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Chapter 37

Datafication in human–machine communication between representation and preferences: An experiment of non-binary gender representation in voice-controlled assistants

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Introduction to datafication in HMC

Datafication is a concept used by Mayer-Schöenberger and Cukier (2013) to illustrate how big data and associated technological manifestations transform humans into data (Bechmann, 2019; Mejias & Couldry, 2019). Within the communication industry datafication is thus the underlying premise of modern Human–Machine Communication (HMC) that mostly rely on massive amount of human data in training, processing and representing machine learning based systems at hand (Bechmann & Bowker, 2019). Datafication is not unproblematic and has given rise to democratic issues most notably *privacy* concerns, *discrimination*, and issues of *representation*.

When more data is available on the individual human being from various sources it becomes increasingly more difficult to manage the self and associated behavior (Bechmann, 2015; Marwick and boyd, 2014) and thus to protect *privacy* for the individual and groups (Franzke et al., 2020). Especially so, as contextual usage is intertwined (Nissenbaum, 2011) and consent most often is provided as either a weak default setting (van Dijck, 2013; Stutzman, Gross, and Acquisti, 2012) or as a check mark in a box where the contract text is seldom read (Bechmann, 2014).

In the same lines *discrimination* has increasingly been a growing concern in datafication. Data does not equally represent all humans in technologies that rely on big data processing (boyd and Crawford, 2012). There has been a long and strong tradition in balancing census data (Anderson, 2015; Desrosières, 2002), and unbalanced big data, however big they are, will also overrepresent some and underrepresent others (Campolo & Crawford, 2020; Crawford & Calo, 2016; DiPrete & Eirich, 2006; Eubanks, 2017; O'Neil, 2016).

As such, data is *representational* biased historically, contextually and culturally, for instance with cases of females identified as housewives (Bolukbasi et al., 2016; Sweeney, 2013). When machine learning systems perform well, they tend to cluster around the mean where such "normality" is represented by individuals and behavior with most data points and by companies training the algorithm. They set the norm and thus the inclusion and exclusion rules for a given system. As Gitelman and colleagues write (Gitelman, 2013) "raw data is an oxymoron," meaning that data will always be subject to selection, (pre)processing, analysis, and reporting no matter how big and "untouched" it is. The system will always be biased against certain “truths” (Henriksen & Bechmann, 2020) over others but these can be accounted for to a larger extent (Bechmann & Bowker, 2019; Henriksen, Enni, & Bechmann, 2021; Kroll, 2020). Another dimension of representational biases is how the system represents the user on the interface. A less prominent dimension of datafication in HMC that distinguishes it from human-human communication is the ability to vary how the system is represented on the user interface and user preferences for such interfaces, potentially varying contextually depending on the task at hand. Due to the relative understudied area outside Human-Computer Interaction, we will investigate this further in this chapter.

In a HMC context, datafication can be defined as the data eco-system that allows the communication between human and machine to take place and this eco-system consists of at least four types of data; training data, interface data, data outcome, and feedback loop data (new training data). Training data is the data that provides the machine/algorithm with experience and memory, interface data is the data (vocal, written, visual) which presents the algorithm to the user, data outcome is the processed communicative response to the user, and feedback loop data is the response from the user that can be fed into the algorithm as new training data and adjusted response. In the following section, we will dig deeper into issues of representation at the interface level and, specifically, the growing interface of voice assistants as a way to address this less researched variance and associated datafication dilemmas of preferences, inclusion, and representation.

Datafication, voice interface representation in HMC, and gender theory

The datafied interface holds great power in deciding who and what norms are represented in the human–machine communication nexus. This especially holds true in voice assistants where only the voice can represent (or not) the user of the system compared to visual interfaces where text, pictures, and layout hold such power. Widely used services from Amazon and Apple and associated voice assistants Alexa and Siri are an integrated part of everyday life and mundane routines that are stipulated by large numbers of users. With reports from Amazon revealing that presumably 500,000 users in 2014 have said “I love you” to Alexa of which half of these have proposed to Alexa (Schweitzer et al., 2019). Despite presumably strong connection to voice assistants, the interface often is representational only of male and female voices (Søndergaard & Hansen, 2018). However, a minority yet growing number of users identify as non-binary and thus have a weak representation when it comes to choosing voices for the assistant (Danielescu, 2020).

