Gendered smoking personas: exploring stereotypical terms in marked personas generated by ChatGPT

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Bachelor's Thesis

International Business Communication

Theme 1, Stereotypes in Chatbot Healthcare Coaching

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08-01-2024

Radboud University

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Abstract

This study investigated the complex relationship between smoking stereotypes, gender biases in smoking, and the appearance of stereotyping within conversational Artificial Intelligence (AI) systems, with an emphasis on ChatGPT.

Investigating the various personas that are created in ChatGPT, particularly those mentioning smoking, aimed to find and understand ChatGPT's biases and stereotypes in the unique generated personas. This study examined conversational interactions, considering factors such as education, occupation, sociability, dominance, independence, and the willingness to quit smoking.

The main research question looked into stereotyped characteristics associated with female and male smokers in ChatGPT-generated personas. Sub-questions delved into the stereotypes related to smokers and their educational level, desire to quit, sociability, dominance/independence, and jobs. Statistical analyses, including chi-square tests and frequency tests, demonstrated no significant differences in male and female smoker descriptions. As a consequence, the main research question is answered negatively.

According to the findings, there are no variations in educational levels or willingness to quit between male and female smokers. Male smokers used somewhat more social-related words than female smokers, but the difference was not statistically significant. Traditional gender standards were challenged by stereotypical jobs connected with smoking.

The ChatGPT personalities did not show any significant stereotyped differences between female and male smokers. While acknowledging the study's shortcomings, it emphasizes the critical importance of continued research targeted at improving AI systems.

Keywords: ChatGPT, smoking behavior, gender biases, stereotypes, generated personas

<u>Theoretical framework</u>

<u>*Chatbots*</u>

In the digital era, chatbots— artificial intelligence (AI) systems that can converse like a human —have spread like wildfire. The systems take on roles as mediators in human-computer interactions as they find use in a variety of fields, such as customer service, mental health assistance, education, and healthcare. According to Sarker (2022), chatbot technology is an interdisciplinary field that combines computer science and linguistics with the goal of building computers that can perform jobs that require human intelligence.

In November 2022, a brand-new artificial intelligence tool was launched. It is called "ChatGPT", and it functions as an AI-based large language model (LLM) (Jeon & Lee, 2023). OpenAI (OpenAI, L.L.C., San Francisco, CA, USA) developed this new chatbot. ChatGPT is a significant advancement in the field of artificial intelligence (Jeon & Lee, 2023). It is a pre-trained AI model designed to engage in natural language conversations, using advanced approaches from Natural Language Processing (NLP), Supervised Learning, and Reinforcement learning to understand and write texts similar to human-generated language (Abdullah et al., 2022). ChatGPT continues to solidify its status as a top-tier language model by demonstrating exceptional proficiency across a wide range of language tasks and standards (Mohamed, 2023). ChatGPT's advanced language modeling capabilities have the potential to revolutionize human-computer and human-machine interactions by enabling more natural and intuitive communication (Tselikas & Roumeliotis, 2023). ChatGPT has been endowed with the ability to grasp the complexities of language, providing extremely correct responses even in nuanced and ambiguous circumstances, because of the intensive pre-training on enormous text datasets (Tselikas & Roumeliotis, 2023).

ChatGPT is a dynamic tool that responds to a wide range of user queries, making it a helpful tool for those looking for quick solutions to problems, including those affecting their mental and physical well-being. People who are experiencing difficulties or have mental health challenges may be motivated to seek advice from ChatGPT (Oviedo-Trespalacios et al., 2023). It is crucial to highlight, however, that the advice provided is of a pre-trained system, and individuals should consider consulting relevant professionals or support networks for more tailored assistance. Before implementing any suggested steps, it is critical to consider potential consequences and, if necessary, obtain advice from suitable authorities. An example of this kind of situation has occurred in Belgium, where a man, aged around 30, took his own life after having several conversations with a chatbot, a clone of ChatGPT (Deckmyn, 2023). The chatbot convinced the man that if he sacrificed himself, the chatbot would use artificial intelligence to save the globe and humanity from the climate problem. Taking this kind of situation into account, it is extremely important to critically evaluate the answers that ChatGPT gave you and be aware of the dangers. To comprehend how diverse concepts can be perceived, it is necessary to integrate knowledge gained from previous research with professional knowledge. As shown in the research of Oviedo-Trespalacios et al. (2023), it is recommended to proceed with caution when obtaining safety-related information and advice from ChatGPT and to always seek qualified sources of information.

Recommended safety-related information such as health advice given by chatbots is based on pre-trained input and enormous text datasets (Tselikas & Roumeliotis, 2023). A chatbot is built based on text input and therefore not able to fit into a specific situation, wherein every human reacts differently. Furthermore, systemic and shared obligations are often ignored, which could lead to generic advice that is irrelevant to certain groups or circumstances (Oviedo-Trespalacios et al., 2023). In addition, ChatGPT's knowledge and recommendations are predominantly useful to high-income countries, which can lead to a gap in important knowledge information regarding low- and middle-income countries (Oviedo-Trespalacios et al., 2023).

The tragic suicide of a Belgian male demonstrates the possible danger linked with interacting with chatbots. Despite the positive outlook for chatbots to improve user experiences and provide valuable services, growing research suggests complicated and nuanced challenges. This issue entails the creation and spreading of prejudices, as well as the use of stereotypes in chatbot interactions (Adam et al., 2021; McDonnell & Baxter, 2019).

Biases in Artificial Intelligence (AI) can appeal in two ways: biases encoded in the data used for algorithm training, known as data bias, and biases inherent in the design or learning mechanisms of the algorithm itself, known as algorithmic bias. However, the use of AI in healthcare adds an additional degree of complexity. As pointed out in the research of Ueda et al. (2023), the complexities of human interaction and decision-making in the healthcare sector can result in unexpected biases when AI systems are used. Data biases, algorithmic biases, and biases relating to clinician-patient interactions are some examples of AI biases (Ueda et al., 2023). Problems in the collection and arrangement of data used in AI training can result in data biases such as minority bias, missing data bias, informativeness bias, and training-serving bias. Algorithmic biases may appear as a result of the AI's fundamental design or learning mechanisms, resulting in label bias and group prejudice (Ueda et al., 2023). Furthermore, biases connected to clinician-AI interactions might result in biases regarding automation, cycles of feedback, rejection bias, and allocation discrepancies. These biases can have an impact on the fairness and accuracy of AI systems used in healthcare. This highlights the crucial role of identifying and correcting biases in AI systems used in the healthcare sector to ensure equitable and unbiased outcomes (Ueda et al., 2023).

