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Which factors influence Belgian Millennials' intention to use a voice assistant in their consumer journey when grocery shopping?

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Academic year 2022-2023

Dissertation for the master's degree 120 in Management with a major in Marketing Strategy for Connected Brands
Daytime schedule

Acknowledgements

First, I would like to thank my supervisor, M. Ludovic Chevalier, for the guidance that he provided me in the making of my thesis and for its open-mindedness on the topic I chose.

Then, I am also grateful to anyone who has answered to my survey and to the individuals who have shared my questionnaire online. I would not have been able to provide these insights, perform the relevant analyses and answer to the research question without them.

In addition, I would also like to thank the Louvain School of Management for the marketing, marketing research and data mining courses that have awakened my curiosity about Artificial Intelligence and without which I would not have been prompted to write my thesis on this subject.

Lastly, my gratitude goes to my family, who has provided me a very strong support from deciding on the topic of my thesis to handing in its final version online. A very warm thank you to my sister, brother and my stepmother for the proofreading.

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Introduction

"Alexa, can you predict the success of our dissertation?"

The development of new technologies has been booming for the last 20 years and these are increasingly embedded in consumers' daily activities. Among these technologies, we can name algorithms, voice assistants, virtual reality and search engines, which have been developed over the last century.

The growth of Artificial Intelligence (AI) has been the focus of much discussions from which different positions emerged: while some view it as potential threat to humanity, others embrace this technological revolution, as it enabled great progress in various fields. This topic is particularly relevant today with the launch in 2022 of ChatGPT by OpenAI. ChatGPT is a conversational agent with which an individual can converse by asking it to perform different type of tasks (OpenAI, 2023). Some view this new technology as concerning since the results provided by the machine are very similar to what a human being could have written (Fleuret, 2023). This recent example further demonstrates that AI is at the centre of current debates, which makes it an even more interesting topic to study.

ChatGPT represents only one of the many examples of AI-developed technologies that are shaping the way we think, make choices and consume. When looking more closely at the case of voice assistants (VAs) in the context of this dissertation, we have noted that they can be very useful for carrying out tasks that do not involve physical contact with a device. These tasks can range from ordering a taxi, turning off the lights, writing a message to your partner to let her know about the list of groceries (Hoy, 2018). The possibility to do grocery shopping through VAs, also named voice commerce, has particularly raised our attention. Voice commerce has benefited from a particularly high penetration rate in the U.S.A (Chevalier, 2022). In addition, several retailers in France and one supermarket chain in Belgium have entered into partnerships with companies that develop these technologies. Therefore, we aim, in this thesis, to discover the incentives which underlies the consumers' willingness to exclusively resort to voice assistants when doing their grocery shopping. We have then refined it to the Belgian market to turn it into: Which factors influence Belgian Millennials' intention to use VAs in their consumer journey when grocery shopping?

The aim of this dissertation is to address this question by determining the factors that can influence significantly the intention of Belgian Millennials to use a VA when grocery shopping. We will identify the weaknesses and the strengths that can impact the intention to use of these technologies. Overall, this study is part of a rather limited theoretical framework on the Belgian market. In fact, given that Belgium is a rather small country and that 3 national languages coexist there, little research has been carried out on the intention of Belgian consumers to use VA for grocery shopping. In addition, although much developed today, VAs fail understanding several languages spoken at the same time, which raises a problem in the intercultural context of Belgium (Moriuchi, 2019).

The first part of this thesis is dedicated to the literature review. It has been designed as a funnel, starting with the two first chapters focusing on the presentation of AI and voice assistants. The third and fourth chapters are dedicated to the consumer journey, and to the development of the theoretical model that served as a basis for the making of the hypotheses. The second part starts with the hypotheses that are later tested through a quantitative analysis. The results of the analyses are then presented, enabling us to confirm or refute the hypotheses developed. After that, the discussion puts the results obtained into perspective with the elements presented in the literature review. Finally, the managerial implications of our research are highlighted to provide retailers and technology firms with perspectives for further development. The limitations of this thesis and recommendations for future research are also outlined in this section.

Part I: Literature review

Chapter 1: Artificial Intelligence

The purpose of this chapter is to provide an overview of what entails Artificial Intelligence (AI), including its origin and its two subsets, namely Machine Learning and Deep Learning.

1.1.What is AI?

The concept of AI has evolved considerably from its original form to the present day, to the extent that it has become an umbrella term for several areas of computer science including the Internet of Things, Machine Learning and Deep Learning. Van Uelsen (2021) describes AI as the ability of a program to accurately interpret external data, to learn on the basis of this data and to achieve particular purposes and tasks by adapting its behaviour to the environment. This flexible adaptation is made possible through the ability of the machine to explore large datasets and to learn from them so as to find patterns among these data which will, in turn, enable the system to evolve autonomously (Van Uelsen, 2021). Overall, it implies that the machine becomes capable of acting and thinking like a human (Poushneh, 2021). Therefore, Mariani, Perez-Vega and Wirtz (2022) argue that machines and systems part of AI can be considered as intelligent since they can replicate smart human behaviour and their way of thinking.

