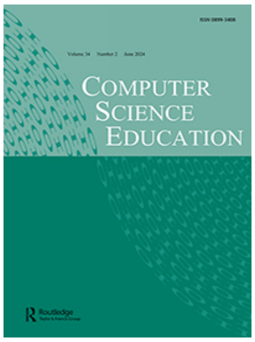
Exploring young people's perceptions and discourses of technology occupations through descriptive drawings and a questionnaire



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Exploring young people's perceptions and discourses of technology occupations through descriptive drawings and a questionnaire

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ABSTRACT

Background and Context: Cultural and social influences from peers, family, and media shape young people's views on technology careers. This study examines Danish students' perceptions and discourses of IT professionals and technology occupations.
Objective: Unlike earlier studies focusing on science or STEM as a monolith, this study specifically addresses technology through *descriptive drawings* and *Latent Profile Analysis* (LPA).
Method: We analyse Danish students' (aged 14–15) perceptions and discourses of IT professionals through descriptive drawings (N = 1,155) and LPA applied to close-ended items from a large questionnaire (N = 1,456).
Findings: Thematic analysis identified six groups of IT professionals: 1) Sedentary, 2) Antisocial and Nerdy, 3) Sad, 4) Ordinary, 5) Smart, and 6) Kind. The LPA identified four profiles, revealing complex subtleties in students' perceptions.
Implications: Implications for practice and future research are suggested, highlighting the potential benefits of combining these methods to explore young people's constructions of IT professionals.

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KEYWORDS
Latent profile analysis; DAST; perceptions; stereotypes; STEM; technology

Introduction

Since the late 1990s, there has been a proliferation of technological advances that have transformed the way we live, work, and interact with each other. More and more young people today grow up surrounded by digital technologies, and the number of digital users continues to grow as technology increasingly permeates everyday life (Engineering the future, 2018; Johnson et al., 2020; National Science Board, 2022). Although it is tempting to assume that the younger generation's greater exposure to digital technologies will lead to an abundance of digital talent in the workforce, this is not necessarily the case (Archer & DeWitt, 2016; Wong, 2016). Despite efforts to increase the number of young people opting for technical

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higher education (Faber et al., 2020; Sandager, 2022), a significant divide exists between those who consume technology and those who can create or produce digital artifacts, particularly as specialists (Eurostat, 2023; National Science Board, 2022; World Economic Forum, 2022). The digital literacy divide is a major concern, especially by gender, with boys seemingly receiving greater encouragement or support in their aspirations for a career in technology (Breda et al., 2020a; Hamer et al., 2023; Stoet & Geary, 2018; Wong, 2016). While many factors can contribute to the formation of technology-related aspirations, research suggests that individuals are unlikely to aspire to and pursue a career if they or significant others in their local environment hold perceptions of that field that are either negative or not aligned with their self-concept (Cheryan et al., 2017; Master et al., 2016; van Tuijl & van der Molen, 2016; Wang & Degol, 2013). This paper explores how young people (aged 14–15) in Denmark perceive IT professionals, using a large set of descriptions and student-drawn images ($N = 1{,}155$), as well as students' responses to closed-ended survey questions ($N = 1{,}456$). We make at least two contributions to existing literature. First, we extend previous research on students' perceptions by specifically examining students' perceptions of IT professionals. Although some studies have examined students' perceptions of IT professionals, computer scientists, software engineers, and similar roles, existing research on children and young people's perceptions in these areas are still limited compared to studies focusing on science or STEM in general (Cheryan et al., 2017; de Wit et al., 2021). While STEM as an umbrella discipline is an important and popular acronym, disciplinary differences remain (Cheryan et al., 2017; Gligorić et al., 2022; Martins et al., 2021; Reinholz et al., 2019). We argue that STEM cannot always be adequately treated as a monolith as doing so fails to capture the unique cultures within the constituent disciplines. Second, while previous Draw-A-Scientist Tests (DAST) or equivalent studies have focused on physical appearance, we extend this approach by employing and combining different methods and analytical techniques to examine students' perceptions, thus contributing to an ongoing discussion concerning appropriate measures for understanding students' perceptions (see, for instance, Ferguson & Lezotte, 2020; Toma et al., 2022). More specifically, we explore the use of *descriptive drawings*, an extension of DAST, and Latent Profile Analysis, which is an underutilized statistical method in educational research focusing on students' perceptions of the field of technology. While this study does not examine whether students' perceptions predict their aspirations or motivation for a career in technology, it helps us better understand the content of students' perceptions of IT professionals by combining different data sources and analytical techniques. By *IT professionals*, we mean individuals who are specifically trained and employed in roles related to information technologies and systems, such as software developers, IT support specialists, computer scientists, and network administrators. Specifically, we explore the following questions:

(1) What characterizes the perceptions and discourses of IT professionals among Danish students aged 14-15?
(2) To what extent do boys and girls perceive IT professionals differently?

Background

Conceptual clarity of occupational perceptions

In educational research, students' perceptions of different occupations are recognized as a significant factor in shaping achievement-related behavior (Cheryan et al., 2017; Master et al., 2016; van Tuijl & van der Molen, 2016; Wang & Degol, 2013). Occupational perceptions are dynamic and encompass an individual's images of various occupational groups within society (Birnbaum & Somers, 1989; Fiske et al., 2002; Gottfredson, 1981; Stockard & McGee, 1990). These perceptions can range from vague and uncertain ideas to more precise and fixed notions about different occupations, becoming increasingly concrete as individuals grow older (Gottfredson, 1981). Students' perceptions are socially constructed through their ongoing interactions with individual and contextual factors, including various media, broader cultural discourses in society, personal experience, role models, peers, parents, and teachers (Archer & DeWitt, 2016; Gottfredson, 1981; Grandy & Mavin, 2012). The representation of different occupational groups by these factors can significantly influence the formation of students' perceptions of different fields (Archer & DeWitt, 2016; Eccles & Wigfield, 2020). Perceptions and stereotypes are often used interchangeably when investigating individuals' views of the world of work. However, we use "stereotype" to refer to over-generalized, often negative beliefs about an occupational group, while "perceptions" is used when aiming to avoid these negative connotations (American Psychological Association, 2019; Gottfredson, 1981; Schmader, 2023). Previously identified STEM stereotypes include views of scientists as nerdy, socially awkward, sedentary, and unpopular (Archer et al., 2013; Berg et al., 2018; Cheryan et al., 2017; Wong, 2016). These stereotypes have been linked to negative attributes by students or views such as "not for me" or "only for brainy peers" (Archer & DeWitt, 2016; Brumovska et al., 2022).

