. Extracts in which a student only mentions an AI application that uses sensory technologies (i.e., vacuum robots) with no explicit reference to the sensory are coded with a value "implicit."	Deductive (Touretxky et al., 2019; Vartiainen et al., 2021) and inductive (the division between explicit and implicit forms of sensory technology)
	Anthropomorphism	The student describes Siri's actions with terms "answers" and "hears", which connote human-like actions.	Deductive (Airenti, 2015; Emmert-Streib et al., 2020; Epley et al., 2007)
	Information retrieval	The student explains that people can use Siri to gain information	Inductive
	Obedient technology	The student explains that Siri' follows the user's commands as it answers the questions the user asks from it	Inductive

[a] Some narrative soothing (Polkinghorne, 1995), such as correcting misspelled words, is done to improve the narrative flow of the data extracts. Student 87, for instance, originally spelled Apple with only one p ("Aple").

overlapped with the conception of AI as a **programmed technology**. In such views, AI was conceptualized as initially traditional human-programmed technology, which, in a finished form, can conduct tasks independently. Student 182 wrote that AI is about "programming machines to do things alone." Student 49 expressed a similar idea by stating that "In my view, AI works so that a certain program is programmed into, for example, robots and machines and that's how machines and such operate without humans."

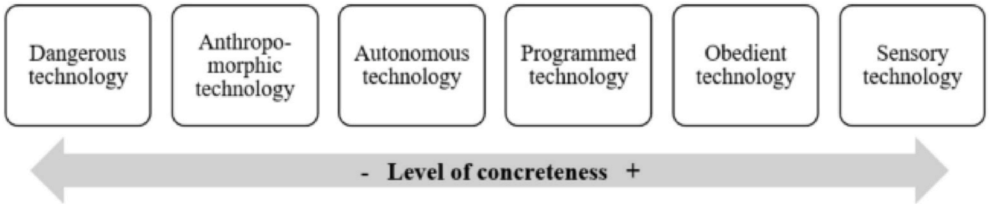

Fig. 1. Students' conceptions of the kind of technology AI is.

The excerpts above also exemplify how AI, as a programmed technology, was described as an overlapping area between obeying technology and autonomous technology in some responses. Put differently, in these responses, programming was conceptualized as preset commands that the robot/machine obeys autonomously with no real-time steering, such as with remote control. The following excerpts provide additional examples of similar arguments.

> [AI is], for example, a human-made robot, which is programmed to do things that are coded in it. (Student 65)

> It [AI] does the thing it is programmed to do. (Student 93)

The excerpts above also contain notable resemblance with the idea of "narrow AI" (Kaplan & Haenlein, 2019), which can only conduct certain predetermined and well-defined tasks. In other words, if the robot Student 65 wrote about was programmed to identify street signs, that would be all it would be able to do. It would not, for example, identify other forms of visual media, such as paintings.

AI was also often described as an **anthropomorphic technology**, that is, a technology that possesses equivalent cognitive qualities as humans. Although one student suggested that "AI can, for example, have its own emotions and personalities" (Student 20), more common were expressions in which anthropomorphism was present as a reference to cognitive processes such as thinking and knowing. The following excerpts provide some representative examples.

> AI means that some devices [have] similar intelligence and knowledge as humans. (Student 4)

> AI means a robot or something other than is not human but acts like a human. (Student 106)

> AI is a skill affiliated with human intelligence, such as reasoning and learning, applied to perceiving the environment and other properties. (Student 2)

In contrast to the idea of narrow AI, the conceptions listed above resemble the definitions of "general and super AI", which are not restricted to conducting certain predetermined tasks but can autonomously solve problems in various areas (general AI) and possess consciousness (super AI) (Kaplan & Haenlein, 2019). Although all forms are hypothetical, none of the extracts above (nor the broader textual context around them) implies that the students would be writing about speculative future technologies. Instead, it appears that they believed such forms of AI already exist. Other students who wrote about anthropomorphic general AI were explicit about the speculative or prospective nature of anthropomorphic AI:

> AI is a human mind but in a machine. It can, for example, think but it has not yet been properly developed. (Student 124)

> AI can, in my opinion, reason like people do. I think it means some kind of future technology. (Student 145)

Lastly, a few students commented that the use of AI also contains risks and threats, describing it as a **dangerous technology**. The downsides were not always specified, as responses such as "it [AI] can be easily used in wrong ways" (Student 14) and "AI might be a good thing, but there shouldn't be too much of it" (Student 21) exemplify. Some students were more specific and explained that the major risks of AI use were world domination or even the end of the world. One student wrote that "eventually, it [AI] will destroy the mankind" (Student 9), while another commented that "it [AI] may become the fate of humanity (Student 11). However, it was not always clear whether the risks and threats were about the ways in which AI could be used (see Section 4.3) or about AI itself.

4.2. Students' conceptions of where AI is

In this section, we report findings regarding students' conceptions of where AI is. Some participants commented that AI is **ubiquitous**, that is, an (almost) omnipresent form of technology by stating that AI is "practically everywhere" (Student 25). Some students, however, were more specific about what the "almost everywhere" (Student 49) meant in practice. Student 9, for example, distinguished between natural and built environments by stating that "AI is everywhere, except in the forest (Student 9). Student 175 was more precise and wrote that "AI is almost everywhere. [It is] in phones, robots, and some workplaces." The concrete examples Student 175 used—robots, (smart)phones, and workplaces—serve as examples of the two derived main categories the students most often referred to: contexts and technological artifacts (see Fig. 2).