To better understand how gender is a vital aspect of a voice-based interface and a marker of representation, or lack thereof, it is important to understand the nature of gender and its interpretation through voice-based cues. Butler (2011) argues for gender as being socially constructed and performed; we are not a specific gender, but we *do* gender. It is through actions that the social is constructed, known as the concept of *Gender Performativity*. This distinction supports the argument that no matter how definitively the biological sex is perceived, social gender is culturally constructed and therefore implies other possibilities. The social gender will therefore occupy a more fluid function that is not locked into the biological gender, which makes it possible to use concepts such as man and masculinity to describe the female voice, and woman and femininity to describe the male voice. The social gender and the biological gender are therefore coherent, as the social gender cannot exist without the biological gender. Discursive practices are automatically embedded in a subject's gender understandings, and “non-binary” and “fluid gender identity” will therefore also appear to be natural, a category covering well above 50 identified gender performances. Non-binary categories help to promote new discourses about gender that are more inclusive and Crawford argues (Crawford, 1995, p. 16) that the widening of the concept of gender therefore also helps to promote the way we talk about our own gender in our everyday life. Historically, and still today, the female and the male are often seen as dichotomous categories. The masculine and the feminine are opposites, each containing its own features (Crawford, 1995), but how does such a voice sound like when gender is performed and not only biological; can we datafy and represent nonbinary gender through a voice?

According to Masahiro Mori (Mori, MacDorman, & Kageki, 2012), our positive emotions for intelligent systems increase when they resemble humans, but as soon as they deviate slightly, they become strangers to us and we feel discomfort. Producing a representation of a non-binary voice must thus be gender neutral (in a binary understanding), as it is not male, nor female without being a stranger. But why even talk about gendered voices? The human brain responds socially to its surroundings. For this reason, we tend to assign technologies human-like characteristics, known as anthropomorphism (Hende & Mugge, 2014; Schweitzer et al., 2019). Humans are attracted to people reminiscent of oneself, as it makes it easier for us to predict behavior and thereby avoid potential danger. We seek to identify others by imitating their personalities, looking for social cues like sound and speech, even when coming from a computer. Speech is a combination of several components such as tension, loudness, breath, vibration, roughness, and pitch, which will make up one's voice (Leeuwen, 1999, p. 140; Mary, 2019, p. 102 ff). Pitch in particular relates to gender and age, and as men and women use their pitch range differently when talking, pitch is often connected to power and status (Karpf, 2006, p. 160; Leeuwen, 1999, p. 134). Therefore, gender and voices cannot stand alone and will automatically be connected. In this sense, gender can be seen as sonic, and sound as the medium in which gender is produced, expressed, and interpreted (Thompson, 2018).

As all humans have a unique combination of the components that make up one's voice, we are extremely fast at distinguishing and identifying others through social and perceptual cues connected to their voice and gender is one of the first attributes the human brain identifies. The human brain has limited processing capabilities and will only be able to assign one gender at any one moment. Therefore, we tend to apply gender stereotypes to voices, even if it is not congruent with our own gender (Nass & Brave, 2005). Despite this, the social-identification processes that voices activate in our brain will bias us either positively or negatively toward gender, leading people to react more positively toward gender that is congruent with our own gender, known as *the gender-schema congruity effect* (Hende & Mugge, 2014). The study found a correlation between positive evaluations of a product and the degree of anthropomorphism, when a gender-oriented promotion of a product and the gender of the participant was congruent. Also, historically females prefer synthesized female voices on a computer, and males prefer male voices, just as male voices evaluated by others male voices are perceived more positively than female voices evaluated by others female voices. In addition, male voices are generally rated more trustworthy than female voices, regardless of the gender of the listener (Nass & Brave, 2005, p. 14 f; Reeves & Nass, 1996, p. 175).

Previous studies have shown that interaction with technology created gender-related social constructions and biases (Carpender, 2019) and that the bias of gender in a voice is based on the perception of what a man or women should sound like is build up over time (Sutton, 2020). To supplement existing research and explore methods to investigate datafication challenges of voice controlled interface representation, we will in the following sections present an experimental case study[1] that explore to what extent female, male, and non-binary users will choose voices for voice-assistants that represent their own gender identity, and if it varies according to the task at hand.

