Chapter 8
Identifying Personality Dimensions for Characters of Digital Agents

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Abstract More and more digital services rely on natural "speech-first" user interfaces. With this trend arriving across industries, character design for digital assistants becomes relevant and along with it arises the fundamental problem of finding suitable personality dimensions. Classic personality models, like the Big Five Inventory or the Myers–Briggs-Type Indicator (MBTI), contain too many dimensions to be practicable foundations for many design use cases. This chapter introduces a method to distill use case-specific personality features from user interactions with broadly diverse characters. In particular, users converse with characters inspired from popular media figures and rate their personalities as well as their user experience and fit to a certain task. As one use case, we demonstrate how fixed parameters and major dimensions for dynamic assistant personalities in an in-car environment can be identified. The method can be used to find out use case-dependent requirements to an assistant personality as well as dynamically customizable character features for personalization purposes.

8.1 Introduction

Current digital assistants can understand natural language and express information through speech synthesis (Porcheron et al. 2018). However, up to now, most assistants lack an interpersonal level of communication which can be helpful to build a relationship with the user. Related research suggests that to become more widely accepted, such systems need to satisfy the expectations users have toward social interaction, like acting proactively and displaying personality (Malle and Thapa Magar 2017; Nass et al. 2005; Schmidt and Braunger 2018). People expect consistent behavior

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they can predict and which fits the environment they experience the assistant (André et al. 1999). Subjective perception of behavior leads to an allotment of personality traits, independent of whether users are interacting with a person or a digital system (Argyle 1988). Hence, assistants should be designed with their application area in mind, as their characters can be perceived differently depending on the context. A risk-taking assistant might be acceptable in a casino, but not in a bank. An overly nice character, in contrast, might be fitting to call center agent but not to a security guard.

Personality is one of the human characteristics we aim to synthesize when we apply the principles of Character Computing. The focus of our work lies in automotive user interfaces, where apart from minimizing driver distraction during manual driving (Maciej and Vollrath 2009; Peissner et al. 2011), researchers are working on the future of interaction in automated vehicles. Natural user interfaces are considered to bridge both of these requirements, as, e.g., speech interfaces also offer a more natural user experience (UX), compared to conventional user interfaces (UI)s in cars (Alvarez et al. 2011), which is of particular interest in the transition toward automated driving (Riener et al. 2017). In this study, we aim to find suitable personality dimensions for an in-car assistant, as our research shows that voice assistants with personality can improve trust and likability in security critical contexts of driving (Braun et al. 2019).

8.2 Background

This work builds upon research on natural language interfaces and the potential benefits of voice assistants with explicitly designed personalities. Psychologists have investigated the perception of behavioral cues as personality markers for decades and in recent years the synthesis of characters for digital agents has been seeing more and more application areas. Intelligent agents with human personalities enable more joyful interaction between man and machine and a communication style which users know from everyday communication (André et al. 1999).

8.2.1 Natural Interaction with Intelligent Agents

Intelligent agents are defined as software which is situated, autonomous, reactive, proactive, flexible, robust, and social (Padgham and Winikoff 2005), while the spatial conjunction and autonomy make such a system intelligent, their core virtue is that they provide natural interaction. An agent with the capability of conversing in natural speech and the knowledge of how to interact socially is easy to use, more efficient, and less error-prone than graphical interfaces (Nafari and Weaver 2013), and can offer accessibility to users with disabilities (Pradhan et al. 2018). On the downside, their human appearance also leads users to expect unlimited versatility and the validity of given information (Bickmore et al. 2018; Luger and Sellen 2016). This problem can be tackled by enhancing digital agents with personalities to limit the expectations users have and possibly guide the formation of a mental model which makes them understand the limits of the system.

8.2.2 In-Car Voice Assistants

The automotive domain is currently experiencing a “speech-first” movement, as voice interaction has been shown to be a valuable alternative input modality in the car (Pfleging et al. 2012; Riener et al. 2017; Roider et al. 2017). Drivers mainly utilize visual and manual cognitive resources for the driving task, without extensively straining vocal and auditory channels (Wierwille 1993). This can be used to optimize voice interfaces for limiting overall cognitive load and limiting negative effects like inattentional blindness (Lavie 2010; Large et al. 2016; Yan et al. 2007). Voice interaction in the car can so unburden the driver from unnecessary workload and responsibilities, and provide space-independent controls to remote user interfaces which are coming to autonomous cars along with bigger screens and free movement within the car.

