Factors influencing students’ perception of computer science

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Preface

You are reading my thesis that has been written for the finalization of the master's Science Education and Communication – Specialization Computer Science, at Delft University of Technology (TUD). This thesis is the last product I will deliver as a student. During my time at the TUD I have struggled, thrived, learned, and developed myself. My biggest struggle was the bachelor of Computer Science and Engineering. By 0.2 points I got my BSA. After that, I thrived through the years by obtaining all the credits needed. I learned from many professors. The biggest lesson was to never give up when something doesn't work. Which is typical in the IT world. There is always a bug in your way. Sometimes literally. There were times I wanted to give up. Corona didn't help much with that either. This last year has been a tough year for me. Emotionally I was drained. Luckily, I had a supervisor who supported and guided me. I could not have reached the end without M.J. de Vries. I am grateful for his kindness and support.

Furthermore, I would like to thank my family who has supported me through this year and SEC in general for proving me with great lectures and assistance. I also want to thank my thesis committee for the feedback they gave me and the flexibility they have shown. In particular, I would like to thank S. Ramcharan. She has not only been a great help by peer-reviewing my thesis, but also a great friend to make this process fun and durable. Words cannot express how thankful I am for her.

Apart from this bad year, I have experienced good times. Through my time at the TUD I have developed myself to become a programmer, scientist, teacher, engineer, and unfortunately a grown-up. Handing in this work of mine, means I am letting go of my student life. For those reading this, cheers!

Lufther Kronstadt

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Abstract

In our digital society, having computer science skills is becoming imperative, yet there is a shortage of computer science professionals and teachers. This shortage is linked to the perception people have of computer science and computer science professionals. This research paper answers two questions through a mixed-method study: to what extent do 7^{th}-grade students with dissimilar backgrounds differ in their perception of computer science?" and "which characteristics of an intervention influence students' perception of computer science?" The first question is answered by the distribution of a survey for 7th-grade students and the second by letting a smaller group play a serious game and asking open-ended questions afterward. The quantitative results showed that students' gender influences the perception of computer science. The qualitative results showed that the factors backstory, interaction, and easiness increased students' interest in computer science but their intention to pursue a career in computer science remained unchanged.

Keywords: Perception, computer science, students, SES, migration, gender

Contents

Introduction

In the Netherlands, there is a shortage of professionals in computer science (cs). This has been a known fact for a long time (EenVandaag, 2022). However, what is even more concerning is that there is a huge shortage of computer science teachers, while ICT skills are essential for society (De Graaf et al., 2022). We live in a dynamic world where a lot of people simply cannot live without computer-based technology anymore. This is exemplified by the usage of mobile devices. Of the seventeen million people in the Netherlands, 96% use the Internet (Kemp, 2022). This shows that most people are connected to computers and computing. Therefore, it is essential to achieve more computer science professionals.

Reasons for the lack of computer science professionals include a lack of diversity (Pournaghshband & Medel, 2020), false perceptions of computer science (Whitney & Taylor, 2018), and inadequate computer science classes (RTL Nieuws, 2021; Tolboom et al., 2014). To illustrate the diversity issue, 70% of the management of Apple consisted of white men (Neate, 2017), less than 40% of Facebook consisted of women (Gravier, 2020), and Google had a disproportionately white, Asian, and male workforce (Umoh, 2020). In the research by Papastergiou (2008), high school students' motivation toward pursuing a career in CS was investigated. The study showed that girls were less likely to pursue a career in computer science than boys, and when girls did choose such a career, generally, it was because of extrinsic reasons rather than intrinsic once. Research on diversity in computer science showed that minorities, apart from Asians, are less likely to be exposed to computer science than Whites (Google Inc. & Gallup Inc., 2016) and that gender stereotypes are developed at a young age (VHTO, 2019). Based on these findings, more diversity should be stimulated in computer science.

False perceptions can be created when an individual is exposed to information or stimuli that does not present the whole truth. To counter false perceptions of computer science, early evaluation, and adaptation of the perception of students are most effective (VHTO, 2019; Whitney & Taylor, 2018). This entails that students should receive computer science classes as early as possible. Currently, in the Netherlands, some children are taught digital literacy at young ages. Digital literacy entails all the skills anyone needs to develop and to come around in a digital society (Digitale Overheid, 2021). Generally, basic classes in digital literacy are provided in primary school (Digitale Overheid, 2021). However, due to untrained and unqualified educators, the quality of these classes can vary too with classed provided by qualified educators. Additionally, because digital literacy has no official test in primary education (Digitale Overheid, 2021), it can be unclear what children should know. Moreover, the ambiguity in the interpretation of digital literacy results in being taught different things that educators think are relevant. In other words, there is no official program for digital literacy in primary school. In secondary school this is different.

In the Netherlands, since 2007, students at secondary schools can choose computer science as a subject in their exam program (SLO, 2020). The only condition for this choice is that these students are required to have a '*Natuur en Techniek*' study program. About 55% of the HAVO and VWO schools provide computer science classes in 2012 (Tolboom et al., 2014). This has decreased to 46% in 2019 (RTL Nieuws, 2021). According to Tolboom et al. (2014), in these schools, only 12% of the students choose computer science in their exam program.

The exam program of computer science consists of specific domains that students need to learn. These domains include skills in design and development, abstraction, data and information, programming, architecture, and interaction (SLO, 2020). Apart from these six domains, there are twelve others from which HAVO students need to select two and VWO students need to select four, for their exam program (SLO, 2020). These domains of choice include algorithms, databases, cognitive computing, programming paradigm, computer architecture, networking, physical computing, security, usability, user experience, the societal and individual influence of computer science, and computational science (SLO, 2020). After secondary school, students can choose to study computer science in higher education.

Nowadays, computer science aspects, such as programming, are integrated into various studies, for example, the studies of aviation and chemistry. This means that it is not necessary to specifically study computer science to gain certain computer science skills. Currently, about a third of the students in the Netherlands that starts a computer science program drop out (Schop, 2017). This is also a problem in other countries (Kinnunen & Malmi, 2006; Pappas et al., 2016). Important factors for retention in computer science studies include the loss of intrinsic and extrinsic motivation and having different expectations (Appel & Kronberger, 2012; Kinnunen & Malmi, 2006). According to Schop (2017), Dutch students indeed have different expectations at the beginning of the study, which results in dropping out or being unable to meet the requirements to proceed.

Additionally, research suggests that retention can be caused by the levels of academic and social integration (Braxton, 2019). Academic integration is defined by Tinto (1993) as the interaction of students in new academic settings and experiences. While social integration is defined as the interaction of students in extracurricular activities and social environments. When these interactions are not experienced as positive, it can have a negative impact on the perception of the study or environment the student is in. For example, if individuals cannot identify themselves with the study because there are not others like them studying the same field, they might feel like they do not belong there, resulting in dropping out.

Problem statement

To increase the motivation of students to study a field that provides computer science skills, it is important to understand what students think of computer science. Moreover, because there is a lack of diversity in computer science, it can be beneficial to focus on motivating students with diverse backgrounds. However, it is unclear how much students with dissimilar backgrounds differ in their perception of computer science and how possible differences can be dealt with.

The backgrounds that are considered are gender, migration, educational level, and social-economic status (SES). Gender differences are important to understand because of gender stereotypes in computer science; educational level and SES can show the difference by the demographic status of the stud, and migration differences are needed to investigate the difference in perception between Dutch and foreign students.

Furthermore, 7th grade students are most likely to have different perceptions of each other than students in higher grades, because they come together from multiple primary schools. To tackle the uncertainty of having differences in perception between students with dissimilar backgrounds, 7th grade students are considered to be a proper option to investigate. Moreover, understanding and tackling misperceptions of 7th-grade students is more effective than tackling misperceptions in later grades (VHTO, 2019; Whitney & Taylor, 2018).

Aim of research

To increase the number of diverse computer science students, it is important to gain an understanding of students' perceptions of computer science. Investigating students' perception of computer science is, is the first step. With an understanding of students' perceptions, action plans can be developed. Therefore, the purpose of the study was to test whether students with different backgrounds would differ from each other in their perception of computer science. Additionally, to deal with differences in perception, this research aims to study which interventions can change students' perception of computer science.

These goals led to the following research questions:

1) *To what extent do 7th-grade students with dissimilar backgrounds differ in their perception of computer science?*
2) *Which characteristics of an intervention influence students' perception of computer science?*

These research questions are supported by the following sub-questions:

- *Do students with dissimilar migration backgrounds differ in their perception of computer science?*
- *Do students with dissimilar genders differ in their perception of computer science?*
- *Do students with dissimilar educational levels differ in their perception of computer science?*
- *Do students with dissimilar SES backgrounds differ in their perception of computer science?*
- *To what extent do students' perceptions of computer science change after an intervention?*

Relevance

Scientific relevance

While many studies have focused on increasing the number of women in the computer science field, more research is needed on 7th-grade students' perception of computer science (Säde et al., 2019). Providing research on 7th-grade students' perception of computer science can give more clarity on what factors influence the choice to study CS. Additionally, Pournaghshband and Medel (2020) examined the inequality in computer science by focusing on students' intersectional identities. To improve minority students' representation, Pournaghshband and Medel suggested future studies to examine cultural variations as well. This suggestion is supported by Ross et al. (2020), who added that researching the background of students allows for explaining how race and gender among others, position people differently in the world. In particular, this research has not been tested in the context of the Netherlands. This research is in the context of Dutch first-year junior high school students, therefore, contributing to research and existing theories.

Social relevance

The social relevance comes from the fact that we need more computer science professionals (NOS, 2017). In this digitalized era with a growing need for computer science professionals, it is important to understand what influences students to choose a career in CS. Moreover, people with a migration background have a higher percentage of unemployment than natives (CBS, 2022a). Therefore, enabling students with a migration background to have an informed perception of computer science could increase their motivation to pursue a career in CS. This could decrease the difference in unemployment between people with and without a migration background.

Additionally, a clear perception will enable students to choose computer science courses for the right reasons. It happens too often that students choose computer science in high school because there is no central exam or other misconceptions (B. de Ruiter, personal communication, November 17, 2021). By researching the perception of computer science and interventions to influence such perceptions, appropriate tools could be used to inform students. This would help students to make an informed decision, therefore, avoiding students from following a course that they do not understand or have the motivation for.

Outline

The introductory chapter provides background information regarding the research question. Next, the literature review discusses relevant literature to formulate the hypotheses of this research. Additionally, detailed information on factors influencing perception and interventions to adjust perceptions is provided. The method section describes the methods which are used to test the hypotheses and find an answer to the research questions. After the method section, the results of the research are presented in the results sections. From the results, a conclusion will be formed to provide an answer to the research questions. Finally, these results are interpreted and explained in the discussion section. Additionally, the limitations are mentioned, and future work is suggested.

Theoretical framework

Terms, definitions, and theories that are relevant to this research are presented in this section. Furthermore, the intervention to influence the perception of students is discussed.

Computer science

For this research, it is important to understand what computer science is. Computer science is the study of computers and computing (Brookshear & Brookshear, 2019). This includes the following fields: hardware, software, mathematics, statistics, data structures, algorithms, programming languages, design, and architecture. In each focus area of computer science, the aforementioned fields are applied. Focus areas are branches of computer science, such as data science, cloud computing, networking, and security. The fields and focus areas are also included in the domains created by SLO (2020). When students choose computer science as a subject in secondary education, they need to adhere to the terms of domains that are included in their exam program. For instance, each candidate of the exam program must be able to develop programming components in an imperative programming language and structure the components in such a way that it is easy to understand and evaluate (SLO, 2020).

Computer science started with algorithms. It is the most fundamental concept of computer science. An algorithm is a set of instructions that defines how a task is done (Brookshear & Brookshear, 2019). For example, there are algorithms for cooking in the form of recipes. When following a recipe for a cake, the result of following these instructions should be a cake. Algorithms are essential to computers. For a computer to work, it needs an algorithm in a form that is understandable for the computer. This is called a program. Developing such programs is called programming and the people who do it are called programmers. Programs that form a collective are called software. The machinery itself is called the hardware.

Computer science began with mathematics because algorithms were used to solve mathematical problems, such as the minimal distance problem. This is why computer science has commonalities with mathematics. Later on, computer science connected to several other fields through its wide application. Due to the broad application of computer science, it can be seen all around us. From the mobile phones people use daily, to the transportation systems all around the world. At some point, computer science became essential to society. The essence of computer science became so big, that 21^{st}-century skills have been introduced. These are skills that anyone needs in the 21st century. The 21st-century skills include: media knowledge, ICT-basic skills, computational thinking, and problem-solving (Stichting Kennisnet, 2020).

Perception

Perceptions are subjective and individualized interpretations and can be based on stimuli, attitude, interest, personality, belief, and experience (McDonald, 2012). This means that different people can perceive the same stimulus differently. Perception is the interpretation and organization of stimuli to create a meaningful image of the world (McDonald, 2012; Pickens, 2005). The input stimuli include visual, touch, sound, flavor, and smell. When processing these stimuli you become aware of the environment and are able to make meaningful associations. Someone’s perception is usually based on prior experiences, beliefs, attitudes, motivations, and personalities (Pickens, 2005). Therefore, an individual’s perception can differ from others and reality (McDonald, 2012; Pickens, 2005). Since we live in a world that is perceived differently by people, it is important to understand the perception of others. Perception is key in understanding human behavior. Because if people’s behavior is based on their perception, we could predict their behavior.

The perception process takes place in three stages, namely, selection, organization, and interpretation (Pickens, 2005). Selection is the focus on an incoming stimulus. Generally, people choose to focus on the stimulus that draws their attention. That is why, in a crowd full of people, you don’t hear or see everything. The organization of stimuli occurs when the received information is categorized. The last stage is interpretation. After categorizing the stimulus, it is given meaning. Generally, this is done subjectively, because the stimulus is interpreted solely on what a person already thinks to know (Wendel, 2020). For example, if there are only men associated with a work, it is possible to conclude that women generally are not interested in that work. However, the fact that there are only men at your office, does not mean this is true for every office in your field.

As illustrated by the example, people can make false interpretations of stimuli. Mistakes in perceptions can be categorized by: illusions, hallucinations, selective perception, and stereotypes. Stereotypes are the generalization of a perception of a whole group of people. These groups are usually stereotyped on behavioral or physical traits, for example, that computer science is a man’s occupation.

Additionally, the intention to perform an action or behavior depends on the perception of an individual. For example, if an individual associates a stimulus with anger, such stimuli could stimulate aggressive behavior. Positive perceptions of ability are linked to aspirations, educational choices, preference for challenging tasks, intrinsic motivation, and persistence (Beyer et al., 2003). Similarly, negative perceptions can prevent students to perform up to their ability (Appel & Kronberger, 2012). Resulting in retention and lack of motivation. This shows that perception is not just processing stimuli, but also has a relation to attitude, interest, personality, belief, and experience.

Diversity

The concept of diversity in computer science is explored in two parts, namely migration background, and gender. In particular, the inequality of these two within computer science. Although diversity consists of many more dimensions, such as sexuality and religion, this research has focused on gender and migration because these two are commonly known issues in computer science.

Migration background

The migration background of an individual is defined by the place individuals and their parents were born. Someone with a migration background was born in another country or has at least one parent who was born abroad. In the Netherlands, 25.7% of the citizens have a migration background (CBS, 2022b). The biggest non-western migration groups are the Turkish, Moroccan, Surinamese, Indonesian, and Caribbean, respectively (CBS, 2020b). Of the students who got a diploma in computer science, 19% had a non-western migration background, 17% had a western migration background, and 64% were Dutch (CBS, 2020c). In particular, of the non-western students that got a diploma in computer science, 13% was Turkish, 10% Moroccan, 13% Surinamese, and 6% were from Aruba, Bonaire, or Curacao, and 58% were defined as other (CBS, 2020c). Of the people who work in the IT sector, 79.1% are Dutch, 8.7% have a western background, and 12.1% have a non-western background. Compared to the population of the Netherlands, these numbers do not correlate. This shows that certain groups are underrepresented in computer science.

In the United States, minorities are underrepresented in computer science (Zarrett & Malanchuk, 2005). This issue is suggested to be the cause of stereotypes, discrimination, and lack of experience (Ross et al., 2020; Zarrett & Malanchuk, 2005). The study by Zarrett and Malanchuk (2005) aimed to investigate factors that influence the intention to pursue a career in computer science. The results (*N=1,482)* indicated that Black men are more likely to aspire to computer science than White men. Similarly, Black women are more likely to aspire to computer science than White women. However, Black women had fewer aspirations for computer science than White men. These results showed differences in intention to advance in computer science by race and gender. Nationality was not considered in this study, therefore, the findings of this research could differ from the findings of this research.

Additionally, these findings showed that Black students' self-perception of computer science was a significant factor to predict the intention to pursue a career in computer science. Zarrett and Malanchuk suggested that minorities should experience computer science at a young age, to stimulate positive self-perception of computer science.

Gender

This section investigates gender inequality in computer science. Gender inequality has been an issue for a long time. There is no doubt that women have been underrepresented in science, technology, engineering, and mathematics (STEM). In computer science, this has also been the student. Literature indicates that the lack of women in computer science has been caused by the label of computer science as a masculine field (Beyer, 2014; Papastergiou, 2008; Vekiri & Chronaki, 2008; VHTO, 2019), lack of role models, unwelcoming (work)climates (Varma, 2007; VHTO, 2019), stereotypes, and a lack of a sense of belonging (Beyer, 2014; VHTO, 2019).

A previous study in the United States by Beyer et al. (2003) examined gender differences in educational goals, interests, knowledge, and confidence in computer science. In their study ($N=56$), they distributed a questionnaire among students who were enrolled in computer science courses. This study found no gender differences in the interests in computer science or the knowledge of computer science. However, they revealed that male students, generally, have more confidence in their computer science skills than female students. Beyer et al. suggested that this lack of confidence could have been caused by negative experiences.

On the contrary, VHTO (2019) has researched gender differences within STEM in the Netherlands and found that there are differences in the interests in computer science between males and females. Since VHTO did their research in the Netherlands, it is expected to find differences between male and female students in this research.