Contexts were further divided into three subcategories—**home**, **work**, and **media**—which were present in the data either explicitly or implicitly. The above excerpt from Student 175 serves as an example of an explicit reference to the context of the work. Most other references to work were related to industry, research, or science. Student 106, for instance, wrote that "AI is used in some factories or in other places,

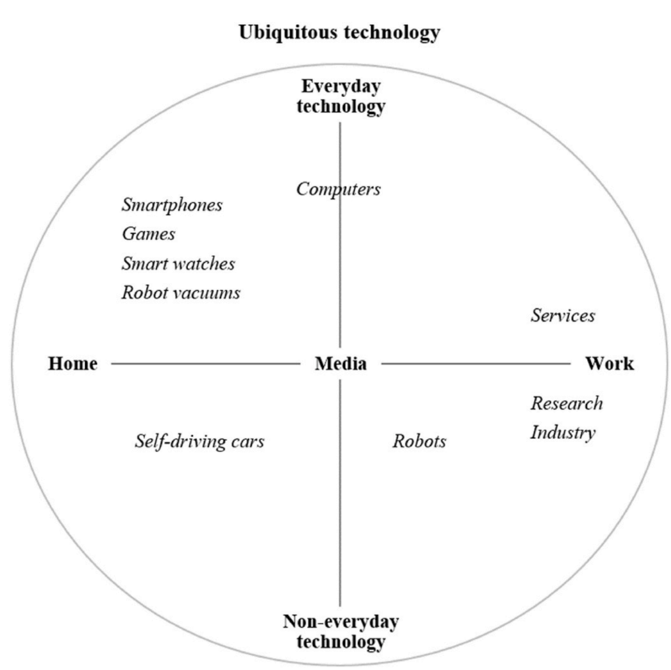

Fig. 2. Students' conceptions of where AI is.

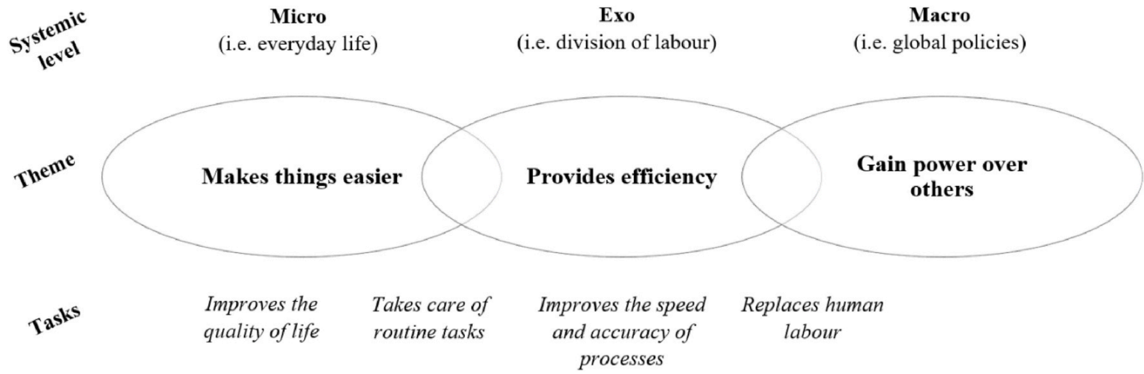

Fig. 3. Students' conceptions of why AI is used.

which might have robots," whereas Student 104 stated that "AI can be used in science."

Industry was also present in Student 14's response that "AI is widely used in teaching, industry, and customer service." The response, however, diversifies the range to include public and commercial services. Science and education (e.g., "schools"; Students 26, 74, 89, 120, "technicians, professors, students, science"; Student 144) and healthcare (e.g., "first aid to recognize diseases" [Student 134]) were examples used from public services, whereas "shops" were one example of commercial services (Student 85). Customer service mentioned by Student 14 can refer to chatbots, which has become a common feature in various public and commercial agents' websites.

Implicit references to contexts included mentions of technologies and activities that typically exist or take place in a certain context. For example, several students commented that (some) digital games use AI. As digital games are typically played during free time, they were placed in the category home/leisure.

> AI is, for example, in the NHL [game] when you play against the computer. (Student 24)

> For instance, in some games, AI can play against you. (Student 141)

As illustrated in Fig. 2, we approach media as a nexus between work and home, as it "occupies more and more spaces in individuals' lives both in intimate and work sphere" (Figueiredo & Bolaño, 2017, p. 26). In many ways, the media acts as a mediator between the intimate and work spheres. Put differently, the everyday (media) technologies people use (at home) contain AI, which works on behalf of companies (work) by gathering and analyzing data from users. This relationship was explicitly addressed in the data from two students. Student 115, for instance, wrote that "it [AI] follows what you do and click and if you look for certain product front the net, you may receive ads of it." In other words, the student explains that AI can be used to collect data from peoples' online activities. These data points can then be analyzed (by AI) to create customer profiles for targeting people with personalized advertisements.

The category of **technological artifacts** was divided into two subcategories: **everyday technology** and **non-everyday technology**. The former label refers to technologies such as "computers, phones, and mobile devices" (Student 15), "smart watches and television" (Student 1) people (in developed Western contexts) have access to and first-hand experiences of, as well as to emerging forms of household technology, such as "a robot vacuum" (Student 3). Non-everyday technology refers to the kinds of technologies that the students were aware of, but which are not, to our knowledge, part of the current landscape of their everyday technology. As the excerpts below illustrate, the most prevalent examples of non-everyday AI technologies were robots (either non-specified or industrial; see also Kreisen & Schultz, 2021; Ottenbreit-Leftwich et al., 2021) and self-driving cars (see also Kerr et al., 2020).