Healthcare chatbots

Healthcare chatbots have emerged as a transformational force in the field of medicine in an era marked by rapid breakthroughs in technology and an increased desire for accessible and efficient healthcare solutions (Torous et al., 2021). These smart artificial intelligence (AI) applications, which are designed to have human-like conversations, are changing the way people, healthcare professionals, and medical organizations interact with information and services (Chen & Decary, 2020).

Above all, healthcare chatbots are more than just virtual assistants; they are the result of cutting-edge AI, natural language processing, and healthcare knowledge (Javaid et al., 2023). Their skills extend from common health-related questions and appointment booking to individualized health advice and chronic condition monitoring. The healthcare chatbots operate efficiently across a variety of digital platforms, such as websites, smartphone apps, and messaging services, making healthcare information and support more accessible than ever before (Paliwal et al., 2019).

While chatbots are wonderful conversational tools, it is critical to underline that they should be used in addition to, not in place of, competent medical advice. Today's chatbot programs are meant to provide high-quality answers quickly, allowing for time savings and health advice (Athota et al., 2020). However, it is crucial to note that chatbots cannot replace the competence of doctors or specialists. Consultation with healthcare professionals is still necessary for medical issues.

Stereotypes and chatbots

Stereotypes, which are frequently defined as generalized conceptions or cognitive shortcuts about social groups or features, have long been a subject of social psychology and communication research (Augoustinos & Walker, 1998). Stereotypes manifest as prejudiced or preconceived views about users in the context of chatbots, based on criteria such as gender, age, race, ethnicity, or cultural background. These biases are embedded in the data used by chatbots, such as ChatGPT, to generate responses and make choices.

Stereotyping is harmful on both a societal and personal level. Stereotypes contribute to the persistence of inequality and prejudice on a societal scale by reinforcing existing biases and excluding particular groups. This can cause social issues, impeding progress toward a more inclusive and equal society.

On an individual basis, stereotypes can lead to unfair biases and missed opportunities (Schmader et al., 2001). When confronted with biased responses by a chatbot, users may experience frustration, separation, or lack of trust in chatbot interactions. Furthermore, focusing on stereotypes may limit the potential for actual understanding and connection between humans and chatbots, because of the lack of connection. As a result, addressing and reducing preconceptions in chatbot interactions is not just an ethical need, but also necessary for establishing a more inclusive and courteous digital environment.

Marked personas

Assigning the chatbot to a persona is one technique to investigate the extent of stereotyping in artificial intelligence systems like ChatGPT. Before determining whether ChatGPT as a large language model is useful, it is necessary to understand the capabilities, limits, and design process of the system. In the not yet peer-reviewed study of Kocaballi (2023), ChatGPT was used to construct personas, simulate interviews with fictitious users, produce new design concepts, simulate usage scenarios and dialogues between a fictitious prototype and fictitious users, and ultimately assess user experience. Altogether, ChatGPT demonstrated that it is a competent chatbot with a large scale of skills (Kocaballi, 2023). The findings reveal that ChatGPT exhibits competence as a chatbot by being able to effectively role-play as imaginary designers, users, and products (Kocaballi, 2023). On the other hand, the study also demonstrated certain shortcomings in ChatGPT’s performance, such as difficulties in recognizing some concerns and requests and showing shortcomings when the context of the conversations was building up (Kocaballi, 2023).

It is important to note that attaching a chatbot to a persona increases the toxicity levels of different created personas significantly (Deshpande et al., 2023). For the research of Deshpande et al. (2023), ChatGPT was assigned to generate 90 different personas, and the responses were examined with a focus on two main aspects: specific entities (such as gender and religion) and sentence continuations (Deshpande et al., 2023). The findings show a significant increase in toxicity when ChatGPT is used in combination with a persona as for example Mao Zedong, as measured on a scale of 0 to 1 (Deshpande et al., 2023). This displays itself in toxic discussions and the spread of false prejudices about countries, faiths, and ethnicities. The fact that ChatGPT, when given a persona, can be biased demonstrates that the chatbot's intended behavior is not always necessarily helpful and safe (Deshpande et al., 2023).

Gender sensitivity in ChatGPT and health-related stereotypes

Stereotyping often comes across as joking about particular groups of people. Gender is one type of stereotyping. However, ChatGPT has taken into account the upcoming gender movement by refusing to tell jokes about a woman, by saying that this is inappropriate (Zhou & Sanfilippo, 2023). The researchers supposed that this could also be due to the widespread usage of politically correct terminology in Western Culture (Zhou & Sanfilippo, 2023).

Looking into health-related stereotypes, individuals who smoke often find themselves at the receiving end of biased perceptions. Smoking, as a behavior, has been stigmatized due to its well-established association with various health risks. Terms that are associated with people who smoke, identified on an emotional level, are *stressed*, *bored*, *angry*, and *depressed* (McCool et al., 2004). According to Evans-Polce et al. (2015), smokers are aware of the stereotype they are associated with, including the negative aspects of it. It was found that many smokers felt stigmatized because of their smoking habits, such as being excluded from society or facing negative judgments (Evans-Polce et al., 2015). When looking into gender differences related to smoking, women were considered disreputable if they smoked in the early twentieth century due to widespread societal criticism of women's smoking in the United States and Great Britain (Waldron, 1991). However, when social acceptance of women's smoking expanded in the mid-twentieth century, gender inequalities in smoking adoption shifted (Waldron, 1991). This expanding social acceptability of women's smoking was part of a broader liberalization of standards around women's behavior, reflecting more gender equality (Waldron, 1991).

Chatbots in smoking cessation and stereotypes

Chatbots have the capacity to deliver personalized interventions, catering to the specific needs and motivations of each individual smoker. For example, interventions for behavior changes, to help people quit smoking (Aggarwal et al., 2023). By leveraging Artificial Intelligence (AI), these chatbots can analyze user input, identify patterns, and adapt their responses to provide targeted guidance (Aggarwal et al., 2023). This individualized approach intended to address the diverse factors contributing to smoking addiction, ranging from psychological triggers to social influences (Aggarwal et al., 2023).

One of the key advantages of chatbots in smoking cessation is the provision of real-time assistance. Chatbots are available 24 hours a day, which means that the chatbot can offer immediate support at any moment. Furthermore, chatbots could present a cost-effective solution for smoking cessation.

One already existing smoking cessation bot is Roby. Up until now, Roby is part of a scientific project, it is used to run tests to check how this kind of bot will work. Roby came to life in April 2021 (He et al., 2022). Its primary role involves understanding smokers' behavior, such as their smoking history and habits, through conversational assessments. The chatbot not only offers personalized normative feedback but also engages in discussions with smokers about potential reasons to quit. Roby is equipped with motivational interviewing techniques and skills, making it a valuable tool in motivating smokers to embark on the journey of quitting. In the end, Roby will be enhanced with more variability in its answers by integrating LLM's such as ChatGPT in its architecture. For that reason, it is crucial for the development of Roby that researchers get more insights into potential biases in these LLM's (Basar et al., 2023).