Measurement: a conceptual framework

As mentioned before, perception is formed through attitude, interest, personality, belief, and experience. To measure the perception of 7th-grade students, items from various questionnaires were analyzed. These questionnaires were selected through a Google Scholar search. The queries used included: “assessing computer science”, “measure computer science”, and “questionnaire” AND “perception of students” AND “STEM”. Questionnaires were selected for analysis if the published questionnaire was peer-reviewed, and it consisted of scales for students. From this search, six subscales were developed to assess the perception of students, namely: experience, interest, usefulness, programmer perception, gender perception, and social value. These six subscales were merged into a single survey and was constructed through peer-reviewed surveys (Hoegh & Moskal, 2009; Leifheit et al., 2020; Mason & Rich, 2020; Rachamatullah et al., 2020), by selecting items that best fit the context of this research. A brief review of each subscale is provided in the following section.

Usefulness

The first subscale in the survey is usefulness. Usefulness is the value that is given to any type of aspect, such as objects or skills, to achieve a certain goal (Mason & Rich, 2020). In this research, usefulness is defined as the value students attach to computer science to achieve certain goals. In particular, usefulness is measured by the importance of computer science for school, future career, and general application. This is the conceptualization of usefulness used in this research. Additionally, usefulness is linked to perception, because of the prioritization of information. When something is considered useful, an individual is more likely to prioritize attention towards it (Wendel, 2020). This means that students could be more likely to aspire to study a field of computer science, if they consider computer science to be useful.

Gender perception

The second subscale in the survey is gender perception. Gender perception is a component that illustrates the distinction between positive and negative images of computer science (Ho, 2016). In this case, a positive image stands for equality between men and women in computer science. A negative image stands for inequality between men and women in computer science. This could be caused by stereotypes. According to research, negative stereotypes of women in computer science are formed through the belief that girls are less capable than boys (Mason & Rich, 2020; Papastergiou, 2008). Based on this, gender perception is measured by students’ opinions on the difference in interest for, skills in, and general application of computer science between male and female students. This is the conceptualization of gender perception.

Social value

The next subscale in the survey is social value. People are influenced by their surroundings (Wendel, 2020). For example, when people around you have a positive opinion on something, you can be influenced to think more positively about the same thing (Mason and Rich, 2020). Based on this, it can be concluded that someone's perception can form and change by others. Social value refers to society's perception of computer science. In this research, social value is measured by students' opinions of how their environment think of computer science. Their environment includes, parents, friends, and themselves. According to Falk et al. (2016), parents' perception of STEM correlates with their child's interest in STEM. This would mean that parents' perception of computer science also correlates with the student's interest in computer science.

Programmer perception

The fourth subscale in the survey is programmer perception. This component illustrates the distinction between positive and negative images of programmers (Ho, 2016). In this case, a positive image stands for the idea that anyone could be and look like a programmer. A negative image stands for stereotypical characterizations of programmers, such as a nerdy look. In this research, the perception of programmers is measured by students' images of programmers. In particular, what students understand what a programmer is, does, and look like.

Stereotypes in computer science are not only related to gender, but also to the social element. For instance, computer science has been illustrated in movies as an impossible job only the nerdiest of people can do (Flincher & Sorkin, 2010). These programmers in such movies usually are isolated and look shabby. Because of stereotypical displays of programmers, it is interesting to see if students believe such images by measuring the students' perception of programmers.

Experience

The fifth subscale is experience. In other research, this subscale has been called confidence or self-efficacy (Hoegh & Moskal, 2009; Mason & Rich, 2020; Rachmatullah et al., 2020). The reason to use experience as the name of the scale is that experience is more tailored to the domain of this research, namely perception. Confidence refers to the belief that an individual can perform a certain goal. This is usually influenced by prior experience (Ho, 2016; Pickens, 2005), therefore, has an effect on perception. Beyer (2014) demonstrated that students' confidence differs in computer science due to differences in computer science skills. Students who had more and earlier experience with computer science had a better understanding and confidence.

In this research, experience is defined by the impression students have been given by the encounters with events or practical contacts of computer science. In particular, experience is measured by student's positive and negative experience with computer science and problem-solving.

Interest

The next subscale in the survey is interest. Interest refers to how much an individual likes or dislikes computer science. The reason to include interest in the survey is the need to understand whether students have positive or negative feelings towards computer science. Variables, such as gender, could have an impact on the interest in computer science. In the study by Beyer (2014), male students had more interest in computer science than female students. As mentioned before, the interest of an individual partly shapes their perception (Ho, 2016; Pickens, 2005). In this research, interest is measured by students' feelings toward computer science and their motivation to pursue computer science in the future. This is the conceptualization of interest.

Influence perception

In order to influence students' perception of computer science interventions could be used, such as, information events, excursions to IT companies, guest lectures, internships, teaching materials, and games (Elfering et al., 2018). In order to successfully implement these interventions Elfering et al. (2018) have researched which conditions should be met. The conditions include: connecting the activity with students' experienced world, incorporate practical elements, provide feedback, make SMART goals, provide a broad image of computer science, provide a challenge, and guide the students in the process.

Particularly, there have been initiatives and factors that positively influence students' perception of computer science (Beyer, 2014; Vekiri & Chronaki, 2008; VHTO, 2019). For example, early exposure to computer science has a significant influence on the perception of computer science (Falk et al., 2016; Varma, 2007; VHTO, 2019; Zarrett & Malanchuk, 2005). In the Netherlands, VHTO[1] focuses on gender diversity in STEM. To encourage girls to aspire to STEM, VHTO has developed activities such as Girls' Day, perception breakers, and IT summer

[1] For more information on VHTO, see https://www.vhto.nl/

camp. These activities have been developed to provide a supportive environment, educate girls on computer science topics, and grow their interests in computer science.

Additionally, students' perception of computer science could be influenced by teaching them about computer science. The amount of knowledge someone has of computer science correlates with the level of interest in computer science (Falk et al., 2016). Especially children in the age range of ten to twelve show a significant increase in interest when interacting with computer science (Falk et al., 2016).

Based on the aforementioned factors and interventions, a serious game was selected to influence students' perception of computer science. A serious game allows for students to learn more about computer science, therefore, possibly increasing interest in the topic. Furthermore, the conditions suggested by Elfering et al. (2018) could be met when using a serious game.

Influence perception through serious game

A player's perception is influenced by many factors of a serious game. Zhonggen (2019) stated six factors. The first is the backstory of the game. The backstory provides information about the goal and the effect of the serious game. This allows for individuals to call upon prior knowledge and start the learning process. The second factor is realism, that refers to "the degree to which the game could meet users' expectations" (Zhonggen, 2019, p. 3). In other words, how much the game correlates with the player's perception. The third factor is adaptivity. Adaptivity entails the technology that is used to meet the players' needs. For example, if a serious game is online, it might be nice to have a mobile version of the game. Furthermore, the interaction influences the perception of players through social value and experience. When a player interacts with the game of other players, the player develops experience, confidence, and negative or positive feelings (Wang et al., 2017). Moreover, with serious games, it is the game factor that motivates players to play, pay attention, and learn consciously and unconsciously (Wang et al., 2017; Zhonggen, 2019). The fifth factor is feedback. Feedback is needed to understand what went well, what could have gone better and what shall be done next time. This is part of the learning process because a player can evaluate their experience with the game. The last factor is easiness. "The easier something is to do, the more likely the player is to do it" (Wendel, 2020, p. 19). On top of that, individuals do not like to fail, therefore, individuals avoid activities they think are too difficult (Wendel, 2020). These six factors can be used to evaluate the effect of a serious game on the perception of individuals.

Method

Research Design

This study tries to establish associations between the predictor variables (gender, educational level, migration, and SES) and the outcome variable (perception). Therefore the design of this study is similar to analytical studies (Ranganathan, 2019). Moreover, analytical studies usually have comparator groups. In this study, the comparator groups consist of students grouped by gender, educational level, migration, and SES. To answer the research questions, this study was divided into two parts, namely an observational part and an interventional part.

The observational part is in the form of a cross-sectional study. In cross-sectional studies, data is collected only once from the population, and information is provided on the associations between studied factors. According to Ranganathan, (2019), there are two limitations to cross-sectional studies. First, causal relationships are not always accurate, because there might be other factors that influence a relationship. Second, the findings of a cross-sectional study can be different at another points of time. The interventional part of this study consists of exposing students to a serious game. After analyzing the perception survey, a game was used to investigate whether students’ perception of computer science changed. In particular, which characteristics of the game affected students’ perception of computer science.

To generate and analyze the results in this study, a mixed-method design has been used. This means that the results are expressed in quantitative and qualitative statistics (Venkatesh et al., 2013). Mixed methods are used to explain or expand upon the understanding of previous findings (Venkatesh et al., 2013). This study employed a quantitative design to investigate students’ perception of computer science. A quantitative design is suitable, because concepts, such as perception, are made measurable and can be processed and analyzed quickly (Venkatesh et al., 2013). Moreover, the coherence between variables can be identified and explained in quantitative data (Babbie, 2016). To follow up on the findings of the quantitative results, qualitative data were analyzed to further investigate and understand the quantitative data. A qualitative design is suitable when an explanation or elaboration on data or an experiment is required (Venkatesh et al., 2013). The same method was used to investigate the effect of the serious game on students’ perception of computer science.

Research Samples

Data to answer the first research question was collected during the spring of 2022 from four junior high schools. These schools were recruited through the network of the researcher. All these schools provided computer science courses. This research involved only grade 7 students. These students generally have the age of twelve or thirteen. The data consists of students within a class, with each class belonging to a school. Figure 1 shows the construction of the sample. The sample is divided into three levels: student-level, class-level, and school-level. School 1 had nine classes and school 2, 3, and 4 and one class of 7^{th}-graders.

Table 1 shows an overview of the characteristics of the participating students. The sample ($N = 279$) contained 47.0% male, 49.5% female, and 3.5% students defined as other. The educational level is distributed as follows: 34.8% mavo, 27.6% havo, and 37.6% vwo. The distribution of the perceived SES shows 23.7% have a high SES, 72,0% have a medium SES, and 4.3% have a low SES. The migration background of the students is distributed as follows: 58.8% Dutch, 5.0% Caribbean, 6.5% African, 7.5% Asian, 8.6% European, 5.4% Middle Eastern, and 8.2% South-American.

To answer the second research question of this study, data was collected by conducting an experiment, namely playing a data center game. All 7^{th} grade students from school 1 were asked to participate in the experiment in their free time after school. From the nine classes of school 1, 43 students volunteered to participate in the experiment. The goal was to collect twenty students. The sample consisted of 18 boys, 23 girls and 2 defined as other. For participation, students did not receive a reward.

Figure 1

Hierarchical Model of the Sample

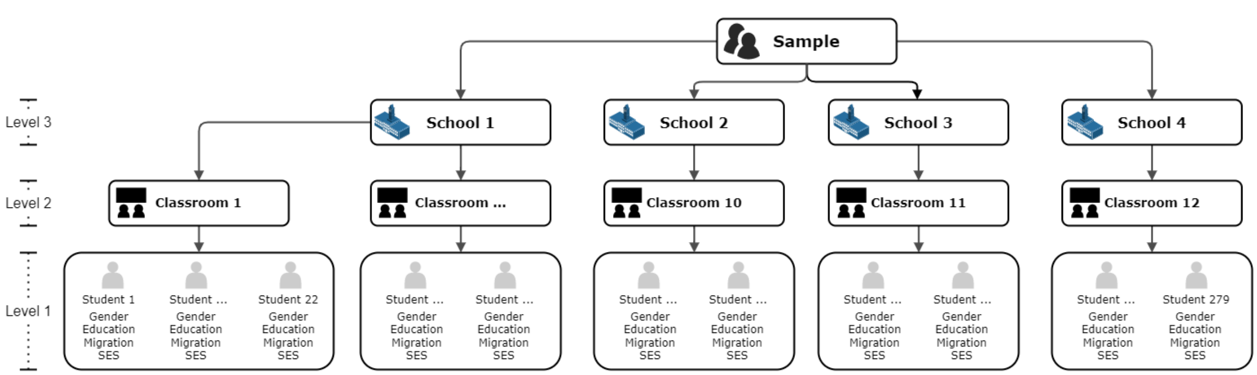


Table 1

Reported Characteristics of Quantitative Survey Respondents.

Characteristics	Category	School 1 *(N=206)*	School 2 *(N=17)*	School 3 *(N=40)*	School 4 *(N=16)*	Total *(N=279)*
Gender	Female	104	8	14	5	131
	Male	95	8	26	9	138
	Other	7	1	0	2	10
Migration background	Dutch	121	7	26	10	164
	Caribbean	13	1	0	0	14
	African	13	4	0	1	18
	Asian	15	0	5	1	21
	European	14	2	6	2	24
	Middle Eastern	12	0	2	1	15
	South-American	18	3	1	1	23
Education	MAVO	97	0	0	0	97
	HAVO	61	0	16	0	77
	VWO	48	17	24	16	105
SES	High	48	7	9	5	66
	Medium	148	8	22	9	201
	Low	10	2	9	2	12

Research Instruments

The research instruments consist of a game and two surveys, one to analyze the differences in the perception of computer science and the other to investigate the effect of the data center game. Before finalizing the surveys, four students were interviewed, to understand whether 7^{th}-grade students could understand what was asked in the surveys. During the interview students were asked to think out loud, to detect whether they understood the questions or if other items were missing from the questions. From these interview sessions, it became apparent that some items had to be modified and some items had to be added to the survey. For instance, to ensure comprehensibility students were asked whether they knew what computer *informatica*, ICT, and *programmeren* meant and if they could explain it. All of them were not able to explain the word *informatica*, but they all could provide a basic explanation of ICT and *programmeren*. Therefore, *'informatica/* ICT/ *programmeren'* was used in the survey instead of *informatica* alone. The construction and modifications of the survey are discussed in the following section.

Perception survey

A survey was conducted to collect data on grade 7 students' perception of computer science. This survey consisted of thirty closed questions and three open questions. Table 2 shows the survey scales, items and sources. The survey was developed with the use of existing questionnaires (Beyer, 2014; Hoegh & Moskal, 2009; Leifheit et al., 2020; Mason & Rich, 2020; Rachamatullah et al., 2020). Additionally, items were added to specifically measure students' perception of programmers. These items were based on the interviews with students and validated by a professor at the Delft Technical University (M.J. de Vries, personal communication, March 30 2020). The finalized survey used for this study was divided into nine parts: (1) consent check, (2) information on the students' backgrounds, (3) the usefulness subscale consisting of five items ($\alpha = .70$), (4) five items on gender perception ($\alpha = .53$), (5) the social value subscale consisting of four items ($\alpha = .54$), (6) the programmers subscale consisting of six items ($\alpha = .64$), (7) the experience subscale consisting of five items ($\alpha = .87$) , (8) five items on interest in computer science ($\alpha = .91$), and (9) three open questions on the perception of computer science.

To construct the survey, first, items were selected by association with the perception of computer science. Next, these items were filtered to associate with the scales considered in this research, namely experience, interest, usefulness, programmer perception, gender perception, and social value. This entails that items, such as 'I do my best with programming tasks' (Leifheit et al., 2020), were disregarded, because these items were not related to the scales used in this study. In total 58 items were selected in the first selection phase. By advice of two teachers, the number of items were decreased from 58 to 30 items (J. Bode & M. Amsink, personal communication, March 22nd 2022). They explained that the attention span of 7th grade students is small, therefore, the survey should not take longer than 15 minutes. Therefore, 28 items were removed to construct a survey of at most 15 minutes. This was done by combining items into a single item. For example, the items 'I am good at coding', 'I am good at problem solving', and 'I can write clear instructions for a robot', were grouped and transformed in 'I am good at computer science'. The effect of such changes is shown through the Cronbach's alphas from the study by Mason and Rich (2020). Table

3 shows the differences in the Cronbach's alpha scores of this study and the study by Mason and Rich (2020). The time estimated to complete the survey was approximately 10 min.

Table 2

Survey: Scales, Items and Sources.

Subscale	Items		Source
Usefulness	U1	Computer science is useful for other courses.	B, C, D
	U2	Computer science is not necessary for a career.	B, C, D
	U3	Everyone should know something about computer science.	B, C
	U4	Computer science is useless.	D
	U5*	Computer science is all around us.	F
Gender perception	G1	Boys and girls should both be good in computer science.	B, D
	G2	In general, boys are better than girls in computer science.	B, D
	G3	In general, girls are better than boys in computer science.	B, D
	G4	Boys like computer science better than girls.	D
	G5	Girls like computer science better than boys.	D
Social value	S1	I would not be friends with someone because they like computer science.	D
	S2	In general, kids that are good at computer science are smart.	D
	S3	Many of my friends think computer science is cool.	D
	S4	My parents think computer science is important.	D
Programmer perception*	P1	I have a good idea of how one can become a programmer.	F
	P2	I think everyone can do something with computer science later on.	F, G
	P3	I have no idea of what one has to do to become a programmer.	F
	P4	I think I know what is possible by using computer science.	F
	P5	I think a programmer has to have determination.	F, G
	P6	I think programmers are nerdy.	A, F
Experience	E1	I could learn computer science quite easily.	B, C, D
	E2	I am good at computer science.	B, C, D, E
	E3	I am good at detecting bugs/errors in a computer program/code.	B, D, E
	E4	I find computer science difficult.	B, C, D
	E5	I am good at solving bugs/errors in a computer program/code.	B, D, E
Interest	I1	I would like to learn more about computer science.	B, D
	I2	Computer science is interesting.	B, C, D
	I3	I find computer science boring.	B, D
	I4	I hope I never have to do something with computer science later.	B, D
	I5	I want to study something with computer science later.	B, D, E

Open questions	O1	What is computer science and what is it used for?	D
	O2	What does a programmer do?	D
	O3	What kind of people are good at computer science?	D

[*] *The P-items were constructed with a university professor from prior interview findings, to investigate the perception of programmers more specifically. Similarly, U5 was added to investigate the general importance of computer science.*

[A] *Beyer et al., 2003;*

[B] *Hoegh & Moskal, 2009;*

[C] *Leifheit et al., 2020;*

[D] *Mason & Rich, 2020;*

[E] *Rachamatullah et al., 2020 ;*

[F] *De Vries, personal communication, March 30th 2022.*

[G] *Prior interview findings*

Table 3

Reliability of Subscales.