> Automated cars? Robots and computers in general. (Student 122)

> Self-driving cars and robots. (Student 19)

4.3. Students' conceptions of why AI is used

In this section, we present findings regarding the students' conceptions of why AI is used (see Fig. 3). A prominent theme in the data was that **AI makes things easier** for people. Typically, AI as a technological aid was discussed on a rather general level, with no reference to specific tasks handled by AI. Student 179 wrote that AI is used "so that people don't have to do everything by themselves," and Student 13 commented that "it [AI] makes peoples life easier." Some students, however, were more specific in their argumentation, commenting that AI could take care of dull and mechanical routine tasks. One student, for instance, wrote that via AI "all software updates would become ready without taking care of them by yourself (Student 146).

According to students, outsourcing different tasks to AI would lead to a situation where "people would have more time to do other things" (Student 158). A few students connoted the quest for ease with a lack of perseverance. These views were often framed with value-laden expressions suggesting that "people have become lazy" (Student 23) or that "people are lazy" (Student 35), and thus they wish to externalize various tasks for AI-based machines and software. Other students, however, addressed the theme from a more equity- and ethic-related perspective. For them, the ease was about using AI to help people either at a general level (To help people [Student 84]; So that people can be helped [Student 63]) or by referring to specific groups, for example, people with disabilities: "It [AI] can help people with disabilities" (Student 58); "It [AI] helps, for example, elderly and others, like visually impaired, and so on" (Student 103).

Various students approached the need for AI from the perspective of work life. A major work-related theme was that **AI provides efficiency**. As illustrated in the excerpts below, not only can AI take care of different tasks faster than humans, but it can also do so in a more accurate manner.

> In my view, it [AI] is used because we want to become aware in a fast and easy manner, and humans cannot know everything at once. AI also provides correct and exact answers. (Student 139)

> It can conduct hundreds of calculations in fragments of seconds. It does not make similar mistakes as humans, and does not request salary or humane working conditions. (Student 14)

The latter excerpt also serves as an example of the intertwined relationship between efficiency and replacing human labor with AI, which, as the excerpts below illustrate, was a recurrent theme in the data:

AI is used because it is, for example, much easier to use [it] for making machines than if people would make them. (Student 78)

AI is used to make things happen faster, like in factories, where the creation of metal pieces would be a more difficult and slower process for a human. (Student 150)

A comparison of the excerpts above also exemplifies the qualitative differences in students' conceptions. Whereas Students 78 and 150 simply wrote that the use of AI makes certain industrial work processes faster and easier, Student 14, however, took the discussion to a more profound level. Like others, the student first remarked that AI can be more efficient than the use of human labor. Then, they continued by noting that other benefits for the company are that it does not have to pay a salary for AI or provide decent working conditions with reasonable working hours and the possibility for breaks.

As a final example, Student 70 replied "world domination" to the question about what AI is used for. Thus, the student likely meant that a nation or another agent could use AI to **defeat and gain power over others**. The theme of dominance, that is, the use of AI for political and/or military power, is common in the media (Slotte Dufva & Mertala, 2021) and commonly evaluated as a likely future scenario by people (Cave et al., 2019).

5. Discussion

This study explored Finnish school students' pre-instructional conceptions of AI by analyzing open-ended answers that the students provided in a questionnaire. The questionnaire inquired about the students' understanding of what AI means, where it is, what it is used for, how it works, why it is used, and the kinds of terms related to it. The present paper is also the first to include data excerpts that provide a more contextual understanding of children's rationales regarding AI.

Our findings carry similarities and differences relative to previous related research. One example of the similarities is that robots were a common theme (see also Kreisen & Schultz 2021; Ottenbreit-Leftwich et al., 2021). We can think of four not mutually exclusive explanations for the prominence of robots. The first is that a robot gives the abstract concept of AI a concrete form, which also embodies many other themes from the data, including autonomy, anthropomorphism, and provision of help, which can lead to replacement of humans (see also Särkikoski et al., 2020). Second, robots and AI are both something that are programmed, an activity that is being made increasingly familiar to students through curricular revisions around the world. Put differently, robots provide a practical example of a (programmed) technology that applies AI; simultaneously, AI serves as an explanation for robots' capability for autonomous operations. The third explanation is that children's conceptions about AI and (social) robots appear to share similarities, as anthropomorphic conceptions are linked to both (Melson et al., 2009). Lastly, both robots and AI are commonly represented as replacers of the human workforce and providers of help in media texts (e.g., Van Aerschot et al., 2020; Brokensha, 2020; Chuan et al., 2019; Fast & Horvitz, 2017; Slotte Dufva & Mertala, 2021).

The main differences revealed concern the possible negative impacts of AI that were less prominent in our data than in previous studies (e.g., Cave et al., 2019; Kreisen & Schultz, 2021; Selwyn et al., 2020). Differences between our and Kreisen and Schultz's (2021) findings can (at least partly) be explained by the fact that their sample consisted of only twelve students. It is possible that the limited sample produced skewed data in favor of negative or cautious attitudes. Another explanation for the observed differences relates to the data collection procedures. In other studies (e.g., Cave et al., 2019; Selwyn et al., 2020), the respondents were specifically asked to evaluate their concerns or the likelihood of negative effects of AI, which produces different kinds of data than using as value-free instructions as possible—the strategy applied in the present study.

Our findings suggest that while students' conceptions vary, many of them can be categorized as ones involving notions of everyday concepts that arise from informal experiences and observations (Vygotsky, 1987). The students either discussed their firsthand experiences with AI (e.g., interaction with non-player characters in digital games) or included themes prevalent in public discussions in their responses (e.g., self-driving cars; see Slotte Dufva & Mertala, 2021). Similarly, the anthropomorphic (Salles et al., 2020) conceptions identified in the data remind us of the ways in which AI is often portrayed as a sentient and intentional agent in news media (Barassi, 2020; Jokela, 2018; Slotte Dufva & Mertala, 2021), commercials (Hanson Robotics, n.d.), and popular media, such as books and movies (Cave & Dihal, 2019). It is also worthwhile to acknowledge that only 19.5% of the students evaluated their knowledge of AI as good. Thus, many conceptions identified in this study may not be deeply rooted but a subject that can be changed with a moderate amount of effort, a perspective that leads us to the pedagogical implications of the study.