2 types of AI exist, namely weak AI, comprising Artificial Narrow Intelligence, and strong AI, which is made of Artificial General Intelligence and Artificial Super Intelligence (IBM, n.d.b). Weak AI is characterised by the machine performing one specific task at a time. It can take the form of autonomous vehicles, voice assistants (VAs) and recommendation systems (IBM, n.d.b). It is assumed that strong AI can solve problems, learn and predict the future (IBM, n.d.b). Super Artificial Intelligence would also have the capacity to surpass humans in even their most developed skills and attitudes (Van Uelsen, 2021). However, this stage has not been achieved yet and no concrete examples of strong AI can be provided at the moment of writing this thesis.

1.1.1. Origins of AI

AI first appeared in the 1950s when Alan Turing aimed to demonstrate that machines could potentially learn. The core of his research was thus based on creating intelligent machines and testing their intelligence through a specific test he elaborated himself (Anyoha, 2017). The term AI has only been introduced by John McCarthy in 1956 at the Dartmouth Conference held in the summer of that year (Cisek, 2021). Allen Newell, Cliff Shaw, and Herbert Simon presented their technology, called the Logic Theorist, which had the purpose to replicate the process of problem solving usually performed by human beings (Anyoha, 2017). Then, several technologies have been launched in this field, including the ELIZA program, developed by Joseph Weizenbaum, who aimed to enable the machine to have a conversation with a human (Cisek, 2021). However, from the mid 1970s, research on AI has been drastically reduced due to excessive expenditure in this area without achieving the expected results, a period referring to AI Winter (Kaplan and Haenlein, 2020). One of the major breakthroughs in the 1990s was the Deep Blue software developed by IBM which managed to beat the world chess champion Gary Kasparov in 1997 (Anyoha, 2017). Since then, many technologies involving AI have been developed including notably VAs and driverless cars[1].

1.2.Machine Learning

As introduced in the presentation of AI, the latter is made of a sub-category, Machine Learning, which is itself comprising another concept, Deep Learning (IBM, n.d.b). According to Cisek (2021), Machine Learning is related to the creation of knowledge by a machine on the basis of large volumes of data. In this case, the machine will rely on input data from human beings which it will explore to find similarities to then analyse it and make decisions (Cisek, 2021). When provided with large amounts of data, Machine Learning algorithms will be able to expand their learning and thus make more accurate decisions.

2 types of learning systems exist in Machine Learning. On the one hand, supervised learning is managed by a human. Individuals will be responsible for providing the machine with input and output data that are labelled to train it (Delua, 2021). Since the expected results are known by the users, they will be able to make comparisons between the answer provided by the machine and the predicted data with the purpose of improving the decision of the machine (Cisek, 2021). On the other hand, in unsupervised learning, the machine learns autonomously. The purpose is to find patterns in data provided without previous training (Cisek, 2021). By finding similarities and differences among the data, the system will build data clusters through a cluster analysis without naming them in order to determine the structure of the unlabelled data (Delua, 2021).

[1] Driverless cars, cf. glossary in Appendix 1

1.3.Deep Learning

The purpose of Deep Learning is to reproduce the functioning of human thinking by developing artificial neural networks, as in human brains (cf. infra p. 8) (Cisek, 2021). Deep Learning and Machine Learning are based on 2 layers: input and output. However, Deep Learning goes further by developing an intermediate layer for artificial neural networks, meaning that the information goes deeper than in Machine Learning (cf. infra p.8). Moreover, Deep Learning can be used in a large number of cases such as reading audio content, detecting smells, etc. (Cisek, 2021). Another difference between Deep Learning and Machine Learning lies in the fact that the first one involves less human help since the machine can perform the analysis more autonomously than with the latter (IBM, n.d.a). Finally, Deep Learning can rely on both labelled and non-labelled datasets as a basis for its algorithms and data does not have to be handled by an individual beforehand (IBM, n.d.a).

Chapter 2: Voice assistants

2.1.What are voice assistants?

The consulted articles mostly propose a definition of voice assistants (VAs) focused on AI, voice recognition and Natural Language Processing (NLP). There also seems to be tendency for the authors to include the ability of VAs to multitask. Overall, from these first insights, VAs can be defined as "*conversational agents that recognize and understand voice-based user requests and communication using natural language processing to accomplish a wide variety of tasks*" (Fernandes and Oliveira, 2021, p.180).