Scales	**Items***	**Cronbach's Alpha**	**Cronbach's Alpha (Mason & Rich, 2020)**
Usefulness	U1, U2[r], U3, U4[r], U5	.697	.727
Gender perception	G1[r], G2, G3, ~~G4~~, G5	.530[a]	.687
Social value	~~S1~~[r], S2, S3, S4	.542[a]	.630
Programmer perception	P1, P2, ~~P3~~[r], P4, P5, P6[r]	.635[a]	n.a.
Experience	E1, E2, E3, E4[r], E5	.869	.785
Interest	I1, I2, I3[r], I4[r], I5	.913	.896

** Crossed out items are items that have a low reliability.*

[a] *These scores are the adjusted scores after removing the crossed items.*

[r] *These items were stated in reverse.*

A five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5) was used in the survey to allow respondents to give their responses to each item. To verify some responses of the students, some items were stated inversely (Field, 2018). These items are shown in Table 3. For the analysis, the reversed items were reversed again to have a single direction of the items, that is, either positive or negative. No abnormalities were found through the inverse statements. The survey also included a set of demographic questions concerning gender, educational level, migration background, and SES.

The reliability of the survey was calculated by the means of Cronbach's alpha. Table 3 shows the Cronbach's alpha per scale. As can be seen, gender perception and social value have poor reliability (Field, 2018). This indicates that some items are not well enough represented by the items, that questions are missing, or that questions have been misinterpreted (Field, 2018). The cause of these low scores is most likely due to the removal of items to make the survey more compact. This means that questions were missing. According to Field (2018), scales with Cronbach's alpha scores below .60 are usually removed. However, the scales from earlier studies had higher Cronbach's alpha scores (Hoegh & Moskal, 2009; Leifheit et al., 2020; Mason & Rich, 2020). Therefore, the scales are not removed, and the research proceeded.

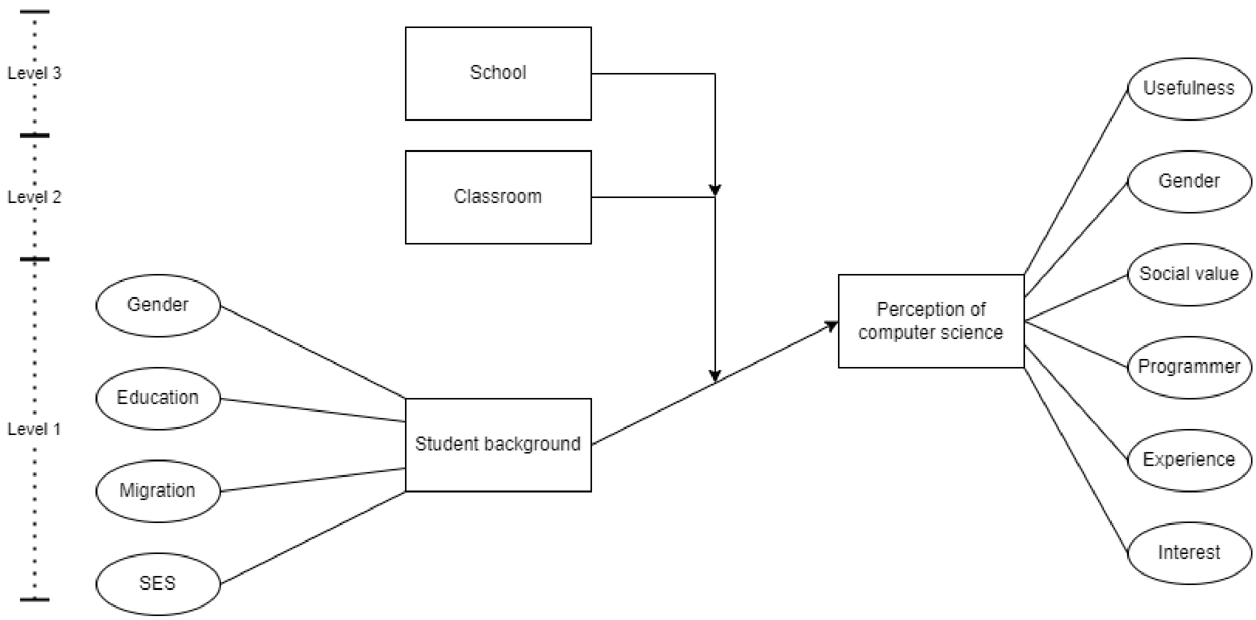
Variables

To illustrate potential differences in the perception of computer science between students with different backgrounds, and to better understand what factors constitute 7th-grade student perceptions of computer science, the scales (experience, interest, usefulness, programmer perception, gender perception, and social value) were separately used as dependent variables. This means that six different analyses are performed to analyze the computer science perception in these areas. For each scale, the scores of the items were added up to a single value. The score of the scales usefulness, programmer perception, experience, and interest can vary from 5 to 25, because there are five items and the lowest score per item is 1 ($5 \times 1 = 5$) and the maximum score of an item is 5 ($5 \times 5 = 25$). The score of the scale of gender perception varies from 4 up to 20 and the score of social value varies from 3 to 15. The scales have been treated as continuous dependent variables.

The independent variables are fixed variables at the student-level. Student-level variables include gender (male = 0, other = 1, female = 2), education (0 = mavo, 1 = havo, 2 = vwo), migration (1 = European, 2 = Caribbean, 3 = Asian, 4 = Middle Eastern, 5 = African, 6 = South-American, 7 = Dutch), and SES (0 = low, 1 = medium, 2 = high). The reason to include the levels of classroom and school is to check if the classroom or school influences the relations between the independent variables and the outcome variables. However, it should be noted that the sample size is smaller than the recommended 50 groups (Lee & Hong, 2021). Therefore, it is possible to obtain redundant and unreliable results. Figure 2 shows the conceptual model of the quantitative part of this research.

Figure 2

Conceptual Multilevel Model



After analyzing the quantitative variables, the relationships between the independent variables and the dependent variables are discussed together with the results of the open questions. The open questions provide explanations to certain findings of the analysis. The responses of the open questions are converted into a code tree and the distinctive responses are processed further by using to elaborate on the differences between students. Table 2 shows the open questions.

Data center game

To understand which factors influence students' perception, the educational game called the data center game was selected. To influence the perception of computer science careers, Kronstadt et al. (2020) developed a game about data centers. This game was created as an educational game, about data centers, for children between the age of 10 and 14. The game presents various diverse people in different positions to illustrate how diverse computer science can be. For instance, in the game women are positioned as managers and employers can have any type of ethnicity. Furthermore, the game can be played alone or in pairs. The game was designed to be played for an hour on a computer.

Data center game survey

To assess possible change in perception of computer science, a survey with open and closed questions was utilized. In comparison to the perception survey, the data center game survey was not produced from another research. Instead, questions were designed to understand what students had learned and how students perceived computer science after playing the game. Additionally, the questions were constructed to find out which influential factors are present in the data center game.

The code tree to analyze the data consists of the categories: backstory, adaptability, interaction, feedback, easiness, realism, usefulness, and change. These categories were constructed through literature (Wang et al., 2017; Wendel, 2020; Zhonggen, 2019). Based on the answers of the students, the codes were constructed. "Codes or categories are tags or labels for allocating units of meaning to the descriptive or inferential information compiled during a study" (Basit, 2003, p. 144). Figure 22 in the appendix illustrates the code tree.

To obtain a higher validity for coding the responses, the intercoder reliability was calculated through Holsti's method[2]. A value of 75% or higher has been considered to be a good reliability. The codes were evaluated by a masters student from the Erasmus University Rotterdam (S. Ramcharan, personal communication, July 27th 2022) and the researcher. The Holsti intercoder reliability score was $\frac{2\cdot 22}{27+27} = .81.$ This entails that the responses of both assessors were consistent. For the codebook and process see Appendix B and C.

Procedure

First, the online perception survey was constructed through literature. Next, items were selected and modified as full questions to examine if students understood the questions. After modifying the survey based on the findings, six schools were approached to participate. These school were approached through networking. Two of the schools were known by the researcher, the rest were found through a network of computer science teachers. Of the six schools, four schools approved the research through online communication. The two schools that did not take part in this study, did not provide computer science as a subject. This resulted in a sample of solely students who had computer science classes. Therefore, the findings of this research cannot be generalized to students who have not received computer science classes. In each school, the students anonymously filled out the online survey through Microsoft Forms.

[2] Holsti (1969). Content analysis for the social sciences and humanities. Reading, MA: Addison-Wesley.

After conducting the perception survey, the questions for the data center survey were generated. To obtain respondents for this part, the researcher went to different classes of a school and asked if students wanted to participate. To participate, they could sign up for a *‘vakuur* informatica’. During this moment, students played the data center game and afterwards filled out the online survey. Everyone was done within an hour.

Data analysis

The following procedure consisted of analyzing the data via the Statistical Package of Social Science (SPSS) (version 26). To investigate students’ perception of computer science, a three-level multilevel analysis was performed. Multilevel analysis can be used to study differences between groups over multiple levels (Field, 2018).

Before the analyses, the data were screened for outliers and impossible values. For the outliers, Cook’s distance was used. After this, three assumptions were tested, because the assumption of independence does not have to be met for multilevel analyses (Field, 2018). These assumptions consisted of normality, no outliers, and homoscedasticity. Normality refers to normally distributed scores within the groups. Homoscedasticity of error variance means that the error variance of the perception variable is equal in all the grouping variables. The answers to the open questions were grouped by repeated answers and used as support for the findings by the quantitative data.

To investigate the influence of the data center game on students’ perception of computer science, a coding system was developed to categorize the qualitative data. Because the answers were collected through a survey, there was no need for transcribing. The answers of the respondents were categorized, based on the coding system. To analyze the quantitative data, a means comparisons test was used.

Multilevel Analysis

The three-level model is conceptually similar to a linear regression model in that the outcome variable is predicted by predictor variable. However, to handle clustered data, the data is hierarchically analyzed. For example, level-1 is each students’ background factor, level-2 is the variation across students within classes, and level-3 is the variation of students within classes within schools.

The hierarchy of the data is included by assuming that the intercepts vary across classrooms and schools. The equation for the level-1 model is as follows:

$$Y_i = b_{0jk} + b_1 gender_{ijk} + b_2 education_{ijk} + b_3 migration_{ijk} + b_4 SES_{ijk} + \epsilon_i$$

where Y_i is the student's score on one a scale, b_{0jk} is the variability of the intercept, b_1 is the fixed coefficient for the predictor variable gender, b_2 is the fixed coefficient for the predictor variable education, b_3 is the fixed coefficient for the predictor variable migration, b_4 is the fixed coefficient for the predictor variable SES, X_{ijk} is the value of the predictor X of student i, and ϵ_i is the residual associated with a student's score. The level-2 equation is:

$$b_{0jk} = b_0 + u_{0jk}$$

where b_0 is the intercept of the overall model, and u_{0jk} is the variability of intercept around that overall model. The level-3 equation is:

$$u_{0jk} = u_{0j} + \gamma_{00k}$$

where u_{0j} is variation in the means across classrooms, and γ_{00k} is the variation in the means across schools. In the case of insignificant factors for the intercept, a value of 0 was appointed to the factor for the intercept, because an insignificant factor indicates no effect (Field, 2018).

Ethical considerations

Before partaking in the surveys, the research requested consent from the schools and teachers. Afterwards, during the survey, students were provided with a short textual introduction to this research. This introduction, included the purpose of this study, expectations of the participants, and an explanation of how data will be handled. They could check a box for consent and understanding of its purpose. Students were also explained by their teacher that they could revoke their participation at any time. This could be done by sending the researcher an email, which was provided at the end of the survey. After checking the consent box, the students could fill out the form. This shows that students have experienced minimal

Additionally, this research upholds the GDPR regulations, as well as the privacy laws in the Netherlands. This is done by only collecting necessary data. Therefore, name, age, and address were not asked. Furthermore, the schools were anonymized to prevent information linkage to students at a certain school and the data was only stored on a private school account from one of the schools.

Lastly, the results of this research will be communicated to the schools, which can distribute the findings to the students. After finalizing this research, the data will be deleted to adhere to GDPR regulations, that is, data should be deleted when the purpose of the data is accomplished. This means that the data of the students will not be stored in any database.

Results perception survey

Assumptions

Assumption of normality

The assumption of normality was tested by assessing the distribution of the dependent variables, via Q-Q plots. The dots that fit the predicted line from the normal distribution indicate that you are safe to assume normality. Figures 3 up until 18 in the appendix, show that the dependent variables are normally distributed for every group. Therefore the assumption is met.

Assumption of no outliers

The ANOVA assumption of no outliers is tested with boxplots. Outliers are denoted in boxplots with circles. Extreme outliers are denoted with asterixis. Figures 19 up until 22 show there are no extreme outliers, therefore the assumption is met.

Assumption of homogeneity of variance

The assumption of homogeneity of variance was tested with Levene's test. This test checks whether the variances in the different groups are significantly different. A significant Levene's test ($p < .05$) indicates that the variances in different groups are in fact not the same, thus violating the assumption of homoscedasticity (Field, 2018). For the gender variable, the Levene's test shows significance ($p = .027$). This indicates that the variance differs between, male, female and others. To account for this violation, Welsch's F is used to interpret the significance of the variable gender. For education, migration, and SES, the Levene's tests showed no significance ($p = .957$), ($p = .199$), ($p = .516$), respectively. Therefore, the assumption is met for these predictors.

Fitness of model

To answer the first research question, the results of the three-level multilevel analysis are used. For each outcome variable, the overall fit of the multilevel model was tested through a chi-square likelihood ratio test. SPSS provides the deviance that is minus twice the log likelihood ($-2LL$). The smaller the value of the log, the better the fit (Field, 2018). Table 4 shows the fit of the model per outcome variable. The results show that for each outcome variable the fit of the model is good, because the values are relatively small. That is, each chi square change value was smaller than the critical value for the chi-square statistic (with 2 *df*), which is 5.99 ($p < .05, df =$

2). The fitness of the model is evaluated by subtracting the log-likelihood of the new model from the value of the old:

$$x^2_{change} = -2LL_{old} - (-2LL_{new})$$

For each outcome variable, the interclass correlation (ICC) was calculated. "The ICC represents the proportion of the total variability in the outcomes that is attributable to the level" (Field, 2018, p. 1191). If a level has a big effect on the students' outcomes, the ICC is big. Conversely, if the ICC is small, this means that the level has little effect on the students' outcomes. Table 4 shows the ICC for each level and outcome variable. The results of the effects the levels have on the outcomes of the students shows that students are not influenced by the classroom or the school. In other words, there are no differences between classrooms and schools. The ICCs were calculated by $\frac{\sigma^2_{class}}{\sigma^2_{class}+\sigma^2_{school}+\sigma^2_{residual}}$ or $\frac{\sigma^2_{school}}{\sigma^2_{class}+\sigma^2_{school}+\sigma^2_{residual}}$.

Table 4

Results About the Fit of the Model

Outcome variable	df_{Δ}	x^2_{change}	ICC_{class}	ICC_{school}
Usefulness	2	.000	.000	.000
Gender perception	2	.000	.000	.000
Social Value	2	.492	.000	.020
Programmer perception	2	.000	.000	.000
Experience	2	.022	.000	.002
Interest	2	3.542	.001	.005

Multilevel analysis

Usefulness

The first analyzed outcome variable in the multilevel analysis was usefulness. The relationship between classroom and perceived usefulness showed no significant variance in intercepts across students, $Var(u_{0j}) = .00, x^2(2) = .00, p < .01$). Additionally, the relationship between school and perceived usefulness showed no significant variance in intercepts across students, $Var(\gamma_{00k}) = .00, x^2(2) = .00, p < .01$). This means that the coefficient for the variability around the overall model (u_{0jk}) is 0.

Table 4

Results of Multilevel Analysis for Outcome Variable Usefulness

Parameter	*b*	SD	*df*	t	*p-value*	*F*
Intercept	16.418376	.257379	279	63.791	.000	2859.791
Gender					.007*	5.065
Other	.228106	.638632	279	.357	.721	
Male	-.723969	.239401	279	-3.024	.003*	
Female[a]	0	0				
Education					.097	.907
HAVO	.080577	.291772	279	.276	.783	
MAVO / VMBO-tl	.120765	.279922	279	.431	.666	
VWO[a]	0	0				
Migration					.288	1.235
European	-.004180	.425904	279	-.010	.992	
Carribean	-.089348	.544134	279	-.164	.870	
Asian	.080897	.446325	279	.181	.856	
Middle Eastern	-1.016362	.521608	279	-1.949	.052	
African	-.969050	.486368	279	-1.992	.047*	
South-American	-.214790	.439004	279	-.489	.625	
Dutch[a]	0	0				
SES					.171	1.777
high	.421212	.282018	279	1.494	.136	
low	-.544828	.577831	279	-.943	.347	
Medium[a]	0	0				

[a] Reference group

* $p < .05$

Gender. The relationship between gender and perceived gender perception was significant, $F(2, 279\ ) = 5.07$, $p =\ .007$. This means that the perceived usefulness of computer science can be predicted by gender. The 138 male students had an average perceived usefulness score of 15.40 ($SD = .27$), the 131 female students have an average score of 16.13 ($SD = .26$), and students who identified as other have an average score of 16.36 ($SD = .65$). From these mean scores male and female students differ significantly $p = .003$. Specifically, male students perceived computer science to be more useful than female students. Students defined as other did not differ in scores from male and female students.

Educational level. The mavo students have a mean perceived usefulness score of 16.02 ($SD = .32$), the havo students have an average score of 15.98 ($SD = .36$), and the vwo students 15.90 ($SD = .34$). The relationship between education and perceived gender perception was not significant, $F(2{,}279) = .097, p = .907$. Therefore, perceived usefulness cannot be predicted by a student's educational level.

Migration background. The predictor migration background had no significant relationship with the perceived usefulness of computer science, $F(2{,}279) = 1.24$, $p = .288$. This means that usefulness cannot be predicted by migration background. Furthermore, from the migration groups only Dutch and African students differ significantly in the mean score $p = .047$. The European students have a mean of 16.28 ($SD = .46$), the Caribbean students have a mean of 16.19 ($SD = .59$), Asian students have a mean of 16.36 ($SD = .50$), the students from the Middle East have a mean of 15.263 ($SD = .54$), African students have a mean of 15.31 ($SD = .51$), the students from South-America have a mean of 16.06 ($SD = .50$), and the Dutch students have a mean of 16.28 ($SD = .29$).

SES. The predictor SES has a no significant relationship with students' perceived gender perception ($F(2, 279) = 1.78, p = .171$). The low SES students have an average perceived usefulness score of 15.46 ($SD = .59$), students with medium SES have 16.00 ($SD = .26$), and students with high SES have 16.43 ($SD = .34$). Between these groups there were no significant differences.

Gender perception

The second outcome variable that was analyzed in the multilevel analysis was gender perception. The relationship between classroom and perceived gender perception showed no significant variance in intercepts across students, $Var(u_{0j}) = .00, x^2(2) = .00, p < .01$). Additionally, the relationship between schools and perceived gender perception showed no significant variance in intercepts across students, $Var(\gamma_{00k}) = .00, x^2(2) = .00, p < .01$). This means that the coefficient for the variability around the overall model (u_{0jk}) is 0.

Table 5

Results of Multilevel Analysis for Outcome Variable Programmer Perception

Parameter	*b*	SD	*df*	t	*p-value*	*F*
Intercept	12.985507	.373809	279.000	34.738	.000	884.628
Gender					.096	2.364
Other	.511739	.927527	279.000	.552	.582	
Male	.754990	.347697	279.000	2.171	.031*	
Female[a]	0	0				
Education					.948	.053
HAVO	.135259	.423759	279.000	.319	.750	
MAVO / VMBO-tl	.033001	.406549	279.000	.081	.935	
VWO[a]	0[b]	0				
Migration					.790	.524
European	.572194	.618568	279.000	.925	.356	
Carribean	.186020	.790281	279.000	.235	.814	
Asian	.188675	.648227	279.000	.291	.771	
Middle Eastern	-.070984	.757565	279.000	-.094	.925	
African	-.761303	.706384	279.000	-1.078	.282	
South-American	-.501256	.637594	279.000	-.786	.432	
Dutch[a]	0	0				
SES					.013*	4.387
high	.530220	.409593	279.000	1.295	.197	
low	-2.072916	.839222	279.000	-2.470	.014	
Medium[a]	0	0				

[a] Reference group

[*] $p < .05$

Gender. The 138 male students have an average perceived gender perception score of 13.23 ($SD = .39$), the 131 female students have an average perception score of 12.47 ($SD = .38$), and students who identified as other have an average perception score of 12.98 ($SD = .94$). The relationship between gender and perceived gender perception was not significant, $F(2, 279\ ) = 2.36, p = \ .096$.

Educational level. The mavo students have an average perceived gender perception score of 12.87 ($SD = .48$), the havo students have an average of 12.97 ($SD = .53$), and the vwo students 12.84 ($SD = .50$). The relationship between education and perceived gender perception was insignificant, $F(2{,}279) = .05$, $p = .948$. Therefore, perceived gender perception cannot be predicted by a student's educational level.

Migration background. The predictor migration background had no significant relationship with the perceived gender perception, $F(2{,}279) = .52$, $p = .790$. Furthermore, none of the groups within the migration background differed in the mean scores of the perceived gender perception. The students from Europe have a mean of 13.52 ($SD =.67$), the students of the Caribbean have a mean of 13.14 ($SD = .86$), the students from Asia have a mean of 13.13 ($SD = .73$), the students of the Middle East have a mean of 12.88 ($SD = .79$), the students from Africa have a mean of 12.19 ($SD = .74$), the students from South-America have a mean of 12.45 ($SD = .72$), and the Dutch students have a mean of 12.95 ($SD = .43$).

SES. The predictor SES has a significant relationship with students' perceived gender perception ($F(2, 279) = 4.19, p = .013$). The low SES students have an average perceived gender perception score of 11.34 ($SD = .85$), students with medium SES have 13.41 ($SD = .38$), and students with high SES have 13.94 ($SD = .49$). Students with low SES think computer science is more for boys than for girls, compared to students with medium SES ($b = -2.073, \mathrm{t}(279) = -2.470, \mathrm{p} = .014$) and high SES ($b = -2.603, p = .004$). There was no significant difference between students with medium and high SES.

Social value

The third outcome variable that was analyzed in the multilevel analysis was social value. The relationship between classroom and perceived social value showed no significant variance in intercepts across students, $Var(u_{0j}) = .00, x^2(2) = .49, p < .01$). Additionally, the relationship between school and perceived social value showed no significant variance in intercepts across students, $Var(\gamma_{00k}) = .02, x^2(2) = .49, p < .01$). This means that the coefficient for the variability around the overall model (u_{0jk}) is 0.02.

Table 6

Results of Multilevel Analysis for Outcome Variable Social Value

Parameter	*b*	SD	*df*	t	*p-value*	*F*
Intercept	9.451725	.304043	34.207	31.087	.000	661.079
Gender					.007*	5.024
Other	.766964	.698183	274.016	1.099	.273	
Male	.839831	.261597	272.503	3.210	.001*	
Female[a]	0	0				
Education					.154	2.122
HAVO	-.321894	.344778	41.740	-.934	.356	
MAVO / VMBO-tl	.216685	.357897	10.080	.605	.558	
VWO[a]	0	0				
Migration					.303	1.207
European	.042704	.465516	273.306	.092	.927	
Carribean	.532324	.595899	276.665	.893	.372	
Asian	.360787	.488901	277.368	.738	.461	
Middle Eastern	.984866	.570482	275.151	1.726	.085	
African	-.513886	.532359	276.207	-.965	.335	
South-American	-.571534	.478870	268.237	-1.194	.234	
Dutch[a]	0	0				
SES					.770	.261
high	-.067845	.309388	278.846	-.219	.827	
low	-.430203	.633185	277.866	-.679	.497	
Medium[a]	0	0				

[a] Reference group

$^{*}p < .05$

Gender. The relationship between gender and perceived social value was significant, $F(2, 279\ ) = 5.26$, $p =\ .006$. This means that the perceived social value of computer science can be predicted by gender. The 138 male students have an average social value score of 10.21 ($SD = .30$), the 131 female students have an average score of 9.37 ($SD = .30$), and students who identified as other have an average score of 10.14 ($SD = .71$). From these mean scores male and female students differ significantly $p = .001$. In particular, male students have a more positive perception of the social value than female students. Students defined as other did not differ in scores from male and female students.

Educational level. The mavo students have an average perceived usefulness score of 10.16 ($SD = .38$), the havo students have an average of 9.62 ($SD = .42$), and the vwo students 9.94 ($SD = .39$). The relationship between education and perceived social value was not insignificant,

$F(2{,}279) = 1.067$, $p = .368$. Therefore, the social value cannot be predicted by a student’s educational level.

Migration background. The predictor migration background has no significant relationship with the perceived usefulness of computer science, $F(2{,}273.90) = 1.25$, $p = .282$. This means that usefulness cannot be predicted by migration background. Furthermore, from the migration groups only Dutch and African students differ significantly in the mean score $p = .047$. The European students have a mean of 9.83 ($SD = .51$), the Caribbean students have a mean of 10.32 ($SD = .65$), Asian students have a mean of 10.15 ($SD = .55$), the students from the Middle East have a mean of 10.71 ($SD = .60$), African students have a mean of 9.27 ($SD = .56$), the students from South-America have a mean of 9.22 ($SD = .55$), and the Dutch students have a mean of 9.79 ($SD = .33$).

SES. The predictor SES has no significant relationship with students’ perceived social value ($F(2, 274.17) = .240, p = .788$). The low SES students have an average perceived usefulness score of 9.64 ($SD = .65$), students with medium SES have 10.07 ($SD = .30$), and students with high SES have 10.00 ($SD = .38$). Between these groups there were no significant differences.

Programmer perception

The fourth outcome variable that was analyzed in the multilevel analysis was programmer perception. The relationship between classroom and the perception of programmers showed no significant variance in intercepts across students, $Var(u_{0j}) = .00, x^2(2) = 3.542, p < .01$). Additionally, the relationship between school and the perceived perception of programmers showed no significant variance in intercepts across students, $Var(\gamma_{00k}) = .01, x^2(2) = 3.542, p < .01$). This means that the coefficient for the variability around the overall model (u_{0jk}) is 0.01.

Table 7

Results of Multilevel Analysis for Outcome Variable Programmer Perception

Parameter	*b*	SD	*df*	t	*p-value*	*F*
Intercept	18.160866	.355017	279.000	51.155	.000	1980.951
Gender					.368	1.002
Other	.267483	.880899	279.000	.304	.762	
Male	.467538	.330218	279.000	1.416	.158	
Female[a]	0[b]	0				
Education					.442	.818
HAVO	-.282617	.402456	279.000	-.702	.483	
MAVO / VMBO-tl	.246553	.386111	279.000	.639	.524	
VWO[a]	0[b]	0				
Migration					.184	1.483
European	.533961	.587472	279.000	.909	.364	
Carribean	1.357751	.750552	279.000	1.809	.072	
Asian	1.427809	.615640	279.000	2.319	.021	
Middle Eastern	.296165	.719482	279.000	.412	.681	
African	-.261580	.670873	279.000	-.390	.697	
South-American	.225385	.605542	279.000	.372	.710	
Dutch[a]	0[b]	0				
SES					.162	1.835
high	-.242363	.389002	279.000	-.623	.534	
low	-1.496691	.797034	279.000	-1.878	.061	
Medium[a]	0[b]	0				

[a] Reference group

$^{*}p < .05$

Gender. The relationship between gender and perceived perception of programmers is not significant, $F(2, 279) = 1.00$, $p = .368$. This means that the perception of programmers is not influenced by gender. The 138 male students have an average perception score of 18.55 ($SD = .37$), the 131 female students have an average score of 18.08 ($SD = .36$), and students who identified as other have an average score of 18.35 ($SD = .89$).

Educational level. The relationship between education and the perception of programmers is not insignificant, $F(2,279) = .82$, $p = .442$. Therefore, the perception of programmers is not influenced by a student's educational level. The mavo students have an average perceived score of 18.58 ($SD = .44$), the havo students have an average of 18.06 ($SD = .50$), and the vwo students 18.34 ($SD = .47$).

Migration background. The predictor migration background has no significant relationship with the perceived interest in computer science, $F(2,279) = 1.48$, $p = .184$. This means that the perception of programmers is not influenced by migration background. The European students have a mean of 18.35 ($SD = .64$), the Caribbean students have a mean of 19.17 ($SD = .82$); Asian students have a mean of 19.24 ($SD = .69$), the students from the Middle East have a mean of 18.11 ($SD = .75$), African students have a mean of 17.55 ($SD = .70$), the students from South-America have a mean of 18.04 ($SD = .69$), and the Dutch students have a mean of 17.81 ($SD = .40$).

SES. The relationship between SES and the perceived perception of programmers is not significant ($F(2, 274.08) = 1.84, p = .162$). This means that students' perception of programmers is not influenced by their SES. The low SES students have an average interest score of 17.41 ($SD = .81$), students with medium SES have 18.91 ($SD = .36$), and students with high SES have 18.66 ($SD = .47$).

Experience

The fifth outcome variable that was analyzed in the multilevel analysis was experience with computer science. The relationship between classroom and perceived experience with computer science showed no significant variance in intercepts across students, $Var(u_{0j}) = .00, x^2(2) = .02, p < .01$). Additionally, the relationship between school and perceived experience with computer science showed no significant variance in intercepts across students, $Var(\gamma_{00k}) = .00, x^2(2) = 022, p < .01$). This means that the coefficient for the variability around the overall model (u_{0jk}) is 0.02.

Table 8

Results of Multilevel Analysis for Outcome Variable Experience

Parameter	*b*	SD	*df*	t	*p-value*	*F*
Intercept	14.164003	.366120	72.822	38.687	.000	736.507
Gender					.044*	3.153
Other	.613129	.898641	277.818	.682	.496	
Male	.781810	.336854	277.494	2.321	.021*	
Female[a]	0	0				
Education					.011*	4.655
HAVO	-1.011685	.415488	64.265	-2.435	.018*	
MAVO / VMBO-tl	-.767264	.403152	19.555	-1.903	.072	
VWO[a]	0	0				
Migration					.800	.511
European	-.453398	.599293	277.688	-.757	.450	
Carribean	.030966	.765915	278.926	.040	.968	
Asian	-.642626	.628242	278.938	-1.023	.307	
Middle Eastern	.338043	.734009	278.095	.461	.645	
African	.328557	.684526	278.691	.480	.632	
South-American	-.554661	.617508	274.816	-.898	.370	
Dutch[a]	0	0				
SES					.744	.296
high	.076910	.397050	278.886	.194	.847	
low	-.462511	.813397	278.989	-.569	.570	
Medium[a]	0	0				

[a] Reference group

[*] $p < .05$

Gender. The relationship between gender and perceived experience with computer science programmers was not significant, $F(2, 277.61\ ) = 2.72$, $p =\ .068$. This means that the perceived experience with computer science is not influenced by gender. The 138 male students have an average experience score of 14.09 ($SD = .38$), the 131 female students have an average score of 13.31 ($SD = .37$), and students who identified as other have an average score of 13.92 ($SD = .91$).

Educational level. The relationship between education and the perceived experience with computer science is significant, $F(2{,}28.6) = 3.38$, $p = .048$. Therefore, the perceived experience with computer science can be predicted by the educational level of a student. The mavo students have an average score of 13.60 ($SD = .46$), the havo students have an average of 13.35 ($SD = .52$), and the vwo students 14.36 ($SD = .48$). The mean difference between havo and vwo was significant, $p = .018$. Vwo students had more (positive) experiences with computer science than havo students. Mavo students did not differ from havo or vwo students.

Migration background. The relationship between migration background and perceived experience with computer science is not significant, $F(2{,}277.39) = .48$, $p = .821$. This means that the perceived experience with computer science is not influenced by migration background. The European students have a mean score of 13.45 ($SD = .65$), the Caribbean students have a mean score of 13.94 ($SD = .83$); Asian students have a mean score of 13.27 ($SD = .70$), the students from the Middle East have a mean score of 14.25 ($SD = .77$), African students have a mean score of 14.24 ($SD = .72$), the students from South-America have a mean score of 13.35 ($SD = .70$), and the Dutch students have a mean score of 13.91 ($SD = .41$).

SES. The relationship between SES and the perceived experience with computer science is not significant ($F(2, 276.85) = .20, p = .820$). This means that students' perceived experience with computer science is not influenced by their SES. The low SES students have an average interest score of 13.44 ($SD = .83$), students with medium SES have 13.90 ($SD = .37$), and students with high SES have 13.98 ($SD = .48$).

Interest

The last outcome variable that was analyzed in the multilevel analysis was interest. The relationship between classroom and perceived interest in computer science showed no significant variance in intercepts across students, $Var(u_{0j}) = .00, x^2(2) = 3.542, p < .01)$. Additionally, the relationship between school and perceived interest in computer science showed no significant variance in intercepts across students, $Var(\gamma_{00k}) = .01, x^2(2) = 3.542, p < .01)$. This means that the coefficient for the variability around the overall model (u_{0jk}) is 0.01.

Table 9

Results of Multilevel Analysis for Outcome Variable Interest

Parameter	*b*	SD	*df*	t	*p-value*	*F*
Intercept	14.062683	.285543	34.517	49.249	.000	2264.994
Gender					.016*	4.188
Other	.625815	.589011	272.384	1.062	.289	
Male	.629243	.220566	271.518	2.853	.005*	
Female[a]	0	0				
Education					.915	.089
HAVO	-.112305	.315779	73.473	-.356	.723	
MAVO / VMBO-tl	-.129026	.363057	14.654	-.355	.727	
VWO[a]	0	0				
Migration					.056	2.074
European	.036437	.392600	271.785	.093	.926	
Carribean	.191319	.503248	273.653	.380	.704	
Asian	.320182	.413167	274.956	.775	.439	
Middle Eastern	.676476	.481572	273.534	1.405	.161	
African	-1.185875	.449580	274.064	-2.638	.009*	
South-American	-.508099	.403208	268.769	-1.260	.209	
Dutch[a]	0	0				
SES					.008*	4.895
High	.659090	.261952	277.370	2.516	.012*	
Low	-.785621	.535376	275.814	-1.467	.143	
Medium[a]	0	0				

[a] Reference group

* $p < .05$

Gender. The relationship between gender and perceived interest in computer science is significant, $F(2, 279) = 4.19$, $p = .016$. This means that the perceived interest in computer science can be predicted by gender. The 138 male students have an average interest score of 14.50 ($SD = .27$), the 131 female students have an average score of 13.87 ($SD = .27$), and students who identified as other have an average score of 14.50 ($SD = .61$). From these mean scores male and female students differ significantly $p = .005$. In particular, male students have a more interest in computer science than female students. Students defined as other did not differ from male and female students in the mean interest score.

Educational level. The relationship between education and interest in computer science was not insignificant, $F(2{,}279) = .09$, $p = .915$. Therefore, the interest in computer science cannot be predicted by a student's educational level. The mavo students have an average perceived usefulness score of 14.243 ($SD = .36$), the havo students have an average of 14.26 ($SD = .37$), and the vwo students 14.37 ($SD = .35$).

Migration background. The predictor migration background has a marginal significant relationship with the perceived interest in computer science, $F(2{,}272.62) = 2.07$, $p = .056$. This means that the interest could be predicted by migration background if the confidence interval was adjusted. From the migration groups African students show significantly less interest in computer science than European ($p = .03$), Caribbean ($p = .032$), Asian ($p = .011$), Middle Eastern ($p = .003$) and Dutch students ($p = .009$). Moreover, South-American students have less interest in computer science than Middle Eastern students ($p = .048$).

The European students have a mean of 14.40 ($SD = .44$), the Caribbean students have a mean of 14.55 ($SD = .56$); Asian students have a mean of 14.68 ($SD = .48$), the students from the Middle East have a mean of 15.04 ($SD = .52$), African students have a mean of 13.17 ($SD = .49$), the students from South-America have a mean of 13.85 ($SD = .47$), and the Dutch students have a mean of 14.36 ($SD = .30$).

SES. The predictor SES has a significant relationship with students' perceived interest in computer science ($F(2, 274.08) = 4.90, p = .008$). This means that the interest in computer science can be predicted by the SES of a student. The low SES students have an average interest score of 13.55 ($SD = .56$), students with medium SES have 14.33 ($SD = .27$), and students with high SES have 14.99 ($SD = .33$). Between these groups low and high SES students differ significantly, $p = .01$. The results show that low SES students have less interest in computer science than high SES students. Similarly, medium SES students have less interest in computer science than high SES students, $p = .012$. There was no difference between low and medium SES students.

Qualitative results

For this section, the most important findings from the open questions are discussed.

What is computer science?

For this question sixty students defined computer science as something that involves ICT. Student 165 said: "This branch is about networking, computers, printers, phones, and much more. Even devices such as traffic lights and elevators involve ICT." Furthermore, 96 students think computer science is something with programming or developing. Student 6 said that "it is programming websites, solving errors, if a computer/ other device is broken to repair it and much more." This entails that many students see computer science as a field that involves interacting with computer systems only. As a confirmation, 80 students mentioned computers in their answer.