5.1. Pedagogical implications

Our findings suggest that the formation of an accurate scientific conception of AI is unlikely to happen through mere informal learning among primary school students. Thus, while seeking to improve students' critical capabilities to make sense of their surrounding worlds now and in the future, our findings support the call for including a form of "AI literacy" in the curricula of compulsory education (e.g., Lee et al., 2021; Long & Magerko, 2020; Vartiainen et al., 2020; 2021; Yang, 2022) as well as contribute to forming the knowledge base for these curricula to build upon.

First, it should be noted that references to the role of data in training of AI-applications were practically non-existent in our sample. While teaching children about data is included in various AI -literacy frameworks (e.g., Kreinsen & Schulz, 2021, October; Long & Magerko, 2020; Touretzky et al., 2019) it is sometimes brought up in a rather late stage (Kreinsen & Schulz, 2021, October). The lack of data-related conceptions in our study suggests that it might be beneficial to introduce the role of data already in the early stages given its crucial role in many AI applications. This recommendation is supported by the fact that, as in the case of AI, children's and adolescents' pre-instructional conceptions of digital data are often inadequate or erroneous (Pangrazio & Selwyn, 2018).

Second, several students appeared to possess anthropomorphic conceptions with notable resemblance with the (still) hypothetical general AI (see Kaplan & Haenlein, 2019). Thus, in line with Long and Magerko (2020) we argue that distinguishing between narrow and general AI is one of the most important contents of AI literacy education in K-12 contexts. There is emerging evidence that everyday encounters with human-like AI such as voice assistants support the development of anthropomorphic conceptions (Szczuka et al., 2022). Thus, it would be valuable to "demystify" AI by exploring the technical principles of the "human-like" AI solutions students encounter in their everyday life. Besides voice assistants, non-player characters of digital games could provide a meaningful case as they were brought up by various participants. The demand of demystification applies to the human-like AI used in schools as well. There is a growing interest towards using AI-enabled social robots (and other kinds of virtual pedagogical agents) already with the youngest of learners (see, e.g., Timms, 2016; Woo et al., 2021) and their use can intensify the development of anthropomorphic conceptions if no alternative explanations are provided (Hughes et al., 1987).

Another possible source for anthropomorphic conceptions is the way how AI is portrayed in news media and popular culture (Cave & Dihal, 2019; Sulmont et al., 2019). Therefore, we see that it is vital to help students to become aware of AI-related influences (e.g., super AI taking over the world) they encounter in media texts, and critically investigate whether some of those influences are only imaginative or whether they are actual risks to be collectively avoided (see also Long & Magerko,

2020) - a notion that builds bridges between AI-literacy and media literacy.

Talking about media literacy, it is important to acknowledge that only two students mentioned the role of AI (and data) in personalized and predictive marketing in online media environments, and that no students mentioned deep fakes or other AI generated media. Various scholars have stressed that AI literacy (and big data) cannot be (fully) distinguished from media literacy in the age of big data and machine learning (see, e.g., Jandric, 2019; Valtonen et al., 2019;Zhang et al., 2022). We agree with these views and recommend that AI-generated media and marketing is explicitly included as a one sub-topic of the societal impact of AI, which is part of various AI literacy frameworks (see Kreinsen & Schulz, 2021, October; Long & Magerko, 2020).

5.2. Limitations and implications for future research

Although this study has provided new and useful information on children's conceptions of AI, it is not without its limitations. Our data were localized to the Finnish context, and it was attained with convenience sampling (see Patton, 2014). Thus, the results may not fully represent the population, nor can they be generalized to apply in other contexts without critical reflection. Comparative studies could provide additional information, as previous research has identified variations in attitudes toward AI and autonomous robots by people living in different geographical and cultural areas (e.g., Dang & Liu, 2021, 2022; see also Druga et al., 2019). Further, the online survey method (i.e., typed answers to questions) may have important details regarding the students' conceptions, although this method allowed us to attain a higher number of responses.

The exploratory nature of our research design restricted us from investigating the possible connections between students' conceptions and their background variables, such as socioeconomic status of the family, technological skills, hobbies or interests, or gender of the respondent. In research on adult populations, university degree on programming/computer science/engineering, and high socioeconomic status and educational levels in general are connected to higher self-evaluated AI knowledge (Selwyn et al., 2020). Research has also found a negative correlation between primary and secondary school students' digital skills and family income and parents' educational level (Leino et al., 2019; Tanhua-Piiroinen et al., 2019). These two notions imply a strong relationship between socioeconomic status and technological capital that favors those in advantage positions. Thus, further exploration in the context of AI is needed to improve educational and societal equity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Airenti, G. (2015). The cognitive bases of anthropomorphism: From relatedness to empathy. *International Journal of Social Robotics, 7*(1), 117–127. https://doi.org/10.1007/s12369-014-0263-x

Andrejevic, M., & Selwyn, N. (2020). Facial recognition technology in schools: Critical questions and concerns. *Learning, Media and Technology, 45*(2), 115–128. https://doi.org/10.1080/17439884.2020.1686014

Bao, L., Krause, N. M., Calice, M. N., Scheufele, D. A., Wirz, C. D., Brossard, D., … Xenos, M. A. (2022). Whose AI? How different publics think about AI and its social impacts. *Computers in Human Behavior, 130*, Article 107182. https://doi.org/10.1016/j.chb.2022.107182

Barassi, V. (2020). *Child data citizen: How tech companies are profiling us from before birth.* MIT Press.

