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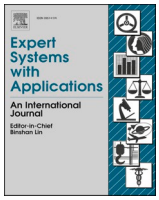

# Is Deepfake Diversity Real? Analyzing the Diversity of Deepfake Avatars

Ilkka Kaate [a], Joni Salminen [b,*], Reham Al Tamime [c], Soon-gyo Jung [c], Bernard J. Jansen [c]

[a] University of Turku, Turku, Finland
[b] University of Vaasa, Vaasa, Finland
[c] Qatar Computing Research Institute, Hamad bin Khalifa University, Doha, Qatar

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ABSTRACT

Deepfake technology is increasingly integrated into global mobile and web services when human representation is not feasible or cost-effective. Our analysis of 202 deepfake avatars from three deepfake providers reveals significant demographic disparities with 18 out of 48 possible demographic groups unrepresented. Deepfake avatars' gender distribution was nearly balanced (49.01% male, 50.99% female), but older age groups (Baby Boomers and Silent Generation) were substantially underrepresented by 64.36% and 76.24%, respectively, relative to the average number of all deepfake avatars. Differences in language representation were present in deepfake avatar providers with only 1.06% of global languages covered. The findings indicate that current deepfake technology lacks diversity, primarily favoring young white individuals, neglecting older demographics, Asians, and Middle Eastern populations, with underrepresentation of 40.59% and 52.48%, respectively, relative to the average number of all deepfake avatars. Only 15.27% of deepfake avatars portray any occupational characteristics. Addressing these diversity gaps is crucial for better serving varied user groups and warrants attention from deepfake providers and caution from those using deepfakes.

## 1. Introduction

A *deepfake avatar* (DA) is a digital entity that has an anthropomorphic (i.e., human-like) appearance that is controlled and operated by a software program to inform, interact, and communicate with users of information systems, apps, or services (see an example in Fig. 1).

Improvements in artificial intelligence (AI) and machine learning (ML) – especially those made in deep learning (DL) – have enhanced the quality of DAs, making DAs more applicable in real-world systems. With the rise of deepfake technologies (Li et al., 2021; Vasist and Krishnan, 2022; Young et al., 2021), integrating DAs into user facing information systems is becoming more feasible. DAs and human users can interact naturally when a human user wants to query information about products or services, making the information system more accessible and immersive to use, as the DA can fulfill the users' requests in natural language. Thus, the research on deepfake technologies is relevant for information systems research (Averkin et al., 2019; Karnouskos, 2020; Khanjani et al., 2021; Mustak et al., 2023; Singh et al., 2022; Sivathanu and Pillai, 2022). Moreover, through the conceptual linkage to user experience (UX), this line of research exemplifies cross-disciplinary collaboration between information systems and human–computer interaction (HCI) research, which is seen as a fruitful endeavor (Zhang and Dillon, 2003).

However, the DA's demographic features may affect the quality of the interaction between the user and the DA (Pär, 2020; Aljaroodi et al., 2019; Wagner, 2009). For example, people in other ethnic groups might not respond optimally if the DA customer service agents only represent Caucasian ethnic groups. Studies on the *digital divide* postulate that the availability of technology can be geographically skewed (Bach et al., 2022; Ming-te, 2001; Vassilakopoulou and Hustad, 2021), leaving some regions and cultures underserved and thus harming the information systems in these areas. This may pose a disadvantage in deploying DAs in globally available information systems.

While demographic diversity involves many differences among people based on factors like age, gender, race, religion, ethnicity, class, socioeconomic status, political views, and educational background (Avgerou, 2008; Chatterjee et al., 2015; Niehaves and Plattfaut, 2014), it is uncertain how demographic diversity is represented in DAs. Addressing this research gap is important for various computer-mediated interactions such as interviews, shopping, customer services,

* Corresponding author.
*E-mail addresses:* iokaat@utu.fi (I. Kaate), joni.salminen@uwasa.fi (J. Salminen), realtamime@hbku.edu.qa (R. Al Tamime), sjung@hbku.edu.qa (S.-g. Jung), bjansen@hbku.edu.qa (B.J. Jansen).

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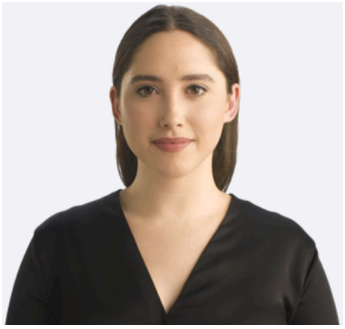

**Fig. 1.** "Anna", the default example of a deepfake avatar in a state-of-the-art deepfake service (.
Source: Synthesia.io). Anna can speak based on a script provided by a human. Anna can be integrated into a large language model such as ChatGPT to respond to user queries realistically. Our study investigates how well deepfake avatars made available to the public represent different demographic groups by age, gender, and ethnic background

education, and other interactions (Pär, 2020; Aljaroodi et al., 2019; Wakefield et al., 2011). The use of DAs is increasing due to a greater reliance of people and businesses on information systems that provide virtual agents (Miao et al., 2022). Overall, DAs strive to give the impression to the users of an information system that the users are talking with a real (or at least highly realistic) human being. For example, Nunamaker et al. (Nunamaker et al., 2011) demonstrate how DAs can exhibit a high level of emotions and interpersonal skills using audio; video, sensors, and advanced analytical software. Such ample communication skills can make DAs serve the needs of demographically diverse users by understanding different notions, contexts, tones, accents, and facial expressions, thus increasing the accessibility and value provided by information systems on a global scale.

Although DAs are emerging as a viable technology, their demographic diversity has not been studied. To this end, we present the following research questions (RQs):

- **RQ1:** What are the central demographic gaps in deepfake avatars?
- **RQ2:** How well do deepfake avatars represent the global population?

To address RQ1, we define a comprehensive framework to investigate different ethnic backgrounds, genders, and age groups. We then observed the frequencies in different demographic groups and paid particular attention to groups with no observations at all. Furthermore, we analyze the proportion of different demographic category values (e.g., the share of male DAs out of the total), to assess if there are biases in the demographic categories. We conducted this analysis at the overall level and separately for each service provider. To address RQ2, we obtained data from the demographic structure of the global population, and we compared it to the demographic structure observed in the three service providers selected for this study. We then investigate whether the representation of demographic attributes in the DAs correlates with the global population. We also tally how many languages the service providers support and compare this to the global languages.