Although computer science is much broader than "working with computers" (Student 67), still many students believe that computer science is limited to image of computer-based work. There were some students who had a deeper meaning of computer science. Student 121 said: "it is for people who later on want to decipher hackers." This statement is interesting, because it touches upon the problem-solving element within computer science. Six other students mentioned this problem-solving element.

What does a programmer do?

For this question a hundred students answered that a programmers programs. Most of the answers were about developing. Student 207 said that "it is a person who can program things and can see what is wrong with the computer." Student 77 said "creates websites and machines". There were also many answers that included the development of games. This entails that many students associate programmers with game developers.

What kind of people are good in computer science?

For this question 45 students mentioned that people that are good in computer science have perseverance. This entails that computer science can be a tough work and that those working in the field of computer science sometimes push through to get the job done. Additionally, 37 students think you need to be smart and 7 other students think you need to be a nerd to be good at computer science. Student 253 said "they are smart people with a lot of perseverance." Student 16 said "a vwo diploma I guess." This is peculiar, because the quantitative results have shown that vwo students have more (positive) experience with computer science.

Results data center survey

From the results of the perception survey, it became apparent there were differences within genders, educational levels, migration backgrounds, and SES, for particular constructs. Gender differences were the found the most in the scales of perception. This is why, this study zoomed in on these differences and an intervention was selected that stimulates diversity in computer science, namely the data center game. To answer the second research question: 'Which characteristics of an intervention influence students' perception of computer science?', 43 7th grade students played the data center game and answered questions about the game and how they perceived computer science afterwards. The content of their answers have been analyzed and coded with Atlas. The qualitative analysis links the factors (backstory, adaptivity, interaction, realism, feedback and easiness) to the survey answers. To ensure the students were not steered into providing desired answers the questions were kept broad.

Qualitative Analysis

The influential factors of the data center game were analyzed with qualitative data. The quotes were coded by backstory, adaptivity, interaction, realism, feedback, and easiness. After discussing these a few extra questions discussed.

Backstory

The backstory of an intervention allows for participants to associate concepts and to stimulate learning (Zhonggen, 2019). In the data center game, this was applied through a story-like roleplay gameplay. At the beginning of the game, players are introduced to data centers. After choosing an avatar that represents an engineer, the players traverse through the data center solving issues of which the cause is unknown. These issues are solved by playing mini-games. These provide more detailed information of certain aspects of the data center. At the end of the game, players figure out what caused all the problems, namely a cat.

The influential factor of the backstory was present in the game because two students mentioned the cat. In the survey, two respondents mentioned the cat. One respondent (student 2) said that the cat was a nice element of the game. The other (student 7) did not like that the cat was the ending of the game. Additionally, 17 respondents believed that learning occurred by playing the data center game. One respondent (student 42) noted that learning takes place while doing something you like: "That they play a game that they like, but then about a subject you need to learn something about." When asked about a specific element of the game, namely when the data center is efficient, 12 respondents replied with green energy. Some other students provided similar answers. For instance, "if the same amount is raised and used" (student 27). There were 11 respondents who did not know the answer.

Although, the backstory allowed for learning to happen, no specific detail was given about the storyline or the order of this in the answers of the respondents. This is probably due to the limitation of using a survey. Respondents were not aided in giving the "correct" responses.

Adaptivity

Adaptivity within an intervention refers to how much of the needs of the participants are met (Zhonggen, 2019). In the data center game, players can choose an avatar which is female, male or binary. Furthermore, explanations are given for each minigame, and a help function is integrated to aid players when needed. This would entail proper adaptivity.

However, according to the respondents, the influential factor of adaptivity was not strongly present in the game. To the question 'what would you improve to the data center game?', one respondent (student 9) said: "more fun and a make little more choices for the avatars." This entails that the game is not adaptive enough, meaning more choice should be given.

Interaction

Interaction with(in) an intervention allows for a participant to develop an experience. This allows the participant to learn (Zhonggen, 2019). The interaction category was divided into four sub-categories, namely: positive experience, negative experience, feelings, and confidence. In the data center game, interaction was stimulated through the use of non-player characters, the mini-games and other players.

According to the respondents, the experience factor, was present in the data center game. When asked about the experience respondents had with the game, there were many aspects mentioned. Almost every respondent enjoyed playing the game 40 out of 43. One respondent (student 14) said, "the game was very fun". This indicates an opinion on the whole game. Other respondents had more specific opinions on their experience. Some of the specific opinions were:

"Putting the question in a fun way in the game." (student 20)

"Because you play games that are actually happening." (student 30)

"That you were able to play it yourself." (student 42)

These positive experiences while playing the game, also included relaxation. This was expressed by student 2 as "being allowed to just play for a while."

Apart from the positive experiences, there were also negative experiences with the game. When asked about the drawbacks of the game, some respondents thought the game would be boring for others. Student 11 said that the people who do not like the game are "people who do not like long boring games and who do not like this like me." Student 15 supported the opinion that the game is too long. Student 15 said "it took too long." It is clear from these responses that the game can be considered lengthy. Therefore, having a negative effect on the experience of the player.

Realism

Realism of an intervention refers to the expectation of the user. With a high realism factor, users expectations are met. The data center game was constructed together with Interxion[3], a multinational that provides data centers. This has ensured realism of the game's content. Additionally, the game was developed for children around the age of 12.

When asked about what type of people would play this game, diverse answers were given. Student 34 said "you need to have persistence". This implies the game can be considered difficult or long, as was mentioned before. Student 12 said "older people probably do not like it, but teenagers and children do not always think it is as fun." Fortunately, adults were not the target group of the game. Moreover, this statement implies that not everyone around the age of 12 would like the game. This is supported by student 14, who said "not everyone likes these games."

Apart type of people who would play the game, student 42 considered the game to be unrealistic. Student 42 said "make the quality better and more beautiful and with better I mean more realistic." This entails that the game is not realistic enough. Realism was in this case only partly present in the game.

Feedback

The feedback factor is focused on the explicit learning of the players. The data center game measures learning through a quiz at the end of the game. In this quiz, question are provided that include all the minigames. Additionally, feedback is provided for all the minigames in the game. These feedback include instructions and information.

When asked about what was learned through the provided information in the game, respondents had diverse answers. Student 31 said "you have to watch out what you do online".

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[3] For more information on Interxion, see www.interxion.com

Student 3 said "there is a lot to learn and do." And student 5 said "you have to watch out for hackers because they can cause a lot of damage." These responses imply that players learn about the dangers online. Additionally, 10 respondents said they had learned more about data.

There were also respondents who did not learn new things. Nine respondents gave the feedback that they did not learn new things. A reason for no learning could be the fact that these students have had computer science courses. This is why feedback is still considered to be strongly present in the game.

Easiness

Easiness refers to the amount of effort that is used to perform an act (Zhonggen, 2019). The data center game was created to last about an hour. The game provides help when a player clicks the help button, and the storyline guides the player to the correct places. This would entail the game is easy to understand and follow.

When asked about the easiness of the game, respondents were more neutral and negative than positive. Fourteen respondents considered the game to be too difficult. While 17 respondents would not have changed a thing to the game. Additionally, most respondents considered the game to be fun, therefore, the easiness of the game is balanced.

Changed perception

To answer the research question, it is essential to know whether students' perception changes through the game and by what exact elements it happens. For the question "has your perception of computer science changed?" most of the students answered no. This means that what they already knew about data centers did not change and that new insights was not obtained.

However, perception is linked to interest and experience. Therefore, the question was asked what they linked about the game. Student 17 said that he liked the walking through the game and solving puzzles. This means that the game element that stimulated interest and a positive experience was a problem-solving aspect and freedom. Furthermore, 15 student like the playing the minigames in the game. This indicates that gamification has impact on the interest and experience of the students.

Quantitative analysis

Apart from the qualitative results, students filled out three 5-point Likert scale questions. These questions could be answered with "strongly agree" up until "strongly disagree". These results were used to have an insight on the interest in and experience with computer science. The problem-solving aspect is also mentioned by four other students.

For the question “I want to do a study computer science later” 47% students answered disagree, 28% neutral, 14% strongly disagree, 7% agree, and 5% strongly agree. This means that most students do not want to do a study of computer science.

For the question “I think computer science is boring” 44% was neutral, 23% disagrees, 16% strongly disagrees, 12% agrees, and 5% strongly agrees. This means that most student lean towards the opinion that computer science is not boring.

For the question “I know what is possible when using computer science” 49% was neutral, 26% agrees, 14% disagrees, 9% strongly agrees, and 2% strongly disagrees. Almost half of the participating students gave a neutral answer.

Conclusion

This research aimed to explore to what extent 7th-grade students with dissimilar backgrounds differ in their perceptions of computer science, and to investigate which characteristics of an intervention influence students' perceptions of computer science. To accomplish these goals a survey was constructed. These scales of the survey were usefulness, gender perception, social value, programmer perception, experience, and interest.

Based on the results of the perception survey, it can be concluded that gender can only be used as a predictor for perceived usefulness, social value, and interest of computer science. The results illustrated that male students think computer science is more useful, than female students think it is. Moreover, male students have more interest in computer science than the female students, and male students perceive their surrounding as more positive towards computer science, than female students. This was supported by qualitative data of students that described a person that is good at computer science. Students chose words such as smart, nerd, man, computers, and hacker.

The education level of the students was a predictor for the experience of the students with computer science. Students in the vwo classes had more positive experiences with computer science. However, the education level of the students did not have a significant relation with usefulness, gender perception, social value, or interest.

The migration background of the students showed no significant relationship with any of the outcome variables. This entails that there are no significant differences between migration groups.

Based on the results, it can be concluded that SES has a significant relationship with gender perception and interest. Students with low SES had more stereotypes than the students with medium SES and high SES. Therefore, teachers should focus on exposing students with low SES to stimuli that could break such stereotypes. Additionally, students from low SES had significantly lower interest in computer science, than students with high SES. Similarly, students with medium SES had lower interest in computer science, than students with high SES. However, education had not influence on usefulness, gender perception, social value, and interest for computer science. Based on these results this means that students in mavo, havo and vwo are equally aligned in their perception of computer science.

Additionally, this research aimed to identify the effects of the data center game on the perceptions of the students. Based on the data center game analysis, it can be concluded that the data center game did not change the motivation of students to pursue computer science careers. When the students were asked if their image of computer science had been changed, most student responded with no. This means that the game exhibited elements that they already knew. However, perception is also based on interests and experiences. The scores for the question about students' interest showed that most of the students are either neutral or positive about the game. Within the game, the fun factor came from the minigames, the freedom and the challenges. Therefore, the factors influencing students' perception of computer science include game elements, freedom, and problem-solving aspects. Moreover, the factors backstory, interaction and easiness can aid in stimulating motivation. Incorporating these factors allows to indirectly influence individual's perceptions.

Discussion

The current research, analyzed the relationship between the predictor variables (gender, education, migration, and SES) and the outcome variables (usefulness, gender perception, social value, programmer perception, interest, and experience), to explore the differences in 7th-graders' perceptions of computer science. The most remarkable finding in the study was that gender influences the perceived usefulness, social value, and interest of computer science. This is consistent with the findings from the literature (Beyer et al. 2003; Varma, 2007; Vekiri & Chronaki, 2008; VHTO, 2018). Female students generally have perceived computer science as less useful and interesting, than male students. A reason for this is a lack of sense of belonging, because females student could think computer science is more a masculine field (Vekiri & Chronaki, 2008). Based on the results, more initiatives should be made to stimulate female students into trying out computer science.

Based on the results, gender perception can be predicted by a student's SES. Students with lower SES have more stereotypes, than medium and high SES. This finding complies with the expectation that students with low SES are less exposed to computer science and qualitative teaching materials, such as laptops (Google & Gallup, 2016). However, SES did not influence usefulness, social value, experience, interest, and programmer perception. For this, it is important to mention the limitation of the SES variable. The SES variable was measured as the perceived SES by the students. In other words, the majority of the students filled in medium or high SES, while their actual SES might be lower. Therefore, it is possible that SES is not well-represented. Because of this limitation, the relationship between SES and each outcome variable should be investigated with a more precise indicator of SES.

Educational level was only found to have a significant relationship with experience. This relation was expected, because the exam program for computer science is only in havo and vwo. Furthermore, it is possible that vwo students do a lot more with computer science than vmbo students, because vwo students are generally more analytical and self-efficient. Therefore, vwo students could have a higher confidence in their computer science skills, than students from the other level.

The results for migration background were all not significant. This was not in accordance with the literature (Zarrett & Malanchuk, 2005). This means that students from different places do not significantly differ from each other. Zarrett and Malanchuk (2005) demonstrated that in America Black people are more interested in computer science than White people. However, in the Netherlands, the distinction between Black and Whites is not of importance. It is more regular to be defined by migration backgrounds. Additionally, the insignificant results were not expected because studies have shown that there are differences between minorities, because of stereotypes, discrimination, and lack of experience (Ross et al., 2020; Zarrett & Malanchuk, 2005). It is possible that 'minorities' is not a good representation of the migration background. Therefore, more research is needed to investigate whether in other another context migration background does not matter for the perceptions of computer science.

The results demonstrated that neither classroom or school had an effect on the relation between the predictor variables and the outcome variables. This means that the variance between classrooms and schools was not significant. A possible reason for this is that students fill out the surveys without being influenced by other. Another reason could be that classroom and school effect were redundant because the sample size was too small. To ensure reliability future work could include the same study but with a larger sample size.

Generally, the results demonstrated more insignificant results, than significant results. A possible reason for this is the use of American studies for this research. The American context differs from the Dutch context. It is possible that students act or think differently than in the Unites States. Another possibility is that the survey was too small. Future work could include redoing this research with a larger set of questions.

To answer the question the second research question, qualitative data was analyzed. The results showed that students enjoyed playing the game and that the students had positive attitudes towards computer science, because the game was challenging, had a backstory and was practical. This complies with the findings of Elfering et al. (2018) who demonstrated that such interventions as the data center game should stimulate a positive attitude towards the topic of the intervention.

However, students did not think their image of computer science changed much. This was unexpected, since the game was developed to stimulate students around the age of 10 to 14 to computer science careers and show different aspects of computer science. A possible explanation for this result, is that the students could not link data centers to computer science or the particular jobs within the data center as computer science jobs. To investigate this possibility future work could explore students' associations with the game. Furthermore, Falk et al. (2016) suggested that the amount of knowledge someone has of computer science correlates with the level of interest. Therefore, a possible reason for the lack of interest could be that the students did not learn enough through the game. The exact learning of the students throughout the game could be evaluated in other studies.

A limitation in this study was the definition of migration background. When individuals have multiple migration backgrounds the problem expands. This entails that more participants or groups are needed to account for the complexity of having multiple backgrounds.

In this research, only students who had computer science classes participated in this study. This disallows for generalizing to the population. Therefore, future work could include a study with students who have not received computer science courses.

Another limitation of this study was the sample size. Because this study was conducted with students in different classes in different school, a multilevel analysis was performed. However, the sample size was too small to claim high reliability. The sample size needed for a three-level multilevel analysis is 50 groups or cases per level (Lee & Hong, 2021), which was not obtained in this research for any of the level. Although the sample size was not big, this study provided new insights in the use of the perception survey, the influential factors of the data center game, and certain differences between students' backgrounds. It is recommended to further investigate students' perception of computer science, because society needs more computer scientists urgently.