Case study on gender representation in voice-controlled assistants

This case study follows a qualitative approach that emphasize users' experience and conceptualizations of voice assistants based on their own gender identity. We manipulated selected variables and based on the theory presented, female, male and non-binary participants in the experiment will most likely try to categorize all voice assistants by gender (H1) and will

[1] The case study is an extraction and rewriting of the unpublished master thesis *Gender Categorized Voices* (Mortensen & Siegfredsen, 2020) supervised by Bechmann. No funding has been received for this work and there is no conflict of interest to report.

prefer the assistant that is congruent with own gender identity (H2). Furthermore, we know from census data that some employment is gender stereotypic, and thus we believe this might have an effect on gender preferences favoring female voices for female stereotypic tasks and the opposite being true for male voices (H3). The study was conducted as a *quasi-experimental method* design (Field & Hole, 2002) with 12 Danish females, males, and nonbinary users. The first variable was the gender identity of the participants. We tested subjects that identified as female, male and non-binary at the moment of the test (Butler, 2011, p. 44) with four participants in each of the three gender categories. We tested participants in the age group 18–30 who are most active users of smart home products in Denmark.[2] Furthermore, most participants have had experience with voice assistants.[3]

When examining how male, female and gender-neutral voices in a voice-controlled assistant are perceived, we needed a representation of a gender-neutral voice. As we have not come across a functional gender-neutral voice for voice assistants, we produced our own, based on Google Assistant (https://cloud.google.com/text-to-speech). The voice was determined through a qualitative test of seven different variations of female and male voices with manipulated pitch, in which 161 informants were to choose if it sounded more as male or female. The voice we used for this case study was the one where most of the informants did not agree on the gender of the voice. To get results that would correspond with the experience for real voice-controlled assistants, we needed to simulate a true interaction with a speech system. Therefore, we conducted an experiment inspired by the Wizard of Oz simulation (Fraser & Gilbert, 1991, p. 81). In this experiment, we simulated that the participants talked to real voice assistants when, in fact, we played pre-recorded audio files of answers to already set questions. The gender-neutral voice was made by altering with the pitch of the male and female voices Google had. After creating the gender-neutral voice, we created a total of 114 audio files to be included in the experiment, providing a total of 38 audio files for each voice. The answers to the questions are written by us based on the six selected tasks within: 1. economics, 2. craftsmanship, 3. health, 4. family & relationships, 5. movies & TV series, and 6. tourism. The selected tasks were sampled according to gender stereotypic employment statistics:[4] tasks that represent the female gender stereotypes are health and family & relationships, and for the male gender craftsmanship and economics. In addition, we chose to include tasks within travel and movies to represent categories that are not statistically linked to a gender stereotype, but rather interests that can cut across gender identities.

Results on representations and preferences in the case study

Previous research has shown that people will connect voices to a gender-like description (Carpender, 2019; Sutton, 2020). This was also the case in this study, as all participants in the tested groups anthropomorphized the voice assistants from gendered descriptions, even when trying not to (H1). In seven out of twelve instances, participants preferred and evaluated the voice assistants better when the perceived gender of the assistant was congruent with the gender identity of the participant (H2). In almost half of the instances (32 out of 72 cases ~ 44,44%) participants chose a female voice for female stereotyped tasks, male voice for male stereotyped topics, or neutral voice for neutral topics (H3).

Categorization of gender, gender congruity, and preference for assistants

During the experiment, several of the participants expressed a need to categorize the assistants by gender. This was shown in the use of pronouns such as “he” or “she” or through gendered,

[2] www.dst.dk/da/Statistik/nyt/NytHtml?cid=36216

[3] 7 had Siri installed, 1 owned a Google Home, 1 had Google Assistant installed. 7 of the participants actively used one of these voice assistants, 3 had previously used them and 2 did not use them at all.