Biber, Ç., Tuna, A., & Korkmaz, S. (2013). The mistakes and the misconceptions of the eighth grade students on the subject of angles. *European Journal of Science and Mathematics Education, 1*(2), 50–59. https://doi.org/10.30935/scimath/9387

Biesta, G. (2010). Pragmatism and the philosophical foundations of mixed methods research. In A. Tashakkori, & C. Teddlie (Eds.), *Sage handbook of mixed methods in social and behavioral research* (2nd ed., pp. 95–118). Sage.

Boeije, H. (2002). A purposeful approach to the constant comparative method in the analysis of qualitative interviews. *Quality and Quantity, 36*(4), 391–409.

Brokensha, S. (2020). Friend or foe? How online news outlets in South Africa frame artificial intelligence. *Ensovoort: Journal of Cultural Studies, 41*(7). http://ensovoort.co.za/index.php/2020/07/02/friend-or-foe-how-online-news-outlets-in-south-africa-frame-artificial-intelligence/.

Carter, N., Bryant-Lukosius, D., Alba DiCenso, R. N., Blythe, J., & Neville, A. (2014). The use of triangulation in qualitative research. *Oncology Nursing Forum, 41*(5), 545–547.

Carvalho, L., Martinez-Maldonado, R., Tsai, Y. S., Markauskaite, L., & De Laat, M. (2022). How can we design for learning in an AI world? *Computers and Education: Artificial Intelligence, 3*, Article 100053. https://doi.org/10.1016/j.caeai.2022.100053

Cave, S., Coughlan, K., & Dihal, K. (2019, January). Scary robots" examining public responses to AI. In *Proceedings of the 2019 AAAI/ACM Conference on AI* (pp. 331–337). Ethics, and Society. https://doi.org/10.1145/3306618.3314232.

Cave, S., Craig, C., Dihal, K., Dillon, S., Montgomery, J., Singler, B., & Taylor, L. (2018). *Portrayals and perceptions of AI and why they matter.* The Royal society. https://royalsociety.org/-/media/policy/projects/ai-narratives/AI-narratives-workshop-findings.pdf.

Cave, S., & Dihal, K. (2019). Hopes and fears for intelligent machines in fiction and reality. *Nature Machine Intelligence, 1*(2), 74–78. https://doi.org/10.1038/s42256-019-0020-9

Chao, P. J., Hsu, T. H., Liu, T. P., & Cheng, Y. H. (2021). Knowledge of and competence in artificial intelligence: Perspectives of Vietnamese digital-native students. *IEEE Access, 9*, 75751–75760. https://doi.org/10.1109/access.2021.3081749

Chuan, C. H., Tsai, W. H. S., & Cho, S. Y. (2019, January). Framing artificial intelligence in American newspapers. In *Proceedings of the 2019 AAAI/ACM Conference on AI* (pp. 339–344). Ethics, and Society. https://doi.org/10.1145/3306618.3314285.

Dang, J., & Liu, L. (2021). Robots are friends as well as foes: Ambivalent attitudes toward mindful and mindless AI robots in the United States and China. *Computers in Human Behavior, 115*, Article 106612. https://doi.org/10.1016/j.chb.2020.106612

Dang, J., & Liu, L. (2022). Implicit theories of the human mind predict competitive and cooperative responses to AI robots. *Computers in Human Behavior, 134*, Article 107300. https://doi.org/10.1016/j.chb.2022.107300

Dey, I. (2003). *Qualitative data analysis: A user-friendly guide for social scientists.* Routledge.

Druga, S., Vu, S. T., Likhith, E., & Qiu, T. (2019). Inclusive AI literacy for kids around the world. *Proceedings of FabLearn*, 104–111. https://doi.org/10.1145/3311890.3311904, 2019, March.

Druga, S., Williams, R., Breazeal, C., & Resnick, M. (2017, June). Hey Google is it ok if I eat you?" Initial explorations in child-agent interaction. In *Proceedings of the 2017 conference on interaction design and children* (pp. 595–600). https://doi.org/10.1145/3078072.3084330

Druga, S., Williams, R., Park, H. W., & Breazeal, C. (2018, June). How smart are the smart toys? Children and parents' agent interaction and intelligence attribution. In *Proceedings of the 17th ACM Conference on interaction Design and children* (pp. 231–240). https://doi.org/10.1145/3202185.3202741

Edwards, S., Nolan, A., Henderson, M., Mantilla, A., Plowman, L., & Skouteris, H. (2018). Young children's everyday concepts of the internet: A platform for cyber-safety education in the early years. *British Journal of Educational Technology, 49*(1), 45–55. https://doi.org/10.1111/bjet.12529

Elements of AI. n.d https://www.elementsofai.com/.

Emmert-Streib, F., Yli-Harja, O., & Dehmer, M. (2020). Artificial intelligence: A clarification of misconceptions, myths and desired status. *Frontiers in Artificial Intelligence, 3*, Article 524339. https://doi.org/10.3389/frai.2020.524339

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864–886. https://doi.org/10.1037/0033-295x.114.4.864

Eskelä-Haapanen, Sirpa, & Kiili, Carita (2019). 'It Goes Around the World' – Children's Understanding of the Internet. *Nordic Journal of Digital Literacy, 14*(3–4), 175–187. https://doi.org/10.18261/issn.1891-943x-2019-03-04-07.

Fast, E., & Horvitz, E. (2017, February). Long-term trends in the public perception of artificial intelligence. In *Proceedings of the AAAI Conference on artificial intelligence* (Vol. 31, pp. 963–969), 1 https://dl.acm.org/doi/10.5555/3298239.3298381.