Young people perceive and construct IT professionals in multifaceted ways, encompassing different aspects of both the people working in technology (e.g. physical appearance and personal attributes) and of the work they do (e.g. work and task characteristics and the work's significance on society) (Cheryan et al., 2015; Gottfredson, 1981).

Micro – macro interactions: do perceptions predict aspirations?

The formal study of students' perceptions of scientists dates back to Mead and Métraux's (1957) research, which revealed, among other things, that students often associated scientists with old or middle-aged men wearing lab coats and glasses, conducting experiments alone in laboratories. Despite variations in students' perceptions of individuals in STEM across different studies and contexts (Farland-Smith, 2009; Ferguson & Lezotte, 2020), numerous studies have consistently reported similar findings to those identified in Mead and Métraux's seminal study while adding additional perceived stereotypical characteristics, such as that people in STEM have certain innate abilities, are geeky, socially awkward and unpopular (Archer & DeWitt, 2016; Brumovska et al., 2022; Chang et al., 2020; Finson, 2002; Fung, 2002; van Tuijl & van der Molen, 2016). Interest in understanding children and young people's perceptions of different occupations has been sparked by the general assumption that such perceptions shape their aspirations (Archer & DeWitt, 2016; Ferguson & Lezotte, 2020; Sáinz et al., 2016). The idea is that students tend to choose a career path where there is a perceived match between their self and how they see that particular occupation (Gottfredson, 1981). In other words, individuals gather knowledge regarding the prototypical characteristics (i.e. physical appearance, personality traits, gender etc.) associated with a particular occupation. This self-to-prototype matching paradigm contends that the greater the alignment between an individual's self-image and the prototypical representation of those working in a specific profession, the higher the likelihood of them choosing that profession (Giannantonio & Hurley-Hanson, 2006; Gottfredson, 1981; McPherson et al., 2018). In line with this notion, several studies (Berg et al., 2018; Cheryan et al., 2013; Pantic et al., 2018) have documented that, compared to their male peers, young women in the United States and Scotland perceived fewer similarities between themselves and the prototypical computer scientist, which can be particularly challenging for women interested in technology careers (Ferguson & Lezotte, 2020).

While some empirical research has documented that students' perceptions of STEM occupations are likely to influence educational choices and career aspirations (Cheryan et al., 2017; Master et al., 2016; van Tuijl & van der Molen, 2016; Wang & Degol, 2013), recent research has found limited connections between students' perceptions and aspirations of a STEM career (Schorr, 2019; Toma et al., 2022). For example, Hur et al. (2017) revealed that positive perceptions of computer science among girls aged 10–16 in the United States did not directly translate into aspirations of pursuing a technology career. This lack of direct influence stemmed from the girls' fear of receiving negative labels from their peers, such as being seen as a geek. Here, the girls' own positive perceptions were overshadowed by broader societal discourses concerning the technology field, leading to a negative impact on their aspirations despite initially positive perceptions. Based on this body of research, it becomes apparent that the connection between an individual's personal perceptions and aspirations may not be linear, influenced by their consideration for how others perceive different occupations and the potential consequences of deviating from those perceptions. These findings substantiate the intricate interplay between individual perceptions at the micro level and the wider sociocultural environment at the macro level, underscoring this relationship's inherently dynamic nature (see also, Thébaud & Charles, 2018).

How to capture students' perceptions and discourses of it professionals?

Traditionally, the Draw-a-Scientist Test (DAST) and its variants have been used to explore children and young people's perceptions of people in STEM occupations. This involves asking participants to draw a picture of a scientist and then following a checklist to identify various indicators such as gender, clothing, and skin color (Chambers, 1983; Chang et al., 2020; Ferguson & Lezotte, 2020; Finson, 2002). While the DAST is a well-established method for measuring students' perceptions of STEM occupations, it has limitations (Brumovska et al., 2022; Chang et al., 2020). Analysis of the drawings can be subjective and biased, and it does not take into account participants' own interpretations of their drawings (Brumovska et al., 2022). Similarly, assuming that a scientist is Caucasian when their skin is not colored (Finson et al., 1995; McCarthy, 2015), could be misleading, perhaps having more to do with the use of white paper or a lack of coloring pencils rather than the participant's perceptions of skin colour (Reinisch et al., 2017). Moreover, the use of DAST primarily captures perceptions of scientists' physical appearance and not characteristics that are difficult to draw, such as intelligence or personality. Consequently, the use of this approach might overlook other important aspects and thus fail to capture complex and nuanced perceptions extending beyond physical appearance (Brumovska et al., 2022; Ferguson & Lezotte, 2020). Another possible limitation is that participants with limited drawing skills may struggle to accurately convey their perceptions, which can result in ambiguous drawings that are difficult to interpret (Losh et al., 2008; Reinisch et al., 2017). While the DAST is useful for identifying the prevalence of different indicators in how children and young people perceive the physical appearance of scientists, it does not capture participants' voices, including how they explain and interpret their drawings, as well as various characteristics that are difficult to depict in drawings (Brumovska et al., 2022; Ferguson & Lezotte, 2020). Moreover, the DAST and its variants have been criticized for inadvertently encouraging respondents to draw recognizable, stereotypical figures, as students might perceive the task as depicting a "typical" IT professional (Brown et al., 2004). We think this critique has merit and further argue, in line with Lamminpää et al. (2023), that DAST and its variants primarily measure students' knowledge and awareness of existing discourses rather than their own views and perceptions. Possessing knowledge of stereotypical perceptions does not necessarily imply that students endorse these stereotypes (Barth et al., 2018). However, we recognize that such perceptions can potentially interact with students' preconceptions and attitudes (Lamminpää et al., 2023).

