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**The Influence of Individual Consumer Characteristics
on the Acceptance of Digital Assistants:
A Grocery Shopping Examination**

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Abstract:

The ever-faster development of the digital environment is also changing our daily lives. One of these changes is that people are increasingly adopting digital companions to support and optimize their daily activities. However, since users are fundamentally diverse and perceive and use digital assistants in a variety of ways, a detailed examination of the acceptance of these assistants is necessary. Based on the conceptual framework of the Technology Acceptance Model (TAM), this thesis answers the research question of how individual characteristics influence the acceptance of digital assistants. Previous research has already examined the effects of various characteristics on the acceptance of new technologies, but has been limited to a small number of attributes. Additionally, the influence of characteristics has not yet been studied in the context of digital assistants. By conducting exploratory research, this work investigates this aspect on a wide scale. First, an extensive literature review was carried out to identify relevant characteristics, which were then used to extend the TAM model. In addition, a video was created introducing the different features of a fictitious grocery shopping digital assistant, called 'Wink'. On this basis, a survey was then conducted with 120 respondents. It was found that none of the characteristics had a significant impact on the acceptance of the digital assistant; however, perceived usefulness proved and emerged as the strongest predictor. Further analysis subsequently showed that social influence and attitude towards digital assistants had a consistent significant indirect effect on the intention to adopt the grocery shopping digital assistant. This study contributes to the literature on future research on the technology acceptance model and provides managers with a guide to enhance the performance of such technologies and to understand in more detail the adoption and user behavior.

Keywords: *Technology Acceptance Model (TAM); Digital assistants; Adopter behavior; Individual characteristics; Perceived ease of use; Perceived usefulness; Exploratory research*

JEL - Codes: *O31; O21; C83*

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1 Introduction

In recent years, digital transformation and new technologies have disruptively changed various areas of everyday life. Furthermore, since the beginning of the COVID-19 pandemic, different entities had to adapt and change formal processes in order to deal with the new situation in the best possible way, resulting in an increase in emerging digital technologies in organizations (Vargo, Zhu, Benwell, & Yan, 2021). But even before the pandemic, technologies such as artificial intelligence and machine learning had become established in various areas of companies (Marr, 2019).

With the rise of new technologies, the interaction between customers and companies also changed. Whereas in the past, every possible contact with the customer was acknowledged and handled individually, today it is new technologies like chatbots or comparable digital assistants that support and advise customers in their concerns (Blut, Wang, Wunderlich, & Brock, 2021; Kushwaha, Kumar, & Kar, 2021).

But there is also a clear movement on the part of consumers towards the support of everyday tasks by digital assistants. According to Tankovska (2020), the number of devices being able to operate virtual assistants will increase to eight billion by 2023. Especially on the micro level with the regard to individual customer experience, service robots (e.g., chatbots, virtual assistants, and AI-based agents like Amazon's Alexa¹ or Apple's Siri²) will have a significant impact in the future (Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2020; Miklosik, Evans, & Qureshi, 2021; Wirtz et al., 2018).

¹ <https://developer.amazon.com/alexa>

² <https://www.apple.com/siri/>

In this work, digital assistants are defined as personal digital assistants (PDA) or intelligent personal assistants (IPA), which are system-based autonomous interfaces that act intelligently at a given time and in a given activity context by using natural language user interfaces (NLUI) to provide information and deliver service through conversation with consumers allowing for human-computer interaction (Balakrishnan & Dwivedi, 2021; de Barcelos Silva et al., 2020; Milhorat et al., 2014; Moussawi, Koufaris, & Benbunan-Fich, 2021; Wirtz et al., 2018).

Previous literature has already explored and analyzed the importance of customer satisfaction and expectation, continuance intention, purchase behavior, and general acceptance of service robots (Ashfaq, Yun, Yu, & Loureiro, 2020; Constantinides, 2004; Fernandes & Oliveira, 2021; Melián-González, Gutiérrez-Taño, & Bulchand-Gidumal, 2021; Ting Yan Chan & Hong Leung, 2021). Additionally, findings showed effects of consumer characteristics on consumer behavior (Cheung, Zhu, Kwong, Chan, & Limayem, 2003; Constantinides, 2004; Mittal & Kamakura, 2001). Although the studies fulfilled their purpose and expanded already existing models for the investigation of technology acceptance (e.g. technology acceptance model and unified theory of acceptance and use of technology) (Jiang, 2009; Lee, Rhee, & Dunham, 2009; Mittal & Kamakura, 2001; Yang, 2005), these human attributes have not yet been related to the specific technology of digital assistants in a wide range.

In current research on the topic of customer service, optimization of the customer experience, and the brand-customer relationship, there is an increasing need for optimization of artificial intelligent services as they still fail to meet customers' needs (Adam, Wessel, & Benlian, 2021). Especially in the section of recommender systems, there is a high demand for research regarding implications for the design and function of future personal digital assistants to increase the trust in them (Benbasat & Wang, 2005) and to optimize purchase decisions in the long run (van der Heijden, Kotsis, & Kronsteiner, 2005).

Overall, there is interest in observing the influence of individual attributes and how they affect the use and adaptation of new digital assistants. An additional examination of different types of adopters can also be determined from the observation. Since user groups and user motivations drastically change on a regular basis, literature needs continuously to be updated. Expanding research in this area will optimize future digital assistant development processes and make the usage of such technologies more convenient for customers.

To investigate the impact of individual characteristics in relation to the adoption of digital assistants and different types of adopters, the following research question is answered:

RQ: *How do individual characteristics influence the acceptance of digital assistants?*

On this basis, the research question is answered by referring to relevant individual characteristics and describing the extent to which they may affect the perceived usefulness (PE) and perceived ease of use (PEOU) of a new technology. These two variables listed are retrieved from the technology acceptance model by Davis (1989). Second, an empirical investigation is conducted to determine the extent to which the researched characteristics influence the actual adoption of a digital assistant. To carry out this analysis, the empirical setting of a supermarket is examined, and an exploratory approach is applied to observe the significance of the characteristics under scrutiny. In order to be able to work out generally valid results, the use of the digital assistant presented in this work will focus on a supermarket setting as an application area since it addresses several age and adopter groups. Furthermore, with regard to current innovations and new developments such as Amazon Go³, this work is intended to address a wide target group of store owners, developers, and entrepreneurs and present an easy-to-

³ <https://www.amazon.com/b?ie=UTF8&node=16008589011>

implement technology to maintain and increase the demand for future supermarket environments.

Since not all characteristics are necessarily relevant for a supermarket assistant, they were narrowed down to the only relevant ones. The breakdown was carried out by merging strongly correlated and/or omitting insignificant attributes. After the examination of the correlations between the individual characteristics and their respective influence on the adoption behavior, conclusions are drawn on theoretical and practical recommendations for action at both the research and the managerial levels. By answering this research question, this work fills the gap in the consideration of individual characteristics in the general acceptance of new technologies and which characteristics actually have a significant impact on the adoption of future digital assistants.

With regard to the societal relevance of this work, the results provide information on the extent to how a digital assistant can be successfully integrated and accepted, particularly in a public environment in the form of a supermarket that is accessible to everyone. The results of the work are intended to show the degree to which companies need to work more intensively on digital assistant solutions in order to increase people's trustworthiness toward these units. Since the topic of trust in relation to new technologies is explicitly mentioned in several examinations in the literature and attention is drawn to its importance, this work is intended to make a valuable contribution to observing and defining the behavior of users more closely, in order to overcome the resistance of new technology adaption in the future (Benbasat & Wang, 2005; Følstad et al., 2021; Gursoy, Chi, Lu, & Nunkoo, 2019; Moussawi et al., 2021; Zierau, Engel, Söllner, & Leimeister, 2020). Ultimately, this work is intended to contribute to a clearer and more detailed understanding of the user behavior of the average individual. In this way, more conclusions can be drawn about what users really look for in digital assistants and which personal attributes will have less influence on the acceptance of future innovations.

With regard to scientific relevance, this work contributes to the literature by providing insight into the more detailed use of the technology acceptance model. Furthermore, this work intends to draw the attention of later research not only to the relationship of the external variables with the internal variables, but also to examine the relationships of the external variables with each other, as is already done with the internal variables in the TAM between PEOU and PU.

This work goes in line with past suggestions for future research regarding the role of individual characteristics in conceptual frameworks for future service robots introduced by Wirtz et al. (2018) and Følstad et al. (2021). A literature review of previous information systems theories showed that the choice of the TAM as a model for analyzing the relationship between the respective individual characteristics and the adoption of digital assistants proved useful due to its simplicity and density of understanding. Appendix I.A 3 provides an overview of the nine relevant individual characteristics considered and the two mediators perceived usefulness and perceived ease of use including their respective questionnaire items.

A survey of the associated characteristics was conducted using items of the previously researched questionnaires from the literature. To provide participants with a general impression of what is meant by a digital assistant for grocery shopping in this thesis, a concept video was embedded in the survey showing an example of a fictional assistant called ‘Wink’ and what functions it would provide. After gathering the necessary data, a concluding analysis of the significant effects of the respective attributes on PU, PEOU, and the dependent variable attitude towards ‘Wink’ (ATW) was carried out. Further, insights into the results of the analysis are presented, and the resulting theoretical and practical implications for prospective improvements of digital assistants are presented. Last but not least, limitations to consider are mentioned, and suggestions for further research in the scope of digital assistants are provided.

2 Literature Review and Theoretical Framework

In the following chapter, the technology acceptance model by Davis (1989) is introduced as the main theoretical concept and an overview of potentially relevant individual characteristics is provided. Furthermore, the individual characteristics that are ultimately included in the empirical analysis are explained, and their corresponding questionnaire items are presented.

2.1 Technology Acceptance Model

To measure the acceptance of the digital assistant presented in this work, the technology acceptance model (TAM) by Davis (1989) was applied. Although other theoretical models for measuring the acceptance and use of new technologies exist, such as the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003) and the service robot acceptance model (sRAM) by Wirtz et al. (2018), the TAM model has become widely accepted in the literature due to its simplicity and straightforward application (Chacko Punnoose, 2012). In the following sections, the major components and application of the TAM will be described.

The general objective of TAM is to investigate of the influence of user beliefs and attitudes towards new information and communication technologies on the acceptance and rejection of these technologies (Yang, 2005). To measure the prediction of usage, two key theoretical constructs are investigated, namely perceived usefulness (PU) and perceived ease of use (PEOU). The perceived usefulness variable explains the tendency of people to use or not use a particular system to optimize the performance of a certain job. Perceived ease of use describes to what extent a particular system is considered easy to apply and handle without effort (Davis, 1989). In the literature these constructs are found regularly, for instance, in the investigation of new technologies in healthcare (Kuo et al., 2009; Park & Chen, 2007), tourism

(Tavitiyaman, Zhang, & Tsang, 2020), and organizational decision making (Cao, Duan, Edwards, & Dwivedi, 2021). Based on the theory of reasoned action by Fishbein & Ajzen (1977), which explains behavior from a psychological perspective, the dependent variable behavioral intention (BI) is explained by PU and PEOU. Due to its validity and robustness, the TAM Model is still used as a common method to assess the acceptance of new technologies (Djamasbi, Strong, & Dishaw, 2010; King & He, 2006; Yang, 2005). In comparison to the other previously mentioned models for the measurement of the acceptance of technology, the TAM model is the most simplified one.