8.2.3 Personalization of User Interfaces

Today, many interfaces and intelligent assistants incorporate features of personalization. These range from knowing the user’s name to content customizations based on models of needs and behaviors (Kramer et al. 2000; Thakur 2016). Such systems can also act as social characters by proactively pointing out information (Nass et al. 1994; Schmidt and Braunger 2018) or by helping users to accept new technologies, for example, by mimicking their behavior in automated driving (Orth et al. 2017).

One frequently used principle to achieve a bond between user and system is the similarity–attraction hypothesis, which assumes that humans like to interact with others of similar personality (Byrne and Griffitt 1969). We found that a personalized voice assistant character can improve trust and likability toward an in-car agent but should only be acted out in non-safety relevant situations (Braun et al. 2019). Personalization of the assistants character can also help in maintaining attachment to cars when ownership and driving are things of the past (Braun et al. 2018).

8.2.4 Designing Personality for Digital Agents

Humans are quick on first impressions, be it with other people or digital systems (Nass et al. 1995). Immediate assessments of personality help us to decide whether we aim to converse with an opponent and allow us to adjust expectations (Cafaro et al. 2016). Assistants can synchronously benefit from a consistent personality as it helps users to predict behavior (André et al. 1999).

A widely recognized approach for the classification of personalities is the Big Five model by McCrae and Costa, consisting of openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN) (McCrae and Costa 1986). Extraversion is the most prevalent dimension in HCI studies as it has high informative value and is easy to observe (Kammrath et al. 2007). Another model, more frequently used in consultancy and workplace analytics, is the Myers–Briggs-Type indicator (MBTI). It works by building combinations of four dichotomies, resulting in 16 combinations. The MBTI is often criticized by psychologists due to its poor viability and unreliable results over time (Furnham 1996). Argyle advocates a more simple model to describe interpersonal attitudes of humans based on the two dimensions hostile—friendly and submissive—dominant (Argyle 1988).

These personality models can also be used for the design of digital characters, yet we need to consider which personality traits are suitable for the agent's area of application. Digital assistants and users need a shared understanding of acceptable behavior (Jung 2017) and users need to know the limits of the systems which can be communicated implicitly through character traits (Bickmore et al. 2018). We can also build upon the similarity–attraction hypothesis to design more likeable agents (Nass et al. 1995) but have to avoid uncanny experiences (Mori et al. 2012).

In related work, Bickmore and Picard show a relational agent capable of social and emotional interaction, which was evaluated with high ratings for trust and likability (Bickmore 2005). Nass et al. applied a similar concept to a simulated driving context and found increased driving performance and attention if an empathic voice assistant is matched to drivers in a similar state (Nass et al. 2005). We are building on these results of this work by exploring appropriate personality dimensions for automotive voice assistants.

8.2.5 Fictional Characters

Character design has been practised in the entertainment industry long before artificial intelligence made digital agents possible. Writers often base characters around stereotypes, which provide a mold for abilities, motivation, and general behavior of an ideal fictional human (Tillman 2012). Archetype characteristics are usually taken from other works or universal stereotypes. During the evolution of a story, stringent continuity of a character's behavior is important to manifest its personality and make it believable (Kline and Blumberg 1999). What is interesting in this approach is that fictional characters can be well liked although they are "the bad ones" if their personal story makes their behavior understandable (Konijn and Hoorn 2005). We can apply this technique to the synthesis of digital agents as we know their intended application and can thus infer a matching archetype, for example, the bank clerk for a finance assistant or the codriver for an in-car assistant. Communication styles could be adapted from examples of such archetype from popular art like movies and TV shows. In the following sections, we describe this process to investigate viable personality traits for an in-car voice assistant.

8.3 Character Design

The main tasks an in-car assistant needs to fulfill are information retrieval and presentation as well as assistance with controlling in-car functionalities. We analyzed popular characters from TV shows and movies and came up with several implementations of two basic stereotypes. The information provider, who is connected to countless sources and can almost always provide the desired details, can be applied to almost any digital assistant. They feature data accuracy in various styles and are represented by characters like Sheldon Cooper (The Big Bang Theory), Sherlock Holmes (Sherlock), Spock (Star Trek), or Hermione Granger (Harry Potter). The second archetype is the sidekick, who can, in an automotive environment, embody a codriver. Examples from popular media are Ron Weasley (Harry Potter), Baloo (The Jungle Book), Donkey (Shrek), Pinky (Pinky and the Brain), and Bender (Futurama). They support the protagonists in their story lines and have mainly entertaining roles, although they often contribute key story points. Some fictional characters also combine both stereotypes as omniscient sidekicks. Examples include C3P0 (Star Wars), Marvin (The Hitchhiker's Guide to the Galaxy), or HAL 9000 (2001: A Space Odyssey).