Figueiredo, Carlos, & Bolaño, César (2017). Social Media and Algorithms: Configurations of the Lifeworld Colonization by New Media. *International Review of Information Ethics, 26*, 26–38. https://doi.org/10.29173/irie277.

Finnish National Board of Research Integrity. (2019). *The ethical principles of research with human participants and ethical review in the human sciences in Finland. TENK Guidelines* (Vol. 3). https://tenk.fi/sites/default/files/2021-01/Ethical_review_in_human_sciences_2020.pdf.

Fjelland, R. (2020). Why general artificial intelligence will not be realized. *Humanities and Social Sciences Communications, 7*(10). https://doi.org/10.1057/s41599-020-0494-4

Fram, S. M. (2013). The constant comparative analysis method outside of grounded theory. *Qualitative Report, 18*(1), 1–25. https://doi.org/10.46743/2160-3715/2013.1569

GDPR.EU. (2022). *Complete guide to GDPR compliance*. https://gdpr.eu/.

Gonzalez, M. F., Liu, W., Shirase, L., Tomczak, D. L., Lobbe, C. E., Justenhoven, R., & Martin, N. R. (2022). Allying with AI? Reactions toward human-based, AI/ML-based, and augmented hiring processes. *Computers in Human Behavior, 130*, Article 107179. https://doi.org/10.1016/j.chb.2022.107179

Grönfors, M. (2011). *Laadullisen tutkimuksen kenttätyömenetelmät.* SoFia-Sosiologi-Filosofiapu Vilkka.

Han, F., & Ellis, R. A. (2019). Using phenomenography to tackle key challenges in science education. *Frontiers in Psychology, 10*, 1414. https://doi.org/10.3389/fpsyg.2019.01414

Hanson Robotics. Sophia. n.d. https://www.hansonrobotics.com/sophia/

Hughes, M., Brackenridge, A., & Macleod, H. (1987). Children's ideas about computers. In J. Rutkowska, & C. Crook (Eds.), *Computers, cognition and development: Issues for psychology and education* (pp. 9–34). Wiley.

Jandrić, P. (2019). The postdigital challenge of critical media literacy. *The International Journal of Critical Media Literacy, 1*(1), 26–37.

Jokela, J. (2018). *Tekoälydiskurssit vuoden 2017 verkkouutisissa*. Tampere University [Master's thesis] https://trepo.tuni.fi/handle/10024/104918.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kerr, A., Barry, M., & Kelleher, J. D. (2020). Expectations of artificial intelligence and the performativity of ethics: Implications for communication governance. *Big Data & Society, 7*(1). https://doi.org/10.1177/2053951720915939

Kim, S., Jang, Y., Kim, W., Choi, S., Jung, H., Kim, S., & Kim, H. (2021, May). Why and what to teach: AI curriculum for elementary school. *Proceedings of the AAAI Conference on Artificial Intelligence, 37*(17), 15569–15576.

Kreinsen, M., & Schulz, S. (2021, October). Students' conceptions of artificial intelligence. In *The 16th workshop in primary and secondary computing education* (pp. 1–2). https://doi.org/10.1145/3481312.3481328

Kurzweil, R. (1990). *The age of intelligent machines*. MIT Press.

Laakasuo, M., Visala, A., & Palomäki, J. P. (2020). Kuinka ihmismieli vääristää keskustelua tekoälyn riskeistä ja etiikasta–Kognitiotieteellisiä näkökulmia keskusteluun. *Ajatus, 77*(1), 131–168. https://journal.fi/ajatus/article/view/100252.

Leaton Gray, S. (2020). Artificial intelligence in schools: Towards a democratic future. *London Review of Education, 18*(2), 163–177. https://doi.org/10.14324/LRE.18.2.02

Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021, March). Developing middle school students' AI literacy. In *Proceedings of the 52nd ACM technical Symposium on computer science education* (pp. 191–197). https://doi.org/10.1145/3408877.3432513

Leino, K., Rikala, J., Puhakka, E., Niilo-Rämä, M., Sirén, M., & Fagerlund, J. (2019). *Digiloikasta digitaitoihin. Kansainvälinen monilukutaidon ja ohjelmoinnillisen ajattelun tutkimus (ICILS 2018)*. Finnish Institute for Educational Research: University of Jyväskylä. https://jyx.jyu.fi/handle/123456789/66250.

Li, Xinge, & Sung, Yongjun (2021). Anthropomorphism brings us closer: The mediating role of psychological distance in User–AI assistant interactions. *Computers in Human Behavior, 118*, Article 106680. https://doi.org/10.1016/j.chb.2021.106680.

Liang, Y., & Lee, S. A. (2017). Fear of autonomous robots and artificial intelligence: Evidence from national representative data with probability sampling. *International Journal of Social Robotics, 9*(3), 379–384. https://doi.org/10.1007/s12369-017-0401-3

Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1–16). https://doi.org/10.1145/3313831.3376727

Lovato, S., & Piper, A. M. (2015, June). Siri, is this you?" Understanding young children's interactions with voice input systems. In *Proceedings of the 14th international conference on interaction design and children* (pp. 335–338). https://doi.org/10.1145/2771839.2771910

Maier, S. B., Jussupow, E., & Heinzl, A. (2019). Good, bad, or both? Measurement of physician's ambivalent attitudes towards AI. In *Proceedings of the 27th European conference on information systems (ECIS)*. Sweden: Stockholm & Uppsala. https://aisel.aisnet.org/ecis2019_rp/115. June 8-14, 2019.