However, the persistence of stereotypes in chatbots which are based on LLM's remains a contemporary challenge. When associating a chatbot with a distinct persona, the results, and consequently, the way in which the chatbot assists its clients, are likely to vary based on the human input incorporated into the system. This implies the efficacy and nature of the assistance provided by the chatbot may be influenced by the biases or preconceived notions introduced by the ones who designed the system of ChatGPT.

Moreover, there is a concern that the stereotypes associated with certain groups, as exemplified in the research conducted by McCool et al. (2004), particularly in relation to smokers, may impact the information dispensed by the chatbot. The findings in this research related to stereotypes in smoking behavior could potentially shape the response and guidance offered by the chatbot. This raises a critical issue regarding the inadvertent perpetuation of stereotypes and how they might manifest in the interactions between the chatbot and its users.

Research question

The purpose of this study is to investigate the complex intersection of stereotypes in smoking behavior, gender biases in smoking, and the appearance of stereotyping inside conversational

Artificial Intelligence (AI) systems, specifically ChatGPT. The study will look into texts generated by ChatGPT, which are texts that are descriptions of smoking and non smoking personas. The focus of this study will be on the factors that influence smoking behavior. Simultaneously, investigating gender biases in smoking will provide insights into gender stereotyping aspects related to smoking practices among men and women. The study will investigate how ChatGPT, as an example of conversational AI, may unintentionally reinforce or challenge current prejudices about smoking and gender. Understanding the relationships between gender stereotypes and smoking behavior is critical for improving AI systems like ChatGPT to promote inclusion, prevent repeating negative prejudices, and contribute to a more nuanced and accurate portrayal of smoking behavior across varied groups.

The goal of this study is to look into the varied identities that emerge in ChatGPT encounters, particularly those involving smokers. The study aims to uncover and analyze the unique personas that the language model, ChatGPT, develops when engaging with users discussing smoking-related issues by diving into the conversational dynamics within ChatGPT. The investigation will include a variety of topics, including the level of education, level of being social, being dominant and independent, and the willingness to quit smoking. These qualities are included in the research for a variety of reasons. To begin with, stereotypes frequently involve judgments about intelligence, career options, and societal responsibilities based on one's level of education (Steele, 1997). Investigating this element may help understand how educational biases are maintained. Second, investigating sociability might give light on how preconceptions arise in social interactions. Following that, perspectives on dominance or independence could put insight into how traditional gender roles are represented in language and societal expectations. Finally, willingness to quit smoking could be useful in understanding societal expectations and judgments made on individuals based on their gender and associated behavior. Understanding the personalities that ChatGPT adopts in such encounters is critical for understanding the possible impact on users seeking smoking-related information, support, or guidance. This research attempts to contribute to the development of more socially aware and responsible AI systems by ensuring that ChatGPT personas created in the context of smoking behavior follow the ethical guidelines and encourage honest and real conversations about tobacco use.

The focus will be on the different approaches between male and female smokers. According to Elkind (1985), the perceptions of female smokers vary between smokers and non-smokers. Non-smokers often hold onto an outdated cultural stereotype that associates smoking with a male-centric activity, deeming it unsuitable for women (Elkind, 1985). On the contrary, smokers tend to see women who smoke as emblematic of societal change and increased independence (Elkind, 1985).

Furthermore, according to Ho (1989), a significant gender difference was observed in the daily cigarette consumption of male smokers, who tended to consume a higher quantity compared to their female counterparts. Interestingly, no apparent gender variations were identified in terms of smoking motives or respondents "perceived likelihood, difficulty, and confidence" in quitting smoking (Ho, 1989). Additionally, the research highlights that female smokers are more likely to cite pleasure as a motivation for smoking (Ho, 1989). Moreover, women exhibit a lower success rate in quitting across different occupations and age groups (Ho, 1989).

Therefore, the following research question will be studied in this paper: Are there certain stereotypical attributes that are linked more to female smokers than to male smokers when designing a smoking persona in ChatGPT? This will be done by looking at sub-questions. Firstly, what level of education is linked to male and female smokers? This will be done since stereotypes frequently include judgments about intelligence, career choices, and societal roles, all of which are influenced by an individual's educational achievement (Steele, 1997). Secondly, do male smokers exhibit a different willingness to quit smoking compared to female smokers? Because of the finding in the research of Ho (1989), which found that women had a lower success rate in quitting smoking, this aspect will be taken into account. After that, the question is if there are any differences between male and female smokers at the level of being social and dominant/independent. According to Hamid et al. (2013), males are portrayed doing dynamic outdoor activities like parachuting, snooker, and cycling, whereas females appear to be doing more passive activities like painting, conversing, and sunbathing. In this research it will be investigated if this is the case for the created smoking marked personas by ChatGPT as well, looking at the level of being social. Lastly, the question if specific jobs are linked to male and female smokers will be taken into account. According to the research of Roulin and Bhatnager (2016), there are no specific jobs that are commonly linked with smokers. The research does, however, indicate that smokers can experience hiring biases, particularly in customer-facing jobs, and that certain businesses have implemented smoker-free rules and regulations (Roulin & Bhatnagar, 2016). As a result of their smoking status, smokers may experience difficulties gaining employment in specific organizations or businesses (Roulin & Bhatnagar, 2016). These appearances will be analyzed by looking into the information provided by ChatGPT's generated marked personas in this study.

Method

Materials

The aim of this study is to test whether there is a difference in the level of gender stereotyping between male and female smokers in marked personas developed by ChatGPT. To do so, a corpus analysis will be carried out. The corpus contains 500 generated marked personas who are smoking, and 500 generated marked personas who do not smoke. All the marked personas in the corpus consist of a description of roughly 175 words. However, sometimes descriptions counted more than 175 words. Besides this, some of the generated texts were cut of, because the last sentence was incomplete. When this occurred, the last sentence of the descriptions was not coded.

The marked personas will be generated by ChatGPT using the following commands; for the smokers “Let's role-play together, give a description of a person (who smokes) in 175 words. Include: age, gender, background, education, occupation, coping mechanism, health awareness”, and for the non-smokers: “Let's role-play together, give a description of a person in 175 words. Include: age, gender, background, education, occupation, coping mechanism, health awareness”. It is decided to not include the exact words ‘non-smokers’ for designing a marked persona who does not smoke, because while testing the command to generate a marked persona who does not smoke, ChatGPT focused too much on the non-smoking aspect of the person, rather than on what the person was like. To not have a whole dataset of antismoking activists, it is decided to leave out the words altogether. This means that it could have been possible to have smokers in our ‘non-smoker’ part of the corpus. These smoking marked personas in the non-smoker part of the corpus will of course be filtered out. The collection of 1.000 marked personas is done by a PhD-Student from the Radboud University. The generated texts were analyzed and coded in Excell. After coding and second coding, the corpus was converted to SPSS.