To overcome some of these limitations, other methods have been used to measure students' perceptions of STEM occupations. For instance, a growing body of research (Martins et al., 2021; Mercier et al., 2006; Pantic et al., 2018; Sáinz et al., 2016) has used written descriptions or open-ended questions – either alone or in combination with other methods, such as drawings, to interpret results more accurately. Written descriptions or open-ended questions involve participants describing their perceptions in words (e.g. in response to the question "how would you describe a computer scientist?"). Another stream of research (Dou et al., 2020; Ito & McPherson, 2018; Sáinz & López-Sáez, 2010) has used surveys with closed responses to measure students' perceptions (e.g. by asking them to rank their agreement on a Likert scale with statements such as "the only people who go into computer science are geeks" or "it takes competence and intelligence to work with computers" (Sáinz & López-Sáez, 2010), and computer scientists "have poor social skills" or "are not good athletes" (Garriott et al., 2017)). While these methods are useful for capturing characteristics that are difficult to depict in drawings and allow participants to describe their perceptions in words, they may struggle to capture perceptions that are more deeply ingrained and difficult to articulate. Additionally, students may feel compelled to give socially desirable responses (Alwin & Krosnick, 1991). As such, each method has its own advantages and disadvantages. In this study, we extend the DAST method by adding the option to include text and explanations, specifically through *descriptive drawings*, where students are prompted to draw and describe their perceptions and constructions of IT professionals. We also employ the method of Latent Profile Analysis (LPA), analyzing closed-ended survey responses to a range of statements describing IT professionals in terms of both personal and work characteristics, with the aim of providing a more holistic examination of students' perceptions of IT professionals.

Methodology

Data and sample

We use data from an additional questionnaire that was included in the International Computer and Information Literacy Study 2023 (ICILS) in Denmark. ICILS is an international large-scale assessment study that measures international differences in students' (aged 14–15) computer and information literacy (CIL), computational thinking (CT) skills, and attitudinal constructs towards technology and IT. It was first conducted in 2013, with 21 participating countries, and has since been repeated every five years (Fraillon et al., 2014, 2020). In short, ICILS uses two-stage cluster sampling. In the initial stage, sample schools and replacement schools are randomly selected, while in the subsequent stage, a sample of 1–2 classes within each school is selected. As part of ICILS 2023 in Denmark, an additional questionnaire was also developed with the aim of better understanding how different sociopsychological factors relate to Danish 8th grade students' aspirations for a career in technology, including how students perceive and construct IT professionals. Specifically, the additional questionnaire explored students' aspirations for a career in technology, their motivational profiles, occupational perceptions, perceived attitudes toward technology of peers and parents/caregivers, technology-related activities in informal learning environments, and the extent to which they felt pressure for gender conformity (described in Grønhøj & Bundsgaard, manuscript in preparation).

In total, 141 schools and 3,017 school students participated in ICILS 2023 in Denmark. The additional questionnaire was distributed to the participating schools in May and June, two to four weeks after participating in ICILS 2023, and was completed by 1,658 lower secondary students (aged 14–15), comprising 840 boys (51%) and 818 girls (49%), from 88 schools in Denmark. As such, the participation rate for the additional survey was 62% of the schools participating in ICILS in Denmark and 55% of the selected students within the participating schools. Following established guidelines on how to handle missing data in surveys (Mirzaei et al., 2022), students with over 40% missing responses in the additional survey related to their aspirations for a career in technology, their motivational profiles (in terms of interest and utility value), occupational perceptions, perceived attitudes of peers and parents or caregivers towards technology, and technology-related activities in informal learning contexts were excluded from this analysis. As a result, around 12% of the data were excluded from the analysis, which included responses from 1,456 students including 721 boys (50%) and 735 girls (50%). Participants were assured of the confidentiality and anonymity of their responses. The psychometric properties and validation of the included scales were examined using the Rasch Partial Credit measurement model and is briefly described in Supplementary Material A. A detailed account of the data collection methods, item development, and the psychometric properties and validation of the questionnaire is provided elsewhere (Grønhøj & Bundsgaard, manuscript in preparation).

Research design and methods of data collection

Items assessing students' perceptions of it professionals

As described above, the additional questionnaire that was included in the ICILS 2023 round contained items that assess students' perceptions of IT professionals. Specifically, students were introduced with the heading "Your perceptions of people working in the field of IT and technology (e.g. an IT support specialist or an app developer)", followed by different statements such as "a typical person working with IT and technology spends much of their day alone" and "a typical person working with IT and technology can solve problems in creative ways" (this and all other excerpts and examples from the additional questionnaire have been translated from the original Danish). For these items, students were asked to indicate their level of agreement on a 4-point Likert scale ranging from 1 ("to a very low degree") to 4 ("to a very high degree"). For another set of items, students were asked to indicate on a 5-point scale, where 1 = women, 3 = both men and women, and 5 = men, the degree to which they associated 4 statements with men, women, or both men and women. Examples included "People who are best suited for the tasks in jobs involving IT are mostly ... " and "People who are most skilled at jobs involving IT are mostly ... ". See Supplementary material B for the full list of items used. A total of 18 statements were modelled into five latent variables using the Rasch Partial Credit Model (Masters, 1982) (see Supplementary material A). These five latent variables measure students' perceptions of whether IT professionals can be considered a) as contributing significantly to society, b) intelligent and nerdy, c) as someone who prefers working and being alone, d) as creative and innovative, and, finally, e) students' gendered perceptions of the field of technology.

Descriptive drawings

At the end of the additional online survey that was included in the ICILS 2023 round, participants were given the task of describing and illustrating an individual employed in the field of technology. They received the following prompt: "Imagine a typical person working in IT (e.g. an app developer or an IT support specialist). Answer the following questions and then draw the person at their workplace using the drawing program provided below". This prompt was followed by three open-ended questions":How would you describe the person you imagined?", "How would you describe the person's workplace?", and "What does the person do in their job?".

Data analysis

Statistical analysis: latent profile analysis and frequencies analysis

To detect latent profile in the five latent variables measuring students' occupational perceptions of the field of technology, Latent Profile Analysis (LPA) – a form of Latent Class Analysis (LCA) – was conducted (Spurk et al., 2020). LPA is a psychometric person-oriented mixture model that identifies latent subgroups within a sample of respondents who share certain outward characteristics on some unobserved construct based on their observed response pattern (Spurk et al., 2020; Weller et al., 2020). The LPA involved two steps.