The sRAM model focuses on the importance of characteristics from the service bots' point of view. It builds on the TAM model and expands it by functional elements such as PU, PEOU, subjective social norms (already known from TAM), social-emotional elements such as perceived humanness (also called anthropomorphism), and relational elements such as trust. These factors combined increase the probability of customers acceptance of service robots (V. N. Lu et al., 2020). As this work focuses on an easy-to-implement and easy-to-use digital assistant in a supermarket, the applied model for measuring acceptance should be both easy to understand and also create a basic picture of how an average person can adapt and use the mentioned assistant. For this reason, the TAM model is applied in the course of this work.

2.2 Technology Adopter Characteristics

After conducting a literature review according to the literature search process introduced by Brocke et al. (2009) (described in more detail in Appendix I.A 1), the following individual characteristics were found and assessed as relevant. Additionally, related characteristics are merged and logically linked based on findings in the literature to refine the number of characteristics considered for the survey to a more application-friendly set.

2.2.1 Attitude Towards Change and Individual Innovativeness

Attitude towards change can be described as an individual's intention and behavioral tendency towards the need for change and whether the organizational capacities are available to make that change successful (Lee et al., 2009). According to Presenter et al. (1989), an employee's attitude is not a sufficient predictor of behavior, as the general attitude towards change can be positive, while a specific change can have the opposite effect. This statement can also be assigned to consumers. To mitigate this problem, it is recommended to merge this characteristic with a strongly correlated characteristic.

A study by Nov et al. (2008) examined the relationship between personal innovativeness and openness as a determinant of personal innovativeness. The findings confirmed a positive relationship between these two variables. Individual innovativeness can be described as a persisting characteristic that enables a differentiation of one individual from another. Furthermore, it refers to the extent to which a person is disposed to try out newly introduced information systems (Kim, Mirusmonov, & Lee, 2010; J. Lu, 2014; Yang, 2005; Yi, Fiedler, & Park, 2006). Studies verified the positive effect of personal innovativeness on adopters' perceived ease of use and perceived usefulness (Kim et al., 2010).

2.2.2 Social Influence

Social influence describes the extent to which a consumer feels that important people (e.g., family and friends) believe he or she should use a particular technology (Venkatesh, Thong, & Xu, 2012). Davis et al. (1989) argued that it is necessary to take the construct of subjective norm into account, as it indicates social influence. They observed that it is hard to distinguish whether the usage of new technology is reasoned by external persons (e.g., recommenders) or driven by their own motivation. Therefore, it is inevitable to include social influence as a characteristic in the further study as it influences the behavioral intention of a

new digital assistant (Malhotra & Galletta, 1999). TAM2, the extension of the original TAM verifies the significant effect of subjective norm on PEOU and behavioral intention to use (Venkatesh & Davis, 2000). A meta-analysis by Schepers et al. (2007) resulted in a similar conclusion, stating that the influence of subjective norm on PU and behavioral intention to use is significant. These findings suggest that an analysis of this variable is certainly recommended.

2.2.3 Past Adoption Behavior

This variable refers, in general, to the adoption of new technologies in the past and measures the degree of previous adoption intention. According to empirical data by Yang (2005) is this variable strongly connected to consumer innovativeness as the latter predicts the general innovation adoption behavior. If a person had a high degree of personal innovativeness, then it was most likely also the case that new technologies were more likely to be adopted in the past. But as attitudes and behavior change over time, it is still necessary to examine this variable separately and include it in the analysis.

2.2.4 Attitude Towards Digital Assistants

Since this variable measures the general attitude towards digital assistants, and accordingly has a high predictive power as to whether the fictional assistant presented in this paper would be accepted and regarded, it is inevitable to include this variable in the empirical analysis process (Balakrishnan & Dwivedi, 2021).

2.2.5 Sociodemographic Variables: Age, Gender, Educational Background, Nationality

Since every individual is unique, has special characteristics and sociodemographic variables have already been introduced in the literature as antecedents about users, they are also used for basic categorization in this study (Blut et al., 2021). Venkatesh et al. (2000) investigated gender differences in the PU and PEOU and found evidence that men value PU

higher than women. On the other hand, PEOU is more detected by women than by men. They argue that men still represent the majority of potential user groups. But as the number of female users increases, managers need to rethink the implementation process of new technologies. In the future new technology needs to consider next to the obvious service-oriented features also social features and keep the axiom 'know the user' in mind. Second, the educational background can also be used to make statements about the degree of innovativeness of a person or the speed with which he or she adopts new technologies. Third, nationality is a significant indicator of the potential adoption of new technologies. Although smart devices are part of everyday life in Asian countries such as China and Japan, and the use of personal data is not perceived as repulsive, the situation is different in western countries such as Germany, where legal regulations also protect against the misuse of personal data. Finally, different age groups differ in the way they perceive and accept new technologies.

2.2.6 Trust

As explained initially in Chapter 1, trust plays an essential role in the assessment and perception of new technologies and the associated user behavior. Pavlou (2003) argued that trust has always been significantly influencing consumer behavior and that the lack of trust leads to less engagement from the adopter side, especially in uncertain environments. On the basis of this, a connection can be drawn to the new digital space in which users must come to terms with a new form of technology. According to Reichheld & Schefer (2000), trust has always been a significant part of customer loyalty and can similar to Pavlou's argumentation also be transferred to environments that come with a certain risk and uncertainty.

Based on the background of uncertainty, potential risks that may occur must also be addressed. These include, above all, privacy issues. Rajak et al. (2021) argue that the adoption of information technologies is influenced by the risk of performance and privacy. They further

argue that increased perceived trust in the products and services is used to circumvent or mitigate these associated privacy concerns. Liu et al. (2022) likewise mention that privacy plays a key role in the acceptance of new technologies and that users show lower perceived insecurity and risk awareness as trust increases in the digital services that are being provided. Given that the constructs of trust and perceived risk are quite interrelated, and both address positive and negative attitudes towards the acceptance of new technologies, it was decided to merge the two constructs into the high-level construct trust.

Gefen et al. (2003) refer further to one of the several ascendants of trust, namely cognition-based trust which is formed via categorization processes where an individual assesses more trustworthiness based on second-hand information. In essence, it is understood in the same way as the subjective norm/social influence, that potential new users rely on the opinions and experiences of the people around them. This in turn implies the importance of an increased past adoption behavior of the individuals recommending new technologies. Considering the fact that trust is linked to various other attributes, it was decided to include this aspect in the further analysis and to investigate the above-mentioned links.

2.2.7 Excluded Variables

In addition to the characteristics mentioned above, several other characteristics will not be examined in this thesis. This decision is based on the stability factor, which must be present to guarantee optimal advisory, especially on a practical level. Stability means that the observed characteristics are stable over time and should therefore hardly or not change at all. In the following, characteristics are listed which are relevant based on the literature but cannot be implemented in the user and development implications.

2.2.7.1 Job Stress

Job stress describes all symptoms that evolve from experiences made during daily life in the workplace. In addition, this leads to an increased sense of aversion to new scenarios, in this case a new technology, as it disrupts the routine in a well-known environment. (Lee et al., 2009; Reeder, Schrama, & Dirken, 1973). As Lee et al. (2009) found mixed results regarding the effect of job stress on perceived usefulness (contrary to the negative effect assumed at the beginning of their study) and perceived ease of use (confirmed negative effect assumed at the beginning of their study) and further indicates that job stress has only very rarely been investigated in connection with technology acceptance, it can be assumed that this variable is irrelevant. Further research up to 2022 also showed no new results on this relationship. In addition, it needs to be mentioned that stress is also strongly time-dependent and could distort the results.

2.2.7.2 Mood

Consistent with the stress mentioned above and its factors, this variable refers to the general emotion of positive and negative mood. Djamasbi et al. (2010) describe the positive effect of positive mood by mentioning the increased organization of thoughts and, therefore, a

more precise and well-connected cognitive system, which deals more easily with complex tasks. Venkatesh et al. (1999) showed that positive and negative mood can influence the attitude towards the usage of new technologies. However, since these two types of emotions influence the rest of the variables already mentioned and are highly dependent on the events that could take place to the participant before the survey, there is a possibility that this could influence the results. Therefore, it was decided to omit this variable from future analysis.

2.2.7.3 Perceived Anthropomorphism

Perceived anthropomorphism describes the perception of human-like characteristics in a nonhuman object or agent (Balakrishnan & Dwivedi, 2021). A study conducted by Gursoy et al. (2019) showed that anthropomorphism is negatively related to the perceived ease of use as it increases the perceived effort to use new technology. The human likeness of a new technology mediates the refusal of an ai-based agent due to its humanlike features, which gives the impression that more work is required to communicate with the digital assistant. However, since this variable is subject to strong fluctuations and people might in the future perceive anthropomorphism positively instead of negatively, the accompanying development and marketing processes are also difficult to control. Therefore, it was decided to exclude this variable from the empirical analysis.

After assessing the relevance of the different characteristics, the following characteristics now emerged as significant and applicable in the further empirical analysis: Individual innovativeness, social influence, past adoption behavior, attitude towards digital assistants, trust, educational background, gender, age, and nationality. The conceptual model in Appendix I.A 2 shows the relationships of the different external and internal variables and the included mediators PEOU and PU.

3 Methodology

This research used an inductive approach by applying a sample survey methodology to test the significance of the previously mentioned individual characteristics which were examined. Since digital assistants are subject to strong variance and can also differ significantly depending on the area of application, exploratory research was suitable. The goal was not to find a final result that could be applied to any new assistant technology, but rather to narrow down the research in this field. As mentioned in the literature review (Chapter 2), one of the goals of this thesis was to include new and not yet in the domain of digital assistants considered characteristics in the technology acceptance model to explore the acceptance behavior of future users of digital assistants and additionally examine a new application environment. In order to achieve this, a survey was conducted in which both the specific impressions of a digital assistant for grocery shopping and the general attitude towards digital assistants were addressed.

A theoretically grounded questionnaire was conducted using items provided by the literature to ensure unbiased results. The survey included a self-created short video that demonstrated different features of the digital assistant 'Wink' and how it can be used in the supermarket environment. A full list of all questionnaire items is provided in Appendix I.A 3. In the following chapters, the data collection process and the conducted survey elements are explained in more detail.

3.1 Data Collection and Description

3.1.1 Participants

The participants of the survey were a random selection. This ensured that a diversified and generally valid picture of society was combined into one data set. To ensure that the results of the subsequent analysis were as accurate as possible and do not deviate significantly, a minimum of 150 data points was set as the target. In addition, sociodemographic attributes of age, gender, and nationality were gathered. Since the supermarket environment is common ground and everyone has the potential option to use the digital assistant, it offered the advantage that respondents were not restricted to specific selection criteria as their properties, such as their area of residence or their income, to participate in the study.

3.1.2 Materials

The survey was created using the online survey tool *Qualtrics*. The access through Utrecht University guaranteed that issues such as privacy and security were carefully addressed. Respondents could see that the survey is from Utrecht University in the link to the questionnaire, the university logo, and the sender address of the student's e-mail. The demonstration video for the grocery shopping digital assistant called 'Wink', shown in the survey was created using the *Powtoon*⁴ tool for animated video creation. Regarding the functions of the digital assistant, based on Miller's (1956) theory of the limits of human information processing capacity, the number of functions presented was limited to six. The features demonstrated in the digital assistant are based on own ideas.

⁴ <https://www.powtoon.com/>

The duration of the completion of the survey amounted to approximately 10 minutes. To ensure a high response quality, a forced response setting and the option to continue the survey at a later point in time were activated. Additionally, a back button was enabled allowing for free navigation between pages and also giving respondents the option to rewatch the demo video if necessary. Qualtrics also allowed activating an option for bot detection to ensure a fully human entered response. Finally, it was not possible to attend the survey again once it had been completed and the IP addresses, location data, and contact information of the respondents were not recorded, making the survey completely anonymous.

3.1.3 Questionnaire Design and Measures

The structure of the survey followed the tailored design method introduced by Dillman et al. (2014) which proposes to group related questions into sections. Therefore, the survey was divided into three blocks, namely demographic background, 'Wink' related questions, and questions about the general attitude towards digital assistants. Further, it used questionnaire items of the literature from which the respective variables were retrieved. This ensured that the results remained stable and valid for the respective variables. The survey used a five-point Likert scale (ranging from 1 = "Strongly disagree" to 5 = "Strongly agree") to guarantee consistency and easier analysis.

The dependent variable in the examined model of this thesis is the attitude towards using 'Wink' based on the technology acceptance model by Davis (1989). The independent variables were all selected stable individual characteristics from the previously conducted literature research, namely individual innovativeness, social influence, past adoption behavior, trust, attitude towards digital assistants, educational background, gender, age, and nationality. According to the technology acceptance model the variables perceived usefulness and perceived ease of use are introduced as mediators that influence the attitude towards using

'Wink'. All except one independent variable were measured based on a Likert scale from 1 = Strongly disagree to 5 = Strongly agree. Only the independent variable past adoption behavior was measured by creating a score of 0 - 10. Respondents were asked to indicate for 10 different past adopted innovations whether they adopted them in the past or not (0 = No; 1 = Yes). Namely, the items that were asked about included Online payment (Paypal, Venmo, Banking, etc.), Voice assistant (Siri, Alexa, Google Assistant, etc.), Travel app (Google Maps, Airbnb, Uber, etc.), Instant-messaging app (WhatsApp, Telegram, Snapchat, Signal, etc.), Online shopping app (ASOS, About You, Vinted, etc.), Online cloud storage (Dropbox, OneDrive, etc.), Online language learning App (Duolingo, Babbel, etc.), Online food delivery (UberEats, Deliveroo, Doordash, etc.), Food tracking app (myfitnesspal, YAZIO, etc.) and Meditation app (7Mind, Headspace, etc.). Based on these 10 asked items the total score of adopted items reached from 0 -10 with 10 indicating that 10 of 10 items were adopted in the past and 0 that none of the mentioned innovations was used in the past. The dependent variable 'Attitude towards using 'Wink'' was measured by a net promoter score (1-10), which was asked at the end of block two. Here, after watching the video and having already been asked specific questions about 'Wink', respondents could state how likely they would be to recommend 'Wink' to a friend or colleague, which in turn indicated their general attitude towards the innovation.

Prior to the survey, information about the purpose of the research and the relation to the research question of the thesis was presented. Furthermore, it was explicitly pointed out that the collected data will be used only for research purposes and will not be forwarded for use elsewhere.

In general, the survey was divided into three blocks, namely demographic background, 'Wink' related questions, and questions about the general attitude towards digital assistants.

The first block consisted of basic questions about gender, year of birth, current place of residence, and educational background. It is important to mention that the gender question also included the third gender, respectively, the non-binary, and that there was also the option not to state an individual's gender.

Following the questions on the general attributes of the respondent, a video of a fictitious digital assistant for food shopping was shown called 'Wink' (the name is derived from the Dutch word for shop/store: *winkel*; pronunciation: ['wiŋkəl]). The video introduced six different features designed to make the supermarket shopping experience smarter and easier for customers. Among the features presented are the ability to enter personal information (favorite cuisine, current diet, allergies, and other preferences), suggestions for new recipes and warnings for allergic products or resisting temptations, different input options for the shopping list (voice, typing or taking a picture of an already written list), an item locator (shows the location of the product being searched for and guides the user to the product using an arrow to navigate), a store map that records all product locations and makes them available for future users to find, and finally, the option to complete purchases using different payment methods (cash, online, card).

After the video presentation, the respondents were redirected to the second block of questions, which referred to the digital assistant 'Wink'. The question block began with the participant's assessment of the perceived ease of use and usefulness of the application. Both variables were evaluated using a Likert scale from 1 to 5 (1 = strongly disagree to 5 = strongly agree) for the respective sub-questions.

Subsequently, the participants were asked questions about the general usefulness of 'Wink' and further to what extent the participant considers 'Wink' useful in his or her personal life. The difference in the questions was intended to obtain both a general evaluation of the digital assistant and a difference in the actual use for the participant's personal needs. A simple

rating from 0 to 100 (0 = Not at all useful to 100 = Extremely useful) using a slider should make the rating for both questions as straightforward as possible and visually appealing.

The next part of the second block of questions related to the individual functions of 'Wink'. First, the functions individually rated, also using a Likert scale of 1 - 5 (1 = Not at all useful to 5 = Extremely useful). Next, the functions were to be ranked according to their usefulness. The respondent was able to use dragging and dropping to arrange the individual functions, with the most useful function at the top and the non-useful function at the bottom.

Since only six functions of the fictional grocery shopping assistant were shown, consideration was given to the following questions and the respondent had the opportunity to indicate whether the app seemed complete to the respondent, whether they were neutral about it or whether they thought the app was not complete. With the help of the display logic function of Qualtrics, only respondents who indicated that they did not find the application to be complete, were forwarded to the question of which additional function they would request within the application. This was to ensure that only respondents who genuinely thought that something was missing in the app would suggest additional functions.

Subsequently, the payment function was also discussed in detail, and the question was asked as to which payment method would be preferred in 'Wink'. Besides the payment methods already presented in the video: cash, online (PayPal, online banking, etc.) and card, the option for alternative payment methods such as decentralized currencies like cryptocurrencies was added. This question offered the respondent the opportunity to make several choices. If the option 'Another payment method' was among the selected options, the respondent was redirected with the help of the display logic function to the question of which payment method they would like to integrate into 'Wink'. Also in this step, the aim was to give only those respondents the option to propose an additional payment method, for whom the standard payment methods are not sufficient.

Finally, a net promoter score of 1 to 10 (1 = Not at all likely to 10 = Extremely likely) was used to ask about the general recommendation rate and the extent to which people recommend 'Wink' to friends, family, or colleagues. The net promoter score was used as the dependent variable to examine the attitude towards using 'Wink' (ATW).

The last and third block of the survey dealt with the general attitude towards digital assistants and included the relevant individual characteristics researched outside the demographic attributes and variables of the technology acceptance model. To present the various characteristics clearly as a question, technical terms and incomprehensible expressions were avoided. For unbiased results for the responses, existing questionnaire items for the individual characteristics were taken from the literature and applied to the survey.

The list in Appendix I.A 3 shows a full list of the questionnaire items derived from the literature, and Appendix I.B 1 shows the survey in detail with its three blocks and also a link to the demo video of 'Wink' that was shown to the participants.

3.1.4 Sample and Procedure

The survey was conducted in the period from the 31st of May 2022 to the 24th of June 2022 over three weeks. It was shared via social media, instant messaging applications, and personal approaches. To ensure a very low dropout rate of responses, the force responses Qualtrics setting was enabled so that each question had to be answered in order to complete the survey. Therefore, of the 180 responses recorded, 60 were discarded due to missing data. Finally, 120 responses were used for the following empirical analysis. Table 1 shows the demographic profile of the respondents. 39,2% of all respondents were male (n = 47), 59,2% were female (n = 71) and respectively 1,6% were nonbinary/third gender or did not prefer to mention their gender (n = 2). With 80,9%, most of the respondents were between 20 and 30 years old (n = 97). But also the older generation of 40 years or older was reached (n =

13;10,8%). Furthermore, 73,3% of the respondents had at least a bachelor's degree (n = 88). At the time of the survey completion, most of the respondents lived in Germany (n = 51; 42,9%) and the Netherlands (n = 49; 40,3%). However, there were also representatives of many different nations among the interviewees (n = 21;17,5%) from Canada, Italy, Latvia, Malaysia, Poland, South Africa, Spain, the UK, Tanzania, and the US.

The sample shows a mixed set of respondents, which creates a more comprehensive overall picture of impressions towards digital assistants.

Descriptive statistics of respondent's characteristics (n = 120)

Measure	Items	Frequency	Percentage (%)
Gender	Male	47	39,2%
	Female	71	59,2%
	Nonbinary / Third-Gender	1	0,8%
	Prefer not to say	1	0,8%
Age	Under 20	10	8,3%
	20-25	59	49,2%
	26-30	38	31,7%
	31-40	8	6,7%
	41-50	1	0,8%
	51 or older	4	3,3%
Education	Less than high school	6	5,0%
	High school graduate	26	21,7%
	Bachelor's degree	51	42,5%
	Master's degree	34	28,3%
	Doctoral degree	3	2,5%
Nationality	Canada	1	0,8%
	Germany	51	42,9%
	Italy	1	0,8%
	Latvia	1	0,8%
	Malaysia	1	0,8%
	Netherlands	49	40,3%
	Poland	2	1,7%
	South Africa	1	0,8%
	Spain	1	0,8%
	United Kingdom	5	4,2%
	United Republic of Tanzania	1	0,8%
United States of America	6	5,0%	

Table 1: Demographic profile of all respondents

In the course of the survey, the respondents were guided gradually from block one, the questions about their demographic data up to the video of the fictitious digital assistant 'Wink', which was intended to bring all respondents to a common understanding of what is meant by a digital assistant in this thesis. In block two, the different functions of the shopping assistant were discussed and gamification elements such as sliders or ranking by drag and drop were implemented to make the survey more interactive. The last block of questions, block three, addressed the main independent variables in which the respondents were able to indicate their classification of the subordinated items based on the five-point Likert scale mentioned above. The survey ended with a note stating that the survey results had been recorded.

4 Results

4.1 Multi-Item Measurement and Variable Properties

Once the data was gathered the output was analyzed using IBM's SPSS Version 28.01. After applying the Kaiser Meyer Olkin (KMO) measure of sampling adequacy which showed an acceptable value of above 0.6 for all components and a further Bartlett's test of sphericity also showed a sufficient correlation between the characteristics ($p \leq .001$), a principal component analysis (PCA) was conducted. The PCA aimed to determine the factor loadings for each construct-related item and to control the allocation of the individual items to their constructs.

Only components with an Eigenvalue greater than 1 were extracted. A varimax rotation was applied to allow for an orthogonal rotation which treats the items as uncorrelated and ensures that every individual item will unbiasedly be assigned to the correct higher-level construct. Additionally, factors with a small coefficient were suppressed. Due to the sample size of 120 responses, the significance level for the factor loadings was set to .5 according to the recommendations of Hair et al. (2009).

Due to several cross-loadings in the variables individual innovativeness and trust, where an underlying item was assigned to more than one construct, and additional different oblique rotation approaches using direct oblimin and promax did not lead to clear factor loadings in only one component respectively, the items TR01 and TR02 were deleted for trust and the PCA for individual innovativeness showed split results. Although the communalities for INI_1, INI_2, and INI_7 indicated insufficient results below .5, they were still included in the factor analysis to ensure the requirement of a minimum of three items per component. The analysis revealed that the underlying questionnaire items of individual innovativeness were divided into

two parts by respondents, namely questions related to new ideas and questions related to new products. As for the respondents, those two were not connected and were therefore treated differently in their responses. Further, the items INI_1, INI_3, and INI_4 had to be reverse-coded as they asked for an opposite measurement on the Likert scale than the other items aligned to individual innovativeness. Additionally, they showed negative factor loadings in the PCA.

Hence, it was decided to split the high-level component of individual innovativeness into two separate components, INID (includes the items INI_1, INI_2, INI_3, and INI_4) indicating the individual innovativeness regarding new ideas, and INIP (includes the items INI_5, INI_6, and INI_7) denoting the individual innovativeness for new products.

After applying the PCA, Cronbach's alphas were determined to identify the reliability of the higher-level components. According to Nunnally (1994) the value for the internal consistency of a construct should be above the .6 threshold to be accepted as reliable. Table A. 3 indicates that all constructs have an alpha above .6. In addition, it presents which items were dropped, which items were reverse-coded, and the factor loadings of the remaining items.

Although INI_3 is not specifically referring to new ideas ('Change frustrates me') it was decided to keep it, as an elimination would otherwise reduce INID's alpha to .62 instead of its actual value of .65 if the items INI_1, INI_2, INI_3, and INI_4 are assigned to it.

Table 2 shows the descriptive statistics and correlations of all independent variables, the dependent variable, and the mediators. Worth noting is the strong correlation between perceived usefulness and the dependent variable attitude towards 'Wink' (.76, $p \leq .01$). It appears that these two variables are very closely related and thus almost explain each other. Further attention should additionally be drawn to the moderate correlation between past adoption behavior and attitude towards digital assistants of .40. The relationship between these variables will be discussed in more detail in later sections.

Descriptive statistics and correlations (n = 120)

	1	2	3	4	5	6	7	8	9	10	11	12	13	Mean	SD
1. Individual innovativeness (Ideas)	-	.33**	-.14	.26**	.16	.00	.14	.02	.05	.05	-.15	.05	-.06	3.63	.70
2. Individual innovativeness (Products)	.33**	-	.12	.10	.25**	.18*	.11	-.21*	.02	.09	.05	-.02	.16	3.13	.82
3. Social influence	-.14	.12	-	.16	.27**	.13	-.14	-.14	-.12	-.06	.33*	.01	.32**	2.71	.89
4. Past adoption behavior ^a	.26**	.10	.02	-	.40**	-.00	-.01	.10	-.17	.14	-.09	.12	.01	7.45	1.73
5. Attitude towards digital assistants	.16	.25**	.27**	.40**	-	.25*	.07	.02	-.03	-.12	.28**	.21*	.27*	3.61	.87
6. Trust	.00	.18*	.13	-.00	.25*	-	-.02	-.01	-.02	.03	.12	-.02	.15	2.62	.87
7. Educational background	.14	.11	-.14	-.01	.07	-.02	-	-.01	-.32**	.10	-.14	-.11	-.07	3.02	.90
8. Gender	.02	-.21*	-.14	.10	.02	-.01	-.00	-	-.17	.04	-.03	-.09	-.13	1.63	.55
9. Age	.05	.02	.12	-.17	-.03	-.02	-.32**	-.17	-	.22*	.00	-.06	.04	25.97	7.53
10. Nationality	.05	.09	-.06	.14	-.12	.03	.11	.04	-.17	-	-.03	-.28**	-.06	103.5	39.99
11. Perceived usefulness	-.15	.05	.33**	-.09	.29**	.12	-.14	-.03	.00	-.03	-	.28**	.76**	3.52	.96
12. Perceived ease of use	.05	-.02	.01	.12	.21*	-.02	-.11	-.09	-.06	-.28**	.28**	-	.25**	4.32	.66
13. Attitude towards 'Wink'	-.06	.16	.32**	-.01	.27*	.15	-.07	-.13	.04	-.06	.76**	.25**	-	6.1	2.30

Table 2: Descriptive statistics and correlations

* $p \leq .05$, (2-tailed).

** $p \leq .01$, (2-tailed).

^a 'Past adoption behavior' is based on a score from 1 to 10 computed out of 10 items (Further information in chapter 3.1.3).

4.2 Multivariate Regressions

Next, multivariate regressions were conducted to distinguish the potentially significant effects of the independent characteristics on the dependent variable ATW and to examine the mediating effects of PEOU and PU on ATW. In addition, it was also investigated to what extent PEOU influences PU. Lastly, the significance of the mediation effects on the dependent variable was studied.

The results of the regressions can be seen in Table 3. Model 1 and model 2 examine the influence of the individual characteristics on PEOU and PU, respectively. While model 3 investigates the direct effect of the individual attributes on the dependent variable ATW, model 4 then incorporates the mediators PEOU and PU to highlight and emphasize significant differences. All models except model 1 are significant at a significance level of $p \leq .001$ based on the ANOVA analysis. The insignificance of model 1 can further be explained by the low F-value of 1.19. Additionally, the individual characteristics explain only 8% of the variance of ATW in model 1. A detailed description of the ANOVA tables can be found in Appendix I.A 5.

Results of the Regression Analyses (β -values)

Independent Variables	PEOU	PU	Dependent Variable Attitude towards 'Wink'	
	Model 1	Model 2	Model 3	Model 4
Main Effects				
Individual innovativeness (Ideas)	.04	-.12	-.08	.01
Individual innovativeness (Products)	-.11	.00	.09	.09
Social influence	-.07	.24**	.23**	.06
Past adoption behavior	.16	-.18*	-.07	.06
Attitude towards digital assistants	.25**	.31***	.22**	-.02
Trust	-.06	.02	.05	.05
Gender	-.15	.03	-.07	-.08
Age	-.08	.02	.06	.05
Mediating Effects				
Perceived usefulness (PU)	-	-	-	.72***
Perceived ease of use (PEOU)	-	0.28**	-	.05
R^2	.08	.20	.17	.61
F - statistic	1.19	3.45	2.84	16.83
R^2 - change	.08	.20	.17	.44
F - change statistic	1.19	3.45	2.84	60.55

Table 3: Regression tests from model 1 to model 4

$n=120$

* $p \leq .10$, (2-tailed)

** $p \leq .05$, (2-tailed)

*** $p \leq .01$, (2-tailed)

First, the individual aspects of models 1 and 2 are observed and, subsequently, the salient differences between those two examined.

In model 1, which refers to the influence of the individual characteristics on perceived ease of use, it can be observed that attitude towards digital assistants ($\beta = .25$, $p \leq .05$) has a positive and significant effect. Gender ($\beta = -.15$, $p = .13$) has a negative, slightly significant effect (close to the threshold of $p \leq .10$) on perceived ease of use. In more detail, while the majority of the male respondents tended to rate their perceived ease of use in the higher

categories (n=41, 4.0 and above), most of the female respondents (n=35, 3.5 until 4.25) would not rate their perceived ease of use above 4.25 (Appendix I.A 6).

Model 2 refers to the direct effects of all individual characteristics on perceived usefulness, including the separate regression of perceived ease of use on perceived usefulness (according to the conceptual model and the technology acceptance model). The results indicate a positive, significant effect of social influence ($\beta = .24, p \leq .05$) on perceived usefulness. Previously, social influence did show a negative and also not significant effect on perceived ease of use. Attitude towards digital assistants ($\beta = .31, p \leq .01$) maintained its positive, significant effect, but indicates a slightly higher effect on perceived usefulness than on perceived ease of use (+ .06). Interesting is the fact that model 2 shows that a higher past adoption behavior has a negative, significant effect on perceived usefulness ($\beta = -.18, p \leq .10$). Also, the negative correlation of -.09 between those two variables shown in Table 2 confirms the negative effect.

The separately own influence of the mediator perceived ease of use on the other mediator perceived usefulness indicates a positive, significant effect ($\beta = .28, p \leq .05$).

Next, the effects of all individual characteristics on ATW are explored in models 3 and 4, respectively. Model 3 indicates that both social influence ($\beta = .23, p \leq .05$) and attitude towards digital assistants ($\beta = .22, p \leq .05$) positively, and significantly influence the attitude towards using a grocery shopping digital assistant. This means that the more people are influenced by the people around them who are additionally positively inclined towards digital assistants in general, the more likely those influenced individuals will become future users. Past adoption behavior does not show any more significant effect on ATW.

In the last model 4, both mediators perceived ease of use and perceived usefulness were included to compare the results of this regression model to model 3. The results of the fourth regression model show that all previously reported statistically significant characteristics

became insignificant once the mediators were included, indicating that there is no statistically significant direct effect from all the relevant characteristics on ATW. The characteristics together with the mediators account for 61% of the variance in users' attitude towards 'Wink'. Only the influence of perceived usefulness ($\beta = .732, p \leq .01$) has a positive, significant effect on ATW. The influence of attitude towards digital assistants is not only not significant anymore, but even shows a negative effect.

4.3 Investigation of Mediation Effects

Since model 4 showed no significant direct effects of the individual characteristics on ATW at all, it can still be presumed that the indirect effects of the characteristics through both mediators perceived ease of use and perceived usefulness might still be significant. First, the mediators are individually addressed and the significance of the indirect effects is evaluated. In the second step, the significance of the indirect effects is investigated considering the influence of both mediators at the same time.

4.3.1 Simple Mediation Model

To investigate this assumption separately for each mediator, Sobel's (1982) tests were applied to examine whether the mediation effects of PEOU and PU on ATW are significant. In general, the Sobel's test investigates the significance of the indirect effect unrelatedly to the total effect (direct effect + indirect effect) of the different individual characteristics on the dependent variable.

The results show that although social influence ($\beta = .06$), past adoption behavior ($\beta = .06$), and attitude towards digital assistants ($\beta = -.02$) do not have a significant direct effect on ATW, the Sobel's test for each characteristic once mediated by PU shows different results. Social influence ($z = 2.30, p \leq .05$), past adoption behavior ($z = 2.01, p \leq .05$) and attitude

towards digital assistants ($z = 3.10, p \leq .01$) indicate a significant, indirect effect via PU on ATW. Regarding the mediation effects via PEOU Sobel's tests showed that none of the characteristics had a significant, indirect effect on ATW. Therefore, it can be assumed that PEOU negatively influences the significance of individual characteristics in general. To verify this assumption, the individual characteristics were observed under the premise of simultaneous inclusion of both mediators PEOU and PU instead of separate consideration.

4.3.2 Parallel Mediation Model

Considering a parallel mediation model, the significance of the mediation effects of each characteristic mediated simultaneously by PEOU and PU was assessed. Using Hayes' (2017) process macro version 3.5.3 with 5000 bootstrap samples and a confidence interval of 95%, the results were slightly different from the outcomes of Sobel's tests. By parallel mediating via PEOU and PU, past adoption behavior no longer indicated a significant indirect effect on ATW. Nevertheless, social influence ($\beta = .24, p \leq .05$) and the attitude towards digital assistants ($\beta = .22, p \leq .05$) still show a positive, significant indirect effect on ATW.

The previous assertion that PEOU generally provides for insignificant effects on the part of the individual characteristics was now proven to be true. Although past adoption behavior had a positive significant indirect effect via PU on ATW when the individual mediators were considered separately, this significance became lost after PEOU became part of the model.

Based on these results, it can be concluded that the majority of the individual characteristics do not influence the attitude towards using a future digital assistant for grocery shopping. With regard to different approaches to the evaluation of the mediation effects on ATW, several differences can be identified. Especially the individual innovativeness regarding ideas and products and the past adoption behavior of the respondents showed a very weak relationship to the attitude towards ‘Wink’ (-.06, .16, .01, respectively). The results of the main regression conducted in model 4 can be seen in Table 4.

Regression results

Attribute → Dependent Variable	β	S.E.	p
Individual innovativeness (Ideas) → Attitude towards ‘Wink’	.01	.22	.93
Individual innovativeness (Products) → Attitude towards ‘Wink’	.09	.20	.18
Social influence → Attitude towards ‘Wink’	.06	.18	.39
Past adoption behavior → Attitude towards ‘Wink’	.06	.09	.39
Attitude towards digital assistants → Attitude towards ‘Wink’	-.02	.21	.85
Trust → Attitude towards ‘Wink’	.05	.17	.48
Gender → Attitude towards ‘Wink’	-.08	.27	.22
Age → Attitude towards ‘Wink’	.05	.02	.45
Perceive ease of use → Attitude towards ‘Wink’	.05	.23	.48
Perceived usefulness → Attitude towards ‘Wink’	.72	.17	< .001
Perceived ease of use → Perceived usefulness	.28	.13	.002

Table 4: Final regression results

5 Discussion and Conclusion

The aim of this work was to investigate the influence of individual user characteristics on the acceptance of digital assistants. For this purpose, a special focus was placed on the environment of a supermarket and an exploratory study was conducted. After an extensive literature review, potential individual characteristics were identified. Using the technology acceptance model as a basis, individual characteristics were incorporated into the model and evaluated within a survey. In addition, a fictional video of a grocery shopping assistant was created in which various potential functions were presented. After analyzing the results, it was found that perceived usefulness had the strongest direct influence on the attitude towards the use of a grocery shopping digital assistant. An analysis of various direct and indirect effects on the attitudes towards using the featured innovation further revealed that only social influence and the attitude towards digital assistants had a significant impact on the intention to adopt a future digital assistant for grocery shopping.

5.1 Theoretical Implications

This study contributes to the literature on technology acceptance in four main ways. First, the study extends the technology acceptance model by implementing nine different external variables. These are the individual characteristics Individual Innovativeness (INI), Social Influence (SOI), Past Adoption Behavior (PAB), Attitude Towards Digital Assistants (ATD), Trust (TR), Gender, Age, Educational Background, and Nationality. Some of these characteristics have already been discussed in the literature and have also been addressed in the context of the technology acceptance model, but not to this extent (Agarwal & Prasad, 1999; Liu et al., 2022; Rajak & Shaw, 2021; Yang, 2005). As it turned out individual innovativeness, social influence and past adoption behavior are distinctly correlated and interconnected, and thus influence the adoption of new technologies. This finding was only possible by combining a large number of characteristics into one model, and thereby allowing to focus attention on connections that had not been addressed in the literature before.

Second, this study examined the digital assistant environment and additionally in the new context of a supermarket that appeals to a larger group of potential users. In combination with the aforementioned implementation of individual characteristics, this study enriches the theory in that it extends the technology acceptance model to the new domain of digital assistants in public space showing that potential adopters rather prioritize the enhancement of their productivity and performance in grocery shopping than the usability and convenience of a new digital assistant.

Third, it confirms the strong predictor effect of perceived usefulness in the context of digital assistants. This finding goes in line with previous studies researching the user acceptance of new technologies (Davis, 1989; Park & Chen, 2007; Sagnier, Loup-Escande, Lourdeaux, Thouvenin, & Valléry, 2020; Yang, 2005). Research should first be conducted on the original

elements of TAM before adding external factors. The study shows that further research is needed to understand why PU is such a strong predictor of digital assistant adoption and why it overshadows the effect of individual characteristics to such an extent that they lose their significant effects in an econometric sense, especially for characteristics that previously showed a moderate correlation with the dependent variable. Therefore, it seems that perceived usefulness has a suppressive effect on the other individual characteristics, which did not show a significant effect on attitudes towards the innovation and should possibly be excluded from some studies researching the acceptance of new technologies which then only allows for a focus on perceived ease of use. Thus, it can be ensured that the effects of variables can be observed without them being overlooked due to the lack of significance caused by a single mediator.

Finally, the study shows that past adoption behavior and social influence are more strongly related to perceived usefulness of a digital assistant than to perceived ease of use. Indeed, once the latter is taken into account, past adoption behavior loses its impact on the adoption behavior of potential users. This result can be related to the findings of Gefen et al. (2003), who found that there tends to be increased trustworthiness of users towards the adoption of new technology once second-hand information is included. Applying this finding to this work, and further assuming that second-hand information can, in essence, be understood as an advancement of social influence as described in Chapter 2.2.6, it can be concluded that once those people, who influence the original potential adopter, also indicate positive past adoption behavior, this will lead to an even greater likelihood that the influenced potential adopter will become a future user of digital assistants. Yang (2005) also found in his study that individual innovativeness is strongly correlated with past adoption behavior, which may also indicate that individuals with a higher level of individual innovativeness are more likely to have adapted innovations in the past. This, in turn, has the indirect effect, also via social influence, that

potential users influenced by their knowledgeable environment will be more likely to use new digital assistants.

Since the results also show that past adoption behavior has a negative influence on perceived usefulness, it can be assumed that individuals with a higher level of knowledge about previous innovations are more likely to assess the digital assistant 'Wink' shown in the video as not marketable and unfinished. Since these individuals have a lot of comparisons, it could be assumed that they rate the increased productivity demonstrated by the digital assistant lower than those with a minor level of knowledge about past digital products. Therefore, the results enrich the literature in that they explicitly point out that, under the assumption that a higher past adoption behavior relates to increased knowledge about comparable products, future adopters expect more of newly released digital assistants. Additionally, past adoption behavior significantly, and negatively influences the perceived usefulness of the introduced innovation. Hence, the effect of past adoption behavior should be investigated in more detail.

5.2 Practical Implications

Regarding the managerial point of view, two main implications can be derived from this study. First, since perceived usefulness acts as a strong predictor of the final adoption of a new digital assistant and mainly relates to the increase in productivity and performance that results from the adoption and subsequent use of such a digital assistant for grocery shopping, more attention should be paid to this dimension in the future. Therefore, if potential users consider the digital assistant to increase their shopping productivity and performance, it will more likely be adopted, but not if the digital assistant is solely easy to understand and operate. Based on respondents' past adoption of innovations, it can be assumed that users take it for granted that a new digital assistant has already been user-tested and thus comes to the market fully ready to use. Since new users do to some extent not want to spend time understanding the digital assistant, but rather using it directly, it can be implied that the development process should focus more on optimizing the product's features and decrease the time until the final adoption. This would increase the productivity of potential users in the long run and also retain users long-term. For further information on which factors slow down the adoption of new technologies and which factors accelerate uptake time, one should refer to Jahanmir et al. (2018).

Second, the adoption of new digital assistants, as already stated in the results, is related to the social environment in the sense of people who are important to an individual and advise him/her to use new technologies and additionally related to the adoption of past innovations. Accordingly, managers and developers must address methods and functions for building a large community of users as these have strong leverage in generating and attracting new users. This in turn ensures a steady diffusion of their respective newly developed digital assistants in the long run. In order to achieve this, the environment in which the digital assistant is introduced

plays an essential role, in addition to the actual users. Ebrahimi (2018) investigated the effects of the infrastructure, environmental factors, and which determinants influence the demand for new technologies. Further, it should be examined based on a user study on what drives potential adopters to use new technology. One way to assess that is by applying usability tests as Lin (2013) applied the method to test the usability of a learning system. To increase the diffusion of a digital assistant also multiple options like for instance advertisements or free promo codes for early-adopter groups can be applied.

5.3 Limitations and Suggestions for Further Research

Although the study has already given important implications for theory and practice, some limitations must be stated, which also require further research.

First, the post-analysis results may have been significantly influenced by the ‘Wink’ demonstration video and the features shown in it. Since the video showed limited and self-derived ideas for a grocery shopping assistant, it could bias the results found. Thus, if other and also a larger number of functions had been presented in the video, the usefulness or impact of the past adoption behavior might be perceived differently. Respondents would be more inclined to say that a feature-rich assistant would work well when compared to previously adopted innovations, while the results of the assistant presented in this work may have expressed dissatisfaction among technology-savvy individuals, who would have expected more based on their expertise.

Additionally, research was only conducted within the supermarket environment. Especially regarding the influence of past adoption behavior and the comparisons that can be drawn to previous digital assistants, further analysis of the characteristics considering new features of a digital assistant and within a new environment may be beneficial and provide new results. As a potential environment to be explored, digital assistants for health services in

hospitals could be considered. Rahimi et al (2018) for instance applied the TAM model in the health service context and also included patients as potential users in their model.

Second, it was not the adoption or intention to adopt a grocery shopping digital assistant measured, but more whether the digital assistant would be recommended to someone else since a net promoter score was utilized as the dependent variable. Therefore, a different construct to measure the intention to use the innovation would yield different results, as it would explain the subjective adoption behavior rather than the leverage impact of recommendations.

Third, the relatively weak and insignificant effect of perceived ease of use on attitudes towards using the introduced innovation could be further explored with a larger sample and an additional study including real-world tasks performed by respondents. Based only on a video and without actual evidence of usage understanding, it is difficult to assess to what extent perceived ease of use has an actual effect on the acceptance of such a digital assistant. This obstacle can be overcome by utilizing the *think-aloud* method for usability tests introduced by Someren et al. (1994). This method aims to provide the subjects with tasks that have to be completed with the help of the digital assistant, but without being interrupted by the examiner. All thought processes are spoken out loud and recorded so that the digital assistant can be optimized later, based on the different results of the experiment. The perceived usefulness of the digital assistant is easier to assess as it can be already derived from a video whether a potential adoption and use of different introduced features would lead to increased performance and higher productivity, whereas the specific and subjective perceived ease of use might prove difficult since the essential intuitive part is missing in the measurement.

Forth, in this thesis, the technology acceptance model was applied. Although this model is an established and widely used framework for analyzing the acceptance of new technologies, newer research models such as the unified theory of acceptance and use of technology (UTAUT) model by Venkatesh et al. (2003) may yield different results. In the UTAUT, in

addition to the constructs of the TAM, those of eight previous models (Social Cognitive Theory (Bandura, 1986), Model of PC Utilization (Thompson, Higgins, & Howell, 1991), Motivational Model (Vallerand, 1997), etc.) are combined into a unified model based on their commonalities. In this case, for example, perceived usefulness is assigned to the new construct performance expectancy, and perceived ease of use to the new construct effort expectancy. New introduced direct determinants of usage behavior are social influence (understood as the same definition used in TAM) and facilitating conditions, where the latter describes the extent to which a person believes that an organizational and technical infrastructure is provided to enable the proper use of the service presented. Additionally, age and gender are used as moderators instead of independent variables.

Using additional factors to assess the likelihood that new technology will be used, expands the range of recommendations for action and reveals in more detail what pre-processes are necessary to facilitate and optimize the adoption of new technology. In particular, analyzing the importance for adopters to consider that there is a stable technology infrastructure behind the new technology (facilitating conditions) can provide insight into the extent to which managers should focus on expanding and improving their current technology foundation.

Finally, as explained in the introduction, people from different countries and cultures perceive digital assistants differently. It would therefore be of great interest to find out how the acceptance of a digital assistant for grocery shopping varies on a multicultural level and how adoption intentions differ across cultures to create a more in-depth understanding of adopter behavior. A similar approach was taken by Dai et al. (2009) who investigated the influence of various factors on the acceptance of mobile commerce and compared the acceptance behavior in the United States with that of users in China. They found that in the US the perceived enjoyment of using m-commerce is valued higher than in China. Additionally, social influence plays a more significant role in the US compared to China. Chinese adopters, on the other hand,

decide on the use of m-commerce based on a balance of potential functions and expenses. Another study conducted by Li et al. (2010) revealed that German participants had a more anxious attitude towards robots than Chinese participants after interacting with the robot used during the study. They further argue that, based primarily on cultural and additionally industrial backgrounds, Germans are more likely to use robots as functional machines than as personal companions.

These studies are just a few that demonstrate the importance of the multicultural level in assessing the adoption of digital assistants. Because of this, it is necessary to examine these differences in the larger context as well and perhaps in a public setting such as the one examined in this paper. For example, it could be examined how the shopping behavior while using a digital assistant varies between countries.

In sum, individual characteristics influence the acceptance of digital assistants in the sense that the study revealed that potential adopters essentially want to boost their productivity by using digital assistants without having to deal with their detailed functionality. Nevertheless, this work shows what potential still lies in digital assistants and how they can indeed be an asset even for less tech-savvy users.

6 References

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Appendix A: Tables and Figures

A 1. Databases, Search Strings, and Amount of Results

Databases	Search String	Amount of Results
Google Scholar	("individual characteristics" OR "individual attributes") AND "technology acceptance" AND ("digital assistants" OR "virtual assistants" OR "service robots" OR "ai-based agents")	440
AISel	("individual characteristics" OR "individual attributes") AND "technology acceptance" AND ("digital assistants" OR "virtual assistants" OR "service robots" OR "ai-based agents")	4177
Science Direct	("individual characteristics" OR "individual attributes") AND "technology acceptance" AND ("digital assistants" OR "virtual assistants" OR "service robots" OR "ai-based agents")	45

Table A. 1: Databases, Search Strings and Amount of Results of the Literature Searching Process

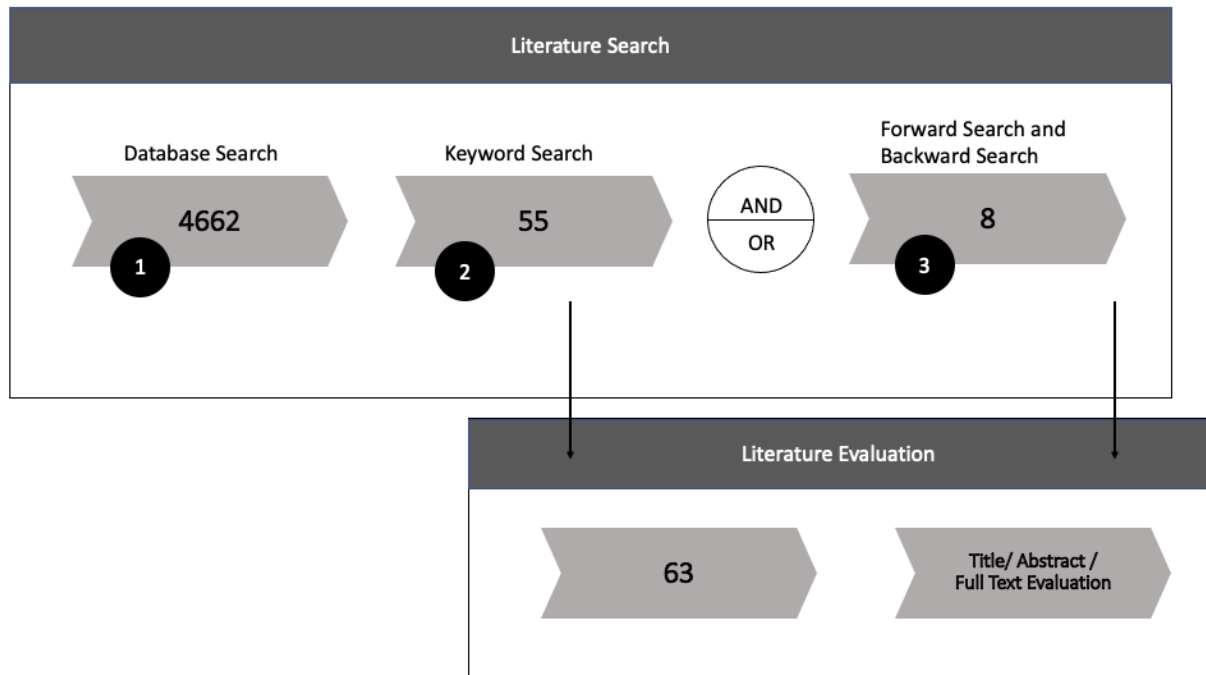


Figure A. 1: Literature Search Process after Brocke et al. (2009)

A systematic literature searching process according to the introduced method by Brocke et al. (2009) was applied using the search string ("individual characteristics" OR "individual attributes") AND "technology acceptance" AND ("digital assistants" OR "virtual assistants" OR "service robots" OR "ai-based agents"). During the searching process the terms digital assistant, virtual assistant, service robots and ai-based agents were used synonymously as different papers referred to the same using different terms. Thus, a detailed search of the data bases Google Scholar, AISEL and Science Direct could be carried out. The initial list of 4,662 articles was then screened manually by scanning titles, abstracts and full texts. Inclusion criteria were the clear recognizability of influences of individual characteristics on the creation or evaluation process of digital assistants and, for the databases Science Direct and AISEL, the inclusion of exclusively peer reviewed articles of the last 20 years (2000-2022). By performing a forward and backward search, it was possible, among other things, to search very frequently cited literature more specifically for current articles and to include them in the search process. After successfully evaluating the literature, nine individual characteristics and the two mediators perceived usefulness and perceived ease of use with their associated questionnaire items could be collected. Those can be found in Appendix A 3.

A 2. Conceptual Model

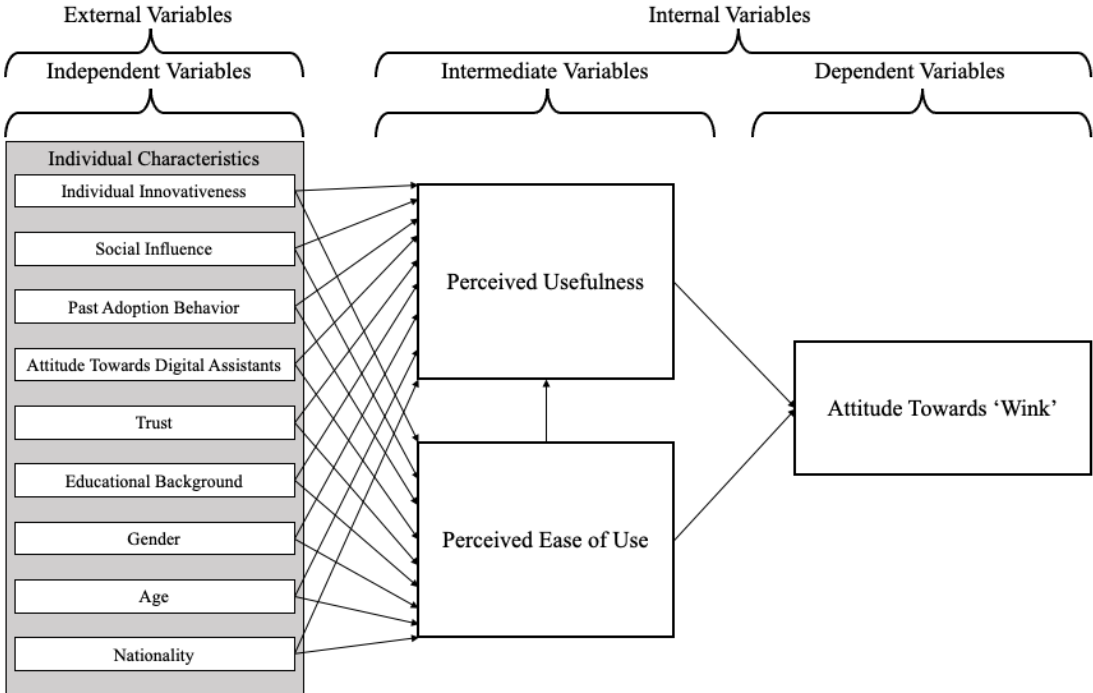


Figure A. 2: Conceptual Model including all External and Internal Variables

A 3. Individual Characteristics and Questionnaire Items

Construct	Questionnaire Items
<p>Individual innovativeness (Kim et al., 2010; J. Lu, 2014; Yang, 2005; Yi et al., 2006)</p>	<p>INI1: I usually resist new ideas. INI2: I usually support new ideas. INI3: Change frustrates me. INI4: I usually hesitate to try new ideas. INI5: I know more about new products before other people do INI6: I am usually among the first to try new products INI7: New products excite me</p>
<p>Social influence (J. Lu, 2014; Venkatesh et al., 2012)</p>	<p>SOI1: People who are important to me think that I should use digital assistants. SOI2: People who influence my behavior think that I should use digital assistants. SOI3: People whose opinions that I value prefer that I use digital assistants.</p>
<p>Past adoption behavior (Yang, 2005)</p>	<p>A past adoption behavior index was conducted by creating a composite score from 10 digital innovations and examined using a score above 5 for a favorable intention to adopt past innovations.</p>
<p>Attitude towards digital assistants (Balakrishnan & Dwivedi, 2021)</p>	<p>ATD1: I like using digital assistants ATD2: I feel good about using digital assistants ATD3: Overall, my attitude towards digital assistants is favorable</p>
<p>Trust (Liu et al., 2022; Rajak & Shaw, 2021)</p>	<p>TR1: I feel confident that I can rely on the benefits provided by digital assistants TR2: I believe that I can trust in the adequate functioning of digital assistants TR3: I believe that digital assistants will protect my privacy TR4: I believe that digital assistants will not abuse my personal information TR5: Using digital assistants would lead to a loss of privacy because the information handled could be used without my knowledge TR6: digital assistants may misuse the user data</p>