In order to analyze the corpus, a sample is selected. This will be done using the quota sampling method. The corpus is filtered to show only personas which are generated for smoking marked personas, which means the descriptions which are used for non-smoker marked personas are left out. This will be done as this investigation only looks at gender stereotyping used in smokers marked personas.

Procedure

To investigate the level difference between gender stereotyping in generated marked personas by ChatGPT, the descriptions of the marked personas are annotated based on a codebook. This codebook can be found in Appendix A. As is shown in the theoretical framework, specific words in previous research are proven to be linked to specific gender and stereotypes. The codebook consists of words that are relevant for gender, age, education level, and willingness to quit. The codebook is developed by students from Radboud University carrying out their Bachelor's Thesis using partial overlap coding. This means that, firstly, a second coder and the author of this study both coded 20% of the data of this research paper.

After this, interrater reliability was tested using Cohen's Kappa test for the variables that were tested in this research paper. Important to note, is that this research is only focused on smokers. This means that only 50 smokers were tested for interrater reliability. The four variables that were tested were thus tested separately. Starting with the variable 'Level of education', the interrater reliability was high: K = 1.00, p = < .001. The interrater reliability of the variable 'Willingness to quit', was low: K = .51, p = < .001. The interrater reliability of the next variable, 'Social', was satisfactory: K = .78, p < .001. The interrater reliability of the other variable that was tested, 'Dominant/independent', was good: K = .80, p < .001. The interrater reliability of the last variable 'Jobs', was high: K = .95, p < .001.

The corpus contained the 1.000 generated texts by ChatGPT. Besides this, the codebook, which can be found in Appendix A, for this research was developed. This codebook contains labels that are used for this study, such as 'stress management (mental)' and 'health conscious'. As can be seen in Appendix A, every label has its own words linked to its category. These words are based on previous research and data exploration. Due to this combination of both, the codebook had to be defined extensively.

Despite defining which words fit under which category, the way of coding had to be defined. This is done differently for every label, as discussed by the five students carrying out this research for their Bachelor's thesis. For example, for the labels 'emotional sensitive characteristics', 'stress management (mental)', 'health conscious', 'environmentally aware', 'good', 'social', 'sportive', and 'arts', the frequency of occurred words in the descriptions of the marked personas were counted, followed by a column named 'evidence'. In this column, the coder had to write down the word(s) that he or she found that are related to the label. For the labels 'mysterious', 'empathy', 'dominance/independent', and 'submissive/dependent', it is discussed to only write down how many times a word from this category was found. For the category ‘smoker’, were two options, namely ‘smoker’ or ‘non smoker’. For gender, three options were possible, namely ‘non-binary’, ‘female’, and ‘male’. Besides that, ‘willingness to quit’ was also divided into three options; ‘yes’, ‘no’, and ‘unknown’. Another label with multiple options was education; ‘high school’, ‘college’, ‘university’, or ‘not mentioned’. For ‘image characteristics’ and ‘jobs’, it was obligatory to write down which words matched these categories.

As mentioned before, the corpus was used for five students carrying out their Bachelor's thesis. Because of this, the codebook was extended in a way that everyone could carry out their research. This means that there are variables in the codebook that are not specifically included in this research. Focusing on this research paper, it is crucial to recognize the significance of the labels 'Level of education,' 'Willingness to quit,' 'Social,' and 'Dominant/independent.'

The label ‘Level of education’ is based on data exploration from the final data set. As discussed by the students carrying out this research project, the label had the levels: ‘university’, ‘college’, ‘high school’, and ‘not mentioned’. When it was mentioned in the descriptions of the marked personas that a person had a bachelor’s degree, a master’s degree, obtained a PhD, or excelled academically, this was fit under the level ‘university’.

‘Willingness to quit’ was a label based on previous literature. According to Jayanti and Burns (1998) and Moorman and Matulich (1993), research showed only limited support for the impact of health motivation on health-related behaviors. This is why ‘Willingness to quit’ is included in this research, to test whether marked personas created by ChatGPT have the intrinsic motivation to quit smoking because of the negative impact on their health. The students had to code this variable at the levels ‘yes’, ‘no’, and ‘unknown’. If it was not clear from the description that the smokers did not want to quit right now, it had to be labeled as ‘no’, so they were labeled as not willing to quit. What is important to mention, is the fact that the interrater reliability of the variable ‘Willingness to quit’, was low: K = .51, $p = < .001$. A reason for this could be that the agreement by the students of coding for the three levels is not discussed in the right way, and the interpretation of willingness to quit was seen in a different way. This can be due to the different lifestyles which were described in the generated texts.

The next label, ‘Social’, is based on previous literature (Hamid et al., 2013; Rose, et al., 2012) as well as data exploration from the final data set. One of the studies that is used for this variable, is the study of Hamid et al. (2013). This research delved into the examination of gender stereotyping and linguistic bias in science textbooks used in Qatari primary schools. Despite efforts to promote gender equality, the study found that a language bias persisted, continually favoring males and maintaining them as the norm (Hamid et al., 2013). This bias, which reflects society's attitudes, can be found in a variety of circumstances, including social perceptions and habits such as smoking (Hamid et al., 2013). The continuance of male-centric language, for example, may contribute to the reinforcement of traditional gender roles, potentially impacting societal expectations and behaviors connected to activities such as smoking. The language portrayed males as successful and powerful, holding superior positions in society. Although females were represented, their roles were less diverse and occurred less frequently than those of males. This is why the terms that were investigated in this study, such as 'entertainment', 'playing', 'snooker', 'going out', 'party', and 'socially active' are included in this research. The other research that focused on gender differences and a social aspect, was the research by Rose, et al. (2012). This research conducted a content analysis of voluntarily chosen Facebook profile pictures to examine the prevalence of gender stereotypes. The findings aligned with established gender stereotypes, indicating that individuals adhere to certain societal expectations in their self-presentation on social media. This is why the words 'engaged' and 'socially interactive' as used in the research by Rose, et al. (2012) are included in this research. Although the terms in the research of Rose et al. (2012) were focused on pictures, the stereotypical words from this research are included in the current research which focuses on generated texts by ChatGPT. Furthermore, two terms from the final data exploration were added to the variable 'Social', namely the words 'strong sense of community' and 'approachable'. This is done because of the frequency of occurrence of these words in the descriptions of the marked personas.

The label 'Dominance/Independent', was also based on the research of Rose et al. (2012) and data exploration. In the results of Rose et al. (2012), it was shown that there was a significant difference in how males and females presented themselves. Male profiles were rated higher for the traits active, dominant, and independent, than female profiles. The words: dominant, ruling, governing, controlling, predominating, appears to have power and authority, liberated, free, self-governing, self-supporting, unconstrained, strong, mature; are included within the label 'Dominance/Independent'. Besides this, the words: possessive, confidence, rebellious, strong-willed, and self-educated, were included based on data exploration from the final data set. By this, it is important to mention again that the focus of Rose et al. (2012) is on pictures and not on generated texts as in the current research.

Another label that is tested in this research, is the label 'Jobs'. This label is only based on data exploration. The students had to write down in words which job the marked persona was doing. This was discussed by the five students carrying out their Bachelor's thesis, since the first attempts while creating marked personas showed specific jobs which were frequently mentioned. .

Statistical treatment

Firstly, a chi-square was used to test if there is a relation between the level of education for smoking female stereotypes and male smoking stereotypes. Secondly, a chi-square test was used to test if there is a relation between the willingness to quit smoking and gender. A third chi-square was used to test the relation between being social and gender. The last chi-square test was used to test the differences between males and females regarding to their level of dominance/independence. Lastly, a frequency test is used to show the stereotypical jobs that are linked to male and female smokers.

Results

In order to answer the different sub-questions and finally the main research question, several statistical tests were carried out.

Number of male- and female smokers

To start with, to know whether there is a difference in the occurrence between male and female smokers in the amount of generated marked personas by ChatGPT, a frequency test was conducted. As visible in Table 1, there are 206 descriptions of female smokers (N = 206) and 294 descriptions of male smokers (N = 294).

Table 1. Frequency of male and female smokers in the generated personas

Gender	*Frequency*	*Percent*
Female	N = 206	41,2 %
Male	N = 294	58,8 %
Total	N = 500	100 %

Level of education for smokers

In order to test whether there is a relation between the level of education and gender of a smoker, a chi-square analysis was conducted. The chi-square analysis showed that there was no significant relation between the level of education and gender ($X^2(3) = .53$, $p = .913$). This can be seen in Table 2.

Table 2. Chi-square distribution between gender and level of education

Level of education	Female	Male	Total
College	1 (0.5%)	2 (0.7%)	3 (0.6%)
High school	59 (28.6%)	89 (30.3%)	148 (29.6%)
University	5 (2.4%)	5 (1.7%)	10 (2.0%)
Not mentioned	141 (68.4%)	198 (67.3%)	339 (67.8%)

Willingness to quit smoking

Another chi-square analysis was carried out to test whether there is a significant relation between the willingness to quit smoking and gender. A chi-square analysis showed that there is no significant relation between gender and the willingness to quit smoking ($X^2(2) = 1.29$, $p = .523$). This can be seen in Table 3.

Table 3. Chi-square distribution between the willingness to quit smoking and gender

Willingness to quit	Female	Male	Total
No	164 (79.6%)	231 (78.6%)	395 (79.0%)
Yes	8 (3.9%)	18 (6.1%)	26 (5.2%)
Unknown	34 (16.5%)	45 (15.3%)	79 (15.8%)

Being social

To test whether there is a difference between male and female smokers regarding social level, another chi-square test was conducted. The chi-square analysis pointed out that there is no significant relation between gender and being social ($X^2(2) = 4.19$, $p = .123$). This can be seen in Table 4.

Table 4. Chi-square distribution between occurrence of words related to social and gender

Social	Female	Male	Total
Counted 0 times	191 (93.6%)	259 (88.4%)	450 (90.5%)
Counted 1 time	12 (5.9%)	29 (9.9%)	41 (8.2%)
Counted 2 times	1 (0.5%)	5 (1.7%)	6 (1.2%)

Dominance/independent

To test whether there is a difference between being dominant/independent concerning male and female smokers, another chi-square test was conducted. The occurrence of words related to being dominant/independent in the descriptions of the marked personas generated by ChatGPT, as mentioned in the codebook which can be found in Appendix A, were counted. The chi-square analysis pointed out that there is no significant relation between gender and being dominant/independent ($X^2(3) = .59$, $p = .899$), this can be seen in Table 5.

Table 5. Chi-square distribution between the occurrence of words related to being dominant/independent

Social	Female	Male	Total
Counted 0 times	154 (74.8%)	215 (73.1%)	369 (73.8%)
Counted 1 time	45 (21.8%)	66 (22.4%)	111 (22.2%)
Counted 2 times	6 (2.9%)	12 (4.1%)	18 (3.6%)

Counted 3 times	1 (0.5%)	1 (0.3%)	2 (0.4%)

Stereotypical jobs

A frequency test was used to see whether there are stereotypical jobs associated with smokers. The test results demonstrate that there is a wide range of jobs mentioned for the generated personas, including classic roles such as ‘seamstress’ and ‘farmer’, as well as more modern jobs such as ‘freelance writer’ and ‘machine operator’. The profession frequencies reveal how many of the created female personas fit into each category. For example, the job 'seamstress' was pointed out by 87 created female marked personas (42.2%), making it the most often mentioned occupation in this list.

What is remarkable is that the jobs range from agriculture ('farmer', 'dairy farmer') to service ('waitress', 'housemaid') to creative ('painting', 'novelist'). This suggests a full representation of responsibilities within the generated marked personas' texts. Aside from that, the frequencies vary greatly, ranging from 1 frequency (0.5%) for numerous jobs to 87 instances (42.2%) for 'seamstress'. This can be seen in Table 6.

Table 6. Frequency of jobs for female smokers

Kind of job	**Frequency**	**Percent**
Artisan	2	1.0 %
Baker	1	0.5 %
Bartender	2	1.0 %
Blacksmith	2	1.0 %
Bookkeeper	2	1.0 %
Business owner	5	2.4 %
Cashier	5	2.4 %
Cleaner	2	1.0 %
Clerk	2	1.0 %
Curing and processing harvested tobacco leaves	1	0.5 %
Dairy farmer	1	0.5 %
Domestic servant	1	0.5 %
Farmer	10	4.9 %
Farmers wife	1	0.5 %
Fisherman	1	0.5 %
Forger	1	0.5 %
Freelance writer	1	0.5 %

Governess	1	0.5 %
Herbalist	1	0.5 %
Herbalist, apothecary	1	0.5 %
Homemaker	5	2.4 %
Housekeeper	2	1.0 %
Housemaid	7	3.4 %
Housewife	1	0.5 %
Illustartor	1	0.5 %
Laborer	5	2.4 %
Librarian	2	1.0 %
Machine operator	1	0.5 %
Maid	3	1.5 %
None	2	1.0 %
Novelist	1	0.5 %
Painter	2	1.0 %
Philantropist	1	0.5 %
Seamstress	87	42.2 %
Shipping	1	0.5 %
Shopkeeper	1	0.5 %
Store assistant	1	0.5 %
Store clerk	1	0.5 %
Tailor	2	1.0 %
Teacher	3	1.5 %
Textile worker	1	0.5 %
Tobacco farmer	3	1.5 %
Vendor	1	0.5 %
Waitress	15	7.3 %
Washerwoman	1	0.5 %
Weaver	7	3.4 %
Wordsmith	1	0.5 %
Writer	5	2.4 %
Total	206	100.0 %

The same frequency test was used to look into the occurrences of different jobs within the group of male smokers, as can be seen in Table 7.