Choi and Drumwright (2021) and Buteau and Lee (2021) add in their definition that speech recognition is another key component of this technology that allows VAs to understand users' voice commands and thus to be conversational agents. A last element discussed by several authors was the "humanized" style of the conversations between VAs and their users (Ammari, Kaye, Tsai and Bentley, 2019; Canziani and MacSween, 2021). Indeed, as developed later in this section, VAs tend to become real companions by mimicking increasingly human being personalities and behaviours (Lim, Kumar, Verma and Chaturvedi, 2022; Wagner and Schramm-Klein, 2019).

2 different types of VAs are currently offered on the market. On the one hand, some VAs are part of devices that aim at fulfilling other needs at the same time, such as computers and phones

(Böhm, Eggert, Garnefeld, Holzmüller, Schaefers, Steinhoff, Woisetschläger, 2022). Siri, for instance, was first integrated to the iPhone (Hoy, 2018). On the other hand, some VAs might only be part of Bluetooth and standalone speakers, as for Alexa through Amazon Echo (Mari, Mandeli and Algesheimer, 2020). Therefore, considering that VAs are smart speakers is fallacious. In fact, the VA is the technology that allows to perform several tasks based on AI, the connected speaker only represents the support for the VA (Schultz and Brüggemann, 2021).

2.1.1. Origin of VAs

The history of contemporary VAs has started in the 1960s when IBM launched the first type of VA, Shoebox (Aitken, 2020). It was able to identify 16 words and numbers from 1 to 9. 10 years later, Carnegie Mellon developed the Harpy Program which was able to recognise 1000 words (Zoomtech, 2018b). Between the 1970s and 2000, several technologies were introduced notably by Microsoft and IBM. The first VA to be integrated into a phone was Siri by Apple. Siri was part of iOS, the operating system of Apple's products and was included in the iPhone 4S for its launch in 2011 (Zoomtech, 2018b). Microsoft Cortana has then been released in 2014. That same year, Amazon announced the launch of its VA, Alexa, and the first home assistant, Amazon Echo, only available for Amazon Prime members at that time (Hoy, 2018). Then, Google developed Google Assistant in 2016. Many Asian companies such as Samsung, Alibaba and Baidu also offer their own VAs on the market. However, due to the massive presence of Amazon, Google and Apple in the European VA market, and because these 3 companies and their VAs are the most known in Belgium, we have decided to focus only on the VAs developed by these American firms (Gaudiaut, 2020; Snoeck, 2019).

The market of the VAs is currently booming worldwide. In fact, Statista (2020) has reported that approximately 4 billion VAs were used globally in 2020. This figure is expected to grow to achieve more than 8 billion users in 2024 (Statista, 2020). The widespread adoption of this technology is linked to the development of the functionalities offered by the VAs (Hoy, 2018).

2.1.2. Scope of use

VAs, by relying on AI and NLP, can perform different types of tasks requested by an individual, as introduced above. Individuals usually make use of VAs to play some music as well as to send and read messages (Ammari et al., 2019; Buteau and Lee, 2021). They can also program calls, set timers and alarms and tell jokes and stories (Hoy, 2018). Interestingly, one of the latest skills developed by firms is the ability of VAs to place orders for the users. This includes any tasks from ordering food with Domino’s Pizza, to booking an Uber to the airport as well as to enabling individuals to do their grocery shopping (Hoy, 2018). Therefore, VAs are involved in the different stages of the consumer journey (CJ) (Zaharia and Würfel, 2021). In consequence, we may safely agree that consumer routines and purchasing behaviours are hence undoubtedly impacted by these developments.

2.2.Functioning of VAs

As mentioned previously, NLP is central to enable VAs to understand users’ requests and to converse with them (Balakrishnan and Dwivedi, 2021). This last feature is based on AI-related technologies such as algorithms and Machine Learning (Böhm et al., 2022). The different stages followed by the system when hearing a voice command will be presented chronologically as they appear in the process of the handling of natural language by VAs.

2.2.1. Speech-to-text

VAs are operational as soon as key words are pronounced by the users to wake them up (Hoy, 2018). These wake words can take the form of "Alexa", "Hey, Siri" or "Ok, Google", depending on the VA. It is also possible to activate the VA by pressing a button on a connected speaker or on the steering wheel of the user's car (Hoy, 2018). Once the VA has heard the user's request, the latter will be turned into written text by the system so that the machine understands the query. This process refers to Speech-To-Text, or voice recognition. The sound signal will be converted into acoustic vectors with background noise being removed (Aw, Tan, Cham, Raman and Ooi, 2022). In addition, the words will be broken down into phonemes so that the system recognises the words used by the individuals, regardless of their accent and voice rate. In fact, since the request made by the users is performed in natural language, the machine will have to translate it into a form that makes sense (Gouliaéva, Dosquet and Moysan, 2020).

2.2.2. