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Picturing the fictitious person: An exploratory study on the effect of images on user perceptions of AI-generated personas

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ABSTRACT

Human-computer interaction (HCI) research is facing a vital question of the effectiveness of personas generated using artificial intelligence (AI). Addressing this question, this research explores user perceptions of AI-generated personas for textual content (GPT-4) and two image generation models (DALL-E and Midjourney). We evaluate whether the inclusion of images in AI-generated personas impacts user perception or if AI text descriptions alone suffice to create good personas. Recruiting 216 participants, we compare three AI-generated personas without images and those with either DALL-E or Midjourney-created images. Contrary to expectations from persona literature, the presence of images in AI-generated personas did not significantly impact user perceptions. Rather, the participants generally perceived AI-generated personas to be of good quality regardless of the inclusion of images. These findings suggest that textual content, i.e., the persona narrative, is the primary driver of user perceptions in AI-generated personas. Our findings contribute to the ongoing AI-HCI discourse and provide recommendations for designing AI-generated personas.

1. Introduction

Personas are fictitious people used to represent a user base and their characteristics (Cooper, 1999). They are commonly used in design, software development, and marketing to represent user or customer insights (Nielsen & Hansen, 2014). Personas can be created in various ways, including using quantitative data, qualitative data, or a combination of both (Jansen, Jung, Nielsen, Guan, & Salminen, 2022). Data-driven personas are created using quantitative data and computational techniques, such as clustering algorithms (An et al., 2018; Lynn Dupree, Devries, Berry, & Lank, 2016). Algorithmic personas are created using algorithms trained on user data (Salminen, Jung, & Jansen, 2020c). Personas can be used for commercial or societally beneficial purposes (Guan, Salminen, Jung, & Jansen, 2023). In general, personas are used to facilitate decision-makers sense-making about users in the design process (Amin, Cambria, & Schuller, 2023).

Personas are widely used in design (Bødker, Christiansen, Tom, & Zander, 2012; Nielsen, 2019; Nielsen & Hansen, 2014) and human-computer interaction (HCI) to represent various user types' needs, wants, goals, and other attributes (Cooper, 1999). In fact, personas have belonged to the 'standard toolbox' of user-centered design (UCD) for a good twenty years already (Cooper, 1999; Grudin & Pruitt, 2002). Throughout this period, the design of personas – i.e., the persona profile or template (Nielsen, Hansen, Jan, & Jane Billestrup, 2015; Salminen et al., 2020b) – has remained relatively unchanged, with a standard profile layout composed of a name, picture, some data or graphs, and various textual information. However, times are changing! There are two issues for persona design in the current day that we address: first, does a persona need a picture in the first place? This question was inspired by seeing this opinion frequently pop up in professional design discussions in social media: namely, that a persona does not necessarily need demographics or facial pictures to be effective.

Second, technology offers new options. Specifically, generative AI with its large language models (LLMs) and image generation models (Amin et al., 2023; Hämäläinen, Tavast, & Kunnari, 2023; Jansen, Jung, & Salminen, 2023) are offering room for persona design to innovate. We can now create personas with the help of AI, using LLMs to generate the persona text descriptions and image generation models to generate the facial pictures of the persona profile. However, 'should we do so?' is a different question. One approach to tackling this question is to analyze users' perceptions of personas (Salminen et al., 2018a, 2020f). These perceptions are crucial indicators of the degree and quality of

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interaction between personas and their users; in turn, the quality of this interaction influences if and how the personas achieve their goal of being helpful design instruments (Grudin, 2006, pp. 642–663).

We focus on investigating user perceptions of AI-generated personas created using a combination of an LLM (GPT-4) and two image generation models (DALL-E and Midjourney). Thus, the personas we generate combine both image and text generation, although we focus on investigating the effect of whether to use an image in these AI-generated personas at all, or whether the persona users find the mere text descriptions satisfactory. From the broader perspective, our research contributes to the on-going research integration and dialogue between AI and HCI (i.e., *AI-HCI research*), a feat transformative to many aspects of how people interact with computer systems (Karahasanović, Følstad, & Schittekat, 2021; Kou & Gui, 2020).

In terms of terminology, note that personas are created to represent user groups. However, in this study, by 'users', we refer to *persona users*, i.e., those using the personas to learn about a group of people. So, 'user perceptions' refer to persona users' perceptions of personas (i.e., the end users of the personas), not to the users that the personas represent.

Our research questions (RQs) are as follows.

- **RQ1:** *How do user perceptions vary among AI-generated personas with (a) no images, (b)* DALL-E*-created images, and (c) Midjourney-created images?*
- **RQ2:** *Do user perceptions vary by different AI-generated personas?*
- **RQ3:** *Do user perceptions of AI-generated personas with (a) no images, (b)* DALL-E *-created images, and (c) Midjourney-created images vary by user gender?*
- **RQ4:** *Do user perceptions AI-generated personas with (a) no images, (b)* DALL-E *-created images, and (c) Midjourney-created images vary by user age?*
- **RQ5:** *Do the perceptions of AI-generated personas with (a) no images, (b)* DALL-E *-created images, and (c) Midjourney-created images vary by users' experience of personas?*

RQ1 matters because, as representations of human beings, the way users perceive personas is critical for their application (Grudin, 2006, pp. 642–663; Salminen et al., 2020f) and in making personas 'work' in practical settings (Friess, 2012; Grudin, 2006, pp. 642–663; Matthews, Judge, & Whittaker, 2012; Nielsen & Hansen, 2014). RQ2 is crucial as it examines whether user perceptions differ based on the specific personas presented, aiding persona designers in tailoring attributes and traits to create more relatable and engaging personas (Frank, 2009; Nieters, Ivaturi, & Ahmed, 2007). RQ3's significance lies in understanding if user perceptions are influenced by participant gender, which can guide persona designers in crafting personas that reinforcing gender biases (Charles et al., 2017; Marsden & Haag, 2016a; Salminen, Nielsen, et al., 2018; Turner & Turner, 2011). RQ4's findings can inform us of whether there is a need to design different personas for different aged populations (Schäfer et al., 2019). For example, it is possible that younger audiences would prefer more visual persona presentations than more mature persona users, or *vice versa*. RQ5 is vital for persona design as it explores how user perceptions vary based on participant familiarity with persona concepts, aiding designers in adapting personas to different user familiarity levels for improved communication and engagement. Persona experience may affect how users interact with and perceive personas (Salminen, Jung, Santos, Chowdhury, & Jansen, 2020e), which is why persona studies may consider this factor (Salminen, Jung, Santos, Kamel, & Bernard, 2021).

So, all RQs are relevant to the overarching question of what kind of personas we should design, especially considering the novel capabilities provided by generative AI technology.

2. Related work

2.1. Pictures in personas

Persona profiles are tools used in user experience design, marketing, and other fields to represent and understand target user groups (Cooper, 1999; Goodman-Deane et al., 2018, 2021; Holden, Kulanthaivel, Purkayastha, Goggins, & Kripalani, 2017; Minichiello, Hood, & Derrick Shawn Harkness, 2018). The inclusion of pictures in persona profiles has been a topic of discussion in the UX community. There is little consensus on whether to include a picture in the profile. However, Nielsen and colleagues' literature review from 2015 found that most persona profiles do have pictures (Nielsen et al., 2015), although a narrative persona description with text-only content also does exist (Nielsen et al., 2015; Salminen et al., 2020b). So, in general, most persona profiles include a facial picture of the person representing the user group of the persona – yet, we do not have strong theoretical arguments neither for nor against such a choice. Despite this lack of definitive guidelines on this matter, various researchers have posed rationale in either direction. We summarize these points of view into four main factors: (1) enhanced memorability and engagement, (2) emotional connection, (3) risk of stereotyping, and (4) contextual relevance.

Concerning *enhanced memorability and engagement*, studies suggest that pictures can make personas more memorable (Matthews et al., 2012; Nieters et al., 2007). This is based on the cognitive factor that visual elements, especially human faces, tend to be more easily remembered than textual information alone (Cooper, Reimann, & Cronin, 2007; Kätsyri & Sams, 2008).

Concerning *emotional connection*, pictures can help stakeholders develop an emotional connection to the persona (Grudin, 2006, pp. 642–663; Grudin & Pruitt, 2002). This emotional connection can lead to greater empathy for the user group the persona represents (Salminen, Şengün, Santos, Jung, & Jansen, 2022). For example, a study found that, when using pictures where the personas looked unhappy, users perceived such persona profiles as more realistic and containing more severe pain points (Salminen et al., 2022). However, the users' designs for these 'happy' personas exhibited higher empathy based on a linguistic analysis (Salminen et al., 2022). The researchers contended that unhappy persona pictures increase realism and perceived severity of pain points, while happy persona pictures yield positive perceptions of the persona. These findings imply that pictures help users mirror the emotions of the persona (Holden et al., 2020; Liao & He, 2020). As perspective taking (Crone & Kallen, 2022) (i.e., viewing the world from the 'shoes' of the persona) is central in the theory of why personas work (Grudin, 2006, pp. 642–663), the emotional connections facilitated by imagery support the use of pictures in persona profiles.

Concerning *risk of stereotyping*, there is a danger that pictures can introduce or reinforce stereotypes (Charles et al., 2017; Salminen et al., 2018b, 2019). If the image does not accurately represent the diversity of the user group (i.e., the 'within-persona diversity') or if it leans too heavily into a stereotype, this can lead to biased design decisions (Turner & Turner, 2011). The concern of personas being too 'centrally focused' while ignoring fringe and outlier user groups is common (Chapman, Love, Milham, Paul, & Alford, 2008; Chapman & Milham, 2006; Goodman-Deane et al., 2018, 2021; Salminen, Jung, & Jansen, 2021). The diversity of pictures does not only refer to the demographic attributes such as age, gender, and ethnicity, but also to emotional diversity; i.e., presenting the persona as 'always positive, always happy' (Salminen et al., 2022), which can skew the designer's understanding of users' personality.

Concerning *contextual relevance*, the effectiveness of pictures in persona profiles can also depend on the context in which they are used. For instance, a study by Nielsen (Nielsen, 2004) suggests that the relevance of the picture to the persona's narrative and background can influence how effective it is in conveying the persona's essence. In other words, the pictures supports the general narrative of the persona, thus potentially enhancing the narrative realism experienced by the persona user (Cho, Shen, & Wilson, 2014). Realism, in general, is a major concern in persona profiles – if the profiles are *not* considered realistic, stakeholders are unlikely to engage with them in a meaningful way (Friess, 2012; Kari, Hellman, Kilander, & Dittrich, 2004; Matthews et al., 2012).

If a decision is made to use pictures in persona profiles, the logical next question is: *What kind of pictures should you use?* Again, studies have examined this question. Hill et al. (Charles et al., 2017) investigated using multiple photos (of both males and females) for a single persona to promote gender inclusiveness without reinforcing stereotypes. Through a controlled laboratory and eye-tracking study, the research compared this approach to personas with just one photo. The findings suggest that personas with multiple pictures can help participants consider multiple genders without diminishing their engagement with the persona. Similarly, Salminen et al. (Salminen, Nielsen, et al., 2018) conducted an eye-tracking study to explore the impact of using multiple photos in persona profiles on the information perceived by end users. They found that while contextual photos enhance the informativeness of a persona profile, images of different people lead to confusion. In yet another study (Salminen, Jung, et al., 2021), researchers tested cartoon style images against more realistic versions of persona pictures and found that users gave persona profiles containing more realistic pictures higher scores on credibility, completeness, clarity, consistency, and empathy. Also, less realistic images were associated with less stereotyping among the users (Salminen, Jung, et al., 2021).

So, two general conclusions can be made here: (1) there are pros and cons in including pictures in persona profiles, and (2) when doing so, the style or type of a picture imposes a selection problem. In a word, the choice of a picture is not a trivial question, and addressing this issue has critical importance for the HCI community.

2.2. AI-generated personas

Here, we give a short summary of the historical development leading to generative AI personas.

Since user personas were introduced in the late 90s (Cooper, 1999), the technological landscape has evolved. In conjunction, the techniques for developing personas have evolved as well. In 2008, McGinn and Kotamraju (Jen McGinn & Kotamraju, 2008) introduced *data-driven personas*, i.e., personas generated using statistical algorithms and quantitative data. The division to quantitative and qualitative personas had been made prior to that (e.g. (Mulder & Yaar, 2006),), but the general progress in data science libraries and online data collection techniques makes it possible to generate personas automatically (Jung et al., 2017) from social media (An et al., 2018) and web analytics (Zhang, Brown, & Shankar, 2016) data. As such, the popularity of data-driven personas has continued to increase (Mijač, Jadrić, & Ćukušić, 2018; Salminen et al., 2020a).

In brief, historically personas are often based on qualitative research methods, such as interviews and observations (Nielsen, 2019). With the rise of big data and machine learning (Kühl, Schemmer, Goutier, & Satzger, 2022), there was growing interest in creating data-driven personas that leverage quantitative data, so-called 'personification of big data' (Phillip Douglas Stevenson and Christopher Andrew Mattson, 2019) or 'giving faces to user data' (Jansen, Salminen, & Jung, 2020). The potential here is mainly driven by the idea that AI can analyze vast amounts of data quickly, possibly leading to more precise and diverse persona profiles than the use of manual methods (An et al., 2018; Salminen, Jung, & Jansen, 2021). This can be especially useful for large platforms or services with millions of users where traditional methods might not be scalable (Spiliotopoulos, Margaris, & Vassilakis, 2020).

While AI can provide scalability and precision, it also has challenges. One concern is the potential loss of the rich, qualitative insights that traditional methods of data collection and analysis offer (Siegel, 2010). Additionally, AI-generated personas might inadvertently reinforce stereotypes or biases present in the data, although to be fair, these potential short comings exist with qualitative approaches. These challenges are discussed in various papers (Chapman et al., 2008; Jen McGinn & Kotamraju, 2008; Salminen, Jung, & Jansen, 2021). Nonetheless, using AI and big data to generate personas brings up new concerns, especially ethical issues regarding user privacy and data usage (Faily & Fléchais, 2014) but also those pertaining to the design of the personas, which is the topic of our study.

To that end, advancements in artificial image generation using AI have yielded technology that now can generate photo-realistic facial pictures of people (Karras, Laine, & Aila, 2019). *Are these pictures good enough to be used in persona profiles? How do users perceive persona profiles with artificially generated pictures? What is the impact on perceptions of using these AI images?* These are interesting questions, and highly relevant ones for the evolution of data-driven personas. Yet, current literature does not adequately address them. We are aware of only one study that addresses these questions, evaluating the applicability of AI-generated pictures in persona profiles using a sample of 496 participants (Salminen, Jung, Ahmed Mohamed Sayed Kamel, Santos, & Jansen, 2020d). The study found that using artificial images in persona profiles did not negatively affect perceptions of authenticity, clarity, empathy, or willingness to use the personas (Salminen et al., 2020d). The interesting feat is that this study is from 2020, a period predating the current state-of-the-art models like DALL-E and Midjourney that generate pictures based on contextual prompts. Contextual prompts are crucially important for persona generation, as details and information about the persona can be included in the prompts (including demographics, personality, pain points), thus shaping the image generation process. This prompt-based conditioning is likely to yield more contextually relevant persona pictures than earlier models.

Overall, the literature review of prior work indicates that the findings on the effects of persona picture on users' perceptions of personas are mixed. Although there are some concerns, the research generally suggests that pictures add value to the persona profile, while also adding some risks (particularly stereotyping), but no definitive indications of actual negative impact. So, our expectation in this research, based on prior literature, is that AI-generated pictures add value to AI-generated persona text descriptions. Moreover, research on image generation suggests that it is possible to generate realistic facial pictures that could be used in persona profiles, with some nascent studies validating AI-generated picture quality. However, the literature is missing an answer to the question, *Should AI-generated personas be presented with or without pictures?* The introduction of this unknown element of AI, which has definitely been shown to generate biased results (Inioluwa & Joy, 2022; Lee & Rich, 2021) at times, warrants an investigation into the potential impacts on persona profile creation. Our study addresses this matter using an experimental design that we present in the following section.

3. Method

3.1. Experiment design

We test the effect of including AI-generated images into an AI-generated persona profile (i.e., text description of the persona) on user perceptions of persona. To test such an effect, we need to vary the condition of including an image or not. So, there are two basic conditions.

- **CONDITION 1 – No-image:** the persona profile includes only text, no image.
- **CONDITION 2 – Image:** the persona profile includes text and an image. In case the profile includes an image, it can be created using one of two different generative AI models:

- o **SUBCONDITION 2a – DALL-E:** An image generation model by Open-AI. We use the latest version at the time of conducting the study, which was DALL-E 2 (July 2023 version).
- o **SUBCONDITION 2b – Midjourney:** An image generation model by Midjourney. We use the latest version at the time of conducting the study, which was the July 2023 version.

We wish to carry out a within-participant study, where each participant is subjected to each condition. In our case, all participants were subjected to both CONDITION 1 and CONDITION 2 (i.e., they saw a persona profile with and without images), and both subconditions within CONDITION 2.

As our RQ2 deals with persona-specific differences, we need to create multiple personas for this study. The personas' text descriptions were created using GPT-4 (July 2023 version). Generally, the persona creation took place in five steps (see Fig. 1). First, we designed the prompt. This involved testing different versions of instructions for creating the personas. The prompts for persona descriptions and the picture generation are shown in Table 1. We found that GPT-4 understands the concept of personas, so there was no need for adding a definition of a persona in the prompt.

Using Prompt 1 (see Table 1), we generated a list of skeletal personas with basic attributes (a 'skeletal' persona refers to a superficial, short persona description with only basic attributes (Zhu, Wang, John, & Carroll, 2019)). Then, we randomly selected three personas from the skeletal personas for 'expansion' in which we asked GPT-4 to write a more detailed persona description. The outcomes were manually reviewed by the research team members and found of satisfactory quality for the experiment (i.e., there were no logical inconsistencies or grammatical errors that would have made the personas difficult to interpret; the writing style also matched the general way in which persona narratives are written). We then used a snippet from each persona's description (see Prompt 3 in Table 1) as a prompt for the image generation models. A snippet was used because, at the time of conducting the study, both image generation tools imposed a character limit, so it was not possible to use the full persona information. The images were extracted and added to the text descriptions to create the image versions of the personas, while the text descriptions were left as the only content for the no-image personas.

So, the personas were entirely AI-generated: the text generated by GPT-4, and the pictures generated by either DALL-E or Midjourney. These models were chosen as they represent the state-of-the-art in generative AI in text and image generation, respectively. As we are examining the effect of image inclusion, we test with two different services to avoid a situation where one service would not produce adequate quality of images for persona profiles. For the text generation, we had done previous validation of the quality, so we could trust GPT-4 can handle this part of the persona generation. The research team members assessed the persona descriptions, deeming them of reasonable quality for the experiment.

Table 1
Prompts used to instruct generative AI models in this study.

Prompt 1 (skeletal personas) →	Prompt 2 (persona expansion) →	Prompt 3 (image generation)
"You are a helpful assistant to a social sciences researcher. Create 30 personas that are addicted to [addiction condition]. Provide the output in a json array, with each dict containing only the following keys: 'index', 'name', 'age', 'occupation', 'background', 'details'."	Expand on the following summary persona: [random selection]. Ensure that all the information provided is used in your expanded persona	*Prompt 3a*: "Harry Jackson is a 47-year-old veteran who has been struggling with alcohol addiction for several years. Before his addiction took control of his life, he served his country with pride and dedication as a soldier in the military." *Prompt 3b*: "Sarah Sinclair is a 31-year-old real estate agent who is addicted to online shopping." *Prompt 3c*: "John Stevens is a 45-year-old male who struggles with a serious gambling addiction. He holds a stable, high-income job as a banker but still finds himself deeply involved in high-stakes poker games and horse races."

Notes: addiction condition refers to the context of persona generation. As the context of this research project focused on studying addiction via LLM-generated personas, the addictions conditions refer to alcohol, online shopping, and gambling. One persona from each addiction condition was randomly chosen from the 30 skeletal personas generated by.

3.2. Experimental procedure

In our study, there are three AI-generated personas, Sarah, John, and Harry (the names along with all other details generated by GPT-4). For each persona, there are three versions: (a) *no image* (i.e., text description only), (b) *DALL-E* (i.e., text description + image created using DALL-E), (c) *Midjourney* (i.e., text description + image created using Midjourney). So, in total, there are 3 personas × 3 profile versions = 9 persona profiles (see Appendix 1). The text was identical on all three versions of the

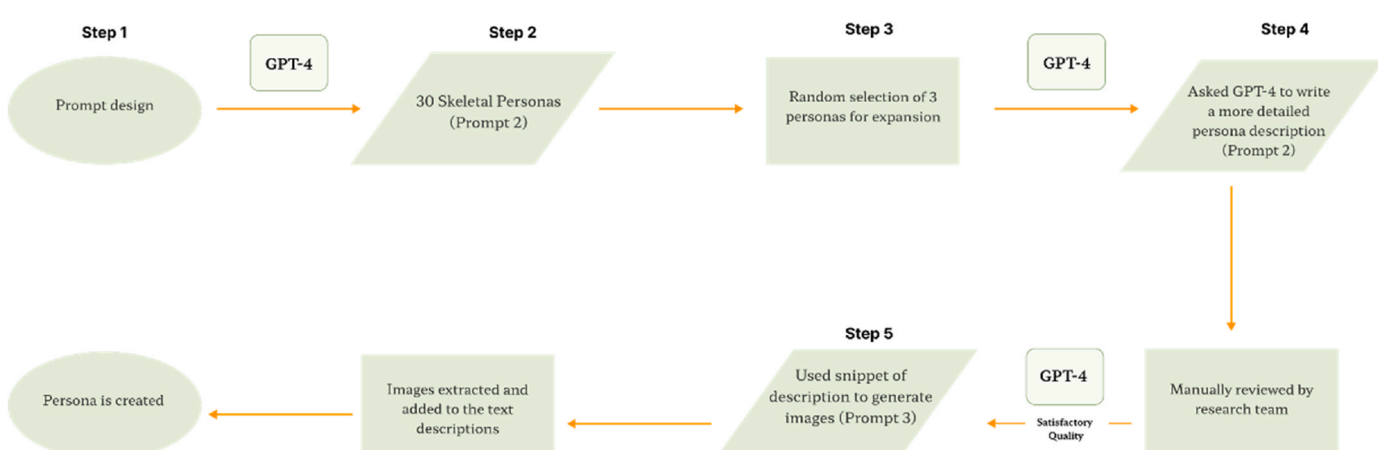

Fig. 1. Persona creation process: Step 1: Prompt design; Step 2: Skeletal personas (Prompt 1); Step 3: Persona selection; Step 4: Persona description creation (Prompt 2); Step 5: Persona image creation (Prompt 3).

profile for each persona (but different across the personas). We seek to investigate how persona perceptions vary by different conditions as specified in the previous subsection.

In the experiment, the order of the personas was randomized such that each participant saw and assessed three personas: one no-image persona and two image personas (DALL-E and Midjourney). The randomization was implemented using Qualtrics' study flow builder. Again, we ensured that the order of personas, the order of image condition, and the selection of DALL-E vs. Midjourney were all randomized (randomization is a vital aspect to mitigate learning and order effects in experiments (Dean, Morris, Stufken, & Bingham, 2015)). The randomization was balanced in the sense that the system allocated a balanced number of participants to each persona, 'image or not' condition, and DALL-E/Midjourney variation.

The evaluation was based on eleven persona perception variables identified from previous research (Salminen et al., 2018a, 2020f) (see Appendix 2 for the questionnaire items): *Clarity* (measures whether the information in the persona profile is communicated clearly), *Compassion* (measures whether the user feels compassion toward the persona), *Completeness* (measures whether the persona profile has adequate information), *Consistency* (measures whether the persona profile's information is non-contradictory), *Credibility* (measures whether the persona profile is believable), *Empathy* (measures whether the user feels empathy toward the persona), *Similarity* (measures whether the user feels he/she is similar to the persona), *Stereotypicality* (measures whether the persona profile presents an oversimplified view of a user group), *Transparency* (measures whether the persona creation process is well communicated), *Usability* (measures whether the persona profile is useable), *Willingness to Use* (*WTU,* measures whether the user would like to use the persona going forward). The measurement items used in the questionnaire are shown in Appendix 2.

3.3. Participants

The participants were recruited in a self-selection process in which the participants belonging to a data collection platform could willingly decide to take the study in exchange for financial compensation. In total, 262 participants were recruited for this study using CloudResearch (Chandler, Rosenzweig, Moss, Robinson, & Litman, 2019), an online participant pool. Of these, 46 failed at least one of the attention checks included in the survey, and as such were excluded from the analysis, leading to a final working sample of 216 participants. Of these, 56% were females ($N = 121$) with the remaining being males ($N = 93$; 43.1%), one participant who identified as non-binary/third gender ($N = 1$; 0.4%), and one participant who preferred to self-describe ($N = 1$; 0.4%). Again, all participants were provided with a definition of a persona and a work task scenario prior to engaging in the study.

In the experiment, the participants were asked to evaluate three persona profiles, one with just the text and two with the respective two image conditions (all shown in random order). The participants were not informed that the personas were AI-generated to avoid presumptions. The participants were financially compensated for taking part in the study. The consent was obtained, and the participants were explained their right to stop the study at any time. No personally identifiable information was collected or used in the analysis. All participants were given a definition of a persona to ensure a baseline understanding (*Personas are fictitious people that describe some user or customer *types*. In other words, personas are not real people, but they describe groups of real people*.), as well as a work task scenario (*In this study, your imaginary task is to create a YouTube video for this persona that would help them overcome their addiction.*).

3.4. Data processing and analysis

In preparation of the analysis, which required the usage of a multi-level model to account for within-participant variability (as each participant received three different stimuli, i.e., personas), the data was transported from the wide into the long format, so that each "case" represented a participant-persona dyad. We employed the *Persona Perception Scale* (PPS) (Salminen et al., 2020f). To establish repeated scale validity, we conducted through Confirmatory Factor Analysis to determine the validity and reliability of the instrument. The intended factorial structure, based largely on previous research, was specified and tested.

At a first iteration, we noted six items[1] which exhibited loadings under 0.50, making them candidates for removal due to low factorial purity (DiStefano, Zhu, & Mindrila, 2009). After removal of these items, the model was respecified. At a final iteration, covariance paths based on modification indices at a threshold of 3 were specified as well (Marôco, 2010). The final model exhibited a fit which could be qualitatively adjudged as reasonable to good depending on the fit index ($\chi2$ (600) = 1833.517, $p < 0.001$; $\chi2/df = 3.056$; GFI = 0.856; CFI = 0.905; RMSEA = 0.056), making it suitable for deployment in this study (Kline, 2016; Paul, 2007). Reliability, which was evaluated through Composite Reliability (CR), was above 0.70 for all sub-scales, with a slightly lower 0.642 for Stereotypicality; nevertheless, this is satisfactory for deployment (Malhotra & Birks, 2006).

In line with the hierarchical nature of the data, a multi-level linear regression model was employed; each persona was treated as a case, which was nested within a participant (as each participant saw three different personas). This allowed us to account for within-subject variability. A power simulation conducted with G*Power indicated that with this design, a sample size of 222 would be required to detect medium-sized effects (Cohen's F of 0.25) with a statistical power of 0.955, closely matching our study's sample size.

4. Results

The first model refers to the multi-level linear regression, which aims to address RQ1, RQ2, and RQ5. The sub-sections interpret the findings for the respective RQs. In the text, we report unstandardized betas (B).

4.1. RQ1: how do user perceptions vary among AI-generated personas?

Surprisingly, our findings indicate that there are no statistically significant differences in any of the variables when comparing personas using images generated through DALL-E, Midjourney, and personas without images. This lack of differences can be best observed in Fig. 2 visually illustrating that the perception evaluations between the persona versions appear highly similar, suggesting that images play a secondary role in how personas are perceived.

Furthermore, the perception scores are generally geared toward the higher end of the evaluation scale for each type of AI-generated personas. So, this implies that the participants generally perceive AI-generated personas to be of good quality. For example, Clarity, Consistency, and Credibility scores are generally in the range of 6 out of 7 (where 7 is the maximum degree of clarity). The scores for Empathy, Compassion, Completeness, Usability, and Transparency, are generally between 5 and 6 (out of 7), again, indicating a favorable assessment.

Somewhat lower scores are given to Similarity (generally ranging between 2 and 3 out of 7), Stereotypicality (generally ranging between 4 and 5), and WTU (also ranging between 4 and 5) (see Fig. 2). These lower values are to be expected: the personas represented people with addictions including alcoholism and other conditions. Similarity with such personas would indicate that the participants also struggle with addictions; while this is possible, it is understandable that the participants as a whole do not consist of personas with these forms of addictions. The generally lower scores for stereotypicality are also

[1] These were the following: CON1_R, CRE2_R, STE3_R, STE2, USA1_R, WTU1_R.

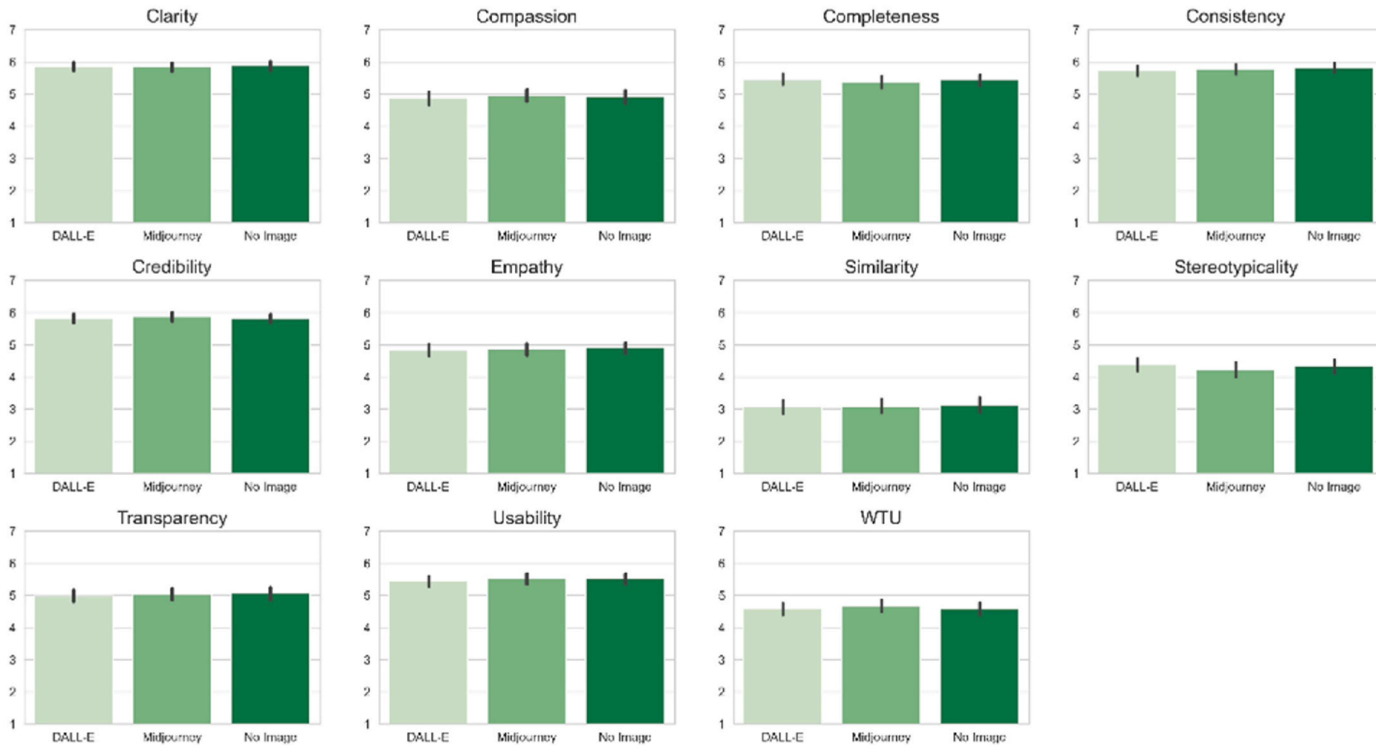

Fig. 2. Barplot comparison of persona image types per variable, with 95% confidence intervals. The user perceptions of personas are highly similar regardless of whether or not an image is used in the persona profile. This lack of differences illustrates that the perception evaluations between the persona versions are highly similar across all constructs.

understandable; as four represents the midpoint value of the scale (1–7), a value close to this indicates that the participants tended to express a neutral stance on assessing the personas' stereotypicality, possibly stemming from the fact that they were not experts in assessing personas with addictions. This also supports prior research that the images have limited effect on biasing end users (Charles et al., 2017). The same

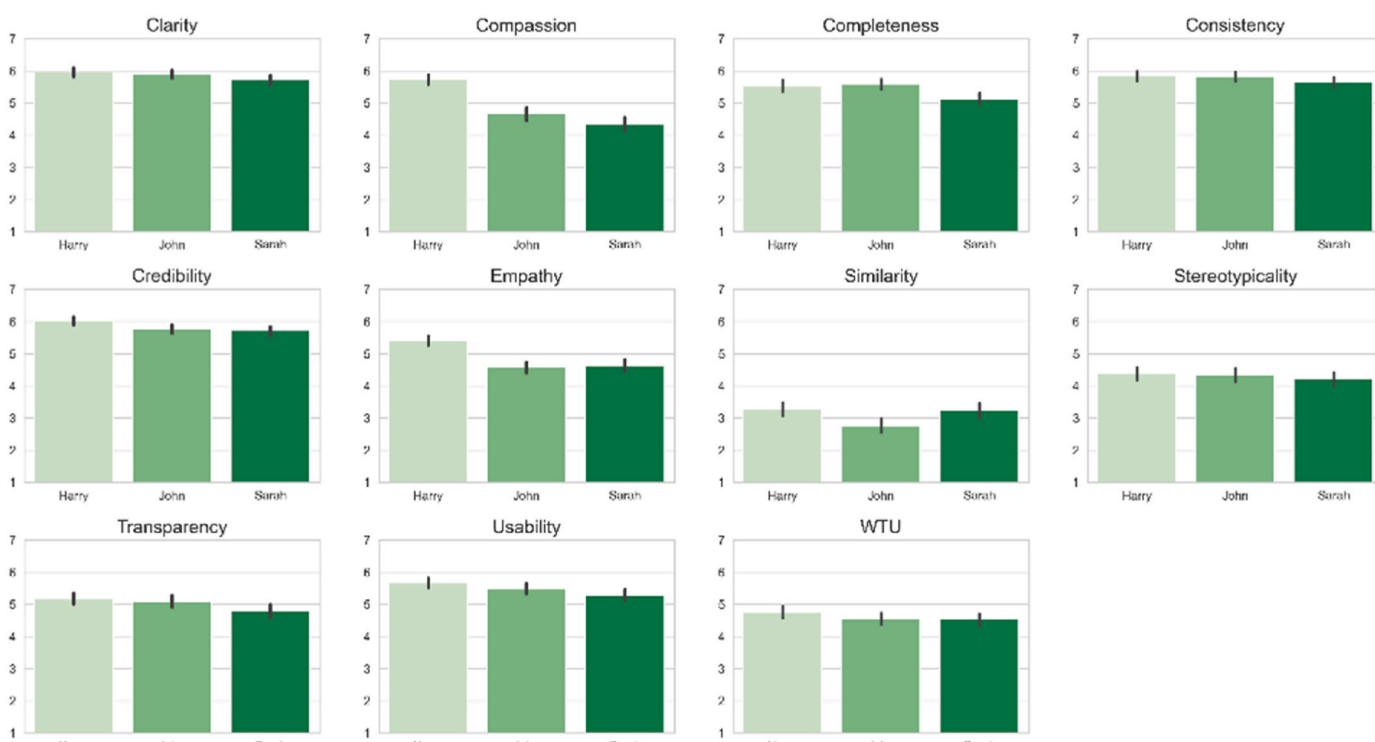

Fig. 3. Barplot comparison of personas per variable, with 95% confidence intervals. We observe several significant differences. Sarah was rated with less Clarity, Compassion, Completeness, Consistency, Credibility, Empathy, Transparency, Usability, and WTU. John also received similarly worse ratings, but in less variables: notably, when compared to Harry, John was rated with less Compassion, Credibility, Empathy, Similarity, and Usability.

interpretation can be given to the generally lower WTU scores (see Fig. 2); most participants likely do not work with addictions in their profession, which naturally limits their willingness to use such personas in decision making (although we gave a work task scenario both in the study's framing for the participants and then repeated it when asking about the WTU).

So, overall, the results indicate that the AI-generated personas seem to "work" in terms of what level of perceptions we would expect to see from good-quality personas.

4.2. RQ2: Do user perceptions vary by AI-generated personas?

Unlike the previous finding, the persona itself did result in differences across attributes. When compared to the baseline persona for comparison (Harry), Sarah was rated with less Clarity ($B = -0.259$, $p < 0.001$), Compassion ($B = -1.386$, $p < 0.001$), Completeness ($B = -0.411$, $p < 0.001$), Consistency ($B = -0.204$, $p = 0.003$), Credibility ($B = -0.309$, $p < 0.001$), Empathy ($B = -0.779$, $p < 0.001$), Transparency ($B = -0.394$, $p < 0.001$), Usability ($B = -0.372$, $p < 0.001$), and WTU ($B = -0.230$, $p = 0.006$). John also received similarly worse ratings, but in less variables: notably, when compared to Harry, John was rated with less Compassion ($B = -1.077$, $p < 0.001$), Credibility ($B = -0.228$, $p < 0.001$), Empathy ($B = -0.824$, $p < 0.001$), Similarity ($B = -0.512$, $p < 0.001$), and Usability ($B = -0.178$, $p = 0.026$). These comparisons can be observed in Fig. 3.

The noteworthy trend here is that, even though there were no statistically significant differences between the 'no image' and 'image' personas, there are several significant differences between the actual personas. This implies that, in general, the participants did not care in a relevant manner whether the persona profile includes a picture or not (i.e., this did not affect their ability to use the persona, empathize with it, etc.), but they did care about *who* the persona was. For example, observe the lower scores for Sarah in Fig. 3 for Compassion (the second subplot from top left); the participants were considerably less compassionate toward Sarah than the two male personas. These findings support the notion that AI-generated personas may be subject to gender effects like non-AI-generated, manually created personas. User biases concerning the perception of personas are likely to transcend to AI-generated personas as well.

The second model is a linear regression exploring the effects of Participant Gender and Participant Age on persona perceptions, grouped by type of image generation (or lack of image). The results are presented in the following subsections.

4.3. RQ3: Do user perceptions vary by user gender?

When an image is lacking, it was found that participant gender played no role in persona perceptions; participant gender had no significant effect in any of the persona perceptions for any of the personas, regardless of the persona's gender.

For DALL-E generated images, significant effects were detected – notably, when compared with females, males tended to rate these images as having less Completeness ($B = -0.339$, $p = 0.041$), Consistency ($B = -0.310$, $p = 0.045$), and Credibility ($B = -0.302$, $p = 0.043$). The effects of gender for Midjourney images were similar to DALL-E images but restricted to fewer dimensions. Males perceived these images as having less Clarity ($B = -0.364$, $p = 0.015$), but no differences were found regarding the other perceptions, including Consistency and Credibility. This would indicate that, for some reason, AI-generated images have a more negative impact on males, relative to females. Prior research has shown males and females process information differently (Jansen, Moore, & Carman, 2013). Our research shows that this extended to AI generated images also.

4.4. RQ4: Do user perceptions vary by user age?

Increased participant age led to reduced perceptions in various aspects. Notably, Age had a negative impact on perceptions of Compassion ($B = -0.016$, $p = 0.011$), Empathy ($B = -0.012$, $p = 0.020$), Similarity ($B = -0.025$, $p < 0.001$), Transparency ($B = -0.014$, $p = 0.013$), and WTU ($B = -0.024$, $p < 0.001$). Again, prior research shows information processing is different in older than young adults (Chaby, Narme, & George, 2011; Ewing, Karmiloff-Smith, Farran, & Smith, 2017; Jaworska et al., 2020). Our research extends this to AI generated personas.

The effects of Age for DALL-E generated images were similar to the ones described above; notably, participant age had a negative impact on Empathy ($B = -0.016$, $p < 0.001$) and Similarity ($B = -0.028$, $p < 0.001$), as well as Transparency ($B = -0.011$, $p = 0.048$) and WTU ($B = -0.015$, $p = 0.005$). However, in these images, participant age positively impacted Consistency ($B = 0.012$, $p < 0.001$) and Credibility ($B = 0.008$, $p = 0.050$). For Midjourney generated images, participant age was found to have a negative impact on Similarity ($B = -0.027$, $p < 0.001$), and WTU ($B = -0.021$, $p < 0.001$), while having a positive impact on Clarity ($B = 0.009$, $p = 0.032$). Thus, age played a role in the persona perceptions.

4.5. RQ5: Do user perceptions vary by user's persona experience?

To test whether previous experience influenced personas perceptions, we employed a mixed ANOVA with Bonferroni post-hoc tests. Previous experience with personas was found to influence perceptions to some degree. Differences were found on Clarity ($F(3, 644) = 3.589$, $p = 0.014$), with participants who had knowledge of personas perceiving higher clarity than those who had only heard about personas before ($p = 0.011$; no other category pairs significant); for Consistency ($F(644, 3) = 3.122$, $p = 0.025$), with post-hoc testing revealing a difference on the threshold of significance between people who had used personas and those who had heard of them ($p = 0.052$); for Credibility ($F(3,644) = 3.367$, $p = 0.018$), with participants who knew what personas were scoring higher than those who never heard of them ($p = 0.031$); for Similarity ($F(3, 644) = 6.693$, $p < 0.001$), with participants who had used personas having higher scores than the three other levels of experience ($p < 0.001$); for Usability ($F(3, 644) = 3.902$, $p = 0.009$), with a difference on the threshold of significance being detected between participants who had used personas and those who never heard of them ($p = 0.057$); and for WTU ($F(3, 644) = 4.495$, $p = 0.004$), with participants who had heard of personas scoring higher than those who never heard of them ($p = 0.005$). These relations are illustrated in Fig. 4.

5. Discussion

5.1. Discussion of findings

We discuss the main findings here. First, contrary to our expectations, the presence of images in AI-generated personas did not significantly impact user perceptions. Despite using advanced models like DALL-E and Midjourney, the inclusion of images did not yield discernible differences when compared to AI-generated personas without images. This finding implies that *textual content appears to be the primary driver of user perceptions in AI-generated personas*.

Second, our results on persona-specific differences underscore the importance of the persona itself in shaping user perceptions. Distinct personas elicited varying perceptions across multiple attributes. The persona's content, encompassing language, tone, and information, emerged as a pivotal determinant of user evaluations. This highlights the significance of crafting personas that are tailored to specific user needs and objectives and employ standard HCI design by pilot testing the personas before actual deployment to assess if there are any harmful biases or distracting information that would undermine user-centric design. Persona creators should consider not only the incorporation of

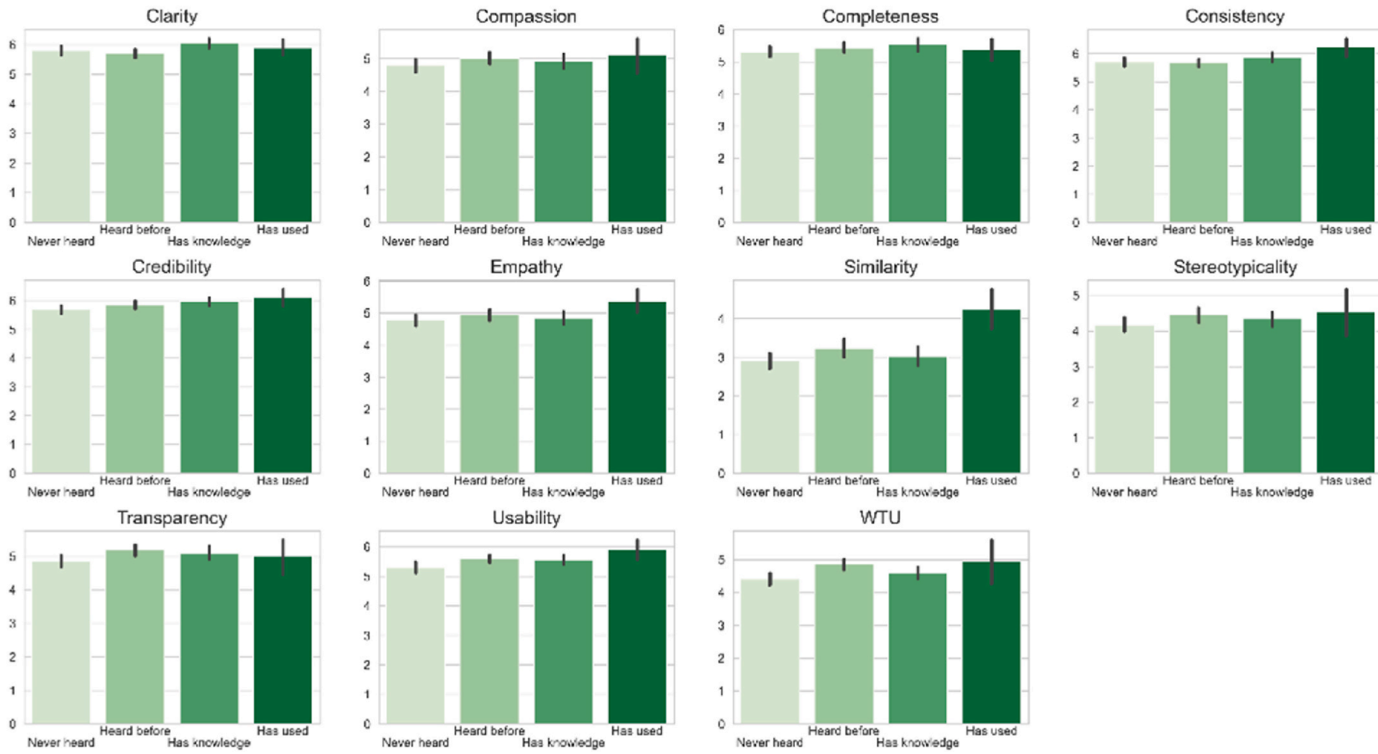

Fig. 4. Barplot comparison of persona perceptions per level of experience, with 95% confidence intervals. Previous experience with personas was found to influence perceptions with differences found on Clarity, Consistency, Credibility, Usability, and WTU.

textual and visual elements but also the characterization of and qualities attributed to the persona, as these factors impact user perceptions.

Third, the effects of participant gender and age on AI-generated persona perceptions highlight important considerations for persona design. Gender differences manifested primarily in the context of persona images generated by DALL-E and Midjourney, hinting at potential nuances in visual preferences among male and female participants. Age, however, exerted a broader influence, impacting various dimensions of user perceptions across persona versions. The interplay among gender, age, and persona attributes necessitates a nuanced approach to personalization, where designers must account for demographic factors to create personas that effectively resonate with diverse user groups.

Again, this points to the need for persona designers to pilot test the persona profiles before actual deployment and analyze the role of demographic factors in the created personas. From the perspective of persona design theory, the main point in our study is that the way people perceive personas is affected by the demographic factors of both the personas and their users. While this is already known from previous persona research (Charles et al., 2017; Salminen, Jung, et al., 2021), our results confirm that these effects also exist for AI-generated personas. In that sense, the perceptions of AI-generated personas and manually-created personas seem to be governed by the same “laws” of persona perception (Marsden & Haag, 2016b).

The impact of persona experience on user perceptions accentuates the relevance of users’ familiarity with personas. Notably, participants with prior knowledge or usage of personas exhibited more favorable perceptions, particularly for clarity, consistency, credibility, similarity, usability, and WTU. This emphasizes the importance of educating end users about personas and their applications, potentially through training, introduction sessions, or workshops. These findings advocate for an integration of persona education strategies into design projects and into organization to enhance user engagement and satisfaction. This implication is in line with the general suggestions for persona adoption in design teams, namely, that the cumulative experience with personas increases the prospect of successful adoption (Nielsen & Hansen, 2014; Salminen, Nielsen, Jung, Bernard, & Jansen, 2021; Seidelin, Jonsson, Høgild, Rømer, & Diekmann, 2014).

5.2. Design implications

We offer five key implications for the design of AI-generated personas.

1. **Emphasize textual content.** Persona designers should prioritize the quality and accuracy of textual content. It appears that images add little value in terms of enhancing user perceptions of personas. On the other hand, they do not seem to harm the user perceptions either. So, as for now, it appears that when one aims to develop AI-generated personas, the choice of including pictures is less impactful than the persona’s text content.
2. **Balance image generation efforts.** Given the limited influence of images on user perceptions, designers can exercise discretion when investing resources into generating persona images. While images can enhance visual appeal, they should be viewed as complementary rather than pivotal. Designers can balance image generation efforts with the overarching goal of creating informative and compelling textual content.
3. **Pilot test.** Users’ perceptions of personas strongly vary by personas. Different personas are perceived significantly differently regardless of their creation method. Therefore, human persona creators do well by pilot testing their personas, whether AI-generated or traditional. If the pilot testing reveals issues concerning a given persona or a group of personas, these could be addressed before deploying the personas into wider use.
4. **Assert control where needed.** Prompting or prompt engineering/design offers a way to govern the attributes that the AI assigns to the persona. For example, John was a banker which we surmised caused a drift compared to other personas who were a real-estate agent a war veteran. The effect of the persona’s professional background

could be controlled by providing a list of similar occupations for the AI to use.

5. **Triangulate.** Persona users might not always be equipped with the necessary information to assess factors such as veracity of the personas. Therefore, it is upon the human supervisor to ensure that the personas are factually correct. This is best done by triangulating the AI-generated information in the persona descriptions with independent information sources, including user interviews, population statistics, surveys, and so on.

Overall, persona creators should engage end users of personas in the evaluation process, seeking their feedback and preferences to refine persona design. Iterative pilot testing, user testing, and feedback loops can help identify and address issues related to persona content, image incorporation, and user perception.

With every word that the AI writes about the persona, it imposes a certain attribute of the persona; while the AI does the work, it is the responsibility of the human persona creator to supervise the process and ensure that the AI-generated personas do not mislead their users or impose other harms.