We clustered examples with related characteristics into seven groups which we sorted into Argyle's two-dimensional model of attitudes toward others (Argyle 1988). The resulting classification is shown in Fig. 8.1. Additionally, we placed a baseline character into the center of the model, to have a representation of medium manifestations of both dimensions. The resulting characters are defined as follows:

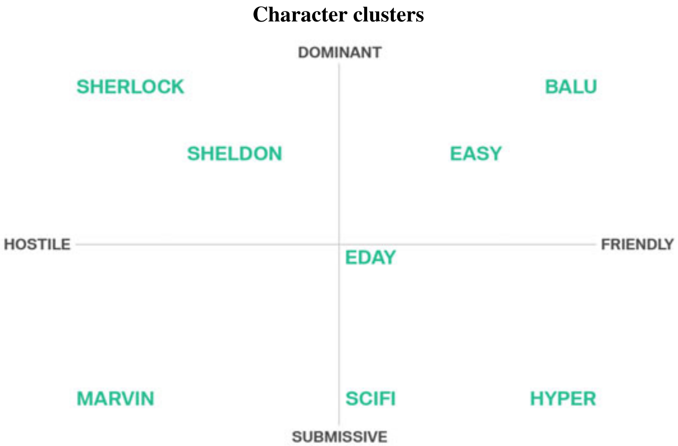

Fig. 8.1 The characters selected for the study placed into the model of attitudes toward others (Argyle 1988)

Eday is the baseline personality which we did not find in fictional characters but composed from medium expressions of the used model.

Balu is a sidekick based on the character from The Jungle Book. He is very friendly and dominant in a way as he can convince others and does not take no for an answer.

Easy is modeled after easygoing sidekick characters like Ron Weasley. He is also rather dominant and friendly but less extreme than Balu.

Hyper is a childlike character inspired by Donkey from Shrek and Vanellope from Wreck-it Ralph, who is rather servile but also overpoweringly affectionate.

Sheldon is an information provider with medium dominance and hostility who can come off as annoying or provocative due to his somewhat arrogant attitude.

Sherlock knows everything better and does not accept different opinions. He feels superior to anybody else and gladly shows this in his behavior.

SciFi is a combination of sidekick and information provider based on Spock and HAL 9000. He is emotionless, submissive, and only reports important facts.

Marvin is the depressed brother of SciFi. He submits to his master but also questions all tasks as for him life is meaningless.

8.4 Use Case: In-Car Voice Assistants

In the following, we demonstrate how the previously introduced method can be applied in the context of an in-car voice assistant. In particular, we let participants experience the above-presented characters in six in-car use cases. The voice samples were recorded by a voice actor and played back while users took part in a passive driving simulation. Although the stereotypes used for the characters are taken from popular media, we put effort into the recording work, so the original characters cannot easily be recognized. The goal of this case study was to identify desired as well as unfeasible personality traits.

8.4.1 Design

We designed six scenarios: three related to driving and three related to entertainment. Each scenario contained a specific task, such as asking the assistant for the nearest gas station. Participants could engage in a dialogue with each of the eight voice assistant characters. The assistants' responses were pre-recorded and reflected the respective placement within the model. During the study, participants experienced the personalities while watching a recorded driving situation on a screen in front of them. All subjects conversed with all eight personalities in randomized order.

Immediately after experiencing each digital assistant, participants filled out a questionnaire consisting of 7-point Likert scales regarding trust (single item), usefulness and satisfaction (Acceptance Scale, Van der Laan et al. 1997), their emotional experience (meCue module III, Minge et al. 2016), and a semantic differential scale with 13 dimensions about the perceived personality. In the end, they answered a semi-structured interview about their preferred and least liked characters.

8.4.2 Participants

We recruited 19 participants from inside a company, consisting of 7 men and 12 women. Age distribution ranged from 19 to 53 years ($M = 35$, $SD = 11$). Participants had little to no experience in voice interaction or personalization.