<p>Perceived ease of use (Davis, 1989)</p>	<p>PEOU1: Learning to operate ‘Wink’ would be easy for me PEOU2: My interaction with ‘Wink’ would be clear and understandable. PEOU3: It would be easy for me to become skillful at using ‘Wink’ PEOU4: I would find ‘Wink’ easy to use.</p>
<p>Perceived usefulness (Davis, 1989)</p>	<p>PU1: Using ‘Wink’ would improve my shopping performance PU2: Using ‘Wink’ during my grocery shopping would increase my productivity PU3: Using ‘Wink’ would make it easier to do my grocery shopping. PU4: I would find ‘Wink’ useful in my daily shopping experience</p>
<p>Educational background (Agarwal & Prasad, 1999; He, Jazizadeh, & Arpan, 2022; Yi et al., 2006)</p>	<ul style="list-style-type: none"> - Less than high school - High school graduate - Bachelor’s degree - Master’s degree - Doctoral degree
<p>Gender (Yang, 2005; Yi et al., 2006)</p>	<ul style="list-style-type: none"> - Male - Female - Non-binary/Third gender - Prefer not to say
<p>Age (Yang, 2005)</p>	<p>Individually entered as birthyear to allow for a better distinguishing instead of using age groups and enable an analysis of age as a continues variable</p>
<p>Nationality (Im, Hong, & Kang, 2011)</p>	<p>Individual</p>

Table A. 2: Constructs, Definitions and Questionnaire Items

A 4. Measures, Factor Loadings, and Cronbach's alphas

Construct	Items	Factor Loadings
<i>Individual Innovativeness (ideas) (INID)</i>	($\alpha^a = .68$) (1=strongly disagree, 5= strongly agree)	
	1. I usually resist new ideas ^b	0.75
	2. I usually support new ideas	0.66
	3. Change frustrates me ^b	0.65
<i>Individual Innovativeness (products) (INIP)</i>	($\alpha^a = .73$) (1=strongly disagree, 5= strongly agree)	
	5. I know more about new products before other people do	0.86
	6. I am usually among the first to try new products	0.88
	7. New products excite me	0.66
<i>Social Influence (SOI)</i>	($\alpha^a = .91$) (1=strongly disagree, 5= strongly agree)	
	1. People who are important to me think that I should use digital assistants	0.93
	2. People who influence my behavior think that I should use digital assistants	0.92
<i>Attitude towards digital assistants (ATD)</i>	($\alpha^a = .89$) (1=strongly disagree, 5= strongly agree)	
	1. I like using digital assistants	0.89
	2. I feel good about using digital assistants	0.93
<i>Trust (TR)</i>	($\alpha^a = .86$) (1=strongly disagree, 5= strongly agree)	
	1. I feel confident that I can rely on the benefits provided using by digital assistants ^c	0.91
	2. I believe that I can trust in the adequate functioning of digital assistants ^c	0.84
	3. I believe that digital assistants will protect my privacy	0.83
	4. I believe that digital assistants will not abuse my personal information	0.80
	5. Using digital assistants would lead to a loss of privacy because the information handled could be used without my knowledge ^b	0.82
<i>Perceived Ease of Use (PEOU)</i>	($\alpha^a = .88$) (1=strongly disagree, 5= strongly agree)	
	1. Learning to operate 'Wink' would be easy for me	0.86
	2. My interaction with 'Wink' would be clear and understandable	0.86
	3. It would be easy for me to become skillful at using 'Wink'	0.84
<i>Perceived Usefulness (PU)</i>	($\alpha^a = .89$) (1=strongly disagree, 5= strongly agree)	
	1. Using 'Wink' would improve my shopping performance	0.87
	2. Using 'Wink' during my grocery shopping would increase my productivity	0.82
	3. Using 'Wink' would make it easier to do my grocery shopping	0.89
	4. I would find 'Wink' useful in my daily shopping experience	0.89

^a Cronbach's alpha is based on standardized items and after cross-loaded Items were deleted

^b Reverse-coded Items

^c Deleted Item

Table A. 3: Measures, Factor Loadings and Cronbach's alphas

A 5. ANOVA Tables: Model 1 to Model 4

Model		Sum of Squares	df	Mean Square	F	Significance
1 ^a	Regression	4.03	8	.50	1.19	.31
	Residual	47.09	111	.42	/	/
	Total	51.12	119	/	/	/
2 ^b	Regression	21.97	8	2.75	3.45	.001*
	Residual	88.32	111	.80	/	/
	Total	110.29	119	/	/	/
3 ^c	Regression	107.1	8	13.39	2.84	0.007
	Residual	522.38	111	4.70	/	/
	Total	629.47	119	/	/	/
4 ^d	Regression	382.00	10	38.20	16.83	<.001
	Residual	247.47	109	2.27	/	/
	Total	629.47	119	/	/	/

* $p \leq .01$, (2-tailed)

^a Dependent Variable: PEOU; Predictors: INID, INIP, SOI, PAB, ATD, TR, Gender, Age

^b Dependent Variable: PU; Predictors: INID, INIP, SOI, PAB, ATD, TR, Gender, Age

^c Dependent Variable: ATW; Predictors: INID, INIP, SOI, PAB, ATD, TR, Gender, Age

^d Dependent Variable: ATW; Predictors: INID, INIP, SOI, PAB, ATD, TR, Gender, Age, PU, PEOU

Table A. 4: ANOVA Tables for each Regression Model

A 6. Outputs of PEOU per Gender

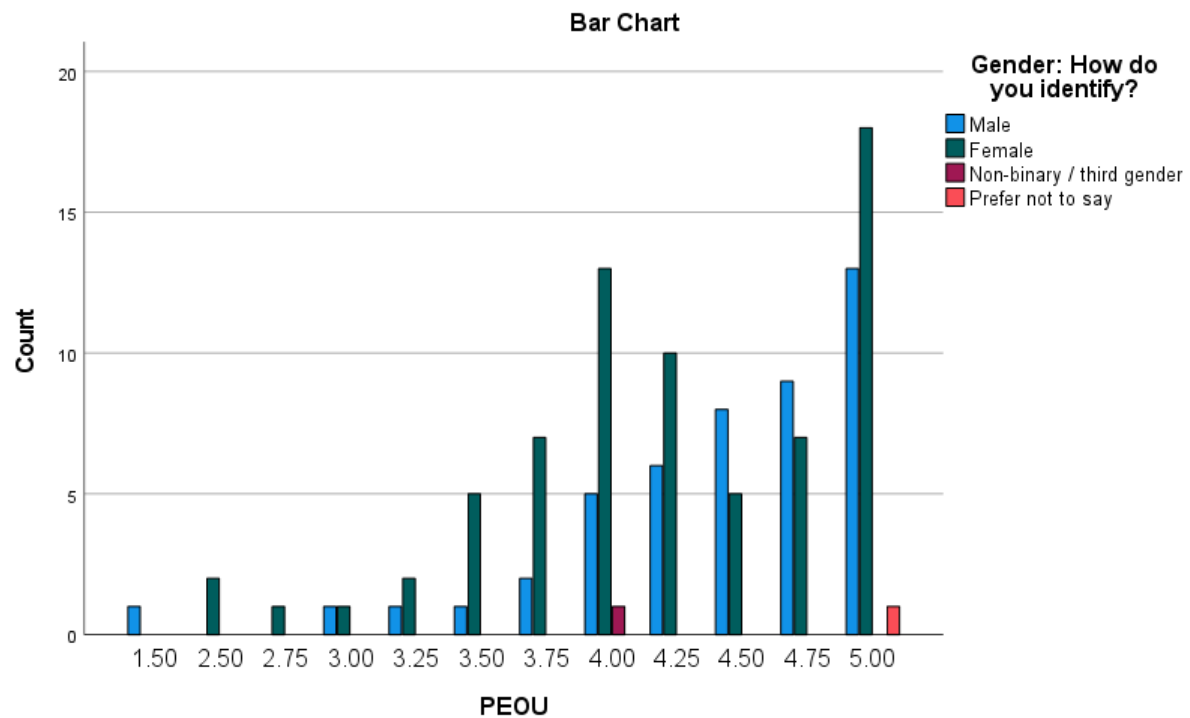


Figure A. 3: Rating of Perceived Ease of Use Per Gender

Appendix B: Survey and ‘Wink’ Screenshots

B 1. Survey

Start of Block: Introduction

Introduction

Dear Participant,

My name is Mike Farahbakhsh and I am a student at Utrecht University.

You are being invited to participate in my study about the influence of individual characteristics on the adoption of new technologies. This study is part of my final thesis of the 'International Management' master's program.

Hereby, I provide you with some further information with regard to the purposes of my study and the use of your data.

If you agree to participate, you will be asked several questions about selected individual characteristics and your general impressions of a digital grocery shopping assistant.

It is anticipated that the entire survey will take approximately 10 minutes.

The data collected will remain confidential and used solely for academic purposes.

If you have any concerns or further questions, please do not hesitate to contact me under my e-mail: m.farahbakhsh@students.uu.nl

Thank you in advance for your participation!

End of Block: Introduction

Start of Block: Demographic Questions

Block 1: Demographic Attributes

In the following, you will first be asked about your demographic attributes and then shown a concept video of the new app 'Wink'.

Q11 Gender: How do you identify?

- Male (1)
 - Female (2)
 - Non-binary / third gender (3)
 - Prefer not to say (4)
-

Q12 What is your year of birth?

Q13 In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (1357)

Q14 What is your educational background?

- Less than high school (1)
- High school graduate (2)
- Bachelor's degree (3)
- Master's degree (4)
- Doctoral degree (5)

End of Block: Demographic Questions

Start of Block: Wink Digital Assistant Video

Video Explanation

You will now see a short introduction video of the fictional grocery shopping digital assistant, called 'Wink'.

Page Break

Wink Video

Please watch the video carefully

Video link: <https://youtu.be/HHpBanRf-sU>



End of Block: Wink Digital Assistant Vide

0

Start of Block: Wink Related Questions

Block 2: Wink Related Questions

Now that you watched the features of 'Wink', please indicate in this section how you perceive the different characteristics that are listed below.

Page Break

Q21_PEOU Please choose which options describe your perceived ease of use of 'Wink' the best.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Learning to operate 'Wink' would be easy for me (1)					
My interaction with 'Wink' would be clear and understandable (2)					
It would be easy for me to become skillful at using 'Wink' (3)					
I would find 'Wink' easy to use (4)					

Q22_PU Please choose which options describe your perceived usefulness of 'Wink' the best.