6. Limitations and future directions

While our study provides valuable insights into AI-generated personas, certain limitations warrant consideration. The investigation focused on a specific set of image generation models, and further exploration with other AI models may reveal additional nuances. Additionally, the study's context of employing online participants may not fully replicate real-world user interactions. However, in terms of strengths, the research employed state of the art AI models, and a sizeable number of study participants using an established validate instrument for personas perception evaluation.

Of the two AI-generated photos of Harry, one represented a Caucasian and the other represented a person of African origin. Ethnic background might cause dynamics in the persona perception scores that we did not test. Future work could address ethnic bias in AI-generated persona pictures. In our case, we repeated the image generation multiple times to see if the ethnic background would vary but each time, DALL-E generated a white Harry and Midjourney a black Harry. So, this seems like an interesting avenue for future research. Furthermore, interpreting the user perception differences based on images generated by different AI tools merits further research: Are the differences due to the quality or type of images, familiarity with the generated content, or other factors?

Overall, a limited number of personas and images were used in the study. There were three written persona descriptions producing three personas without images and six with images. With this number of personas, it is possible that differences (or non-differences) in user perceptions to the different personas were due to the particular choice of images rather than the presence or absence of images *per se*.

Furthermore, to generate the images, we used a snippet of persona information because, at the time of conducting the study, both image generation tools imposed a character limit, so it was not possible to use the full persona information. This approach captures limited data and generates images based on that limited data, which may result in adverse consequences, such as stereotyping. Thus, future research would benefit from an increased context window within the image generation models.

Concerning the gender effects, we note that there was only one female persona and two male ones. The lower scores for the female persona could have been due to many other factors, such as the topic of the persona (on-line shopping addiction may be a less compelling issue), the particular choice of images (e.g., the female images displayed different emotions than the male ones), different details in the written persona, the persona's age, etc. A more controlled experimental design is required to verify the gender effects.

In this study, we focused on AI-generated personas. Nevertheless, a full comparison to human-generated persona profiles would be worthwhile. For this, we propose a simple research matrix that entails the possible combinations of how the persona profile can be constructed (see Table 2). So, this is an area for future research in this exciting conflux of HCI and AI. It appears certain that AI can add value to persona creation, but it also appears clear that humans continue having a role in this process beyond the mere 'user' of AI-generated outputs.

Our findings yield further questions to investigate, including the following.

- *What if the personas were human-created? Do the findings still hold true?*
- *What if the quality of the AI-generated text description would drop or contain issues? Would the role of images then increase as an additional source of information?*
- *What if the personas were in a domain with a high degree of 'visual' ends users (*e.g.*, art, modeling, fashion, architecture, interior design)?*

Such questions are essential for the effective persona design in the era of generative AI. Furthermore, there might be contexts or scenarios where images could play a more critical role, such as in visually driven industries. This might affect the generalizability of the finding that text predominantly affects user perceptions of AI-generated personas. Other open questions include whether the findings are applicable across different cultures or industries? If not, under what conditions might they differ? Future research is needed to tackle these questions.

7. Conclusion

The findings underscore the centrality of textual content in AI-generated persona profiles, emphasize the influence of text-communicated persona characteristics in how users form their impressions of the persona, and shed light on demographic and experiential factors that shape user perceptions, showing that these factors apply to AI-generated personas. The findings also raise questions about the future of persona design and the role of humans in the process, which remains to be delineated and defined.

Ethical remarks

The personas generated were intended for the controlled experiment, not for actual deployment. The personas were evaluated for factors such as believability and consistency, to examine if different persona versions yield different levels of persona perceptions. Because the personas were not evaluated for factuality, we do not recommend applying them in real-world decision making (while they can be used for general persona studies as we have done here). To generate personas for actual decision making, we recommend either verifying the factuality of the AI-generated personas with independent information sources or using precise primary data about users to generate the personas. Using a generative AI model is likely to incorporate a mixture of primary and secondary data which can yield personas with varying levels of

Table 2
Possible combinations of AI-generated and human-created persona profiles for future studies on this topic.

Pictures		
Text description	Human-created	AI-generated
Human-created	**Full human-created personas** (i.e., traditional persona profiles)	**Hybrid personas** (i.e., human-created text and AI-generated images)
AI-generated	**Hybrid personas** (i.e., AI-generated text and real human photographs)	**Full AI-generated personas** (i.e., generative AI personas)

inaccuracy. Furthermore, the precise sources of data for the persona generation are not tractable, which means that general models like ChatGPT cannot be used for transparent and fully explainable persona creation.

CRediT authorship contribution statement

Joni Salminen: Conceptualization, Data curation, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **João M. Santos:** Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Soon-gyo Jung:** Conceptualization, Software. **Bernard J. Jansen:** Conceptualization, Funding acquisition, Project administration, Resources, Writing – original draft, Writing – review & editing.

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

During the preparation of this work the author(s) used Open AI's ChatGPT (GPT-3.5 and GPT-4), GPT-4 via API, Midjourney via Discord, and Dall-E 2, in order to generate the personas, assist us in the analysis, and provide material for addressing the 'blank page' problem in writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

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

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APPENDIX 1. FULL-SIZED PERSONA PROFILES

(a) Harry-no-image

Persona: Harry Jackson
Age: 47
Occupation: Veteran
Background: Returned home with PTSD after military service
Details: Began drinking heavily to numb painful memories

Expanded Persona Description:

Harry Jackson is a 47-year-old veteran who has been struggling with alcohol addiction for several years. Before his addiction took control of his life, he served his country with pride and dedication as a soldier in the military.

During his time in the service, Harry experienced many difficult challenges and saw his share of devastating events. Upon returning home, he realized he wasn't the same person he was before his deployment. He had difficulty readjusting to civilian life, and he couldn't escape the traumatic memories that haunted him day and night. After being diagnosed with Post Traumatic Stress Disorder (PTSD), Harry sought help from various therapists and support groups. However, he found little relief from his symptoms.

Feeling desperate and looking for a way to cope, Harry turned to alcohol as a means of self-medication. It started as an occasional drink to calm his nerves and numb his emotional pain, but it quickly spiraled out of control. He began to drink heavily and the alcohol consumed him. He lost interest in activities he once enjoyed, he became distant from his friends and family, and his once stellar military career started to come crashing down.

As Harry's addiction deepened, he found it increasingly challenging to maintain a stable job and personal life. His relationships grew strained, and many of those close to him have tried to intervene but with little success. Soon, his life became defined by the cloud of alcohol that followed him wherever he went.

Despite this, Harry is not without hope. Even during these dark times, he still carries within him the courage, strength, and resilience that made him a respected soldier. With the right support and treatment, it's possible for Harry to regain control of his life and find healthier ways to cope with his PTSD.

(b) Harry-image-dalle

Persona: Harry Jackson
Age: 47
Occupation: Veteran
Background: Returned home with PTSD after military service
Details: Began drinking heavily to numb painful memories

Expanded Persona Description:

Harry Jackson is a 47-year-old veteran who has been struggling with alcohol addiction for several years. Before his addiction took control of his life, he served his country with pride and dedication as a soldier in the military.

During his time in the service, Harry experienced many difficult challenges and saw his share of devastating events. Upon returning home, he realized he wasn't the same person he was before his deployment. He had difficulty readjusting to civilian life, and he couldn't escape the traumatic memories that haunted him day and night. After being diagnosed with Post Traumatic Stress Disorder (PTSD), Harry sought help from various therapists and support groups. However, he found little relief from his symptoms.

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As Harry's addiction deepened, he found it increasingly challenging to maintain a stable job and personal life. His relationships grew strained, and many of those close to him have tried to intervene but with little success. Soon, his life became defined by the cloud of alcohol that followed him wherever he went.

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. (*continued*).

(c) Harry-image-midjourney

Persona: Harry Jackson
Age: 47
Occupation: Veteran
Background: Returned home with PTSD after military service
Details: Began drinking heavily to numb painful memories

Expanded Persona Description:

Harry Jackson is a 47-year-old veteran who has been struggling with alcohol addiction for several years. Before his addiction took control of his life, he served his country with pride and dedication as a soldier in the military.

During his time in the service, Harry experienced many difficult challenges and saw his share of devastating events. Upon returning home, he realized he wasn't the same person he was before his deployment. He had difficulty readjusting to civilian life, and he couldn't escape the traumatic memories that haunted him day and night. After being diagnosed with Post Traumatic Stress Disorder (PTSD), Harry sought help from various therapists and support groups. However, he found little relief from his symptoms.