Our study contributes to the field of computer science and HCI by exploring the demographic diversity of DAs, an area that has received minimal attention in the literature. While there is research focusing on *emotions and emotional diversity* in deepfakes (Kaate et al., 2024; Toshpulatov et al., 2023), our study delves into how various demographic factors—such as age, gender, and ethnicity—are presented in DAs. Understanding AI applications and AI applications' societal implications is important particularly in user-centered design (UCD) that is inclusive and representative of diverse populations, and DAs' demographic diversity, still, is an uncovered field in HCI.

## 2. Literature Review

### 2.1. Why Does Diversity Matter for Deepfakes?

Research from HCI implies that the more a DA looks to be anthropomorphic, the more it seems credible and competent (Nass and Moon, 2000). An anthropomorphic impression of a DA encourages interaction and engagement among users (Miao et al., 2022). A more human-like appearance of DAs can also increase the credibility or goodwill among users (Chattaraman et al., 2012; Holzwarth et al., 2006). Furthermore, the more diverse DAs are, i.e., the bigger the chance there is that the DAs resemble the users' own demographic background, the easier it is for the DA users to interact and engage with the DAs (McDuff and Czerwinski, 2018; Soo Youn et al., 2016) and the easier it is to increase societal understanding among people (Hall et al., 2013). However, it is a challenge for a DA to communicate with people of different backgrounds and cultures if there is limited ability to represent the diverse people's facial features, expressions, and languages.

Based on prior research, the diversity portrayed by DAs may be especially critical for organizations or professionals acting in diverse geographical locations with clients of different races, ages, genders, cultures, locations, religions, and educational backgrounds (Behrend et al., 2012). For an inclusive deployment of DAs, an increased understanding of differences is crucial for DAs to adequately engage with people from different demographic backgrounds. The research in this domain highlights the overall narrative that DAs require a degree of adaptation to the user's circumstances, including their demographics (Häkkilä et al., 2020).

Overall, DAs that can behave like humans with high emotional and social skills and with an anthropomorphic appearance are more likely to be successful and acceptable in different cultures (Dormehl, 2018). Jack et al. (Jack et al., 2012) questioned the ability of DAs to interpret a wide range of demographics correctly to display culturally adapted content. Ultimately, DAs should represent the diversity among people related to ethnicity and race (Turner and Turner, 2011). With a broader ethnic and racial representation among DAs, we can justify the actual demographic diversity among the user base. Otherwise, one-sided representations of DAs could negatively impact UX. For example, Nakamura (Nakamura, 2002) highlights that DA creation software does not provide ample options to display ethnicity and racial diversity during the DA creation. This is possibly a major shortcoming among the software services for DA design and development, which can then cause issues in information systems that use DAs.

The existing literature on deepfake technologies primarily emphasizes emotional representation and emotional connections towards a deepfake, such as the studies by Kaate et al. (Kaate et al., 2023) and Kaate et al. (Kaate et al., 2024), the latter highlighting emotional biases in DAs. Our work builds upon this foundation by addressing the lack of research on demographic diversity in DAs, showing that while the emotional expression of DAs is important, understanding the broader demographic representation in DAs is crucial for DAs' acceptance and effectiveness in various applications. For instance, while previous studies have focused on deepfake detection frameworks (such as work by Gao et al. (Gao et al., 2024) and Habbal et al. (Habbal et al., 2024), our research uniquely highlights how the demographic diversity of DAs is not currently taken into consideration in deepfake service providers. Overall, diversity is increasingly receiving recognition in HCI and information system studies (Himmelsbach et al., 2019).

### 2.2. Opportunities and Challenges of Demographic Diversity

A virtual or digital representation of oneself through DAs gives chances for multiple parties to convey more social information about one another in communication. Telecommunication, such as video conferencing and instant messaging software have become more common than face-to-face physical media (Huffcutt and Culbertson, 2011).

While these leaner media provide less social information about people, a virtual environment with DAs offers an opportunity to present diversity through social information access (Behrend et al., 2012).

Though their DAs might not be a true replica of actual people, users can respond to appealing DAs more positively than actual face-to-face interactions (Nowak and Rauh, 2008). Hence, virtual environments can promote demographic diversity in real places such as offices, education centers, and other places of human activity.

Bias in digital user representation can originate from multiple sources. This bias can concern age, gender, or other attributes of the DAs, and it generally decreases when more DAs are provided, as many DAs are more likely to cover diverse demographics. In other studies, it has been found that demographic bias is likely inherited from the dataset used for training generative ML models (Salminen et al., 2020). Deepfake technologies are not immune to any biases in the training data.

Some technological advances have been taking place to make more diverse DAs. For example, MetaHuman Creator is a browser-based application that enables people to create photorealistic DAs within minutes. The tool provides ample options for displaying different physical characteristics like teeth, hair, bone structure, facial color, wrinkles, skin tone, specific hair color, or various bone structures. Hence, it enables a wider demographic diversity to take place in the virtual world through diversity among DAs (Fang et al., 2021). These software tools cater to demographic diversity and mitigate the monotonous nature of DAs. With this opportunity, more people with demographic diversity could be encouraged to participate in computer-mediated communication. This demographic diversity would make virtual places more equal, just, natural, and livable.

Ideally, through a diverse representation, the virtual world can have a civilized system running on equality, rationality, and justice – perhaps more so than in the real world. Virtual places influence life and livelihood in the real world as well. This influence is only expected to increase with the development of the Metaverse (Dwivedi et al., 2022), an environment where deepfake technology can significantly affect human-AI interaction via DAs. Going beyond this, Galvão et al. (Galvão et al., 2021) even suggested the vision of human immortality through DAs who would take care of the digital legacy of a person posthumously. DAs might, therefore, become an ever-central instrument for digital participation and digitalized portrayal of humans in the future.

### 2.3. Research Gap

While there is a nascent stream of research conducted on deepfakes (Broad et al., 2020; Gamage et al., 2022; Karnouskos, 2020; Mustak et al., 2023), an investigation of DAs' demographic diversity is lacking. Meyer et al. (Meyer et al., 2020) investigated demographic bias in *Automatic Speech Recognition* models to mitigate bias in speech recognition systems. The researchers discovered a significant accent bias in their baseline model that yielded less accurate transcriptions for Indian English compared to American English. However, the researchers did not report any notable gender bias in their study. Other studies have investigated demographic bias in face detection (Garcia et al., 2019; Terhörst et al., 2020), facial datasets (Georgopoulos et al., 2021), natural language processing (e.g., word embeddings (Sweeney and Najafian, 2019), and named entity recognition (Mishra et al., 2020), but no study we are aware of investigates demographic bias in deepfake avatars. Therefore, this study undertakes a novel, impactful task. Another, perhaps more general, aspect of deepfake research to which this research contributes is the fact that most studies on deepfakes tend to focus on negative effects such as misinformation and other forms of deception (e.g., Darke and Ritchie (Darke and Robin, 2007); Luca and Zerva (Luca and Zervas, 2016). However, deepfakes also offer opportunities for businesses and other organizations, especially when deployed in an ethically sustainable manner (Mustak et al., 2023). Therefore, it is integral that there should also be studies focused on the opportunities, and not only the risks, of deepfakes for information systems, which this study provides.