[4] www.statistikbanken.dk/LIGEAI2

human-like descriptions of the assistants, despite the fact that we throughout the experiment only talked about the assistants as “it.” All participants across the groups described the assistants as “he” or “she” after hearing a voice for the first time. Therefore, we found that the theory of anthropomorphism is also applicable to our experiment. In particular, the need to categorize our gender-neutral assistant resulted in descriptions based on binary gender understandings, and for some also sexual orientation. Here, four participants talked about the neutral assistant from female descriptions, and six from male descriptions. Gendered and sexual descriptions like tomboy, cis male, or lesbian came across. This confirms the existing theory about the need for categorizing voices by gender (H1), even when it does not match our own gender identity (Thompson, 2018; Nass & Brave, 2005, p. 16). Several of the participants also switched between their understanding of the gender, thus always deciding on one gender, no matter what voice was speaking. According to results from existing research, we expected the assistants would be evaluated more positively if the understanding of the gender of our assistants matched the gender identity of our participants (H2). In the experiment, all participants assigned human attributes to the assistants, including gender categorization, even when deliberately trying to avoid categorizing an assistant by gender.

We found a similarity between the participant’s gender identity and the understanding of the assistant's gender as a reason for the preference in seven out of twelve cases. The male assistant was preferred by all male participants, two female participants and one non-binary participant. Common for the reasons for this preference was that the voice sounded more human and personal, calm, and warmer. The male participants evaluated and perceived the assistant better than the female and gender-neutral assistants, and all participants across the groups generally perceived the male assistant as more trustworthy than the other assistants, confirming existing studies. The reason for this was associated with the subject the male assistant assisted in and the voice itself, that for the participants seemed more credible and authoritarian. The female assistant was preferred by one female participant, no male participants and two non-binary participants, one of whom perceived the voice as gender-neutral. The participants who identified as female or non-binary evaluated and perceived the assistant better than the male participants. According to these participants the voice was pleasant, soft, and kind. However, one of the non-binary participants understood the assistant as neutral and without gender with a slight incline to the feminine side. However, the gender-neutral assistant was only preferred by one female participant, no male participants, and one non-binary participant. Common to the preference for the gender-neutral assistant was that the participants found the assistant having more personality. The non-binary participant related to the masculinity of the voice whereas the female participant liked the personality and “quirkiness” of the voice, which was described as a feminine guy.

Preferences in relation to gender stereotypical tasks

In the experiment, we found that the pairing of the female voice with female gendered stereotypical tasks took place 10 times out of a total of 24 possible instances across the groups. Here, the group of women and the group of non-binary participants, chose a female stereotyped tasks four times in total, whereas the group of men selected these tasks two times for the female assistant. Here, both female, male, and non-binary participants associated the female voice to service jobs. Also, the female participants did not choose a male stereotyped task for the female assistant at any time. On the other hand, the male participants chose as many male stereotyped tasks for the female assistant as female stereotyped tasks. The non-binary participants chose a female stereotyped task two times and only one male stereotyped task.

Pairing of the male stereotypical tasks with the male voice occurred 13 times out of a total of 24 possible instances across the groups. Here, the group of women chose to pair a male voice with a male stereotyped task four times, the group of males chose to pair a male voice with a male stereotypical task five times, and the group of non-binary participants chose to pair the male voice with a male stereotypical task two times. In half of the instances, the female participants chose a male stereotyped task for the male assistant. One of the participants also expressed the need to choose male voices for her GPS, as it reminded her of her father guiding her when driving. For the male participants, the male stereotyped tasks were chosen in five out of eight instances. For the non-binary participants only two male stereotyped tasks were chosen; however, a participant wanted to choose a male stereotyped task after hearing the voice. Pairing of neutral gender voice with the neutral tasks occurred nine times out of a total of 24 possible instances across the groups. Here, the group of women chose a neutral task-voice pairing three times, the group of males chose a neutral task-voice pairing four times, and the group of non-binary participants chose a neutral task-voice pairing two times. However, we did not find as strong a similarity between the perceived gender of the assistant and choice of task in as many instances as the female and male assistant. Here, the different perceptions of the gender of the assistant might have caused them to pair with more diverse tasks and the voice itself affected the evaluation and perception of the assistant.

The results show that male stereotyped tasks were chosen in most instances when the voice was male. The female stereotyped topics was more closely related to a job function in the service sector across the groups of participants. This confirms existing knowledge where historically, a representation of an assistant or service person is often shown as female (Søndergaard & Hansen, 2018). In addition, the choice of task was more diverse for the non-binary participants and did not relate to the gender of the assistant in as many instances as for the female and male participants (H3). Stereotypes on the gender-neutral assistant, on the other hand, were more closely linked to sexual orientation.