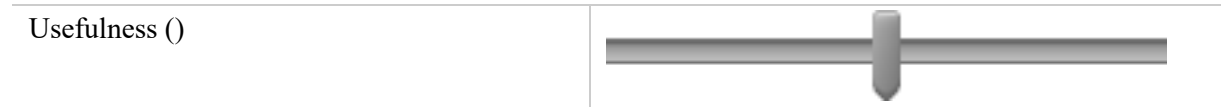
	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Using 'Wink' would improve my shopping performance (1)					
Using 'Wink' during my grocery shopping would increase my productivity (2)					
Using 'Wink' would make it easier to do my grocery shopping (3)					
I would find 'Wink' useful in my daily shopping experience (4)					

Page Break

Q23 Please indicate how useful you would consider 'Wink' in general.

Not at all Slightly Moderately Very Extremely
useful useful useful useful useful

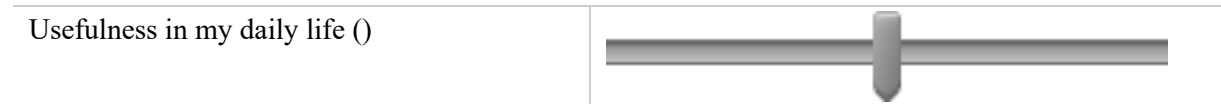
0 10 20 30 40 50 60 70 80 90 100



Q24 Please indicate how useful you would consider 'Wink' in your personal daily life.

Not at all Slightly Moderately Very Extremely
useful useful useful useful useful

0 10 20 30 40 50 60 70 80 90 100



Page Break

Q25 Please indicate how you would rate the features of 'Wink'.

	Not at all useful (1)	Slightly useful (2)	Moderately useful (3)	Very useful (4)	Extremely useful (5)
Personal information (favorite cuisine, current diet, allergies & other preferences) (1)					
Suggestions/Warnings based on personal information (recipes, unsafe products, resist temptations) (2)					
Different 'Add an Item' commands (voice, type, photo of written list) (3)					
Item locator (an arrow shows you where the products are) (4)					
Saving item location for future customers (store map) (5)					
Easy payments through different methods (cash, online, card) (6)					

Q26 Please rank 'Wink's features based on their usefulness by drag and drop (Top = Very useful; Bottom = Not useful).

- _____ Personal information (1)
- _____ Suggestions/Warnings (2)
- _____ 'Add an Item' commands (3)
- _____ Item locator (4)
- _____ Saving item location (5)
- _____ Easy payment methods (6)

Q27 Would you consider the app to be fully complete and ready to use?

- No (1)
- Neutral (2)
- Yes (3)

Display This Question:

If Q17 = No

Q28 Which functions do you think are missing and should be included in 'Wink' (discounts, sharing function, etc.)? Please enter below.

Q29 Which would be your preferred payment method using 'Wink'?
(multiple selections possible)

- Cash (1)
- Online payment (PayPal, Online-Banking, etc.) (2)
- Debit/Credit Card (3)
- Another payment method (Cryptocurrency, Apple/Google/Ali Pay, etc.) (4)

Display This Question:

If Q19 = Another payment method (Cryptocurrency, Apple/Google/Ali Pay, etc.)

Q210 Which payment method would you like to include in 'Wink'?
Please enter below.

Q211 How likely are you to recommend 'Wink' to a friend or colleague?

- 0 (0)
- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 (6)
- 7 (7)
- 8 (8)
- 9 (9)
- 10 (10)

End of Block: Wink Related Questions

Start of Block: Digital Assistants in General Questions

Block 3: Attitude Towards Digital Assistants

In this last section you will be asked questions regarding digital assistants in general and your attitude towards them.

Page Break

Q31_INI

Please choose which options describe how you address new ideas and products.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I usually resist new ideas (1)					
I usually support new ideas (2)					
Change frustrates me (3)					
I usually hesitate to try new ideas (4)					
I know more about new products before other people do (5)					
I am usually among the first to try new products (6)					
New products excite me (7)					

Q32_SOI

Please choose which options describe the best what role other people play in your decision making processes.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
People who are important to me think that I should use digital assistants (1)					
People who influence my behavior think that I should use digital assistants (2)					
People whose opinions I value prefer that I use digital assistants (3)					

Q33_PAB

Please indicate which of these digital innovations you have used in the past.

	Yes (1)	No (2)
Online payment (Paypal, Vemno, Banking, etc.) (1)		
Voice assistant (Siri, Alexa, Google Assistant, etc.) (2)		
Travel app (Google Maps, Airbnb, Uber, etc.) (3)		
Instant-messaging app (WhatsApp, Telegram, Snapchat, Signal, etc.) (4)		
Online shopping app (ASOS, About You, Vinted, etc.) (5)		
Online cloud storage (Dropbox, OneDrive, etc.) (6)		
Online language learning App (Duolingo, Babbel, etc.) (7)		
Online food delivery (UberEats, Deliveroo, Doordash, etc.) (8)		
Food tracking app (myfitnesspal, YAZIO, etc.) (9)		
Meditation app (7Mind, Headspace, etc.) (10)		

Q34_ATD

Please choose which options describe your attitude towards digital assistants the best.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I like using digital assistants (1)					
I feel good about using digital assistants (2)					
Overall, my attitude towards digital assistants is favorable (3)					

Q35_TR

Please choose which options describe your perceived trust towards digital assistants the best.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I feel confident that I can rely on the benefits provided by digital assistants (1)					
I believe that I can trust in the adequate functioning of digital assistants (2)					
I believe that digital assistants will protect my privacy (3)					
I believe that digital assistants will not abuse my personal information (4)					
Using digital assistants would lead to a loss of privacy because the information handled could be used without my knowledge (5)					
Digital assistants may misuse the user data (6)					

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End of Block: Digital Assistants in General Questions

B 2. Screenshots of 'Wink'

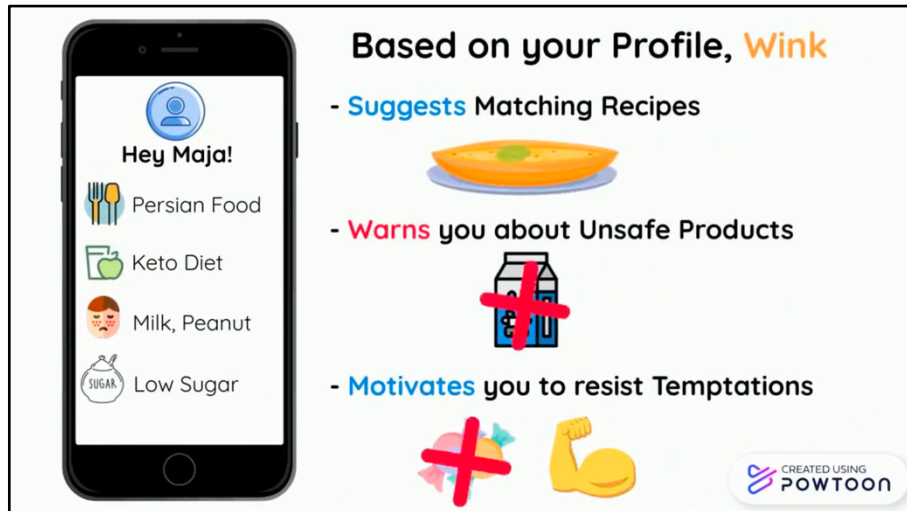


Figure B. 1: Suggestion and Warning Feature of 'Wink'

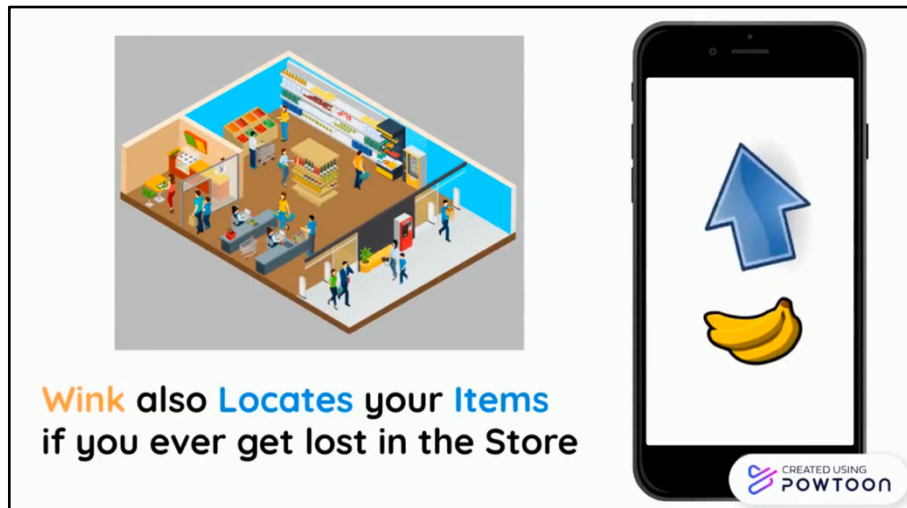


Figure B. 2: Item Locator Feature of 'Wink'

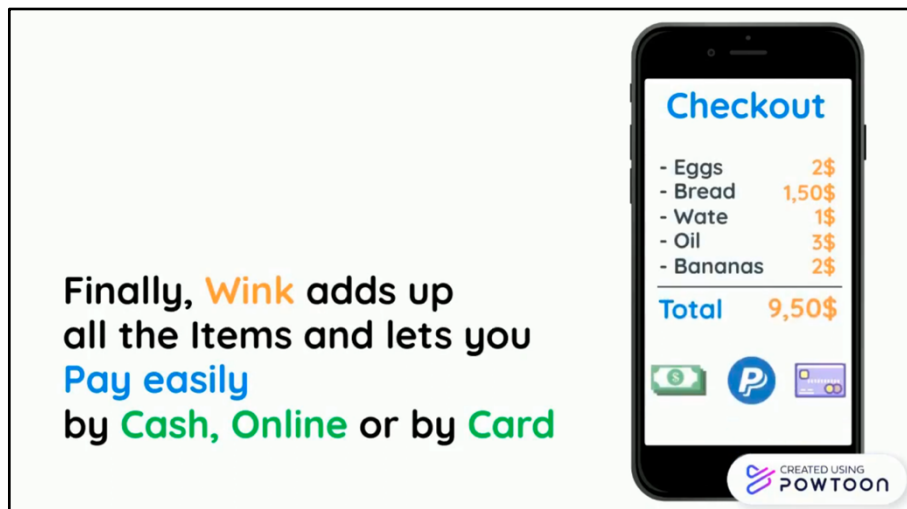


Figure B. 3: Payment Methods of 'Wink'

Declaration of Authorship

The copyright of this thesis rests with the author. The author is responsible for its contents and opinions expressed in the thesis. U.S.E. is only responsible for the academic coaching and supervision and cannot be held liable for the content.

I, Mike Farahbakhsh, hereby confirm that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Utrecht, 01.07.2022

A handwritten signature in black ink, appearing to read 'Mike', is written over a solid horizontal line. The signature is stylized and cursive.