## 3. Methodology

The study procedure is depicted in Fig. 2. The first step was to select deepfake service providers suitable for the study. Three deepfake service providers were chosen for this study: *Synthesia*,[1] *Elai*,[2] and *Colossyan*.[3] These three service providers were chosen primarily due to their quality; the inspected DAs, based on our pilot testing, appeared adequately realistic to be applicable in real-life use cases. These deepfake service providers are marketed for use by companies and other client organizations to create deepfakes for their required purposes, such as customer service, sales support, online presentations, or even for pro-government information campaigns and other political aspirations (Satariano and Mozur, 2023). Each of the providers offers deepfakes generated from pre-recorded videos of real human actors. Deepfake service providers use libraries of human avatars, created from real people, and each service provider also allows custom avatars by recordings via webcam. The service providers use AI to analyze facial expressions, movement, and Synthesia synchronizing of acted videos with generated voiceovers. The service providers also offer high-quality voice cloning in multiple languages with integrations to voice cloning platforms, such as ElevenLabs (Lukan, 2024; Schwartz, 2024).

Next, a template for the demographic inspection of the DAs was created in a spreadsheet. Demographic variables were drawn from classifications by the American Psychological Association (APA: Racial and ethnic identity (Association, 2022) and Kiersz (Kiersz, 2015). The APA demographic classification identifies six ethnic categories: (a) *People of African origin*, (b) *People of Asian origin*, (c) *People of European origin*, (d) *Indigenous Peoples around the world*, (e) *People of Hispanic or Latino ethnicity*, and (f) *People of Middle Eastern origin*.

In terms of age, Kiersz (Kiersz, 2015) identifies four age categories: (a) *Millennials* (age 18–34), (b) *Generation X* (age 35–50), (c) *Baby boomers* (age 51–69), and (d) *Silent generation* (age 70–87). In addition, gender was defined as biological sex, i.e., male and female. The ethnic and age categories were then tabulated for each gender and each deepfake service provider separately, resulting in 24 different demographic groups (six ethnic and four age groups). We leave the investigations of other ethnic categories, age groupings, and gender identifications to future research.

Each service provider was individually studied, and each presented DA was inspected (see examples in Fig. 3). A random sample of DAs in Fig. 3 shows a low number of demographic varieties between DAs with a bias towards young Caucasian DAs. If a DA was presented, for example, from a different angle or with a different outfit, each variation was considered a unique DA. A screenshot of each DA was saved and *meta*-tagged after the demographic classification by APA and Kiersz (Kiersz, 2015) for further analysis. A total of 202 unique DAs were found on the three service providers. Screenshots of the DAs and the image nomenclature are provided in the supplementary material.[4] After saving all 202 screenshots, the service provider, gender, age, and ethnic information of every DA was entered into a spreadsheet. Data on the provided languages were gathered from each service provider (Colossyan., 2022; Elai., 2022; Synthesia, 2022). Additional data on the global population was also collected from the United Nations (UN) (United Nations, 2022a), and on the world languages from Ethnologue (Ethnologue, 2016).

[1] https://www.synthesia.io/.
[2] https://elai.io/.
[3] https://www.colossyan.com/.
[4] Link to online supplementary material containing the screenshots: https://osf.io/jwr58/?view_only=c61bf036f83b40b98563ea5e353d6e39.

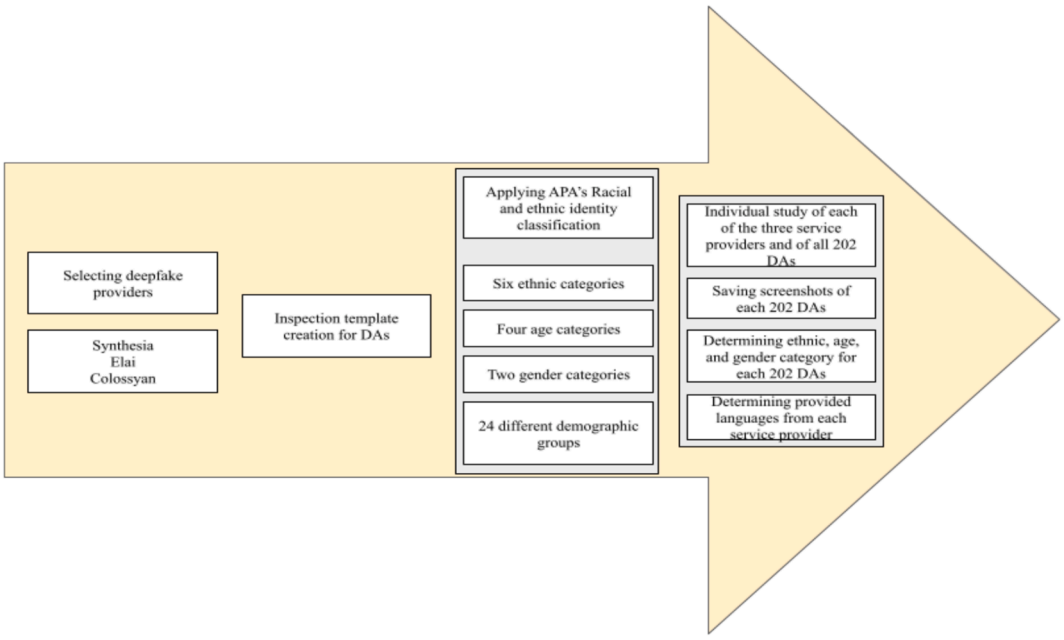


**Fig. 2.** The study procedure.


**Fig. 3.** Examples of deepfake avatars in different deepfake services. In total, 202 unique avatars are investigated in this research.

## 4. Results

### 4.1. RQ1: What Are the Central Demographic Gaps in Deepfake Avatars?

The gender distribution of deepfake avatars among analyzed deepfake service providers varied between deepfake service providers (see Fig. 4). In total, there were 99 male and 103 female deepfake avatars on the analyzed deepfake service providers. This results in a total of 202 DAs. Demographic data (age and ethnicity) collected from the three deepfake service providers was tabulated by deepfake service providers and gender. Also, data for both genders were combined to analyze age and ethnic background without respect to gender. Overall, there are 2 genders, 4 age groups, and 6 ethnic groups (n = 48). These groups were analyzed first separately by gender and then both genders combined, dividing gender, age, and ethnicity into groups representing different demographic combinations.

Considerable differences in demographic attributes can be observed between deepfake service providers (see Table 1). Synthesia has the largest coverage of different demographic groups for males (n = 12, 25.00 %), females (n = 11, 22.92 %), and when considering male DAs and female DAs together (*overall*) (n = 9, 18.75 %), while Elai has the least coverage for male (n = 18, 37.50 %), female (n = 18, 37.50 %) and overall (n = 16, 33.33 %) (see Fig. 5). Synthesia covered 52.1 % (n = 25) of the total possible demographic combinations; Elai covered 25.0 % (n = 12); and Colossyan covered 37.5 % (n = 18) (Fig. 5). Overall, a Chi-squared test of independence showed no significant association between deepfake service provider and gender, $X^2$ (4, N = 110) = 0.02, p = 0.10.

Nine male (18.75 %) and nine female demographic groups (18.75 %) were not covered by any deepfake service provider out of a total of 48 possible demographic groups, and seven demographic groups (14.59 %) were not covered by any deepfake service provider when gender was left out of the inspection. In total, 18 demographic groups (37.50 % of all possible 48 demographic combinations) were unavailable in any of the deepfake service providers (Table 1). Nevertheless, all deepfake service providers differed in the demographic group coverage between genders. Each platform had occasions where one gender had a gap in an age-ethnicity group while the other gender did not have a gap in that age-ethnicity group.

**Table 1**
Demographic groups that were not available in any deepfake service providers.

| Age Group | Male | Female |
|---|---|---|
| Generation X | Indigenous Peoples around the world | Indigenous Peoples around the worldPeople of Asian origin |
| Baby boomers | Indigenous Peoples around the world<br>People of African origin<br>People of Asian origin<br>People of Middle Eastern originPeople of Hispanic or Latin ethnicity | People of Asian origin<br>People of Middle Eastern originPeople of Hispanic or Latin ethnicity |
| Silent generation | Indigenous Peoples around the world<br>People of Middle Eastern originPeople of Hispanic or Latin ethnicity | Indigenous Peoples around the world<br>People of Asian origin<br>People of Middle Eastern originPeople of Hispanic or Latin ethnicity |

All deepfake service providers had differences in their demographic group coverages between genders, which can be seen when comparing values for each platform's gender column and the column *Both genders have gaps* in Table 2. For example, Synthesia has 12 gaps for males and 11 for females but only nine gaps when results are observed with no respect to gender *(Both genders have gaps)*. This means that three gaps present in male groups were covered by female age-ethnicity groups, and two gaps in female age-ethnicity groups were covered by male age-ethnicity groups.

Genders are quite well-balanced across the deepfake service providers (see Table 3). Both genders' proportions of the whole DA population are around 50 %, but Synthesia has a slight over-representation of female DAs, which also pulls the overall gender balance towards the

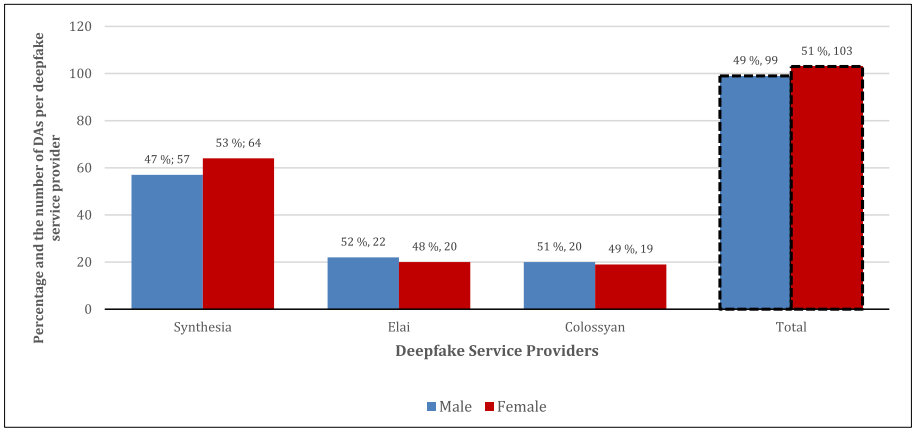


**Fig. 4.** Gender distribution of deepfake avatars among the analyzed deepfake service providers.

| | Synthesia | Elai | Colossyan | All DASs together (overall) |
|---|---|---|---|---|
| Male African Millennial | 4 | 1 | 0 | 5 |
| Male African Gen X | 8 | 0 | 1 | 9 |
| Male African Baby Boomers | 0 | 0 | 0 | 0 |
| Male African Silent generation | 2 | 0 | 0 | 2 |
| Male Asian Millennial | 2 | 3 | 1 | 6 |
| Male Asian Gen X | 2 | 4 | 0 | 6 |
| Male Asian Baby Boomers | 0 | 0 | 0 | 0 |
| Male Asian Silent generation | 1 | 0 | 0 | 1 |
| Male European Millennial | 11 | 0 | 1 | 12 |
| Male European Gen X | 10 | 4 | 9 | 23 |
| Male European Baby Boomers | 6 | 5 | 0 | 11 |
| Male European Silent generation | 0 | 0 | 3 | 3 |
| Male Indigenous Millennial | 0 | 0 | 1 | 1 |
| Male Indigenous Gen X | 0 | 0 | 0 | 0 |
| Male Indigenous Baby Boomers | 0 | 0 | 0 | 0 |
| Male Indigenous Silent generation | 0 | 0 | 0 | 0 |
| Male Hispanic Millennial | 4 | 0 | 2 | 6 |
| Male Hispanic Gen X | 6 | 0 | 1 | 7 |
| Male Hispanic Baby Boomers | 0 | 0 | 0 | 0 |
| Male Hispanic Silent generation | 0 | 0 | 0 | 0 |
| Male Middle Eastern Millennial | 1 | 0 | 0 | 1 |
| Male Middle Eastern Gen X | 0 | 5 | 1 | 6 |
| Male Middle Eastern Baby Boomers | 0 | 0 | 0 | 0 |
| Male Middle Eastern Silent generation | 0 | 0 | 0 | 0 |
| Female African Millennial | 2 | 4 | 3 | 9 |
| Female African Gen X | 4 | 0 | 0 | 4 |
| Female African Baby Boomers | 3 | 0 | 0 | 3 |
| Female African Silent generation | 5 | 0 | 0 | 5 |
| Female Asian Millennial | 4 | 2 | 1 | 7 |
| Female Asian Gen X | 0 | 0 | 0 | 0 |
| Female Asian Baby Boomers | 0 | 0 | 0 | 0 |
| Female Asian Silent generation | 0 | 0 | 0 | 0 |
| Female European Millennial | 13 | 4 | 5 | 22 |
| Female European Gen X | 8 | 5 | 4 | 17 |
| Female European Baby Boomers | 2 | 0 | 1 | 3 |
| Female European Silent generation | 0 | 0 | 1 | 1 |
| Female Indigenous Millennial | 0 | 0 | 1 | 1 |
| Female Indigenous Gen X | 0 | 0 | 0 | 0 |
| Female Indigenous Baby Boomers | 1 | 0 | 0 | 1 |
| Female Indigenous Silent generation | 0 | 0 | 0 | 0 |
| Female Hispanic Millennial | 14 | 2 | 2 | 18 |
| Female Hispanic Gen X | 2 | 0 | 1 | 3 |
| Female Hispanic Baby Boomers | 0 | 0 | 0 | 0 |
| Female Hispanic Silent generation | 0 | 0 | 0 | 0 |
| Female Middle Eastern Millennial | 4 | 0 | 0 | 4 |
| Female Middle Eastern Gen X | 2 | 3 | 0 | 5 |
| Female Middle Eastern Baby Boomers | 0 | 0 | 0 | 0 |
| Female Middle Eastern Silent generation | 0 | 0 | 0 | 0 |
| Covered male demographic groups | 12 | 6 | 9 | 15 |
| Covered female demographic groups | 13 | 6 | 9 | 15 |
| Covered demographic groups | 25 | 12 | 18 | 30 |
| Coverage percentage of all groups | 52,1% | 25,0% | 37,5% | 62,5% |