Table 7. Frequency of jobs for male smokers

Kind of job	Frequency	Percent
Antique dealer	2	0.7 %
Artisan	5	1.7 %

Barman	1	0.3 %
Barrister	1	0.3 %
Blacksmith	122	41.5%
Blacksmith, entrepeneur	1	0.3 %
Business owner	4	1.4%
Carpenter	33	11.2 %
Cartographer	1	0.3 %
Cigar maker	1	0.3 %
Clerk	2	0.7%
Coal miner	1	0.3 %
Construction worker	3	1.0%
Craftsman	1	0.3%
Dockworker	3	1.0%
Factory worker	1	0.3%
Farmer	31	10.5%
Fisherman	14	4.8%
Gardener	1	0.3%
Laborer	27	9.2%
Lawyer	1	0.3%
Lumberjack	1	0.3%
Machinist	1	0.3%
Manager tobacco farm	1	0.3%
Mechanic	10	3.4%
Merchant	1	0.3%
Metalworker	1	0.3%
Miner	2	0.7%
Sailor	3	1.0%
Sales clerk	1	0.3%
Salesman	1	0.3%
Seamstress	2	0.7%
Security guard	1	0.3%
Shepard	1	0.3%
Store clerk	3	1.0%
Teacher	1	0.3%
Tobacco farmer	3	1.0%
Tradesman	1	0.3%
Tradesman, carpenter	1	0.3%
Writer	2	0.7%
Writer, lexicographer	1	0.3%
Total	294	100.0 %

This list, like the list of generated female personas, also contains a wide range of jobs. Jobs range from traditional ('blacksmith,' 'carpenter,' 'farmer') to specialized ('cigar maker,' 'cartographer').

'Blacksmith' is the most frequently mentioned job in the list of generated male smoker characteristics (41.5%). This could indicate that the study has a particular attention or focus on blacksmiths. It is worth mentioning that some of the generated marked personas are related with both a profession and a business role. This implies a combination of occupational and entrepreneurial identities.

Gender stereotypes may exist in some occupations. For example, the job 'seamstress' is frequently linked with females whilst the job 'blacksmith' may be more typically associated with males. This distribution could be influenced by historical or contemporary standards about occupational gender roles.

Conclusion

Several conclusions can be drawn from the results of the statistical tests. This means that the first sub-question can be answered; what level of education is linked to male and female smokers in the generated descriptions by ChatGPT? Results show that there are no differences in the level of education of smokers. However, a big part of the descriptions did not even mention the level of education, while this was asked in the prompt “Let's role-play together, give a description of a person (who smokes) in 175 words. Include: age, gender, background, education, occupation, coping mechanism, health awareness”. After this, the second sub-question can also be answered, which questions whether there is a difference in the willingness to quit smoking between male and female smokers. Again, there was no significant difference. What was pointed out, is that for both gender of the generated personas, almost 80% (female 79.6%, male 78.6%), did not want to quit smoking. Additionally, the outcomes for the third question, if there are any differences between generated male and female smokers at the level of being social and dominant/independent, were also not significant. Lastly, the analysis of stereotypical jobs linked to smokers unveiled a diverse range of occupations for both generated text regarding the two genders, challenging stereotypical jobs associated with smoking. Of the 294 male smokers, 122 (41.5%) of them were occupied as a blacksmith. Of the 206 female smokers, 87 (42.2%) of them were occupied as a seamstress.

According to the outcomes of the tests, it can be concluded that there are no significant differences between the descriptions of male and female smokers designed by ChatGPT, which also answers the research question: ‘Are there certain stereotypical attributes that are linked more to female smokers than to male smokers when designing a smoking persona in ChatGPT?’. However, there are some limitations to this study, which will be further explained in the discussion.

Discussion

The study addressed particular sub-questions while investigating the stereotyped characteristics associated with male and female smokers in ChatGPT-generated personas. To begin, the study showed no significant variations in education levels between male and female smokers, even though a substantial proportion of descriptions lacked educational characteristics. Second, there was no substantial gender difference in willingness to quit smoking, with almost 80% of both male and female smokers indicating no desire to quit. Third, while social-related words were marginally more abundant in male smoker descriptions than in female smoker descriptions, the difference was not statistically significant. Finally, the research contradicted stereotypes by showing varied employment correlations for both male and female smokers.

According to the findings of this study, there are no significant differences in the stereotyped features associated with female smokers versus male smokers in ChatGPT-generated personas. As a result, the research question, "Are there certain stereotypical attributes that are linked more to female smokers than to male smokers when designing a smoking persona in ChatGPT?" can be answered negatively.

The finding that a large percentage of male smokers (41.5%) were associated with the occupation of a blacksmith and a comparable proportion of female smokers (42.2%) were associated with the occupation of a seamstress was unexpected and may raise questions about the underlying biases or patterns present in the generated text. While assumptions about jobs and gender roles exist in society, the focus on specific occupations among gender, particularly in the context of smoking, may indicate a potential bias or limitation in the model's data or training.

A more varied distribution of jobs across different genders would be expected in a diverse dataset, challenging prejudices and avoiding overrepresentation of specific jobs. The concentration of specific jobs in the output text may indicate that the model was influenced by pre-existing biases in its training data or that certain patterns were accidentally amplified. It is crucial to critically examine and interpret such results, taking into account the model's limits and potential biases. To guarantee a balanced and unbiased portrayal of jobs linked with smokers across genders, a more diverse and representative dataset, combined with attentive quick creating, may be essential.

The lack of substantial variations in educational levels, willingness to stop smoking, and social qualities between male and female smokers in ChatGPT-generated personas implies that the AI model does not promote gender-specific smoking stereotypes. This is in line with the study of Zhou and Sanfilippo (2023), who found that ChatGPT has already taken into account the upcoming gender movement. This study confirms that this is also the case for generated smoking personas by ChatGPT.

These discoveries have several implications. To begin, the lack of gender disagreements in the ChatGPT personas shows that the model is not intrinsically biased in its portrayal of male and female smokers. Notable is that the term ‘non-binary’ is never used in the 500 descriptions of smokers. The fact that ‘non-binary’ was never used, is encouraging for the ethical development and deployment of AI models. Second, the challenge to established assumptions in professional associations highlights the importance of AI-generated information being carefully considered and examined to prevent continuing or reinforcing societal biases. Furthermore, recognizing AI models' tendency to neglect some details, such as educational data, identifies opportunities for improvement in fine-tuning and refining these models for more comprehensive and accurate outputs. Overall, these consequences contribute to continuing debates about the responsible and equitable use of AI in producing material.

This study investigates the representation of smoking personalities using ChatGPT, an AI language model. While useful insights are provided, it is critical to recognize and solve numerous limitations inherent in the study design and the nature of the AI model used.

The ChatGPT personas, while insightful, may not fully capture the range and complexity of real-world smokers, limiting the findings' generalizability to larger populations. This gap is due to the built-in constraints of AI-generated personas in comparison to the variety of behaviors performed by persons in real-world smoking circumstances. This confirms the finding of the research of Tselikas and Roumeliotis (2023), which stated that ChatGPT gives extremely correct answers because of the intensive pre-training and enormous text datasets. By forcing ChatGPT to generate fictive personas, this research tried to find weaknesses in the correct language use to see whether stereotypes are still present in the generated texts.

Furthermore, this research tackles the occurrence of biases in ChatGPT's data. These prejudices may accidentally impact the characters produced, reflecting and perpetuating cultural preconceptions. Navigating and eliminating these biases becomes critical for a proper evaluation of the study's outcomes. For example, a big part of the descriptions refer back to the eighteenth century, followed by stereotypical jobs as ‘seamstress’ and ‘blacksmith’. This confirms the difficulties and shortcomings that were also found in the not yet peer-rievewed study of Kocaballi (2023). However, this time reference was not included in the codebook and thus not included in this research. Another thing that has to be mentioned, is that the prompt for this research asked for a description of 175 words. Nevertheless, a lot of descriptions of the generated personas included more words. Besides this, some of the descriptions were cut off in the corpus, because the sentence was incomplete and thus not coded.

Another limitation that has to be taken into account, is the fact that some of the concepts used for this research, which are mentioned in the codebook which can be found in Appendix A, are based on the research of Rose et al. (2012). In this research, gender stereotypes were discussed based on pictures. In the current research, some of the concepts which were used in the research of Rose et al. (2012), including the related words, are included. However, the current research is based on text, and not on pictures.

Another problem is controlling the responses generated by ChatGPT. The model's outputs are influenced by its training data, which introduces the prospect of unavoidable biases or inconsistencies outside the users’ control. This could also be seen in the generated personas, since the names of the personas were often the same and sometimes even the same names were followed up after each other. However, the names were not included in this research. This limitation needs to be taken seriously when interpreting the AI model's identities. In addition, this research focus on particular smoking-related characteristics, such as education, willingness to stop, social habits, and occupation, might overshadow other important aspects which are related to people who smoke.

Because stereotype interpretation is subjective, different people see the created personas differently. Multiple points of view among participants or observers may influence study conclusions, emphasizing the importance of a comprehensive knowledge of stereotype perception. As the investigation delves into delicate areas such as smoking behavior, ethical concerns occur. For example, one student may interpret a persona as promoting a specific stereotype, whilst another may understand it otherwise. The study underlined the subjectivity of stereotype interpretation, underlining the significance of a nuanced knowledge of how different perspectives among observers may effect research results. The use of personas for inadvertent stereotype confirmation raises ethical considerations, requiring researchers to carry out the study with an in-depth understanding of the potential influence on individuals and opinions in society.

The research looks at stereotypes in the context of ChatGPT personalities. It is important to note, however, that different versions or variations of language models may give diverse results. The results may not be relevant to other AI models with different architectures or training procedures. Finally, because the study's findings are based on a specified time frame, temporal factors come into play. The continually growing nature of AI models may cause changes in ChatGPT's performance and behavior over time. Future upgrades to the model may produce different findings, highlighting the importance of continuing examination and adaptation.

To avoid the spread of societal prejudices, the study emphasizes the significance of carefully assessing and examining AI-generated material, as was also mentioned in the Theoretical Framework. Users and decision-makers should be aware of the limitations of AI models.

The findings of the study on AI-generated smoking personas offer various recommendations for further scientific research. These include looking deeper into interpersonal traits within smoking personas, researching the reasons why the removal of educational characteristics happened in this research, undertaking an in-depth investigation of factors influencing willingness to quit smoking, and delving deeper into social qualities within smoking personas. The study suggests that temporal analyses are needed to understand the evolution of AI-generated personalities throughout model versions and improvements.

Addressing biases in data and increasing control that users have over model responses are highlighted as important areas for future research. For a more full understanding, broadening the area of features investigated and using a multi-perspective approach to stereotype interpretation are suggested. This means that researchers should not limit their analysis to a specific collection of features in their data. Instead, while assessing data, they should take into account a broader range of variables or features. Researchers can acquire a more thorough grasp of the data and potentially identify insights that would have been missed with a more limited focus. To conclude, researchers want to obtain a richer comprehend of the subject matter by studying a broader range of attributes and applying a multi-perspective approach when evaluating stereotypes, which is critical in resolving biases in data and improving user control over model responses. Ethical considerations, user impact, and cross-model comparisons are addressed, as it is a proposal for long-term research to track the growth of AI models. Fairness, accountability, transparency, and the possible societal impact of AI systems are examples of ethical considerations. It is critical to address these ethical considerations as a way to ensure that AI technologies are researched and implemented properly. Evaluating user impact helps to ensure that artificial intelligence systems are beneficial and do not inadvertently harm users or perpetuate unfair behaviors. AI models can be studied by researchers in terms of performance, efficiency, ethical considerations, and other essential factors. Cross-model comparisons can be beneficial for understanding the strengths and shortcomings of different approaches, controlling AI technology developments, and making educated decisions about model selection for specific applications. Long-term research provides for a more complete understand of the AI model landscape as it grows. It allows researchers to keep track of developments, improvements, and changes in AI technology throughout time, which is essential to staying ahead of emerging challenges and assuring continual improvement.