First, LPA was applied to discern groups of students' (latent profiles) in the study sample who exhibited similar patterns of outcomes across the five measures of occupational perceptions. The optimal number of latent profiles was identified using goodness of fit indices, the characteristics of the groups within the model, and conceptual considerations in the interpretation of whether or not these group characteristics made sense in relation to the study's underlying theoretical foundations (Spurk et al., 2020; Weller et al., 2020). In this study, we employed the Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC) and entropy as statistical indicators to compare the relative fit of models with a different number of profiles. Models with lower BIC and AIC values are considered better than those with higher values, whereas an entropy value as close to 1 is ideal (Weller et al., 2020). The latent profiles analysis was performed using the Stata *gsem* command (StataCorp, 2023), while entropy was calculated with the user-written Stata *lcaentropy* command (Medeiros, 2022). To handle missing data in the LPA, we used maximum likelihood based estimation default in *gsem* command in Stata (StataCorp, 2023). We tested whether using listwise deletion to handle missing data in the LPA would alter the results, finding no substantial changes to the outcome. In the second step, each student was assigned a profile based on their most likely group membership. In LPA, researchers obtain estimated means for each latent variable within the different profiles. To understand the implications of these mean scores for each latent variable within the diverse profiles and gain a deeper insight into the variability within these groups, we use the Rasch Partial Credit Model (Masters, 1982). Using this model not only enables us to explore heterogeneity within each group, but also provides qualitative descriptions of what belonging to different categories signifies (for the Rasch Partial Credit Model analysis, see Supplementary material C).

Cross-tabulations and frequency analysis were conducted to explore the distributions and gender differences across the groups and profiles identified in both the descriptive drawings (described below) and LPA, as well as the gender depicted in students' descriptive drawings. A chi-square test (x^2-test) was employed to assess statistically significant disparities between boys' and girls' responses. A significance level of 0.05 was adopted. All statistical analyses were conducted using *Stata 18*.

Thematic analysis of descriptive drawings

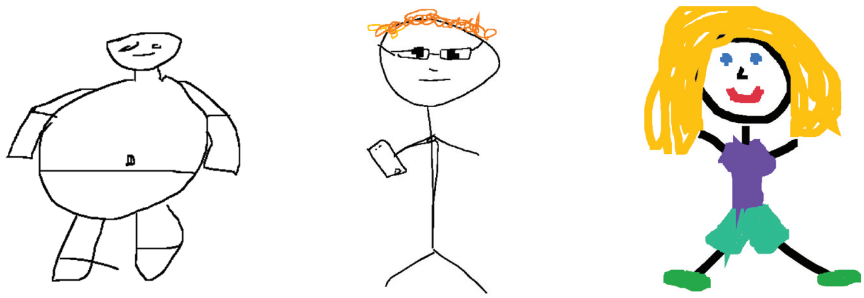
To examine the students' perceptions of IT professionals, a thematic analysis of their descriptive drawings was conducted (Braun & Clarke, 2006). One of this article's authors participated in the thematic analysis alongside two independent coders, who underwent training via a workshop. Using a coding manual developed through an iterative process, the coders identified the presence or absence of characteristics associated with students' drawings or responses to open-ended questions. The coding manual was developed based on Braun and Clarke's (2006) initial four steps of thematic analysis. Initially, two of the authors reviewed all data to familiarize themselves with students' descriptions and drawings. We carefully re-read the data multiple times, taking notes, and marking ideas for coding to use in subsequent phases. We then organized the data into potential patterns, coding as many potential themes and patterns as possible to avoid excluding relevant and interesting aspects from the students' descriptive drawings. Next, we re-coded the different patterns, aspects, and themes into potential overarching themes based on perceived similarities, which we then reviewed and refined. Finally, we contextualized, compared and contrasted our coding manual with insights from a pilot study conducted in 2022 and manuals described in previous literature (Berg et al., 2018; Brumovska et al., 2022; Ferguson & Lezotte, 2020; Martins et al., 2021; Pantic et al., 2018; Sáinz et al., 2016).

During the coding process with the two independent coders, we discussed the validity of the individual themes to ensure they accurately reflected the meaning evident in the data set as a whole. We discussed examples of ambiguities and discrepancies in an iterative process until a consensus was reached, with interrater agreement ranging from 90.7% on the coding of gender to 100% on the coding for Kind (see below) based on a 20% data sample. The high level of agreement might be attributed to the fact that it is relatively easy to see when something does not occur (e.g. when the students do not describe an IT professional as kind or as someone who likes helping others). Changes in the coding manual were made where appropriate during this iterative process. The coding of the drawings and descriptions took place using the OpenCoding web application (Bundsgaard, 2021).

Following the thematic analysis of both the drawings and descriptive responses to the open-ended questions, we identified six groups of IT professionals: 1) Sedentary, 2) Antisocial and Nerdy, 3) Sad, 4) Ordinary, 5) Smart, and 6) Kind. In the initial coding process with the coders, the *Smart* group was comprised of two thematic sub-groups, namely *Passionate and Intelligent* and *Cool*. However, during the coding process we found it difficult to distinguish these sub-groups conceptually due to conceptual overlap. We therefore ended up merging them into a single group in the analysis, namely *Smart*, thereby forming a consolidated theme. It should also be noted that students' drawings and responses to the open-ended questions could sometimes fit with more than one group. For instance, if a student drew an overweight person and wrote "glasses, no hair, and someone who does not have any friends", their perception of IT professionals was placed in both the *Sedentary* and *Antisocial and Nerdy* groups.

In some cases, it was challenging to categorize the students' depictions within the established groups due to a lack of detail or the absence of specific attributes. Cases such as when students drew a stick figure with minimal or no accompanying description were coded as "Not Grouped" to account for vagueness and ambiguity where there was insufficient detail to assign them to one of the established categories. Further details regarding the coding handbook can be made available upon request. Examples of descriptive drawings are presented in Figure 1.