**Fig. 5.** Representation of demographic groups in the analyzed deepfake services. None of the services represent all possible demographic groups. Red indicates zero DAs in the demographic group, light yellow indicates 1–3 DAs in the demographic group, dark yellow indicates 4–7 DAs in the demographic group, light green color indicates 8–12 DAs in the demographic group, darkest green colors indicate 13–23 DAs in the demographic group.

**Table 2**
The number of demographic gaps in all deepfake service providers. Values in parenthesis indicate the percentage of demographic gaps from all possible demographic groups (24 possible groups). The lower the values, the more each deepfake service provider covered demographic groups.

| Deepfake Service Provider | Male | Female | Both genders have gaps |
|---|---|---|---|
| Synthesia | 12 (25.00 %) | 11 (22.92 %) | 9 (18.75 %) |
| Elai | 18 (37.50 %) | 18 (37.50 %) | 16 (33.33 %) |
| Colossyan | 15 (31.25 %) | 9 (18.75 %) | 13 (27.09 %) |
| Overall | 9 (18.75 %) | 9 (18.75 %) | 7 (14.59 %) |

**Table 3**
Gender balance in each deepfake service provider and overall. Values in parenthesis indicate the percentage of each DA's gender from total DAs in each deepfake service provider and overall.

| Deepfake Service Provider | Male DAs | Female DAs | Total DAs |
|---|---|---|---|
| Synthesia | 57 (47.11 %) | 64 (52.89 %) | 121 |
| Elai | 22 (52.38 %) | 20 (47.62 %) | 42 |
| Colossyan | 20 (51.28 %) | 19 (48.72 %) | 39 |
| Overall | 99 (49.01 %) | 103 (50.99 %) | 202 |

female side since Synthesia forms the majority of all the DAs in the sample. Elai and Colossyan have a slight emphasis on male DAs (Table 3). The overall percentages for both genders are close to the 50 % ideal, having less than a 1 percentage point difference from it. A Chi-squared test showed no significant association between deepfake service providers and gender, $X^2$ (4, n = 404) = 0.45, p = 0.80.

There is a strong emphasis on younger age groups in the deepfake service providers (see Table 4). Millennials and Generation X form most DAs on each deepfake service provider, and overall, Millennials are the largest age group on all deepfake service providers except for Elai. The values of over- and under-representation reveal that the over-representation for Millennials above the mean number of avatars is 82.18 %, and for Generation X it is 58.42 %. In turn, Baby Boomers and the Silent Generation are under-represented by 64.36 % and 76.24 %, respectively. A Chi-squared test showed no significant association between deepfake service providers and age group, $X^2$ (6, n = 202) = 8.99, p = 0.17.

Ethnic groups are differently distributed in each deepfake service provider (see Table 5). People of European origin are overrepresented in each deepfake service provider, where the European proportion of the whole DA population for each deepfake service provider is 41–61 % and also overall (173.27 % over-representation compared to the mean). Indigenous peoples, people of Middle Eastern origin, and people of Asian origin are underrepresented on each deepfake service provider and overall. A Chi-squared test showed a significant association between deepfake service providers and ethnic groups, $X^2$ (10, n = 202) = 32.25, p = 0.00036.

Finally, to effectively represent end-users for design purposes, occupation can be valuable information for user representation, as professional identity matters for a variety of information system development contexts. To this end, we examined the occupational diversity in the analyzed DAs (see Table 6).

DAs cover only a small number of possible occupations. Seven unique job occupations were recognized by the service providers: businessperson, construction site supervisor, medical doctor, office worker, construction worker, nurse, and police officer (Table 6). Business and office (businessperson and office worker), caretaking occupations (nurse and medical doctor), and construction-related occupations (construction worker and construction site supervisor) are the main occupational areas found on the DAs. However, a variety of occupations of DAs can be seen from the service providers.

Additionally, the job occupations observed by the service providers are limited and many occupations are not covered by any of the three service providers. Only approximately 15 % of DAs had occupational characteristics such as clothes or headwear, and considerable differences were observed between service providers. Elai showed occupational characteristics on approximately 30 % of DAs, Colossyan on

**Table 4**
Age group balance in each deepfake service provider and overall. Values in parenthesis indicate the percentage of DAs of a certain age group in each deepfake service provider. Mean is the mean number of DAs in each deepfake service provider per age group. Also, the over- or under-representation of each age group compared to the mean is presented as a percentage (bottom row).

| Deepfake Service Provider | Millennial | Gen X | Baby Boomers | Silent generation | Mean |
|---|---|---|---|---|---|
| Synthesia | 59 (48.76 %) | 42 (34.71 %) | 12 (9.92 %) | 8 (6.61 %) | 30 |
| Elai | 16 (38.10 %) | 21 (50.00 %) | 5 (11.90 %) | 0 (0.00 %) | 11 |
| Colossyan | 17 (43.59 %) | 17 (43.59 %) | 1 (2.56 %) | 4 (10.26 %) | 10 |
| Overall | 92 (45.54 %) | 80 (39.60 %) | 18 (8.91 %) | 12 (5.94 %) | 50.5 |
| Over / underrepresentation (relative to the macro average) | +82.18 % | +58.42 % | −64.36 % | −76.24 % | |