8.4.3 Procedure

Participants were invited to our lab and experienced all six scenarios with each voice assistant in randomized order (total of 48 interactions). The use cases consisted of (1) onboarding and destination input, (2) a suggestion to listen to music, (3) proactive information on the route, (4) a takeover command switching to autonomous driving mode, (5) a notification of low fuel level and ensuing query for the next gas station, (6) and a traffic jam warning and rerouting. After each assistant, we had participants fill in abovementioned questionnaires. At the end, we conducted a semi-structured interview on their subjective perception of the experienced personalities.

8.4.4 Results

Characters were assessed using a combination of predefined questionnaires as well as feedback from a semi-structured interview. Significant findings are reported when a t-test for direct comparisons showed values of $p < 0.05$.

8.4.4.1 Likability and Trust

Most test persons perceive Balu and Eday as the most likable personalities (Fig. 8.2). They have in common that they are both very friendly and authentic. SciFi was also rated rather positively, while the characters Sherlock and Marvin were liked the least.

When it comes to trust, participants rated the characters SciFi, Balu, and Eday as significantly more trustworthy than all others. We can see a slight discrepancy between likability and trustworthiness as SciFi is trusted more but liked less than Balu

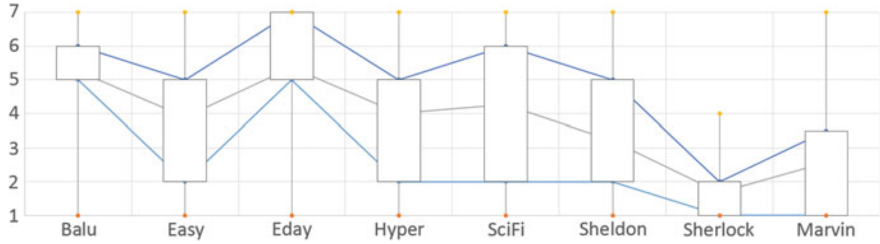

Fig. 8.2 Likability ratings for the experienced characters. Balu and Eday are rated significantly more likable than all others, Sherlock and Marvin were liked the least (t-test)

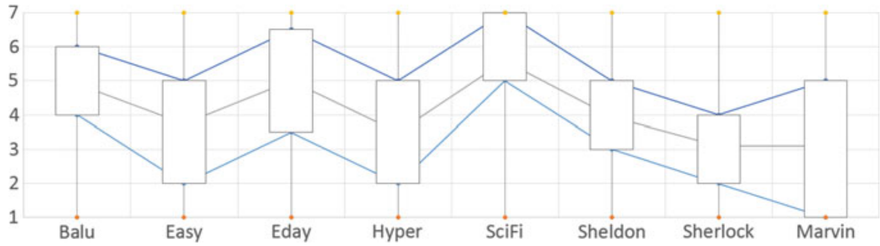

Fig. 8.3 The characters Balu, Eday, and SciFi are rated significantly more trustworthy than all others, Sherlock and Marvin conversely are trusted the least

and Eday (compare Fig. 8.3). It seems the emotionless nature of the character supports trustful interaction. As with likability, Sherlock and Marvin are rated significantly worse than all other characters.

8.4.4.2 Usefulness and Satisfaction

The assessment of usefulness and acceptance provides a similar image as trust and likability: Balu and Eday are rated best, SciFi is also perceived as useful, and Sherlock and Marvin are seen as very unsatisfying (see Fig. 8.4).

8.4.4.3 Emotional Experience

The evaluation of the meCue questionnaire shows that Balu and Eday triggered the most positive experiences (see Fig. 8.5). Sherlock and Marvin are again rated significantly worse than all others. What sticks out in this measure is that the character SciFi is not connected to positive feelings, although it was assessed positively regarding usefulness and trust.