Marton, F. (1981). Phenomenography—describing conceptions of the world around us. *Instructional Science, 10*(2), 177–200. https://doi.org/10.1007/bf00132516

Melson, G. F., Kahn, P. H., Jr., Beck, A., Friedman, B., Roberts, T., Garrett, E., & Gill, B. T. (2009). Children's behavior toward and understanding of robotic and living dogs. *Journal of Applied Developmental Psychology, 30*(2), 92–102. https://doi.org/10.1016/j.appdev.2008.10.011

Merikivi, J., Myllyniemi, S., & Salasuo, M. (2016). *Media hanskassa: Lasten ja nuorten vapaa-aikatutkimus*. Nuorisotutkimusseura.

Mertala, P. (2019). Young children's conceptions of computers, code, and the Internet. *International Journal of Child-Computer Interaction, 19*, 56–66. https://doi.org/10.1016/j.ijcci.2018.11.003

Mertala, P. (2020). Young children's perceptions of ubiquitous computing and the Internet of Things. *British Journal of Educational Technology, 51*(1), 84–102. https://doi.org/10.1111/bjet.12821

Ministry of education and culture (n.d). Ryhmäkokoselvitykset. https://okm.fi/ryhmakokoselvitykset.

Ministry of Economic Affairs and Employment. (2019). *Leading the way into the age of artificial intelligence Final report of Finland's Artificial Intelligence Programme 2019*. Publications of the Ministry of Economic Affairs and Employment: Competition and consumers: 41 https://julkaisut.valtioneuvosto.fi/bitstream/handle/10024/161688/41_19_Leading%20the%20way%20into%20the%20age%20of%20artificial%20intelligence.pdf?sequence=4.

Ng, D. T. K., Luo, W., Chan, H. M. Y., & Chu, S. K. W. (2022). Using digital story writing as a pedagogy to develop AI literacy among primary students. *Computers and Education: Artificial Intelligence, 3*, Article 100054. https://doi.org/10.1016/j.caeai.2022.100054

Obozintsev, L. (2018). *From Skynet to Siri: An exploration of the nature and effects of media coverage of artificial intelligence*. University of Delaware [Master's thesis] https://udspace.udel.edu/handle/19716/24048.

Official Statistics of Finland. (2021). *Use of information and communications technology by individuals* [e-publication]. ISSN=2341-8710. 2021. Statistics Finland http://www.stat.fi/til/sutivi/2021/sutivi_2021_2021-11-30_tie_001_en.html.

Ottenbreit-Leftwich, A., Glazewski, K., Jeon, M., Hmelo-Silver, C., Mott, B., Lee, S., & Lester, J. (2021, March). How do elementary students conceptualize artificial intelligence?. In *Proceedings of the 52nd ACM technical Symposium on computer science education* (p. 1261). https://doi.org/10.1145/3408877.3439642, 1261.

Pangrazio, L., & Selwyn, N. (2018). It's not like it's life or death or whatever": Young people's understandings of social media data. *Social Media+ Society, 4*(3). https://doi.org/10.1177/2056305118787808

Parviainen, J. (2021). Tekoäly talouden, tieteen ja politiikan risteyskohdassa: Humanoidirobotti Sophian mediaspektaakkeli. In P. Raatikainen (Ed.), *Tekoäly, ihminen ja yhteiskunta: Filosofisia näkökulmia* (pp. 235–258). Gaudeamus.

Patton, M. Q. (2014). *Qualitative research & evaluation methods: Integrating theory and practice*. Sage.

Pelau, C., Dabija, D. C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior, 122*, Article 106855. https://doi.org/10.1016/j.chb.2021.106855

Polkinghorne, D. (1995). Narrative configuration in qualitative analysis. *International Journal of Qualitative Studies in Education, 8*(1), 5–23. https://doi.org/10.1080/0951839950080103

Rücker, M. T., & Pinkwart, N. (2016). Review and discussion of children's conceptions of computers. *Journal of Science Education and Technology, 25*(2), 274–283. https://doi.org/10.1007/s10956-015-9592-2

Säljö, R. (1997). Talk as data and practice—a critical look at phenomenographic inquiry and the appeal to experience. *Higher Education Research and Development, 16*(2), 173–190. https://doi.org/10.1080/0729436970160205

Salles, A., Evers, K., & Farisco, M. (2020). Anthropomorphism in AI. *AJOB neuroscience, 11*(2), 88–95. https://doi.org/10.1080/21507740.2020.1740350

Sandelowski, M. (2001). Real qualitative researchers do not count: The use of numbers in qualitative research. *Research in Nursing & Health, 24*(3), 230–240. https://doi.org/10.1002/nur.1025

Särkikoski, T., Turja, T., & Parviainen, J. (2020). *Robotin hoiviin? Yhteiskuntatieteen ja filosofian näkökulmia palvelurobotiikkaan*. Vastapaino.

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards artificial intelligence scale. *Computers in Human Behavior Reports, 1*, Article 100014. https://doi.org/10.1016/j.chbr.2020.100014

Selwyn, N., Cordoba, B. G., Andrejevic, M., & Campbell, L. (2020). *AI for social good: Australian public attitudes toward AI and society*. Monash University. https://www.monash.edu/data-futures-institute/news/ai-for-social-good-australian-public-attitudes-toward-ai-and-society.

Severson, R. L., & Carlson, S. M. (2010). Behaving as or behaving as if? Children's conceptions of personified robots and the emergence of a new ontological category. *Neural Networks, 23*(8–9), 1099–1103. https://doi.org/10.1016/j.neunet.2010.08.014

Slotte Dufva, T., & Mertala, P. (2021). Sähköä ja alkemiaa: Tekoälydiskurssit Yleisradion verkkoartikkeleissa. *Media & Viestintä, 44*(1), 95–115. https://doi.org/10.23983/mv.107302

Southgate, E., Blackmore, K., Pieschl, S., Grimes, S., McGuire, J., & Smithers, K. (2019). *Artificial intelligence and emerging technologies in schools: A research report*. Australia: University of Newcastle.

Suddaby, R. (2006). From the editors: What grounded theory is not. *Academy of Management Journal, 49*(4), 633–642. https://doi.org/10.5465/amj.2006.22083020

Sulmont, E., Patitsas, E., & Cooperstock, J. R. (2019, February). Can you teach me to machine learn?. In *Proceedings of the 50th ACM technical Symposium on computer science education* (pp. 948–954). https://doi.org/10.1145/3287324.3287392

Su, J., & Zhong, Y. (2022). Artificial Intelligence (AI) in early childhood education: Curriculum design and future directions. *Computers and Education: Artificial Intelligence, 3*, Article 100072. https://doi.org/10.1016/j.caeai.2022.100049

Su, J., Zhong, Y., & Ng, D. T. K. (2022). A meta-review of literature on educational approaches for teaching AI at the K-12 levels in the Asia-Pacific region. In *Computers and education* (Vol. 100065). Artificial Intelligence. https://doi.org/10.1016/j.caeai.2022.100065

Szczuka, J. M., Strathmann, C., Szymczyk, N., Mavrina, L., & Krämer, N. C. (2022). How do children acquire knowledge about voice assistants? A longitudinal field study on children's knowledge about how voice assistants store and process data. *International Journal of Child-Computer Interaction, 33*, Article 100460. https://doi.org/10.1016/j.ijcci.2022.100460

Tanhua-Piiroinen, E., Kaarakainen, S. S., Kaarakainen, M. T., Viteli, J., Syvänen, A., & Kivinen, A. (2019). *Digiajan peruskoulu. Valtioneuvoston selvitys ja tutkimustoiminnan julkaisusarja 6*. https://julkaisut.valtioneuvosto.fi/handle/10024/161383.

Tedre, M., Toivonen, T., Kahila, J., Vartiainen, H., Valtonen, T., Jormanainen, I., & Pears, A. (2021). *Teaching machine learning in K-12 computing education: Potential and pitfalls*. https://doi.org/10.48550/arXiv.2106.11034. *ARXIV*.

Tight, M. (2016). Phenomenography: The development and application of an innovative research design in higher education research. *International Journal of Social Research Methodology, 19*(3), 319–338.

Timms, M. J. (2016). Letting artificial intelligence in education out of the box: Educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education, 26*(2), 701–712. https://doi.org/10.1007/s40593-016-0095-y

Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019, July). Envisioning AI for K-12: What should every child know about AI. In *Proceedings of the AAAI conference on artificial intelligence* (pp. 9795–9799). https://doi.org/10.1080/13645579.2015.1010284

Turja, T. (2021). Robotit hoitajin silmin. In T. Särkikoski, T. Turja, & J. Parviainen (Eds.), *Robotin hoiviin? Yhteiskuntatieteen ja filosofian näkökulmia palvelurobotiikkaan* (pp. 149–184). Vastapaino.

Zhang, Helen, Lee, Irene, Safinah, Ali, DiPaola, Daniella, Cheng, Yihong, & Breazeal, Cynthia (2022). Integrating Ethics and Career Futures with Technical Learning to Promote AI Literacy for Middle School Students: An Exploratory Study. *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-022-00293-3.

Uudet lukutaidot.(2022). https://uudetlukutaidot.fi/.

Valtonen, T., Tedre, M., Mäkitalo, K., & Vartiainen, H. (2019). Media literacy education in the age of machine learning. *Journal of Media Literacy Education, 11*(2), 20–36. https://doi.org/10.23860/JMLE-2019-11-2-2

Van Aerschot, L., Hämäläinen, A., & Pirhonen, J. P. T. (2020). Robotiikasta apua hoivaankin? In T. Särkikoski, T. Turja, & J. Parviainen (Eds.), *Robotin hoiviin: Yhteiskuntatieteen ja filosofian näkökulmia palvelurobotiikkaan* (pp. 115–147). Vastapaino.

Vartiainen, H., Tedre, M., & Valtonen, T. (2020). Learning machine learning with very young children: Who is teaching whom? *International Journal of Child-Computer Interaction, 25*, Article 100182. https://doi.org/10.1016/j.ijcci.2020.100182

Vartiainen, H., Toivonen, T., Jormanainen, I., Kahila, J., Tedre, M., & Valtonen, T. (2021). Machine learning for middle schoolers: Learning through data-driven design. *International Journal of Child-Computer Interaction, 29*, Article 100281. https://doi.org/10.1016/j.ijcci.2021.100281

Vygotsky, L. S. (1987). *The collected works of LS Vygotsky: The fundamentals of defectology* (Vol. 2). Springer Science & Business Media.

Wennås Brante, E., & Walldén, R. (2021). *Internet? That's an app you can download". First-Graders use linguistic resources to describe internet and digital information. Education inquiry*. https://doi.org/10.1080/20004508.2021.1950273

Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology, 45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

Woo, H., LeTendre, G. K., Pham-Shouse, T., & Xiong, Y. (2021). The use of social robots in classrooms: A review of field-based studies. *Educational Research Review, 33*, Article 100388. https://doi.org/10.1016/j.edurev.2021.100388

Yang, W. (2022). Artificial intelligence education for young children: Why, what, and how in curriculum design and implementation. *Computers and Education: Artificial Intelligence, 3*, Article 100061. https://doi.org/10.1016/j.caeai.2022.100061

Zhang, B., & Dafoe, A. (2020, February). US public opinion on the governance of artificial intelligence. In *Proceedings of the AAAI/ACM conference on AI* (pp. 187–193). Ethics, and Society. https://doi.org/10.1145/3375627.3375827.