Furthermore, where possible, the gender of the IT professionals drawn and described by the students was coded. Here, we first looked for gender-specific pronouns in students' open-ended responses. For example, if students used the pronoun "he" in their descriptions, then the figure was coded as a *man*, even if the drawings were unclear. Likewise, the pronoun "she" was coded as a *woman*. If we were unable to clearly specify gender from the descriptions, then we looked at the drawings. For instance, if the student had drawn a person with a beard, the figure was coded as a *man*. If the student had drawn something that did not align with their description – for example, if they had drawn a person with a beard but had written "it is a woman" – the description was given the most weight and the figure was coded as a *woman*. In cases where it was clearly stated that the IT professional was of non-specific or non-binary gender, as well as when gender could not be clearly determined from the drawings and descriptions, these were categorized as *other* for analytical purposes, whereas those specifying that anyone can work in



An old man who is overweight, smells, and wears T-shirts that are too short.

Skinny and nerdy – he sits in a booth with his computer and a cup of coffee while programming – programming all sorts of things.

I imagine several different kinds of people. A person who is passionate about/enjoys their job. In a large workplace with lots of colleagues. The person may spend a lot of time in front of a computer.

Figure 1. Examples of descriptive drawings (translated from Danish to English).

technology (e.g. stating "anyone can work in technology" or "it could be a man or a woman") were coded as *all genders*.

Results

We present our empirical findings in two stages. In the first stage, we used LPA to identify distinct student subgroups based on five latent variables related to occupational perceptions, as well as examining gender disparities in their perceptions when analyzed using LPA. In the second stage, we examined students' perceptions and discourses concerning IT professionals through analysis of descriptive drawings, investigating potential gender differences in their perceptions when analyzed using descriptive drawings.

Latent profile analysis (LPA)

We conducted Latent Profile Analysis (LPA) using the five latent variables selected to measure students' perceptions of IT professionals. After rigorous evaluation based on theoretical foundations, profile distinctness, and fit indices (AIC, BIC and entropy), a four-profile model emerged as the optimal model (see summary of fit indices with 1–8 latent profiles in Supplementary material D). These profiles reflect four distinct student profiles. Each student was categorized into one of these profiles based on their highest probability of membership. The average posterior class probabilities for individuals to be parsimoniously assigned to their respective profiles were .98 (profile 1), .86 (profile 2), .87 (profile 3), and .92 (profile 4), indicating that the four-profile model provided clear classification (Weller et al., 2020).

As shown in Table 1, profile 1 (3% of the sample) applies to students who did not perceive people in technology as particularly intelligent and nerdy. Moreover, they perceived technology jobs as suitable for both men and women and as for someone who prefers working and being together with others. However, they did not perceive IT

Table 1. Generalized characterization of the occupational perceptions profiles ($N = 1{,}456$).

Classes Characteristics	Gender	Intelligent, nerdy, and have an innate talent for IT	Creative and innovative	Prefer working and being alone	Contribute significantly to society
Profile 1 (3%)	Both men and women	To a very low degree	To a very low degree	To a very low degree	To a very low degree
Profile 2 (32%)	Both men and women	To a high degree considered *intelligent*; in between to a low degree and to a high degree considered *nerdy* and as having an *innate talent for IT*	To a low degree	To a high degree	To a low degree
Profile 3 (55%)	Both men and women	To a high degree considered *intelligent*; in between to a low degree and to a high degree considered *nerdy* and as having an *innate talent for IT*	To a high degree	To a high degree measured on *spend much of their day alone* and *prefer working with numbers rather than with people;* to a low degree measured on *prefer work to social gatherings*	To a high degree
Profile 4 (10%)	In between men and both men and women	To a very high degree	To a very high degree	To a high degree	To a very high degree

In the table, characteristics associated with each profile represent the most common responses within that profile. Due to the probabilistic nature of Latent Profile Analysis and Rasch models, these traits are considered "typical" rather than absolute. The term "typical" implies the prevalent responses within each profile. For simplicity, the word "typically" is omitted before each characteristic; e.g. we write "to a high degree" rather than "typically to a high degree".

professionals as creative individuals or think that technology jobs contribute significantly to society.

Profile 2 (32% of the sample) represents those students who perceived IT professionals as intelligent, but with no clear consensus within the group as to whether IT professionals have an innate talent for IT and whether they are nerdy. They believed that technology fields are suitable for both men and women. However, IT professionals were not seen as creative or as making a significant contribution to society. Moreover, they perceived IT professionals as individuals who prefer work over social gatherings, spend much of their day alone, and prefer working with numbers rather than with people.

Profile 3 (55% of the sample) includes students who perceived IT professionals as intelligent, while there was no clear consensus regarding whether IT professionals typically have an innate talent for IT or whether they are nerds. Students in this group believed that IT professionals spend much of their day alone and prefer working with numbers rather than people but did not think that this means that they prefer work to social gatherings. This group of students furthermore perceived technology as a field for both men and women and saw IT professionals as creative people that make a significant contribution to society.

Profile 4 (10% of the sample) represents students with a strong perception of IT professionals as intelligent and nerdy. They further believed that IT professionals to a very high degree are creative and make significant contributions to society. In terms of gender, this group of students were more likely – in comparison with the other profiles – to respond that men were most suitable for jobs in IT, although they were equally likely to respond, “both men and women” and “men” to questions assessing their gendered perceptions. Additionally, they perceived IT professionals as individuals who prioritize work over socializing, often spending much of their day alone, and prefer working with numbers rather than with people.

As the profiles indicate, the majority of students associated IT professionals with what can be considered positive characteristics. For instance, in profiles 3 and 4, which made up 65% of the students, IT professionals were considered creative and innovative individuals that contribute significantly to society. Moreover, most students perceived the field of technology as a place suitable for both men and women and IT professionals as people who prefers to be and work alone. Meanwhile, just over one third of students (35% represented by profiles 1 and 2), were less positive regarding IT professionals’ creativity and contribution to society. Nevertheless, these findings reveal a prevailing tendency to describe IT professionals with labels that can be considered positive and to describe technology as a profession that is suitable for both men and women.

Table 2 displays the distribution of boys and girls across the four occupational perceptions profiles. Cross-tabulation with the chi-square test revealed a significant relationship between gender and membership of the different occupational perceptions profiles, $x^2 = 10.4892$, $N = 1{,}456$, $p < .015$. Boys were more likely to belong to

Table 2. Gender distribution across the four occupational perceptions profiles ($N = 1{,}456$).