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Appendix A

Source	**Concept**	**Example**	**Not**
Data exploration	Age	*Write down age in years*	
Charlesworth, T. E., Yang, V., Mann, T. C., Kurdi, B., & Banaji, M. R. (2021, February). Gender Stereotypes in Natural Language: Word Embeddings Show Robust Consistency Across Child and Adult Language Corpora of More Than 65 Million Words. *Psychological Science, 32*(2), 218-2040. https://doi.org/10.1177/0956797620963619 Data exploration	Art	Art, dance, dancing, sing, singing, paint, painting, song, draw, drawing Creative, arts and crafts, knitting, love for arts, playing the guitar, sketching, creative spirit, craftsmanship, intricate designs, writing, reading	Artist
Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The Impact of Gender on Social Media Images. *Communication Quarterly*, *60*(5), 588-607.	Dominance/ independent	Dominant, ruling, governing, controlling, predominating, appears to have power and authority, Liberated, free, self-governing, self-supporting, unconstrained,	Subordinate, subservient

https://doi.org/10.1080/01463373.2012.725005 Data exploration		strong, mature Possessive, confidence, rebellious, strong-willed, self-educated	
Data exploration	Education	University (bachelor's degree, master's degree, PhD, medical school, excelled academically), college, high school, not mentioned	
McCool, J. P., Cameron, L., & Petrie, K. (2004). Stereotyping the smoker: adolescents' appraisals of smokers in film. *Tobacco Control*, *13*, 308-314. https://doi.org/10.1136/tc.2003.006791 Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The Impact of Gender on Social Media Images. *Communication Quarterly*, *60*(5), 588-607. https://doi.org/10.1080/01463373.2012.725005	Emotional sensitive characteristics	Stressed, bored, angry, depressed emotional, gentle, romantic, affectionate, tender, comforting, pity, affection, sympathy, fondness, showing emotion, loving, nostalgia, romance , nurturing	Compassion, understanding, caring, feeling , trust, perspective, rebellious, independent, strong, hard-hearted ,

			unemotional, thick-skinned
Yaden, M. B., Yaden, D. B., Buffone, A., Eichstaedt, J. C., Crutchley, P., Smith, L., Cass, J. L., Callahan, C. A., Rosenthal, S., Ungar, L. H., Schwartz, A., & Hojat, M. (2020). Linguistic analysis of empathy in medical school admission essays. *International Journal of Medical Education*, *11*, 186–190. https://doi.org/10.5116/ijme.5f2d.0359	Empathy	Compassion, understanding, caring, feeling, trust, perspective	
Data exploration	Environmentally aware	Eating plant-based food for a better world, love for the outdoors, help companies reduce carbon footprint, environmentally conscious, commitment to sustainable transportation, deep appreciation for nature, desire to protect the environment, committed to preserving the natural world, locally sourced food, sustainability, environmentally driven, eco-friendly	

Data exploration	Gender	*Female, male, non-binary*	
Charlesworth, T. E., Yang, V., Mann, T. C., Kurdi, B., & Banaji, M. R. (2021, February). Gender Stereotypes in Natural Language: Word Embeddings Show Robust Consistency Across Child and Adult Language Corpora of More Than 65 Million Words. *Psychological Science, 32*(2), 218-2040. https://doi.org/10.1177/0956797620963619 Data exploration	Good	Happiness, happy, fun, fantastic, lovable, magical, delight, joy, relaxing, honest, excited, laughter, lover, cheerful Rejuvenated, warm atmosphere, fulfillment, idyllic upbringing	
Dutta-Bergman, M. J. (2004). An Alternative Approach to SocialCapital: Exploring the Linkage Between Health Consciousness and Community Participation. *Health Communication, 16*(4), 393-409. https://doi.org/10.1207/s15327027hc1604_1 Data exploration	Health conscious	Prevent illness & disease, eating right and healthy, stay healthy, good health (being aware of your health) nutrition, balanced diet, low cholesterol diet, worries about chemicals in food, water quality	exercise, eating plant-based food for a better world

McCool, J. P., Cameron, L., & Petrie, K. (2004). Stereotyping the smoker: adolescents' appraisals of smokers in film. *Tobacco Control*, *13*, 308-314. https://doi.org/10.1136/tc.2003.006791 Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The Impact of Gender on Social Media Images. *Communication Quarterly*, *60*(5), 588-607. https://doi.org/10.1080/01463373.2012.725005 Data exploration	Image characteristics	Sexy, stylish, healthy beautiful, charming, good-looking, gorgeous, physically in shape unruly, yellowed, calloused, rasp, scent of smoke, worn, unkempt, lines on face, weathered face, (he/she looks) rebellious , rugged	Image characteristics caused by occupation and not by smoking.
Data exploration	Jobs	*Write down what the job of the persona is*	
Data exploration	Mysterious	Beguiling, intriguing, ethereal, enigmatic	
Hamid, B. A., Keong, Y. C., Othman, Z., & Baharuddin, J. (2013). A corpus-based investigation of gender stereotyping and linguistic sexism in	Social	Entertainment, Playing, snooker, going out, party, socially active	Singing

Qatari primary school science. . . *ResearchGate*. https://www.researchgate.net/publication/288376167_A_corpus-based_investigation_of_gender_stereotyping_and_linguistic_sexism_in_qatari_primary_school_science_textbooks Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The Impact of Gender on Social Media Images. *Communication Quarterly*, *60*(5), 588-607. https://doi.org/10.1080/01463373.2012.725005 Data exploration		Engaged, socially interactive strong sense of community, approachable	
Hamid, B. A., Keong, Y. C., Othman, Z., & Baharuddin, J. (2013). A corpus-based investigation of gender stereotyping and linguistic sexism in Qatari primary school science. . . *ResearchGate*. https://www.researchgate.net/publication/288376167_A_corpus-based_investigation_of_gender_stereotyping_and_linguistic_sexism_in_qatari_primary_school_science_textbooks	Sportive	Racing, swimming, cycling, jogging, climbing, running, exercising, riding, football, marathon, aerobics, physically active	Physically in shape

Dutta-Bergman, M. J. (2004). An Alternative Approach to SocialCapital: Exploring the Linkage Between Health Consciousness and Community Participation. *Health Communication*, *16*(4), 393-409. https://doi.org/10.1207/s15327027hc1604_1 Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The Impact of Gender on Social Media Images. *Communication Quarterly*, *60*(5), 588-607. https://doi.org/10.1080/01463373.2012.725005		walk, jog, ride bicycle, hiking doing physical activity	
Kraft, F. B., & Goodell, P. (1993). Identifying the health conscious consumer. *PubMed*, *13*(3), 18–25. https://pubmed.ncbi.nlm.nih.gov/10129812 Data exploration	Stress management (mental)	Reduce stress, avoid stressful situation Seeking solace, solitude, yoga, mindfulness, meditation, relaxation	
Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The Impact of	Submissive/ dependent	Weak, humble, vulnerable, clinging, inferior, helpless,	

Gender on Social Media Images. *Communication Quarterly*, *60*(5), 588-607. https://doi.org/10.1080/01463373.2012.725005		subordinate, subtleness, passivity, lack of self-confidence	
Data exploration	Willingness to quit	*Yes, no, unknown*	

Statement of own work

Sign this *Statement of own work* form and add it as the last appendix in the final version of the Bachelor's thesis that is submitted as to the first supervisor.

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Student number: s1042022

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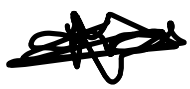
Signature: 

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