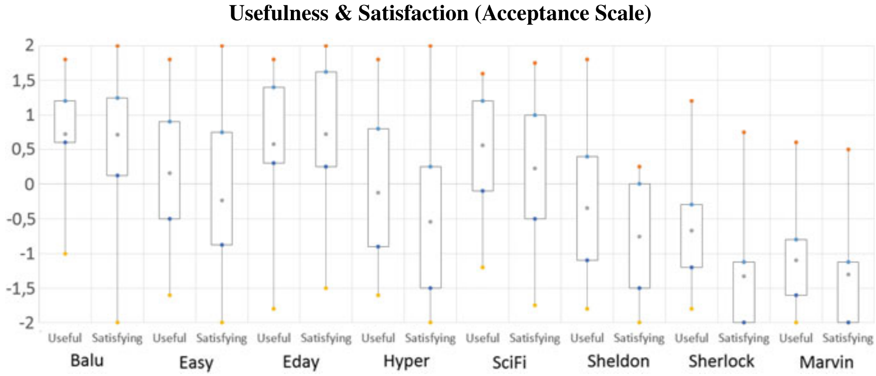

Fig. 8.4 Acceptance scale ratings range from −2 (not useful/not satisfying) to 2 (useful/satisfying). Balu and Eday score best while Sherlock and Marvin are rated poorly

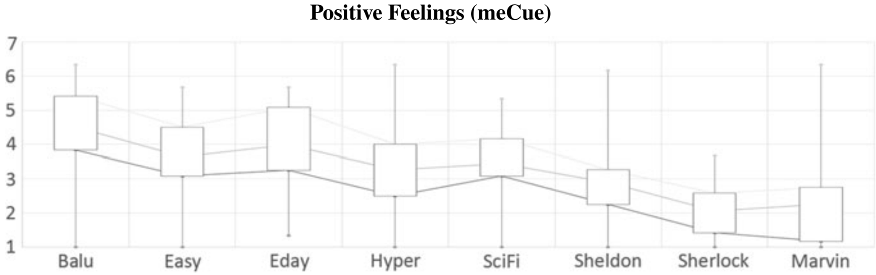

Fig. 8.5 Results of the meCue module III (positive feelings). Values range from 1 (no positive feelings) to 7 (very positive feelings)

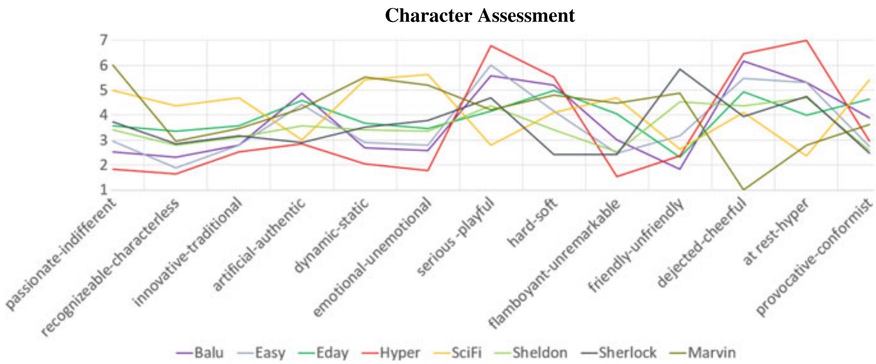

Fig. 8.6 Average semantic differential scale ratings for the characters presented in the study

8.4.4.4 Character Assessment

Participants rated the experienced characters on 13 semantic differential scales meant to closer describe the perceived personality (see Fig. 8.6). Subjects rated Balu as most authentic and rather cheerful. Easy mostly ranges in average values, except for its higher cheerfulness. The character Hyper was rated the most extreme. It is perceived as very passionate, emotional, playful, and generally outgoing. Sheldon was perceived as very provocative, relatively conspicuous, and somewhat unfriendly, only Sherlock was rated as even more unfriendly, provocative, and hard. SciFi is seen as very serious, professional, but also character and emotionless, and conformist. Finally, Marvin seems highly dejected and indifferent.

8.4.4.5 Subjective Feedback

Answers from the final interview can be clustered into seven main reasons why characters were liked or disliked. We identified several aspects which are to be avoided when designing in-car assistants. Some were desired by most users, whereas on others the feedback was divided.

Recognition. Several participants said that certain characters reminded them of people they know personally, which had a positive influence on their evaluation. One said, such an assistant would be "like my friend being with me in the car" and that they "would just trust her". This was also the case for the only participants who rated Marvin positively. They recognized the assistant's behavior as similar to the movie character and found his depressed personality funny instead of disheartening. Users also remarked that famous characters would be a nice option—similar to when GPS systems first came to the consumer market.

Humor. Unsurprisingly, humor is a topic on which opinions tend to differ. Some participants, for example, found Marvin's hopelessness and Sherlock's arrogance amusing, and others untenable. Easy was taunted as being sexist for whistling after another car by one subject, while others found it hilarious.