**Table 5**
The balance of ethnic backgrounds in each deepfake service provider and overall. Values in parenthesis indicate the percentage of DAs of a certain ethnic background from the total DAs in each deepfake service provider. Mean is the mean number of DAs in each deepfake service provider per ethnic background. Also, the over- or under-representation of each ethnic group compared to the mean is presented as a percentage (bottom row).

| Deepfake Service Provider | African | Asian | European | Indigenous | Hispanic | Middle Eastern | Mean |
|---|---|---|---|---|---|---|---|
| Synthesia | 28 (23.14 %) | 9 (7.44 %) | 50 (41.32 %) | 1 (0.83 %) | 26 (21.49 %) | 7 (5.79 %) | 20 |
| Elai | 5 (11.90 %) | 9 (21.43 %) | 18 (42.86 %) | 0 (0.00 %) | 2 (4.76 %) | 8 (19.05 %) | 7 |
| Colossyan | 4 (10.26 %) | 2 (5.13 %) | 24 (61.54 %) | 2 (5.13 %) | 6 (15.38 %) | 1 (2.56 %) | 7 |
| Overall | 37 (18.32 %) | 20 (9.90 %) | 92 (45.54 %) | 3 (1.49 %) | 34 (16.83 %) | 16 (7.92 %) | 33.67 |
| Over / underrepresentation (relative to the macro average) | +9.90 % | −40.59 % | +173.27 % | −91.09 % | +0.99 % | −52.48 % | |

**Table 6**
Occupational appearances found on DAs on each service provider and overall. Percentages in parentheses are the percentage of DAs with occupational appearances from all the DAs. Mean is the average value of DAs with occupational appearance per service provider.

| Service Provider | Number of DAs with an occupational appearance | Occupations found |
|---|---|---|
| Colossyan | 10 (25.64 %) | businessperson<br>construction site supervisor<br>medical doctoroffice worker |
| Elai | 13 (30.95 %) | construction worker<br>medical doctor<br>nursepolice officer |
| Synthesia | 8 (8.26 %) | businessperson<br>construction worker<br>medical doctornurse |
| Overall | 31 (15.27 %) | businessperson<br>construction site supervisor<br>construction worker<br>medical doctor<br>nurse<br>office workerpolice officer |
| Mean per service provider | 10.33 (5.09 %) | |

**Table 7**
Ranks of age groups worldwide (United Nations, 2022b) and in deepfake service providers. Rank 1 is the most common age group, and rank 5 is the most uncommon age group.

| | Millennial | Gen X | Baby Boomers | Silent generation | Other age groups |
|---|---|---|---|---|---|
| Rank globally | 2 | 3 | 4 | 5 | 1 |
| Rank in service providers | 1 | 2 | 3 | 4 | 5 (N/A) |

approximately 25 %, and Synthesia on approximately 8 % of DAs. Job occupations are also limited to seven occupations, which reduces the possibility of addressing most people by their occupation. For example, Birt (Birt, 2022) lists the 25 most common occupations in America only four of which were somewhat recognized among the DAs (construction worker, medical assistant, police officer, office clerk), medical assistant being an equivalent of a nurse and an office clerk an equivalent of an office worker. Some common occupations missing from the DAs include cashier, food preparation worker, bookkeeper, waiter, bartender, and

**Table 8**
Ranks of ethnic groups in the world (United Nations, 2022b) and in deepfake services. Rank 1 means the most common ethnic group, and rank 6 means the most uncommon ethnic group.

| | African | Asian | European | Indigenous | Hispanic | Middle Eastern |
|---|---|---|---|---|---|---|
| Rank globally | 2 | 1 | 3 | 6 | 4 | 5 |
| Rank in deepfake services | 2 | 4 | 1 | 6 | 3 | 5 |

**Table 9**
The languages offered by each deepfake service and overall, and the overall percentage of the spoken languages in the world (Ethnologue, 2016).

| | Number of languages offered on each service provider | Percentage of all the languages in the world (7151 languages) |
|---|---|---|
| Synthesia | 65 | 0.91 % |
| Elai | 68 | 0.95 % |
| Colossyan | 57 | 0.80 % |
| Overall | 76 | 1.06 % |

mechanic.

### 4.2. RQ2: How Well Do Deepfake Avatars Represent the Global Population?

Deepfake service providers strongly emphasize younger age groups, and in comparison with the global age groups, there are some differences to be seen (see Table 7). Other age groups (age under 18 or over 87) that were not found on any of the examined service providers have the highest rank globally. Aside from that, the youngest age groups are the most common, and age group ranks become rarer with the groups' increasing age on service providers and in the global population. Spearman's rank correlation indicated no relationship between age group prevalence and age groups' rank in the global population and the deepfake service providers, $r(3) = 0$, $p = 1$.

In terms of gender, there is nearly an even number of female and male DAs (male: n = 99, 49.01 %, female: n = 103, 50.99 %). Globally, the male population covers 50.3 % and the female population 49.7 % of the total population (United Nations, 2022b). Males are under-

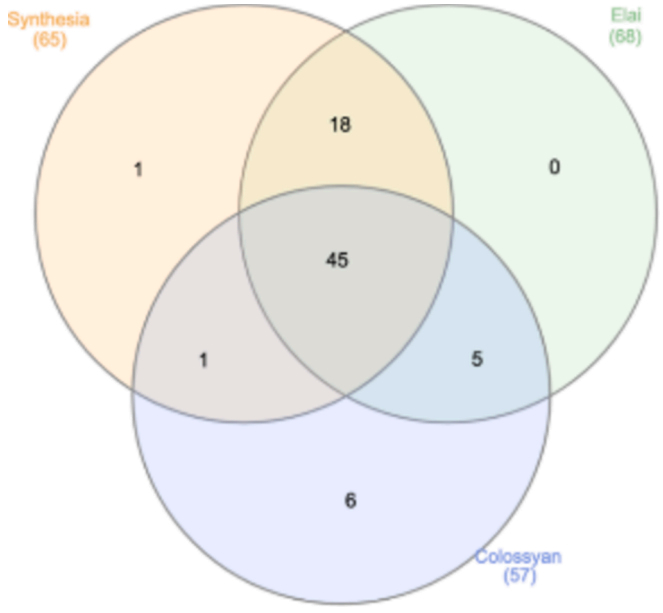


**Fig. 6.** A Venn diagram of languages in the service providers. All three services provide the same 45 languages(Arabic, Bengali, Bulgarian, Chinese, Croatian, Czech, Danish, Dutch, English, Estonian, Filipino, Finnish, French, German, Greek, Hebrew, Hindi, Hungarian, Icelandic, Indonesian, Italian, Japanese, Kannada, Korean, Latvian, Lithuanian, Malay, Malayalam, Maltese, Norwegian, Polish, Portuguese, Romanian, Russian, Serbian, Slovak, Slovenian, Spanish, Swedish, Tamil, Thai, Turkish, Ukrainian, Urdu, and Vietnamese.).

represented by 1.29 percentage points, and females are over-represented by 1.29 percentage points compared to the global population. Moreover, the DAs have a strong emphasis on European and African populations, while Europeans are not ranked as a common ethnic group in the global data (see Table 8). The Asian population is the most common globally, leaving the European population in third place. Spearman's rank correlation showed a significant relationship between ethnic group prevalence and ethnic groups' rank in the global population and among the service providers, $r(4) = 0.6$, $p = 0.50$.

In terms of language, the DAs cover only a small percentage of the world's spoken languages (see Table 9). Together, the three service providers cover only 1.06 % of all 7151 languages spoken globally. There are differences among the service providers. Elai has the most languages to offer (68), while Synthesia has 65 and Colossyan has only 57 languages. Then again, only 20 of the most spoken languages cover 50 % of native speakers worldwide (Ethnologue, 2016). All of these 20 languages, except Nigerian, Pidgin, and Marathi, are found on all three services. There is a strong overlap of languages among the deepfake services, as seen from Fig. 6.

## 5. Discussion

### 5.1. Discussion of Findings

The findings from our research show that there are demographic gaps in DAs from service providers, which may impact their uniform usefulness. In terms of *ethnic group*, people of European origin are over-represented in each deepfake service. In terms of *age*, demographic gaps were found for male and female DAs in all age groups except for millennials. While Millennials and Generation X form the majority of the DAs, the representation of different age groups does not correlate with their representation in the global population, again indicating limitations of DAs' usefulness currently. Regarding *gender*, there was no bias in any of the deepfake service providers, the genders were almost fully balanced. So, in terms of representation, this is a positive.

The languages of these DAs cover approximately 1 % of the languages spoken in the world, but the 20 most spoken languages cover over 50 % of the global population, and eighteen of these twenty languages are found in the DAs. It is quite natural that there is a wide variety of the most spoken languages worldwide, but when compared to the global racial demographic data, there are gaps between DAs and spoken languages. For example, languages like Lahnda, Pidgin, Marathi, and Telugu which are spoken by millions of people are not represented in DAs. This means, again, limited or no options for developers who would like to create native-speaking DAs for these language groups.

Though we did not explicitly investigate why the generated DAs have demographic gaps and biases, saving this for future research, based on prior research (Mustak et al., 2023), we surmise that this is due to overlooking demographic diversity in the process of creating the deepfakes. One source of bias may be the *country-of-origin* effect. Synthesia and Elai were founded in the US, and Colossyan was founded in Germany, so the service providers studied here are from the Western world. Thus, each of the platforms could have its own demographic bias towards European DAs, for example, based on their current market. This may not be from explicit bias, but it could also be due to the availability of data and samples from which to generate DAs.

Alternatively, an explanation would be the *disparity between high- and low-resource localization*, which refers to the uneven distribution of ML training datasets for some locals. The NLP (natural language processing) community has reported several gaps in terms of low-resource language modeling (Alam et al., 2020). In image generation, Salminen et al. (Salminen et al., 2020) investigated the use of ML to generate facial images and found that the images trained to use models are skewed toward young people, particularly white women. The gaps and biases in the training datasets are likely to resurface in the created outputs, such as DAs.

However, our analysis provides valuable findings on the demographic diversity of DAs. Our study highlights significant underrepresentation of older age groups and ethnic minorities in DAs, yet it does not fully address the cultural, social, or economic factors that may contribute to these imbalances not previously studied in the context of Das, which would be a fruitful area of future research. The effects of demographic representation in DAs on user engagement and trust require, still, deeper exploration. Research indicates that individuals can react more favorably to digital representations that align with their demographic identity (Renier et al., 2024). Consequently, it is crucial to investigate how demographic mismatches affect UX in deepfake technologies, as this understanding is vital for improving the effectiveness of DAs across various applications.

Also, previous studies have emphasized the importance of emotional expressiveness in DAs, (Kaate et al., 2024; McDuff and Czerwinski, 2018) revealing that DAs, at the moment, properly portray a narrow range of emotions with a considerable positivity bias (Kaate et al., 2024). Analyzing how the emotional portrayal of DAs intersects with demographic factors could provide a deeper understanding of the two diversities' effectiveness across user groups. The underrepresentation of specific demographics in DAs can perpetuate stereotypes and biases, ultimately affecting users' perceptions and interactions with DAs (Nakamura, 2008). By studying deeper into these areas, future research can enhance the understanding of the factors influencing demographic diversity in deepfakes. This will contribute to the field of HCI and ensure that AI applications remain ethical and representative of the varied user base they aim to serve (Abbas and Taeihagh, 2024). Also, younger generations could be seen as the primary target group of technology to begin with, which would explain the absence of demographic gaps in the youngest generation. This *youth bias* effect (Amirtha and Sivakumar, 2018) could explain why older age groups are substantially less represented among the DAs.

Our research advances the discourse on deepfake technology by systematically analyzing demographic diversity in DAs. Unlike prior studies that predominantly examine mainly emotional aspects, including the emotional diversity of DAs (Kaate et al., 2024), our work reveals gaps in how different demographic groups are represented in

**Table 10**
Design implications based on the findings of demographic bias in Das.

| In response to… | Designers could… |
|---|---|
| major demographic biases in all the analyzed service providers, with some groups over-represented (e.g., young Europeans) and others under-represented (e.g., older Asians) | →Prioritize demographic inclusivity, ensuring equal representation of all age groups and ethnicities, including older Asians, in the service providers. |
| overrepresentation of young white people, with only a small representation of Asian or Middle Eastern people or older demographics. | →Develop deepfake avatars with a broader racial and age spectrum, particularly enhancing the representation of Asian, Middle Eastern, and older demographics. |
| ethnic focus of deepfakes misalignment with the global population | →Align the ethnic representation in the service providers with the global demographic distribution, focusing on a more equitable representation of all ethnic groups. |
| major differences in the demographic coverage between different service providers | →Standardize demographic representation across various service providers to minimize disparities and promote uniform diversity. |
| small coverage of the world's spoken languages | →Expand the linguistic capabilities of service providers to include a wider array of the world's spoken languages, reflecting global linguistic diversity. |
| small variety of occupations represented by deepfakes | →Diversify the occupational representation in service providers to encompass a broader range of professions, reflecting the vast diversity of occupations worldwide. |

DAs. This is particularly relevant given that AI systems have demonstrated biases in recognizing and responding to emotions across different demographic groups, leading to implications for UX (Gao et al., 2024; Habbal et al., 2024). By emphasizing the importance of including diverse representations in deepfake technologies, we aim to enhance user engagement and satisfaction in digital interactions and AI applications.