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Figures

Figure 3

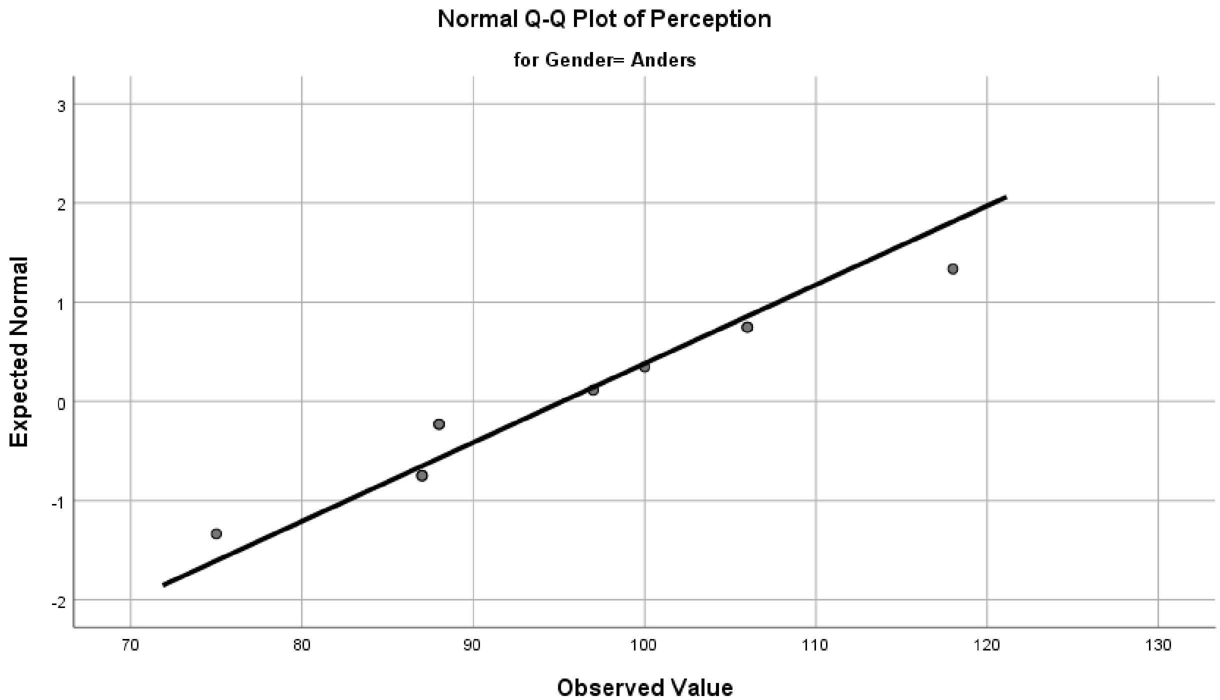


Figure 4

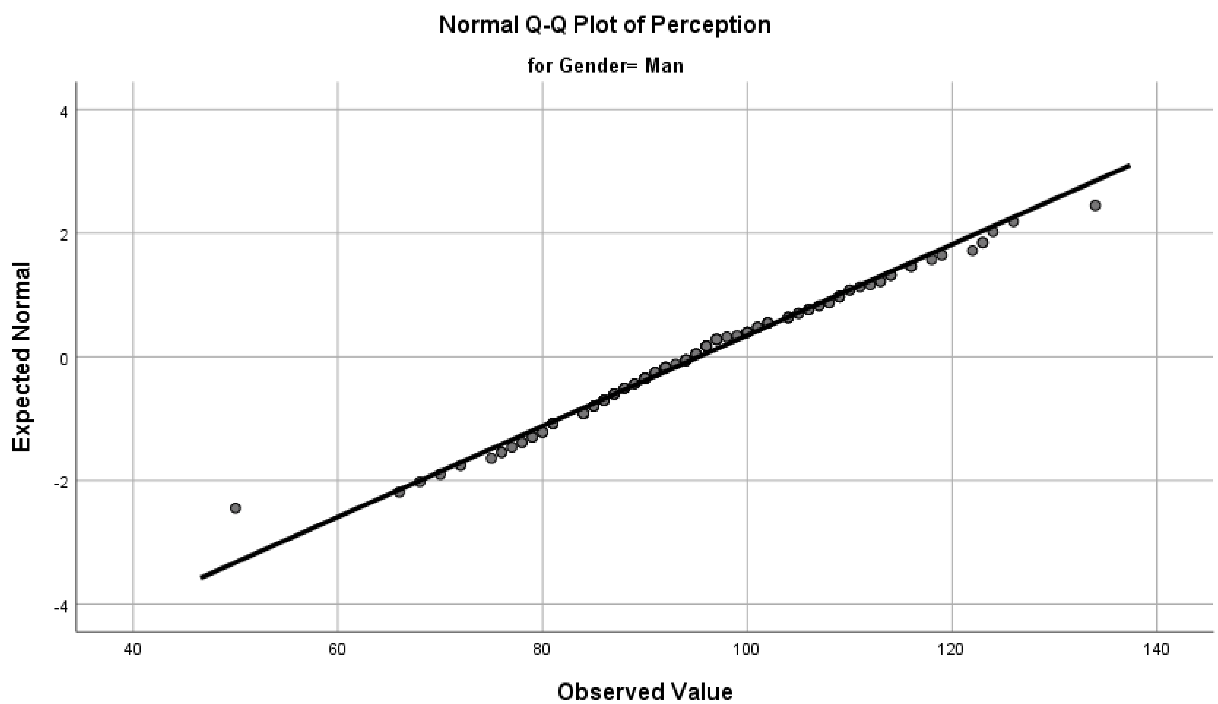
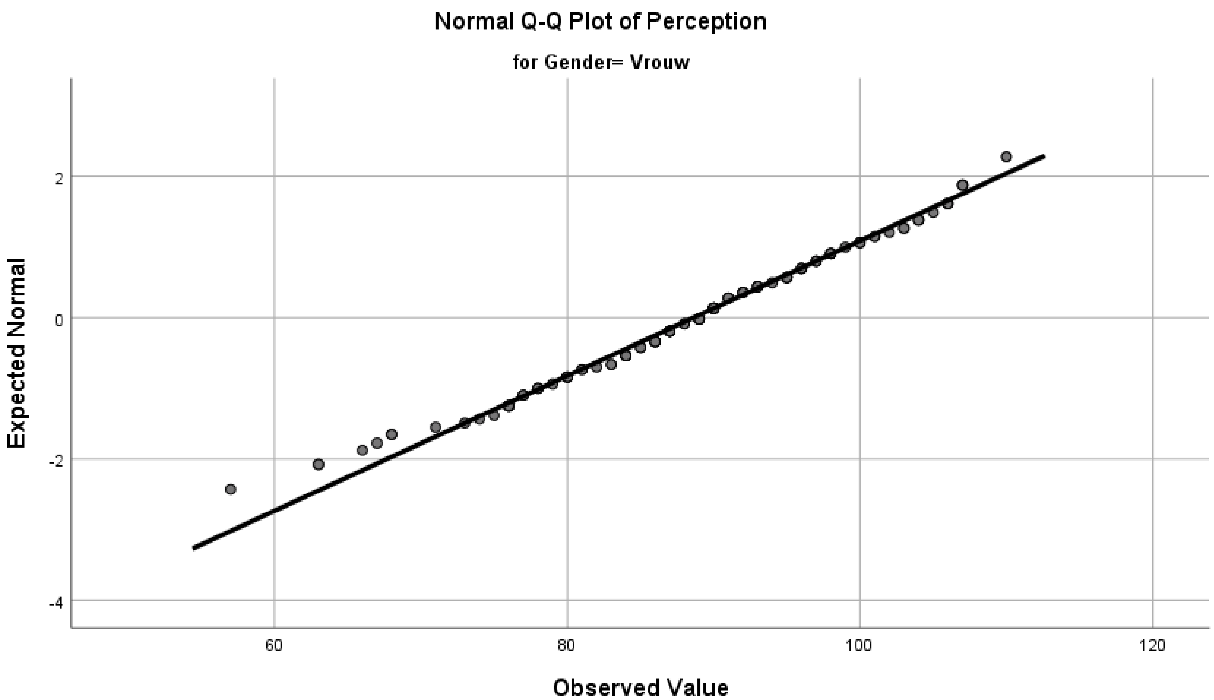


Figure 5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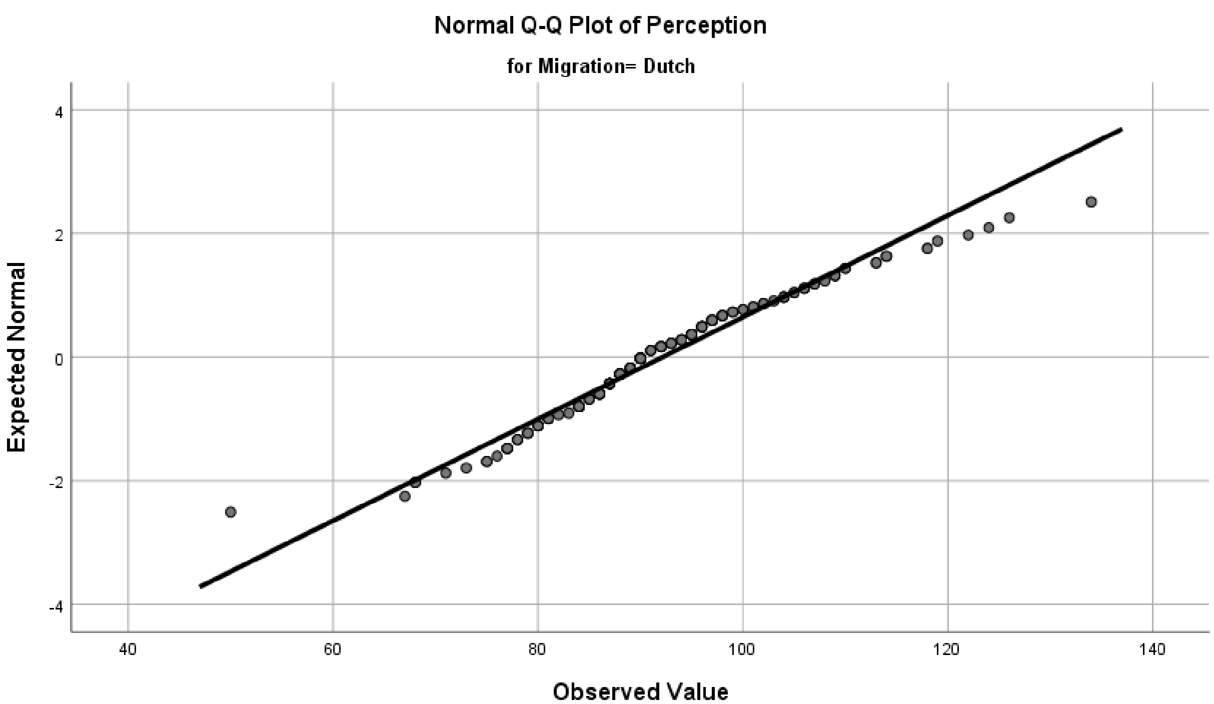
for Gender= Vrouw
Expected Normal
2
0
-2
-4
60
80
100
120
Observed Value

Figure 5


Normal Q-Q Plot of Perception
for Migration= Dutch
Expected Normal
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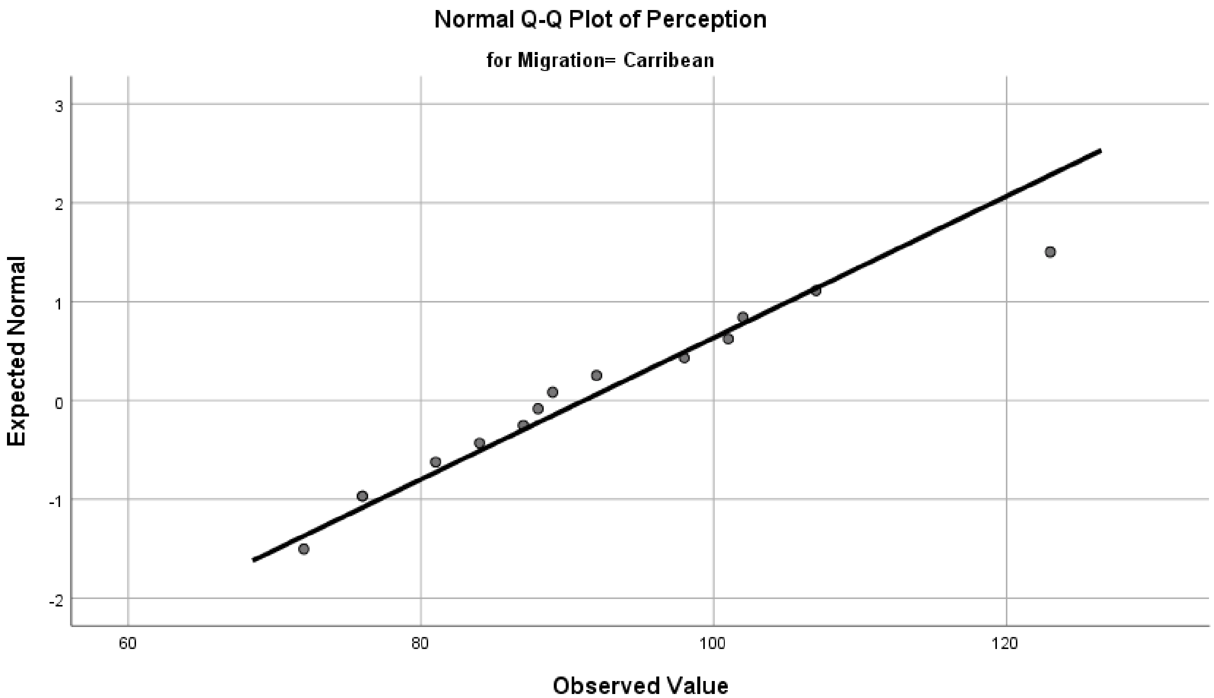
2
0
-2
-4
40
60
80
100
120
140
Observed Value

Figure 7



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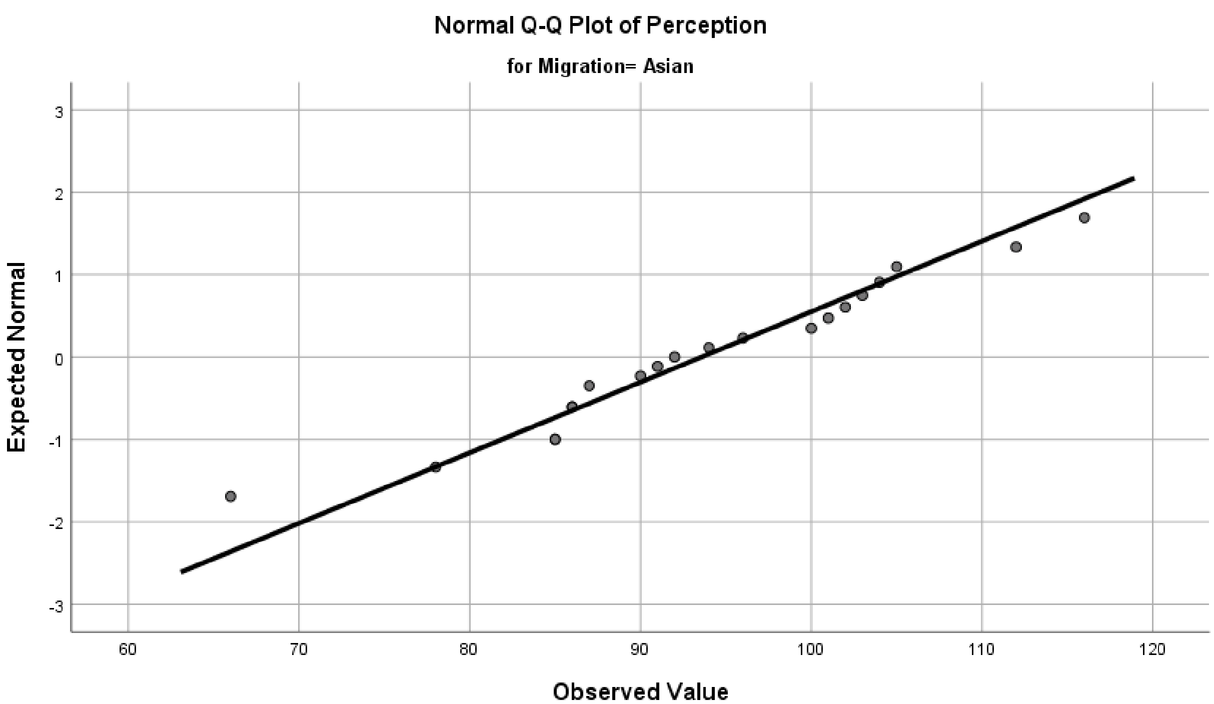

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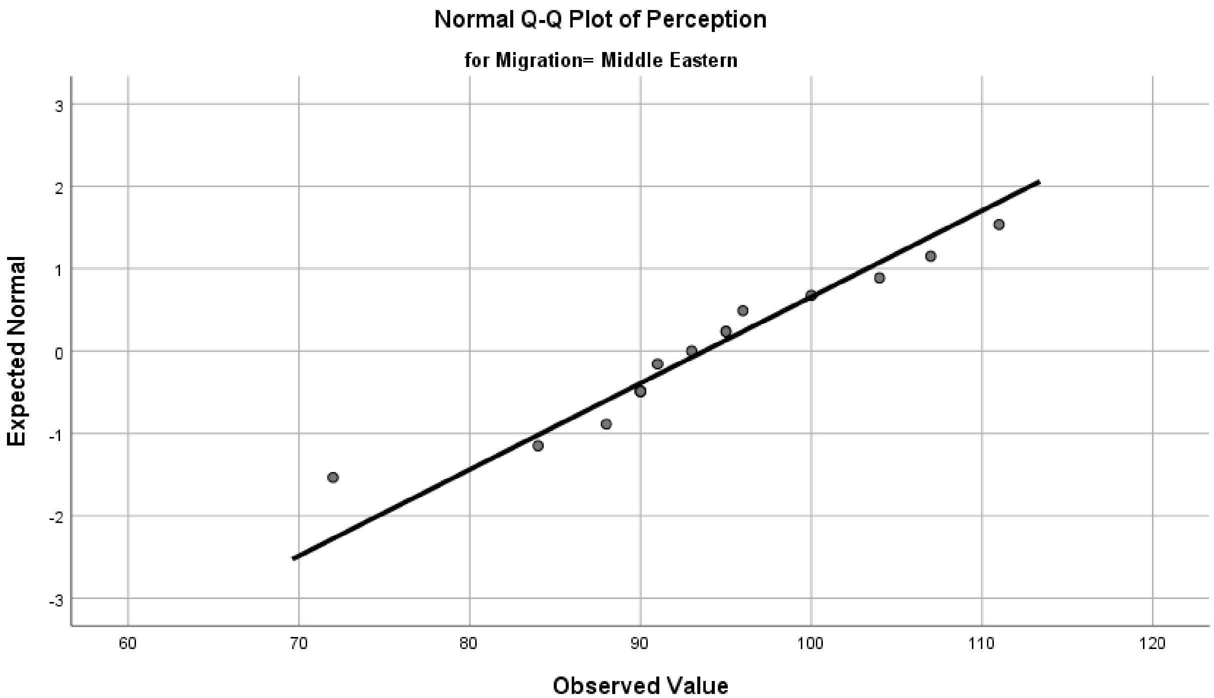

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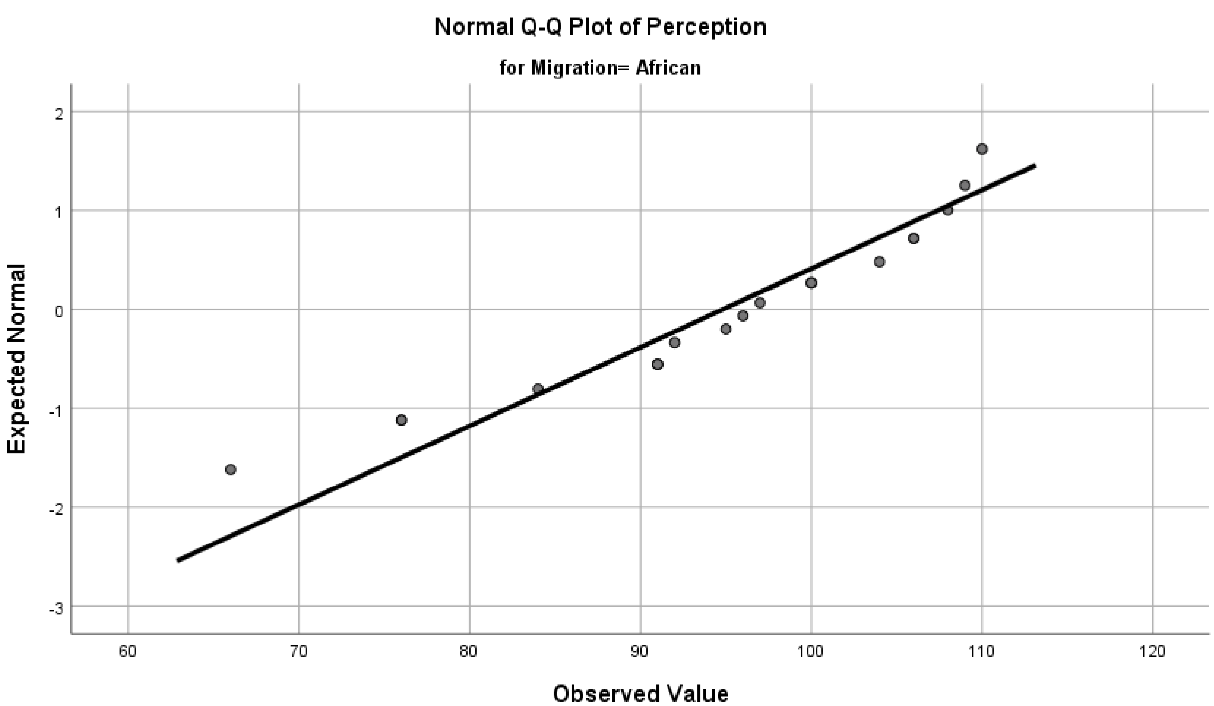