Intelligence. Another point where different opinions exist is the intelligence of the digital assistant. On one hand, participants state that the digital assistant should act just as intelligent as it can truthfully be. On the other hand, subjects also said their assistant should not be able to outsmart them. One participant found fault that an intelligent system would need help with refueling.

Number of Words. Most participants criticized the characters for talking too much, although many found the interactions entertaining. In a real driving context, assistant would need to adapt their output quantity to the driving situation and the accompanying workload.

Relational Level. Feedback regarding the relationship between user and assistant was highly heterogeneous. Some participants felt that certain characters were too close to them, which was, for example, apparent in the usage of the word "we".

Others welcomed the personal connection and stated that they wished for the assistant to become like a real friend.

Balance of Power. Assistants with an arrogant stance (Sheldon, Sherlock) were throughout rated badly. However, there was varying feedback, stating assistants should either be at eye level with the user or take a rather subordinate attitude.

Professionalism. Subjects highly emphasized that seriousness and professionalism are very important for an in-car assistant. One group argued that a too serious personality would be boring to interact with, while others said the most important part is service orientation and thus correct information delivery.

8.5 Summary and Discussion

Results from the meCue and acceptance scale questionnaires and personal interviews identify unfriendly behavior and excessive talking as unacceptable traits for an in-car assistant. Assistants with an open and friendly attitude were liked by most participants. The data shows a dissent on the desired levels of distance between assistant and user, the assistant's professionalism (i.e., how respectful it behaves toward the user), and the balance of power within the conversation. Furthermore, we observed that some users prefer hedonic qualities in voice assistants, while others attach value to pragmatic service orientation.

From these findings, we derive fixed behavioral cues for an in-car voice assistant: it should act naturally and friendly, talk in minimum appropriate detail, and adapt to the user regarding its humor, professionalism, and social relation. We can imagine an adaptive assistant personality to start with a medium of expressiveness like we designed for Eday, which gradually takes over traits from Balu to cater to hedonic experiences or from SciFi to appear more subordinate.

Even though this chapter focused on in-car voice assistants, the methodology can well be applied to other use cases. It is important to note that while some traits of an assistant may be of equal importance in these use cases, others may be more or less important. Two fundamental traits that we expect to be prevalent in many other

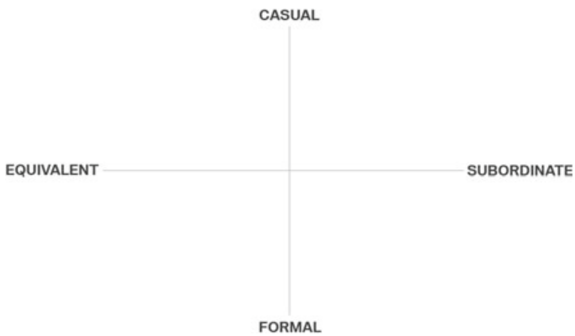

Fig. 8.7 Apart from the identified dos and don'ts for in-car assistant personalities, the feedback showed two dimensions with varying user demands. These can be used to adapt the assistant's character to the user

cases as well are illustrated in the two-dimensional model in Fig. 8.7. Here, one axis depicts the balance of power and social relationship (equivalent–subordinate) and one axis depicts the conversational professionalism (casual–formal). The subjective feedback from our participants hints at some characteristics that need to be considered in different use cases. For example, the number of word is of particular importance in certain driving situations. This may be different in less safety–critical settings. The same is true for professionalism, whereas when traveling with a customer or colleague in the car this might be important, people might prefer less serious assistants in their homes.

8.6 Conclusion

We present an approach to identify relevant personality dimensions for digital assistants in distinct environments. Our example application suggests the automotive context as viable environment which comes with limitations regarding available modalities and the safety–critical aspect of driving. These limitations are explored in a user study with 19 participants, who experience eight assistant characters developed from stereotypes in popular media. As a result, we propose a model with fixed personality traits which were accepted by the majority of users and introduce a two-dimensional model in which characters can be adjusted to fit different types of users. This concept is evaluated in research on personalized voice interaction in the car, which we performed as follow-up to this work (Braun et al. 2019).

Future work could apply this technique to other domains with limiting factors for interaction, such as social robotics, augmented reality, or professional training, and extend the scope to other characteristics such as appearance, behavioral cues like posture and gestures, or how they process and express affect.

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