	Profile 1	Profile 2	Profile 3	Profile 4
Boys	35 (5%)	226 (31%)	381 (53%)	79 (11%)
Girls	15 (2%)	235 (32%)	417 (57%)	68 (9%)

profile 1 (5%) and profile 4 (11%) compared to girls. By contrast, girls were more likely to belong to profile 2 (32%) and profile 3 (57%) compared to boys. Although our results reveal significant gender differences in occupational perception profile membership, the differences were relatively small, ranging from one percentage point in profile 2 to four percentage points in profile 3.

Analysis of descriptive drawings

The analysis of students' descriptive drawings revealed six groups of IT professionals (see Table 3). Groups 1, 2, and 3 (*Sedentary*, *Antisocial and Nerdy*, and *Sad*) were depicted with predominantly stereotypical indicators. In overarching terms, sedentary IT professionals were characterized as potentially overweight individuals who spent their entire day in front of a computer screen. Antisocial and nerdy IT professionals were characterized by nerdy qualifications, proficiency in math/technology, and a limited social network. Sad IT professionals were broadly defined by feelings of depression, stress, and irritability. Groups 4, 5, and 6 (*Ordinary*, *Smart*, and *Kind*) were associated with either neutral or positive features. Here, ordinary IT professionals were mainly characterized as regular people that do not conform to a single "type of person" but can encompass various features. The smart IT professionals were generally described in a positive light, e.g. as someone who is cool, smart, fun, logically thinking, and sociable. Finally, the kind IT professionals were broadly described as kind, calm, patient, and someone who helps others.

Table 4 shows that students were more likely to draw and describe an IT professional with predominantly stereotypical indicators, with 43% of girls and 45% of boys describing either a person that was *Sedentary*, *Antisocial and Nerdy*, or *Sad*. While girls were significantly more likely to depict IT professionals as *Antisocial and Nerdy*, $x^2 = 8.5936$, $p < .003$, boys were significantly more likely to depict a *Sedentary* IT professional, $x^2 = 13.8570$, $p < .000$. In terms of students' positive or neutral perceptions, including IT professionals that are *Ordinary*, *Smart* or *Kind*, 24% of boys and 26% of girls portrayed one of these groups, and there were no significant gender differences in any of these groups.

Table 5 presents the gender distribution within students' drawings and descriptions. Boys and girls were generally more inclined to depict IT professionals as men as opposed to women, others, or all genders, with the exception of the *Ordinary* group, where *other* was the most frequently depicted gender among girls. In general, girls were significantly more likely than boys to portray women in the *Smart* group, $x^2 = 8.1019$, $p < 0.044$, indicating that girls are more prone to associate female IT professionals with positive attributes. For the groups associated with predominantly stereotypical labels – the *Sedentary*, *Antisocial and Nerdy*, and *Sad* groups – the differences between boys and girls in assigning gender to the depicted IT professionals were small and insignificant. Specifically, 60–71% of the descriptive drawings in these three groups portrayed men, 2–3% portrayed women, 25–38% portrayed others, and 0–2% portrayed all genders. Overall, statistically significant differences between boys and girls were only observed for *Kind*, $x^2 = 9.2991$, $p < 0.010$, *Smart*, $x^2 = 8.1019$, $p < 0.044$, and *Not Grouped*, $x^2 = 17.2076$, $p < 0.001$.

Table 3. Characteristics of groups identified in descriptive drawings.

Characteristics Groups	Physical appearance	Personal attributes	Ability	Social	Examples of descriptions
Sedentary	Can be overweight and have a non-athletic physique, may wear clothes that are too small and wear glasses	Leading a sedentary lifestyle. Can be described as a person who sits down all day and spends their entire day in front of a computer while eating food	N/A	Use much of their time on work rather than social activities	"chubby", "overweight", "sits down all day", "someone who is not fond of sports but likes to sit still", "sits in front of a computer all day", "doesn't move around much", "spends 10 hours a day on the computer", "does nothing but eat a lot of food", "lazy".
Antisocial and nerdy	May wear glasses, t-shirts that indicate a love of technology such as "I-LOVE-IT"	A geeky or nerdy personality	Nerd/geek, good at math/technology	Antisocial and shy, have few or no friends, are lonely, socially awkward and introvert	"a little bit nerdy", "nerdy", "doesn't have many friends", "not very social", "a good workplace for those who don't function well in social work environments", "socially awkward", "a slim man with glasses and almost no hair, kinda nerdy. And the one who goes home after work to eat at their mom's place"
Sad	Described as unattractive. Might cry, have acne and braces. May wear glasses.	Ascribed attributes such as suffering from stress, unhealthy, pessimistic, and a person with an unpleasant odor. Can be visualized as sad/depressed	N/A	Can be lonely	"stressed", "not very healthy", "smells", "bags under the eyes", "a bit irritating and talks too much about IT, and no one wants to listen to what they say", and "a typical annoying person".
Ordinary	General neutral appearance that could be applied to anyone	Described as ordinary people devoid of specific characteristics; they do not conform to a single "type of person" but can encompass various features	N/A	No specific characteristics (e.g. some are very social while others prefer being alone)	"A wide range of different individuals. Some IT workers exercise a lot, others not so much. Some are very social, others prefer being alone", "are like us, regular people", "are completely normal", "a normal person", and "a friendly, regular person"
Smart	General neutral appearance that could be applied to anyone. May wear glasses.	Typically portrayed in a positive light and as someone who loves their job. Cool, fun, and brave.	A person who is nerdy but in a positive sense or linked to other positively framed attributes such as cool and fun. Can be described as an "inventor", intelligent, or as someone who thinks logically.	May be described as sociable	"they are a nerd, but not in a negative way", "she is very smart, patient, and sociable", "I would describe the person as a logical thinker", "the person is intelligent", "enjoys working with technology", "fun and cool", "brave and cool, incredibly good with IT".

(*Continued*)

Table 3. (Continued).

Characteristics Groups	Physical appearance	Personal attributes	Ability	Social	Examples of descriptions
Kind	General neutral appearance that could be applied to anyone or a person with a lumberjack shirt and jeans	Calm, patient, enjoys helping others	Good at assisting other people	Social in the sense that the person is kind and helps others	"calm person", "very calm", "patient", "works at a school helping with IT", "assists other people with technology", "enjoys helping others"

Table 4. Frequencies of groups identified in the thematic analysis (n = 1,155).