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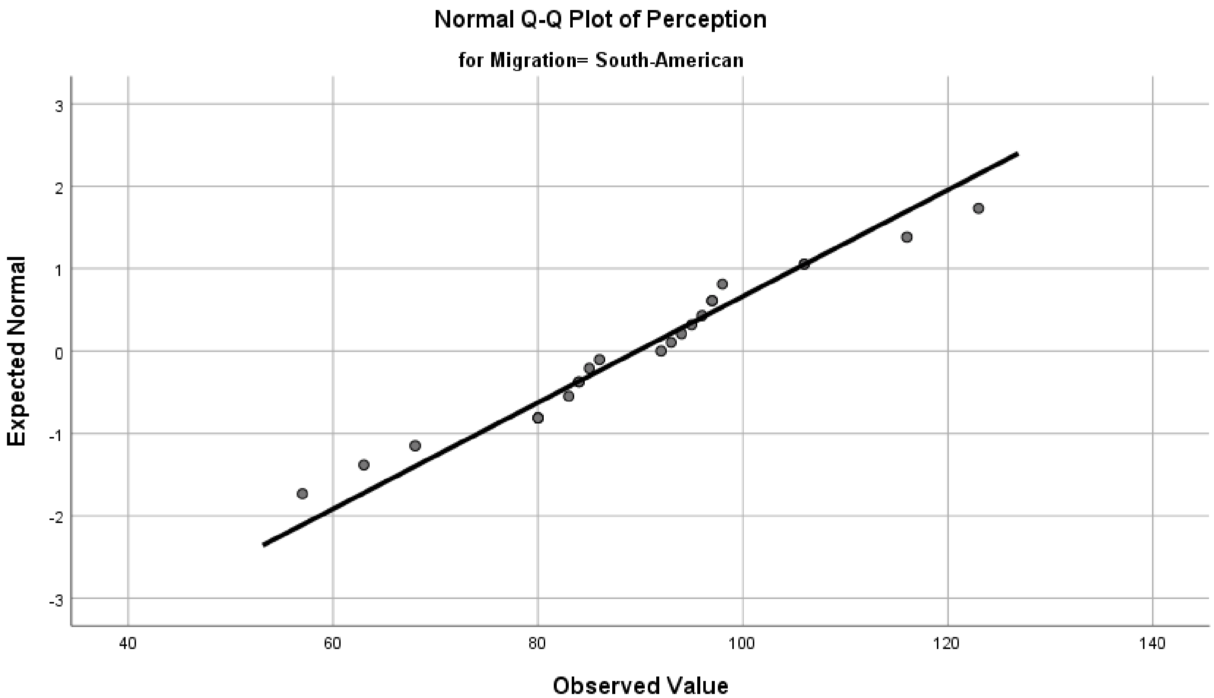

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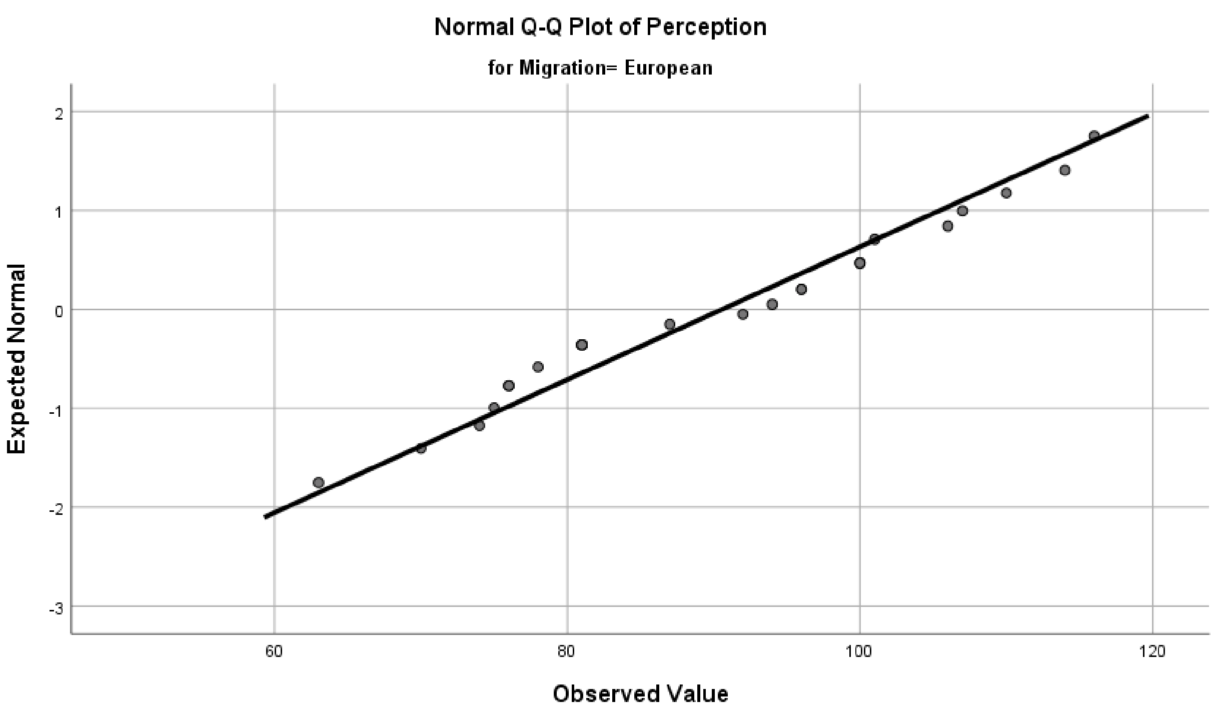

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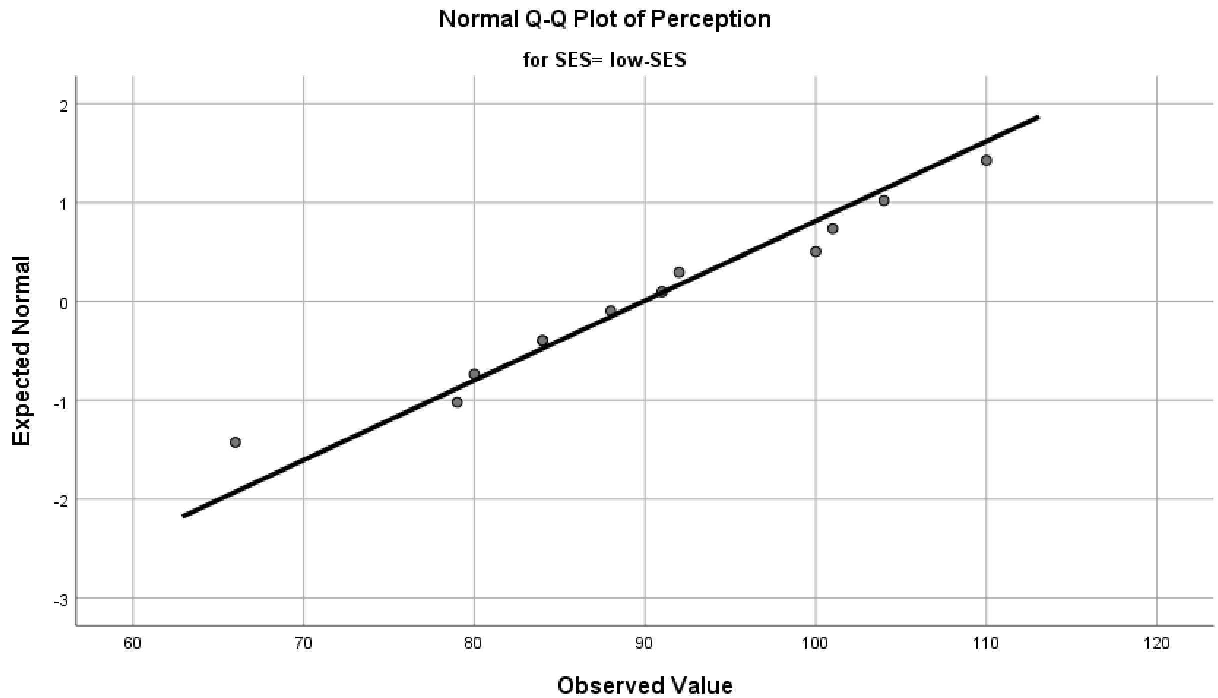

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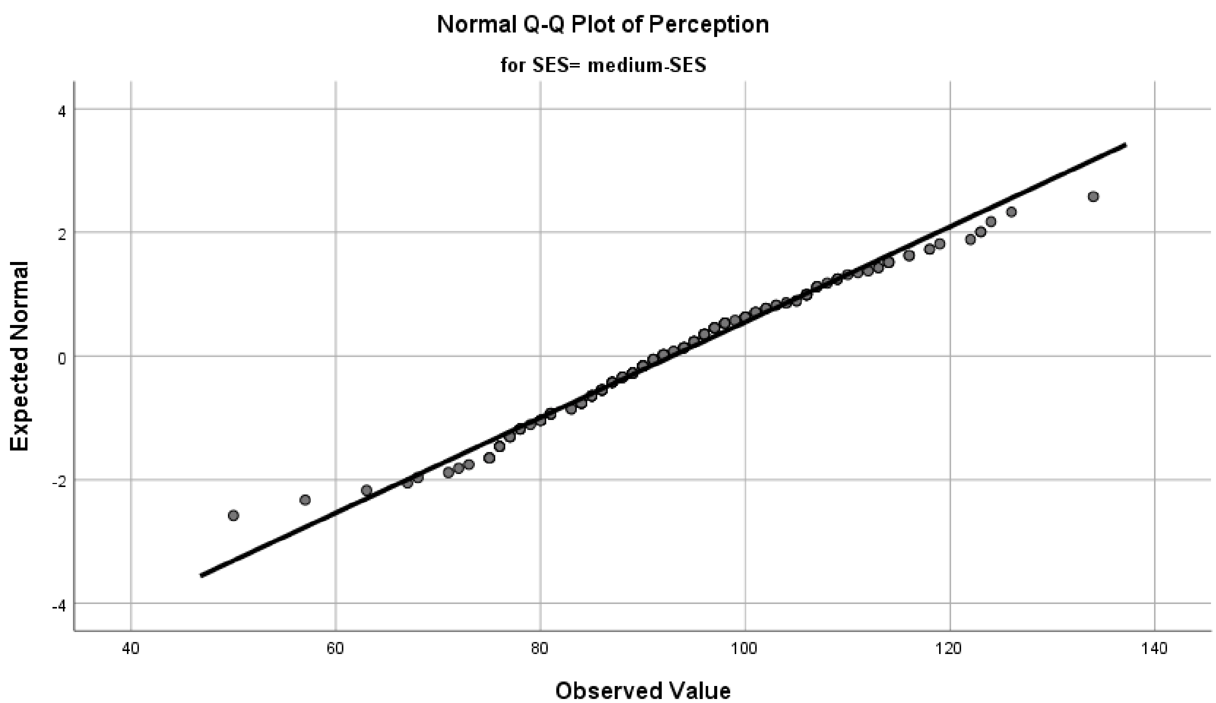

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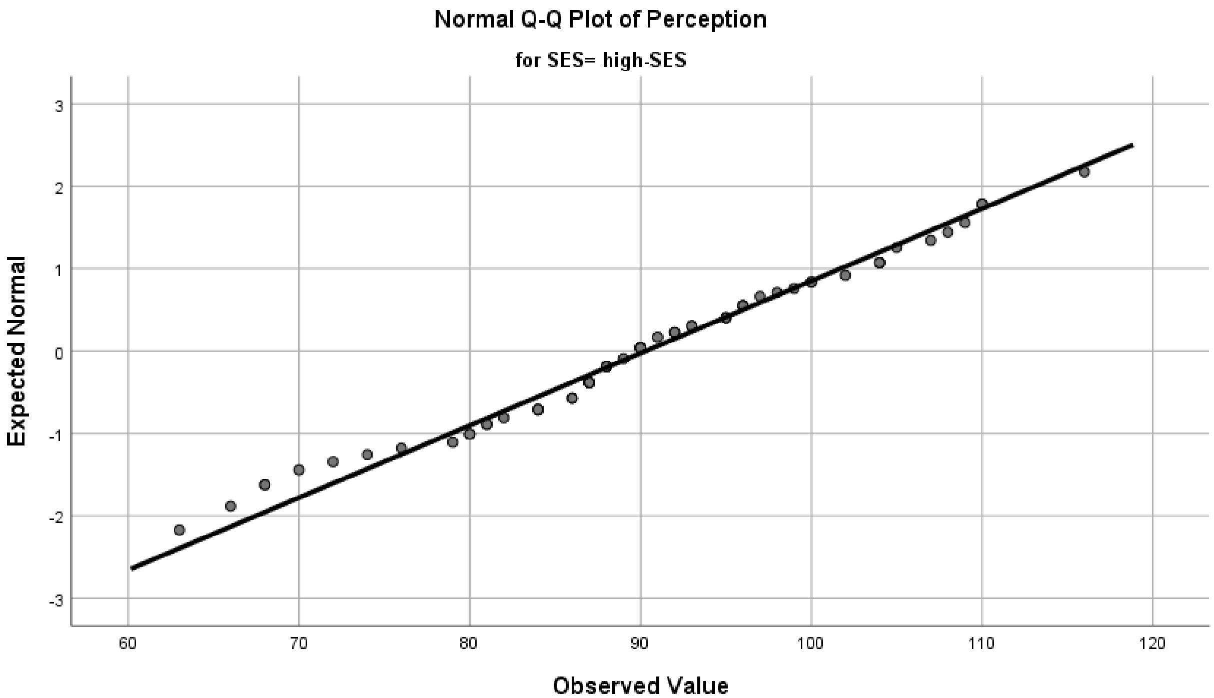

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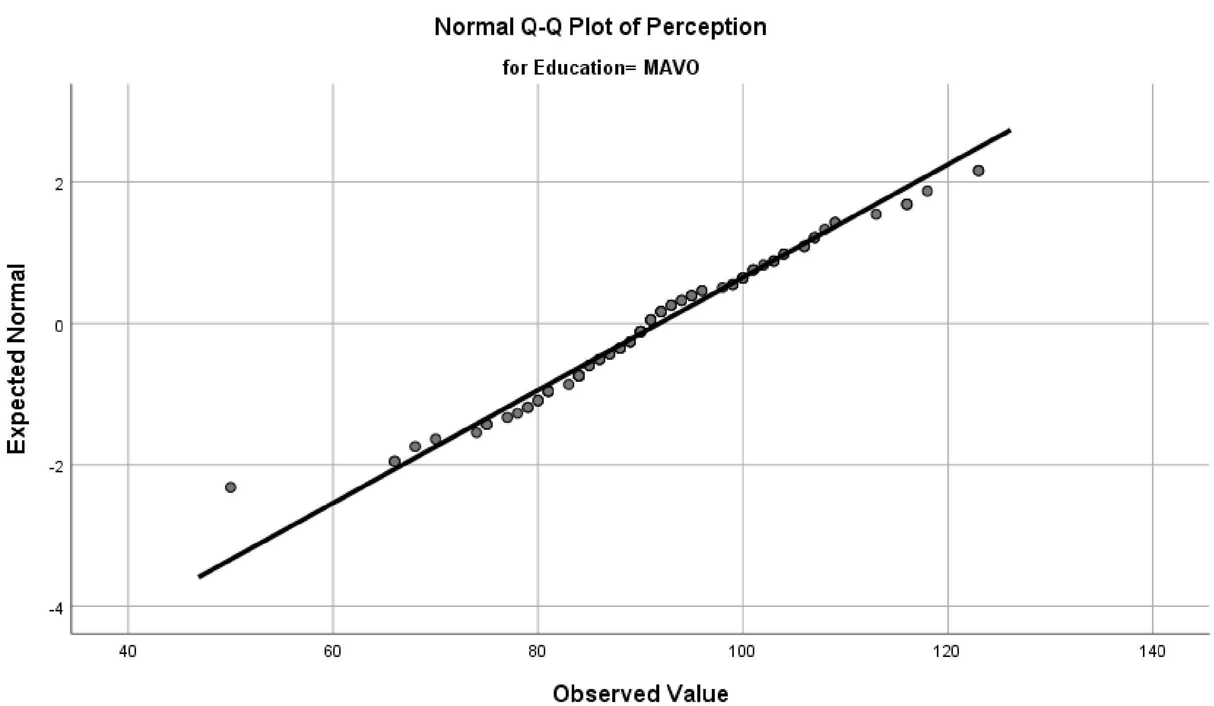