Strong binary gender categories or uncanny valley effect?

Common to the participants who have used or were using voice assistants prior to the experiment is that the assistant was used for playing music, searching for information, as GPS or for writing a text or making a call. For this reason, most of the participants across the groups perceived the assistants from a servant-function, where the assistants were to help solve a specific task. The male group especially perceived the assistants from this type of relationship with three out of four participants. For others, the assistants were rated less reliable, which was particularly linked to robot-like descriptions and a fear of secretly being intercepted. This we consider as a master-function, where the assistants were perceived as having too much self-control. This was especially shown for the gender-neutral assistant. Again, the theory of uncanny valley supports the idea that the synthesized voice of the gender-neutral assistant might have caused less favorable perceptions and evaluations of the assistant. If the participants cannot identify with the assistant, it will make them less likely to anthropomorphize and prefer the voice according to the gender-schema congruity effect. However, we cannot definitively conclude whether the reason for this is the participants' lack of social identification with the gender-neutral assistant or it is due to the robot-like descriptions and associations of the assistant. However, we are aware that our manipulation with the pitch of this voice may have created a greater degree of unnaturalness in the voice, just as it may have made it harder for the participants to place and thus identify socially with the voice. Common to the three groups was that several participants compared the female assistant with existing voice assistants such as Siri and Alexa. These assistants were described as female, both in choice of gendered pronouns but also by name of the assistant. This existing perception and comparison to voice assistants like Siri and Alexa made several participants across the groups prefer our male assistant. In addition, in several cases during the experiment, comments were made on the content of the conversations that the participants had with the assistants. Here, differences in content, response length, source references and grammar had an influence on the participants' experience with the assistants.

Conclusion

The chapter has outlined how datafication can seen as a data eco-system of at least four types of data: training data, interface data, data outcome, and feedback loop data (new training data) with associated challenges of privacy, discrimination, and representation. The chapter has focused on datafication as representation in voice (interface) and how to study challenges that arise in this context through the use of gender theory. As a norm of a machine is set by the organization and developers that deliver the technology and handel the training data, inclusion and exclusion of human beings are thus datafied into the machine but can always be changed with new data. This is the reason why a system will always be biased against certain representational biases or "truths" (Henriksen & Bechmann, 2020) i.e. exemplified in this chapter by norms of binary gender and thus the downplay of non-binary. The experimental case study of 12 males, females, and non-binary participants presented in the chapter showed how it is difficult to transgress the dominating binary gender voices. For instance, how do we define a non-binary voice without reference to the binary genders and does the different genders prefer their own gender in relation to all tasks, or are tasks binary gender stereotypic? The study showed that participants prefer their own gender identity in almost half of the instances, and that they tend to assign gender to the associated stereotypical tasks in many cases. Furthermore, the study participants reproduced known gendered descriptions of the male, female, and non-binary voices, in general favoring male voices to be more trustworthy. We also found that the majority of participants, especially males, tend to see voice-assistants as servants, and that the gender-neutral voice was less favorable and to some extent caused robot-like descriptions. Still, we cannot confidently say that preference necessarily follows representation of one's own gender. This is an important finding as it supplements existing studies on datafication on the training data level (see e.g. Bechmann & Bowker, 2019) that people tend to be very conservative in their choices and thereby favoring stereotypes and familiar voices even though society and technology companies try to break these in their regulation and construction of systems by making alternatives available.

Underpinning this datafication dilemma in interface data on a theoretical level, the study has shown that it is not a trivial task to represent social gender in voice as we do not have the same mental boxes for what a gender-neutral voice is and how it is distinguished from an uncanny robotic voice. If creating a gender-neutral voice by a manipulated voice as has been the case in this study, it is crucial to identify the *spot between comfort and discomfort*; or to *move the cognitive scheme culturally*. This is a large challenge for HMC datafication that needs further scientific attention in the field. To fully understand the relationship between preferences and representation in datafication, larger experiments need to be conducted where this small study might serve as an illustrative case and as an inspiration for design and hypotheses. Yet, the chapter as a whole and the case study in particular show that user preferences in HMC does not necessarily follow representation and societal needs for inclusion and diversity, one of the great dilemmas to be solved techno-culturally.

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