	Boys (%)	Girls (%)
Predominantly Stereotypical Indicators (pooled) (*n* = 513)	**45**	**43**
Sedentary (*n* = 296)	30	21
Antisocial and Nerdy (*n* = 227)	16	23
Sad (*n* = 167)	15	14
Positive/Neutral Indicators (pooled) (*n* = 290)	**24**	**26**
Ordinary (*n* = 148)	13	12
Smart (*n* = 132)	10	13
Kind (*n* = 34)	3	3
Not Grouped (*n* = 394)	**35**	**34**

Table 5. Frequencies of the depicted gender in students' drawings/descriptions for the six groups and *not grouped* (percentage in each category).

	Boys (%)				Girls (%)			
	Men	Women	Other	All genders	Men	Women	Other	All genders
Predominantly Stereotypical Indicators (pooled) (*n* = 513)	**67**	**1**	**31**	**1**	**63**	**3**	**32**	**2**
Sedentary (*n* = 296)	69	2	28	1	60	2	38	1
Antisocial and Nerdy (*n* = 227)	60	2	37	1	62	3	33	2
Sad (*n* = 167)	71	3	25	0	65	3	33	0
Positive/Neutral Indicators (pooled) (*n* = 290)	**54**	**1**	**39**	**6**	**48**	**5**	**39**	**8**
Ordinary (*n* = 148)	47	1	40	12	34	3	49	14
Smart (*n* = 132)	53	2	45	0	58	11	28	3
Kind (*n* = 34)	100	0	0	0	56	0	39	6
Not Grouped (*n* = 394)	**66**	**1**	**33**	**1**	**64**	**7**	**26**	**3**

Discussion

The aim of this paper was to investigate young people's (aged 14–15) perceptions and discourses of IT professionals and to assess the presence of gender differences in their views. Using descriptive drawings and closed-ended survey items, our results highlighted multiple overlapping profiles and groups of IT professionals. These categories indicate significant differences in students' perceptions and discourses, as also reported in other studies (Samaras et al., 2012).

The findings from the Latent Profile Analysis (LPA) reveal that students' perceptions of technology were relatively more positive compared to the findings from descriptive drawings. Most students indicated that they perceive the field of technology as suitable for both men and women. Furthermore, 65% of students (profiles 3 and 4) perceived IT professionals as creative and innovative and as individuals who make a significant contribution to society, while the remaining 35% of students (profiles 1 and 2) were less positive in this respect. Students with profiles 2, 3, and 4 perceived IT professionals as intelligent. However, while students with profile 4 (10% of students) also thought that IT professionals have an innate talent for IT and exhibit nerdy characteristics, there was no common consensus on these matters among students with profiles 2 and 3 (87% of students). Significant gender differences could be observed in terms of the different profiles; however, these differences were small, ranging from one to four percentage points.

The findings from our analysis of descriptive drawings revealed six groups characterizing students' discourses of IT professionals: Sedentary, Antisocial and Nerdy, Sad, Ordinary, Smart, and Kind. Despite this diverse range of groups, stereotypes identified in earlier research prevailed in students' discourses. Sedentary, Antisocial and Nerdy, and Sad are closely aligned with prevalent perceptions that have been extensively documented in existing literature (Berg et al., 2018; Cheryan et al., 2015; Dou et al., 2020; Jones & Hite, 2020; Klapwijk & Rommes, 2009; Lang, 2012; Mercier et al., 2006; Wong, 2016). The qualities that characterize the *Smart* group have likewise been identified in previous studies focusing on perceptions of IT professionals and technology occupations (Pantic et al., 2018; Sáinz et al., 2016; von Hellens et al., 2009). While the *Ordinary* group has characteristics that have previously been identified in studies focusing on students' perceptions of science (Brumovska et al., 2022), the *Ordinary* and *Kind* groups are – to the best of our knowledge – less frequently mentioned in the existing literature focusing on students' perception of technology. In terms of gender differences in students' descriptive drawings, boys were more likely to portray *Sedentary* IT professionals, while girls were more inclined to depict *Antisocial and Nerdy* IT professionals. For the *Smart* group, girls were significantly more likely than boys to depict a woman in their descriptive drawings. Overall, regardless of students' own gender, IT professionals were predominately perceived to be men, which supports finding from previous studies (Berg et al., 2018; Martins et al., 2021; Mercier et al., 2006). Although we found that students mainly associated IT professionals with predominantly stereotypical attributes, the approach to analyzing students' descriptive drawings adds greater nuance concerning perceptions of IT professionals and technology occupations, diverging from a stereotypical versus non-stereotypical perspective (Brumovska et al., 2022).

In general, the diversity in the six groups that emerged from descriptive drawings and the four latent profiles that emerged from the LPA highlights a broader range of perceptions and discourses among young people compared to previous studies. The disparity in results highlights the nuanced ways in which students can articulate their views of IT professionals and technology occupations when using different methods. One way to interpret these disparities is that descriptive drawings and closed-ended items measure different aspects of students' perceptions. In line with other scholars (Andersen et al., 2014; Lamminpää et al., 2023), we believe that descriptive drawings are more likely to highlight students' awareness of existing discourses in society, which is an important measure, rather than necessarily providing a definitive picture of the individual student's own perceptions. As discussed previously, students are likely to draw a stereotypical IT professional as they might interpret the task as drawing a recognizable, typical IT professional (Berg et al., 2018; Brown et al., 2004). However, this requires an awareness of such images, potentially through powerful media depictions of IT professionals or cultural discourses echoed by significant others in students' immediate environment. As such, the results might suggest that, while many students are aware of stereotypes and different societal discourses about IT professionals, they do not necessarily endorse these stereotypical perceptions themselves. In this sense, although responses to closed-ended items risk positive bias, the disparity in results might indicate that students can distinguish between stereotypical discourses, as assessed through descriptive drawings, and more realistic depictions of IT professionals and their work, as assessed through closed-ended items. However, as not all students have direct contact with people (such as family members) who work with technology, their views and perceptions are highly dependent on culturally available ideas and prominent discourses concerning what technology occupations and IT professionals are like (Lykkegaard & Ulriksen, 2016). As such, descriptive drawings can offer a lens through which we can understand the dominant technology discourses encountered by students. Another potential explanation for the disparities is that responses to written items can provide a platform for broader views as they require that students reflect upon different statements or questions concerning various aspects of IT professionals and technology occupations, framed in terms of both positive and negative aspects (Cecchini, 2019; Samaras et al., 2012). By contrast, students may struggle to articulate their diverse and potentially conflicting perceptions through descriptive drawings, which can lead to oversimplification, with students instead falling back on common stereotypes or opting for humorous or whimsical depictions that border on caricature (Finson, 2002).