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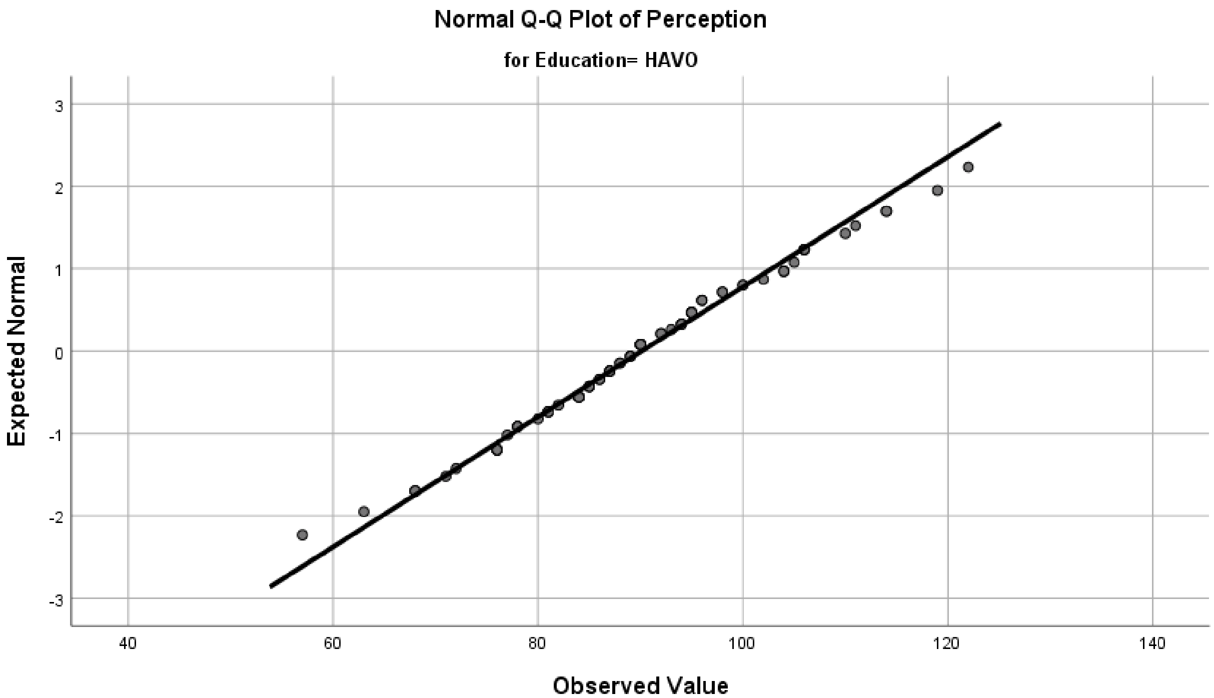

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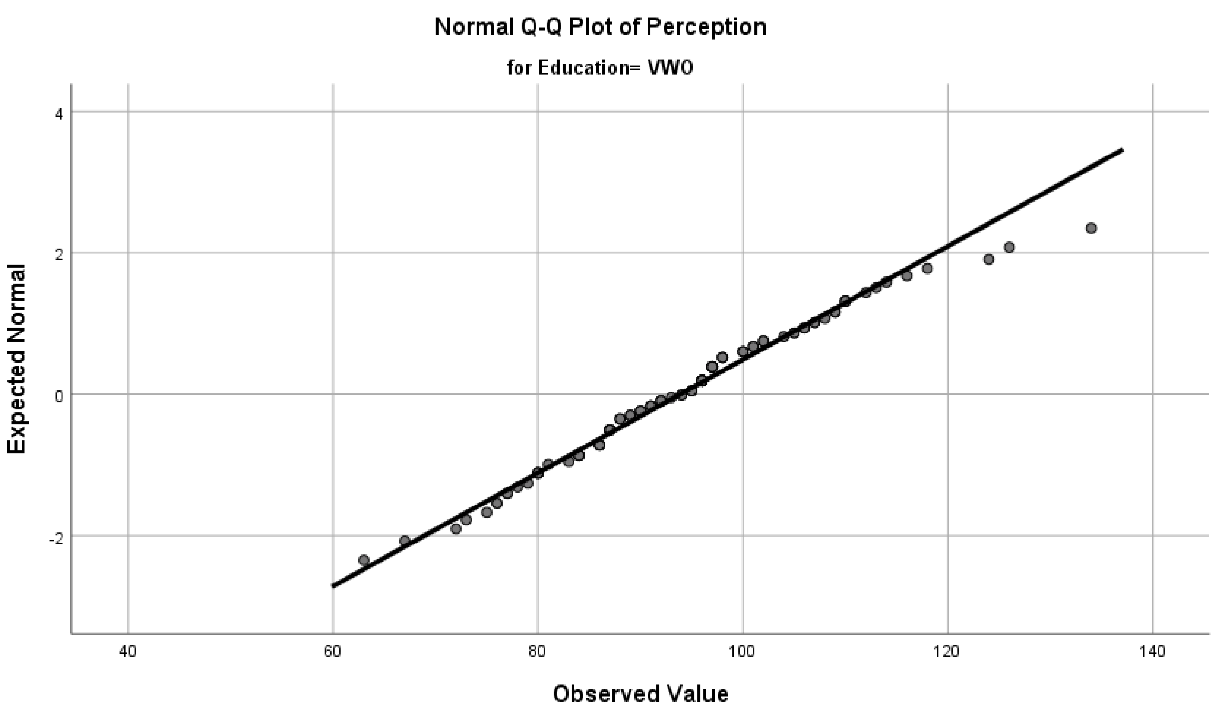

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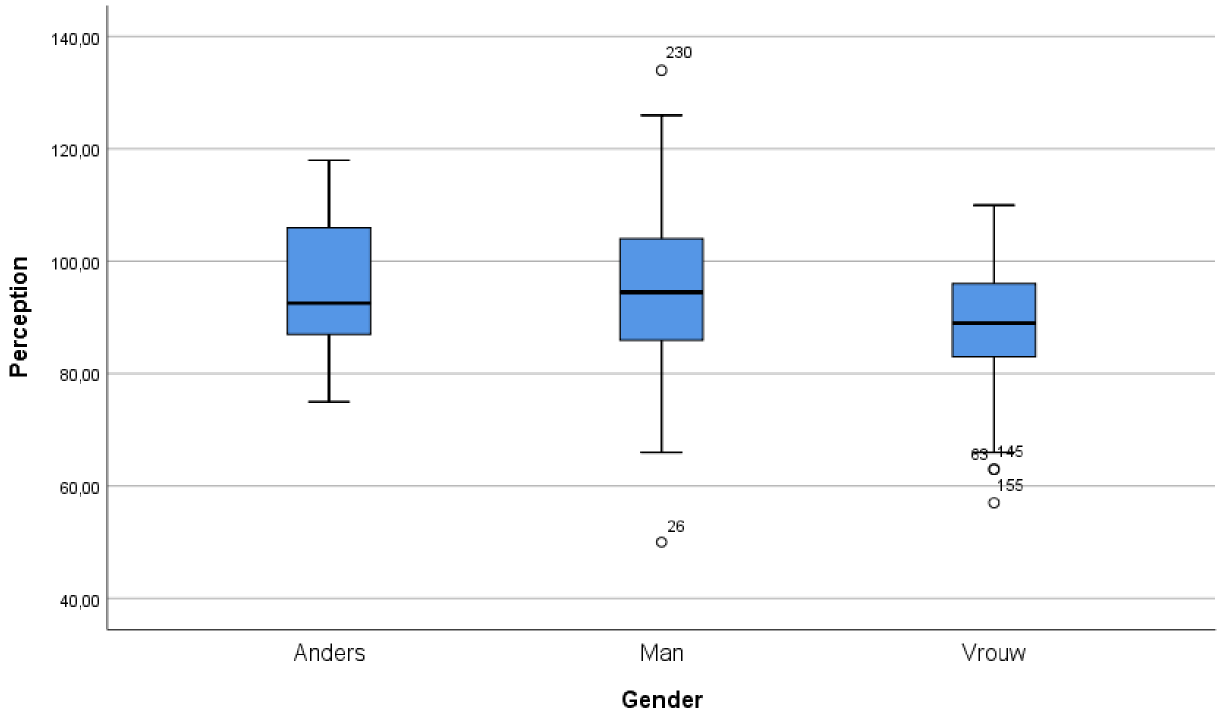
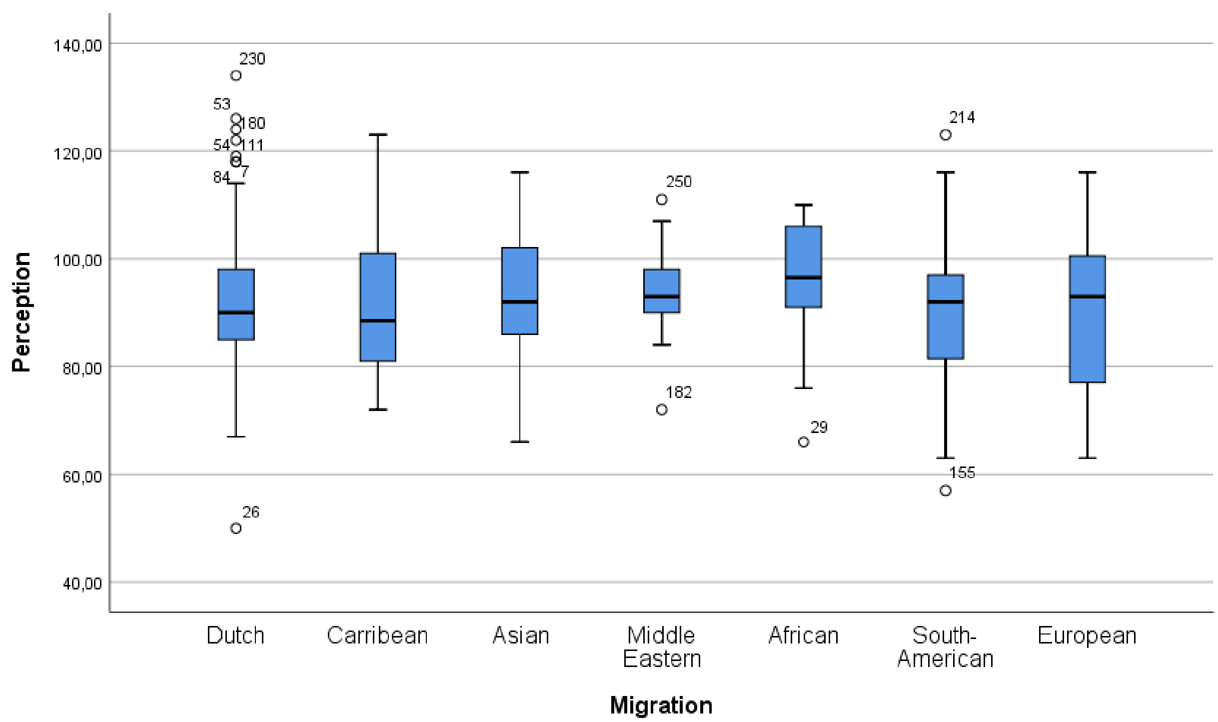


Figure 20



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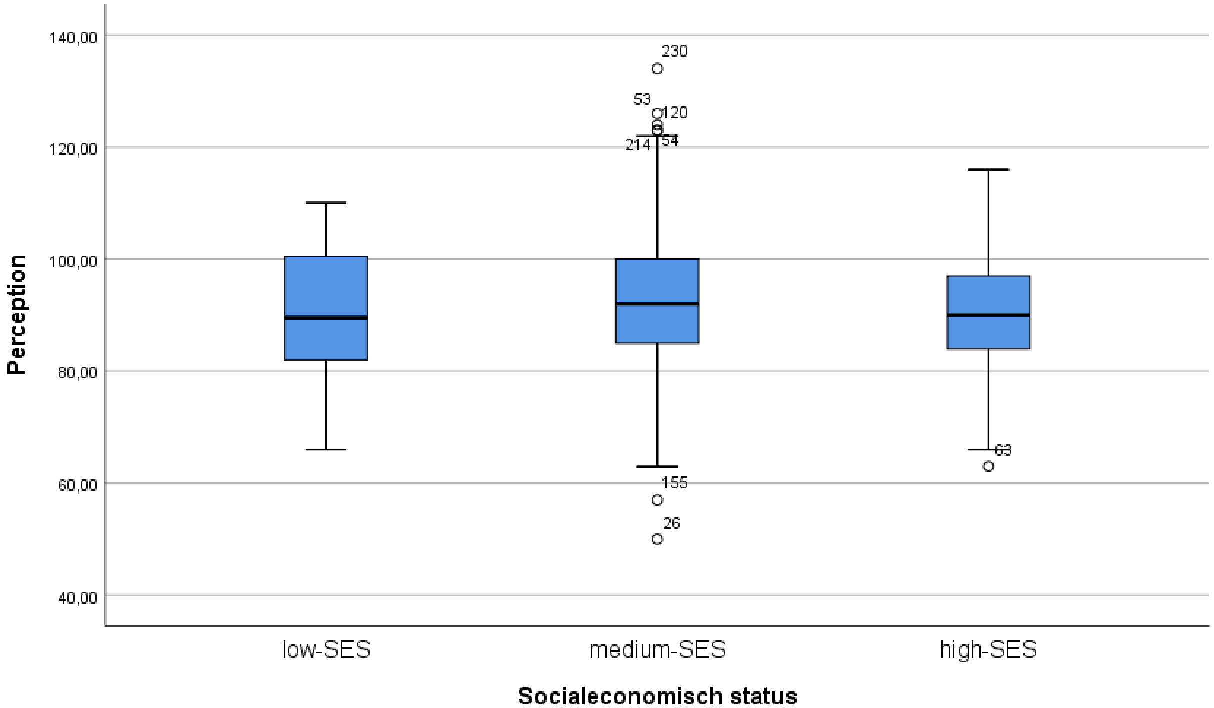
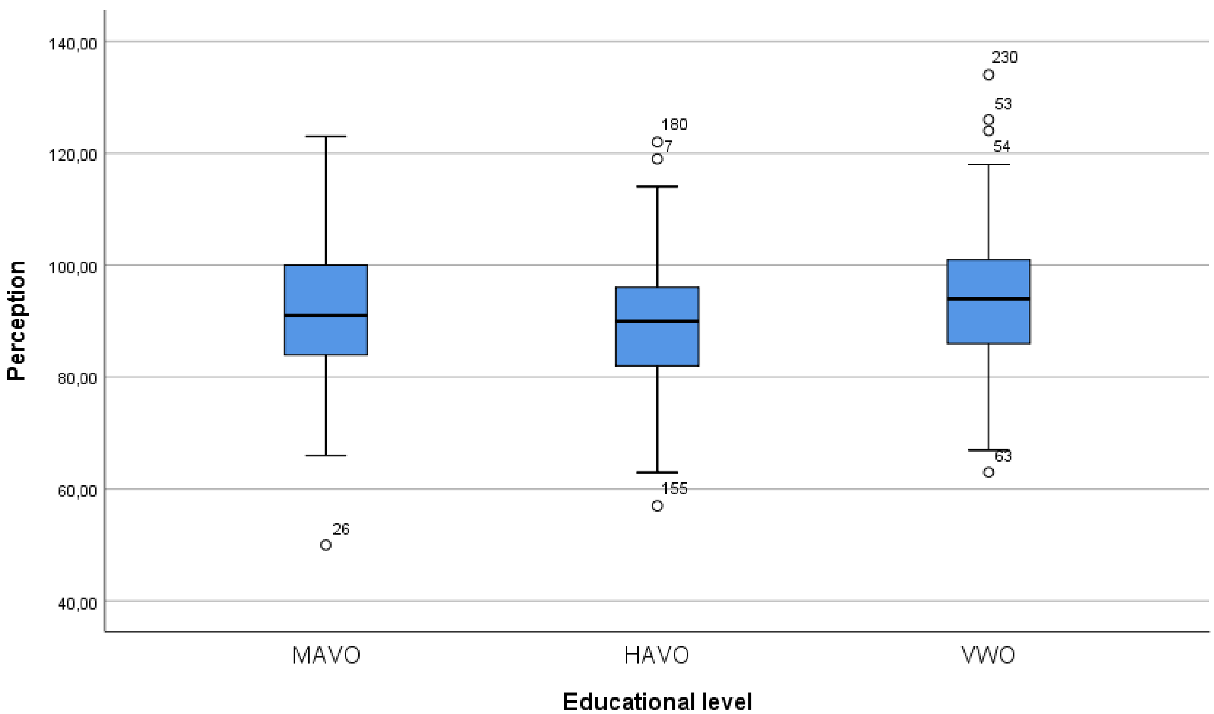


Figure 22



Appendix

Appendix A

Interview Questions for Prior Research

- Wat is jouw migratieachtergrond? (eventuele uitleg: Nederlandse achtergrond, westerse migratieachtergrond, niet-westerse migratieachtergrond)
- Waar is je moeder geboren?
- Waar is je vader geboren?
- Waar ben jij geboren?
- Wat is jouw schoolniveau?
- Welke opleidingsniveau heeft je mama/verzorger gehad? (WO, HBO, MBO, NIKS)
- Welke opleidingsniveau heeft je papa/verzorger gehad? (WO, HBO, MBO, NIKS)
- Wat is volgens jou informatica?
- Wat vind je van informatica?
- Wat maakt informatica leuk/interessant/makkelijk?
- Wat maakt informatica saai/stom/moeilijk?
- Denk je dat informatica belangrijk is (voor Nederland)? Waarom?
- Waar allemaal denk je dat computers in zitten?
- Hoe denk je dat het Internet werkt?
- Wie bepaalt wat daarop staat?
- Gebruik je Whatsapp/ Tiktok/Instagram? Hoe denk je dat sociale media werkt?
- Wat doet een programmeur zoal denk je?
- Hoe word je een programmeur?
- Lijkt het je leuk om programmeur te worden?
- Hoe zou jij iemand beschrijven die veel weet van computers?
- Wat denk je dat iemand die informatica heeft gestudeerd/geleerd allemaal kan (worden)?

Appendix B

Intercoder Reliability process

The formula to calculate I.R. is $\frac{2 \cdot M}{N_1+N_2}$, where M is the total amount of decisions by two coders, and N_1 and N_2 are the number of decisions made by coder 1 and coder 2, respectively. The process that was used is as follows:

1. Individually both assessors read the responses of the students.
2. Codes that seemed meaningful were highlighted by each assessor.
3. The code book in Appendix C was filled in individually by each assessor. Due to the large sum of options, three quotes were selected per code. Codes could not be used twice.
4. Next, the codes were compared. For each code with at least one similar quote, the calculated considered the decision as an agreement.
5. The I.R. was calculated based on 27 codes.

Appendix C

Code Book of Qualitative Data

	Category	**Sub-category**	**Code**	**Quote**
Factors influencing perception through serious game	Backstory	Backstory	-	
	Adaptivity	Adaptivity	-	
	Interaction	Pos experiences	Fun game	
			Playing the game	
			Relaxation	
		Neg experience	Boring	
			Too long	
			More support	
		Feelings	Pos feelings	
			Neg feelings	
	Feedback	Learning	Informative game	
			More information about ICT	
		No learning	-	
		Learning through game	Importance data	
	Easiness	Difficulty	Not fun because difficult	
	Realism	'Degrees of fun'	Game for everyone	
			Persistence	
			Not fun for all age groups	
			Not fun for people with no interest	
			Not fun because difficult	
			Fun if interest in games	
			Fun if you love connecting	
	Usefulness	Useful in the future	-	
		Usefulness data center	-	

	Change	Change of perception	-	
		No change of perception	-	
		Not sure	No idea	