These biases and limitations in DA design can lead to products and services that are less inclusive and equitable and less effective and appealing to a global user base. The unbalanced demographics of DAs raise significant theoretical concerns regarding representation and social identity. The lack of diversity can limit societal understanding and perpetuate stereotypes (Hall et al., 2013). Individuals derive part of their identity from group affiliation; thus, underrepresenting demographic groups in DAs can lead to alienation (Tajfel and Turner, 1986). Furthermore, the reliance on biased training datasets for AI applications contributes to algorithmic bias, raising possible ethical issues about fairness and equity in technology usage (Himmelsbach et al., 2019). Addressing these issues is crucial for creating DA designs that are truly representative, accessible, and beneficial to a diverse audience worldwide (Häkkilä et al., 2020; Nielsen et al., 2013; Seidelin et al., 2014).

### 5.2. Design Implications

In terms of design, the lack of diversity in DAs can hinder DAs' accessibility and alienate potential users (Habbal et al., 2024; Himmelsbach et al., 2019). The lack of DA diversity can exacerbate social conflict by marginalizing user groups, while inclusive design and diverse training datasets for DA generation tools are essential for ethical DA technology development (Crawford, 2021). More advanced versions of AI techniques, data algorithms, and ML algorithms are likely required to develop DAs that better represent people from diverse backgrounds. To address this issue, DA service providers can strive toward increasing the diversity within the training sets used to train the AI models to create more diverse deepfakes. The findings from our research have implications for developers and practitioners in the field of AI. By identifying gaps in demographic representation in DAs, we advocate for creating DAs that reflect the diversity of user populations. This is critical not only for ethical considerations but also for practical applications where user engagement is essential. As highlighted by previous research, such as the exploration of Habbal et al. (Habbal et al., 2024) and Himmelsbach et al. (Himmelsbach et al., 2019), understanding diversity can aid in developing AI and DA systems that are more reliable and trustworthy. We recommend using a combination of deepfake service providers for organizations that want to use DAs, to ensure the broadest demographic coverage. The implications of our findings to the international design community are presented in Table 10.

The findings about the demographic, ethnic, linguistic, and occupational biases in DA systems can be considered harmful for design in several ways:

1. Perpetuating stereotypes. The over-representation of certain groups (like young Europeans) and under-representation of others (like older Asians) can reinforce stereotypes and marginalize minority groups, possibly leading to designs that do not reflect the diversity of users.
2. Alienating the global user base. Bias towards young white people in DAs fails to represent the global population's diversity. This exclusion can result in designs that alienate users from different ethnic backgrounds and age groups, thus enhancing, not reducing, the digital divide.
3. Inconsistent user experience. Major demographic coverage differences among different deepfake service providers can lead to inconsistent user experiences. Users might feel represented in one system but excluded in another, which can be confusing and frustrating.
4. Limited design usefulness. Covering an extremely small proportion of possible occupations limits the relevancy and applicability of DAs in various professional contexts, reducing their utility and potential for positive impact in design use cases where understanding a user's professional identity plays a role.

### 5.3. Limitations and Future Research Directions

In terms of future research, the study should be replicated in the future to reassess the ever-changing situation. As new DA service providers emerge, these should be included in the study. However, the effects of the lack of diversity on DA users should be investigated, which is an interesting human-centered AI line of inquiry. In addition, we propose three research directions (RDs) for future research:

*RD01: Increasing the diversity in deepfake datasets.* Investigating methods to create more diverse training datasets for deepfake models can lead, perhaps, to their broader employment. This research could explore strategies to include a broader range of demographic groups, such as older individuals, Asians, and Middle Eastern populations, which would involve collecting and curating more representative data for training. An interesting approach for a more diverse DA population would be to explore novel text-to-image generation (Yauri-Lozano et al., 2024).

*RD02: UX and trust in deepfake services.* Investigating how the lack of diversity in deepfake technology affects UX and trust in information systems that rely on DAs has profound impacts on a range of systems. Research could include user studies to understand how users from different demographic backgrounds perceive and interact with DAs and the role of demographic similarity in this interaction, including DA detection (Cho et al., 2023).

*RD03: Ethical and regulatory frameworks for DA development.* Examining the ethical implications of biased deepfake technology and exploring the development of regulatory frameworks to promote diversity and fairness in DA development would help ensure the equitable development of DA technologies. This research could involve collaboration with policymakers and ethicists to establish guidelines and best practices for service providers.

Addressing these RDs, future research could address the identified disparities in deepfake technology and work toward a more inclusive and equitable future for its use in user-facing systems.

## 6. Conclusion

The demographic attributes observed on DAs do not adequately represent the demographic attributes of the global population. The current state of the diversity of deepfake avatars is biased towards young white people, with a relatively small representation of Asian or Middle Eastern people or older demographics, while also not including many different occupational "skins". The lack of diversity is considered harmful to the current state of deepfakes. Still, considering the fast development of AI technologies, we are hopeful that deepfake avatars will start adopting more globally balanced demographics. Diversity is likely to grow in each facet studied in this research. If the deepfake technology is to expand into wider markets, a demographic deepfake match with the target market is important. The implications of demographic representation in DAs on user engagement and trust warrant further examination. Research has shown that individuals often respond more positively to digital representations, such as DAs, that reflect their own demographic backgrounds. Therefore, understanding how demographic mismatches can impact UX in DAs is essential for enhancing the effectiveness of DAs in various applications.

## Ethical statements guidance

Approval was not needed because of the study type. This article does not contain any studies with human or animal participants. It is based on observational data from a range of computer systems.

## CRediT authorship contribution statement

**Ilkka Kaate:** Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Joni Salminen:** Conceptualization, Writing – original draft, Writing – review & editing, Resources, Supervision, Project administration, Funding acquisition. **Reham Al Tamime:** Conceptualization. **Soon-gyo Jung:** Software, Data curation, Resources. **Bernard J. Jansen:** Supervision, Validation, Writing – review & editing.

## 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.

## Data Availability

The data used in the research during and/or analyzed during the current study are available online: https://osf.io/jwr58/?view_only=c61bf036f83b40b98563ea5e353d6e39 Upon request, additional datasets are available from the corresponding author.

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