Feeling desperate and looking for a way to cope, Harry turned to alcohol as a means of self-medication. It started as an occasional drink to calm his nerves and numb his emotional pain, but it quickly spiraled out of control. He began to drink heavily and the alcohol consumed him. He lost interest in activities he once enjoyed, he became distant from his friends and family, and his once stellar military career started to come crashing down.

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. (*continued*).

(d) Sarah-no-image

Persona: Sarah Sinclair
Age: 31
Occupation: Real Estate Agent
Background: Married and expecting a baby
Primary Motivations: Creating the perfect home and nurturing environment for her growing family

Sarah Sinclair is a 31-year-old real estate agent who is addicted to online shopping. Married and expecting a baby, she has a strong desire to provide a comfortable and loving home for her family. Her chosen profession indicates that she has an understanding of and affinity for home values, aesthetics, and space management. This knowledge likely fuels her desire to create the perfect atmosphere for her child to grow up in.

Sarah's online shopping addiction mostly revolves around searching for baby and home products. As an expectant mother, she is determined to ensure that her baby's needs are met and that they are given the best start in life. She spends hours browsing websites, looking for the perfect items to add to her home and nursery, such as cribs, bedding, storage solutions, and clothing.

More than just the excitement of purchasing items, Sarah's addiction to online shopping is motivated by her nesting instincts and her desire to create an ideal space for her family. She imagines every appliance, piece of furniture, and decoration as an integral part of her future child's memories, and she wants to invest all her efforts into giving her baby a nurturing environment.

As she researches and purchases items for her home, she not only focuses on the functionality and safety of the products, but she also pays attention to their aesthetic qualities. Sarah aims to create a space that feels warm, cozy, and inviting for both her growing family and their guests.

In addition to her online shopping addiction, Sarah may also be navigating the challenges of balancing her career as a real estate agent with her role as a mother-to-be. The pressure of juggling professional and personal responsibilities might contribute to her need to seek solace in her online shopping, providing a sense of accomplishment and control over her environment.

In conclusion, Sarah Sinclair is a 31-year-old expectant mother and real estate agent who is addicted to online shopping. Driven by her nesting instincts, desire to create the perfect home, and need for a sense of accomplishment, she spends hours searching for and purchasing baby and home products to create a nurturing and loving environment for her growing family.

. (*continued*).

(e) Sarah-image-dalle

Persona: Sarah Sinclair
Age: 31
Occupation: Real Estate Agent
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. (*continued*).

(f) Sarah-image-midjourney

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In conclusion, Sarah Sinclair is a 31-year-old expectant mother and real estate agent who is addicted to online shopping. Driven by her nesting instincts, desire to create the perfect home, and need for a sense of accomplishment, she spends hours searching for and purchasing baby and home products to create a nurturing and loving environment for her growing family.

. (*continued*).

(g) John-no-image

John Stevens is a 45-year-old male who struggles with a serious gambling addiction. He holds a stable, high-income job as a banker but still finds himself deeply involved in high-stakes poker games and horse races. As a divorced father of two, John faces the challenges of balancing his personal life and his compulsive gambling habits. He comes from a wealthy family, which might have influenced his inclination towards high-stakes bets and adventurous pursuits.

John's gambling addiction has caused him significant emotional and financial turmoil. Despite working in a prestigious profession, his monetary success is jeopardized by his ongoing gambling activities. He is drawn to games of chance and skill, such as poker and horse racing, wherein he consistently wagers large sums of money on high-stakes tables and bets.

John's addiction to gambling can be traced back to his upbringing in a wealthy family, where he was exposed to an environment of affluence, risk-taking, and a desire for entertainment. This exposure likely fostered a sense of invincibility or a belief that he could gamble without consequences. As a result, John has become a risk-taker, consistently seeking out the adrenaline rush associated with high-stakes gambling.

Consequently, his addiction has had a negative impact on his relationships, particularly with his ex-spouse and children. The strain of his gambling habits contributed to the breakdown of his marriage and continues to challenge his ability to maintain strong connections to his children, who are directly affected by his financial instability and emotional instability caused by addiction.

Nonetheless, John's persona illustrates a complex and multi-dimensional human being who is struggling to overcome his addiction. He is an intelligent professional with the potential to excel in his career and support his family—however, his continued engagement in high-stakes gambling places him, his job, and his family in a precarious position.

To help John recover from his gambling addiction, it is essential for him to seek professional help and support from loved ones. His journey towards recovery will require a comprehensive approach, involving therapy, support groups, and potentially medication, to address both the psychological and physiological aspects of his addiction. By focusing on the root causes of his gambling compulsion, such as family upbringing, thrill-seeking tendencies, and financial mismanagement, John can work towards regaining control of his life and repairing his relationships with his family.

. (*continued*).

(h) John-image-dalle

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. (*continued*).

(i) John-image-midjourney

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. (*continued*).

APPENDIX 2. MEASUREMENT ITEMS USED IN THE QUESTIONNAIRE

Variable	Item ID	Item	Reverse
Clarity	CLA1	The information about the persona was presented clearly.	
Clarity	CLA2	I struggled to understand the information about the persona.	x
Clarity	CLA3	The information about the persona was easy to understand.	
Compassion	CMP1	I experienced sympathetic concern for the sufferings or misfortunes of the persona.	
Compassion	CMP2	I did not really care about the persona.	x
Compassion	CMP3	I had an urgent desire to aid the persona.	
Completeness	COM1	The persona provided enough information to make decisions about the people it describes.	
Completeness	COM2	The persona was detailed enough to understand the type of people it describes.	
Completeness	COM3	The persona lacked critical information for my task.	x
Consistency	CON1	Some parts of the persona were contradicting each other.	x
Consistency	CON1	The persona communicated a coherent story.	
Consistency	CON1	The persona was consistent.	
Credibility	CRE1	The persona could exist in real life.	
Credibility	CRE2	The persona had artifacts; i.e., something artificial, a distortion.	x
Credibility	CRE3	The persona appeared natural.	
Empathy	EMP1	I felt like I understood the persona as a human being.	
Empathy	EMP2	I did not feel strong ties to the persona.	x
Empathy	EMP3	I could imagine a day in the life of the persona.	
Similarity	SIM1	The persona felt similar to me.	
Similarity	SIM2	The persona and I think very differently.	x

(*continued on next page*)

(*continued*)

Variable	Item ID	Item	Reverse
Similarity	SIM3	The persona and I share similar interests.	
Stereotypicality	STE1	The persona was stereotypical, i.e., it related to a widely held but fixed and oversimplified image or idea of a particular type of person.	
Stereotypicality	STE2	The persona conformed to qualities that people usually expect of a particular type of person.	
Stereotypicality	STE3	The persona contained surprising insights into the type of person it represents.	x
Transparency	TRA1	I was provided with information on how the persona was created.	
Transparency	TRA2	I did not understand how the persona was created.	x
Transparency	TRA3	I could understand how the information about the persona was obtained.	
Usability	USA1	Using the persona required a lot of mental effort.	x
Usability	USA2	I found the persona easy to use.	
Usability	USA3	Using the persona was clear and understandable.	
WTU	WTU1	If given the choice, I would not have used this persona for my task of [creating the YouTube video].	x
WTU	WTU2	I can imagine multiple ways to make use of the persona in my task of [creating the YouTube video].	
WTU	WTU3	This persona improved my ability to make decisions about the people it describes.	
WTU	WTU4	I am open to adopting this persona to enhance my work performance when it comes to understanding user needs.	
Usability	USA4	Using the provided persona helped me better understand the target user and their needs.	
Transparency	TRA4	The sources and methods used to gather information for the persona are clearly outlined, enhancing the credibility and trustworthiness of the presented details.	
Stereotypicality	STE4	The persona portrays characteristics that align with commonly held stereotypes rather than reflecting the diversity and complexity of real individuals.	
Similarity	SIM4	I can relate to the persona's characteristics and find similarities between myself and the portrayed user.	
Empathy	EMP4	I feel a sense of understanding towards the persona's challenges and experiences.	
Credibility	CRE4	The information presented in the persona appears to be trustworthy and reliable, accurately representing the characteristics and behaviors of the target user.	
Consistency	CON4	The information provided about the persona remains consistent throughout, with no contradictions or discrepancies in their characteristics, goals, or behaviors.	
Completeness	COM4	The persona includes comprehensive details about the user's background, preferences, and motivations, leaving me with a thorough understanding.	
Compassion	CMP4	I am genuinely concerned about the well-being and experiences of the persona, and I want them to have positive interactions and outcomes.	
Clarity	CLA4	The persona's characteristics, needs, and goals are presented in a clear and understandable manner, making it easy for me to grasp their profile.	

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