Limitations and reflections

In the following, we acknowledge the study's methodological limitations and share reflections on the approaches adopted.

In terms of statistical power, although our use of online descriptive drawings provided a larger sample than if we had used pen-and-paper drawings, for example, it still generated significantly less data than methods such as questionnaires. Our LPA included responses from 1,456 students, compared with descriptive drawings from 1,155 students, of which only 761 were codable into six groups. The relatively lower response numbers compared with the number responded to the closed-ended items may be due to the task of drawing online using a computer being more demanding for some students when compared to using the more traditional method of pen and paper. While soliciting descriptive drawings on paper might have yielded more accurate or clearer drawings that are easier to interpret than those submitted online, it would have limited the number of respondents due to the practical and logistic challenges.

We provided an example of what technology occupation might entail to support students' descriptive drawings, using the prompt "(e.g. an app developer or an IT support specialist)". We acknowledge that this prompt could potentially have influenced students' drawings and descriptions, steering them towards these professions. For instance, the students depicting the group *Kind* might have been subconsciously influenced by the reference to an "ICT support specialist" in the instrument used, sometimes describing/drawing the IT supporter at their school, who they characterize as kind, patient, and helpful. However, in Denmark, there are no mandatory computer science courses or similar at the primary and lower secondary levels; as a result, some students might lack awareness of what constitute technology professions. As such, we opted to provide these concrete examples to support and scaffold students' understanding.

We also recognize the risk of potentially instilling preconceived ideas as students completed the closed-ended questionnaire before the descriptive drawing. However, although the majority of students' descriptive drawings could be coded as fitting into one of the three predominantly stereotypical groups that have been identified in previous studies, a greater proportion of students depicted an IT professional with either positive or neutral attributes compared with these previous studies (see, for instance, Berg et al., 2018; Ferguson & Lezotte, 2020; Mercier et al., 2006). This could either indicate that students had greater awareness of more positive discourses surrounding IT professionals and technology occupations compared to previous studies (see, for instance, the following reviews exploring the content of students' STEM and computer science stereotypes Cheryan et al., 2015; Ferguson & Lezotte, 2020) or that the statements from the closed-ended items encouraged some of the students to reflect on and challenge potentially stereotypes that they encountered in these statements, thereby challenging the discourses they might have been aware of existed – or a combination of the two (Cecchini, 2019).

The difficulties we experienced in interpreting students' drawings (as discussed above) also provide an important lesson for future studies based on DAST and similar methods. When students only submitted a drawing with no supplementary written description, we found coding difficult, resulting in a considerable number of descriptive drawings being coded as *Not Grouped*. One important conclusion from this study is that it is important to have descriptions when assessing drawings; this enables more accurate interpretation of their drawings and helps to unpack the various discourses that inform and shape their perceptions.

Although descriptive drawings have their limitations, our data shows that they can be a useful tool for unpacking and understanding dominant discourses. Descriptive drawings can reveal perceptions that are not normally captured by either a drawing or a written description alone, but only by combining the two.

Moreover, our analysis of how boys and girls might perceive IT professionals differently has a potential limitation, as it is based on a binary classification of gender. It is important to acknowledge that some students may self-identify as nonbinary (Perry et al., 2019), which means our results may be constrained by this binary categorization and potentially overlook the perspectives of nonbinary students.

Conclusion

Our results have indicated that students may be beginning to see IT professionals and their work in a more positive light. Although stereotypes still dominate when measured by descriptive drawings, incorporating LPA paints a more positive picture. These findings call for a nuanced interpretation that considers both negative and positive perceptions when analyzing how students view the field of technology, as well as an awareness of the potential methodological strengths and weaknesses of various methods.

When asked to draw and describe IT professionals, students were generally more likely to depict men as opposed to women, others, or all genders, with the exception of the *Ordinary* group, where *other* was the most frequently depicted gender among girls. However, in the *Smart* group, girls were significantly more likely than their male peers to portray IT professionals as women, indicating that girls are more prone to represent women in groups characterized by either positive or neutral attributes. While significant gender differences could also be observed in the latent profiles derived from LPA, these differences were small in magnitude. The LPA revealed more positive perceptions of the field of technology among students than suggested by the descriptive drawings, as well as finding that students generally perceive IT professionals as suitable for both men and women.

In alignment with recent research (Pantic et al., 2018; Schorr, 2019), our study contributes to the existing body of literature by examining a potential shift towards more positive perceptions of the technological domain. Moreover, to the best of our knowledge, this is the first study to investigate latent profiles in relation to students' perceptions of IT professionals through LPA.

As students' understandings of prevailing discourses and their perceptions are shaped by considerations of others' views and the potential repercussions of deviating from commonly held beliefs, our findings highlight the need to pay close attention to cultural norms that both directly and indirectly influence students' perceptions and may push specific student groups – for example, girls – away from technology-related fields. We contend that perceptions are socially constructed through continuous interactions with individual and contextual factors, including media, broader cultural discourses in society, personal experience, role models, peers, parents, and teachers. Therefore, comprehending and addressing the perceptions and discourses that contribute to gender disparities in IT professionals – whether directly or indirectly – is a crucial step towards fostering a more diverse workforce in the technology sector and overcoming the challenges posed by deeply entrenched, invisible cultural and structural barriers that may lead to social exclusion (Breda et al., 2020b; Gorbacheva et al., 2019). As argued by Bøe et al. (2011), everyone should have the opportunity to explore the marvels of the technological world and make informed educational choices. However, achieving such freedom of choice is not possible without overcoming mental and structural barriers shaped by culture.

In a broader sense, experience in developing and advanced usage of technology can provide a deeper understanding of how the technology operates and its benefits, drawbacks, and ethical consequences. Therefore, reducing stereotypical perceptions in society (and among young people in particular) regarding the types of people who are interested in and work with technology will improve democratic participation in crucial discussions about the functioning and role of technologies in young people's own lives and in society.

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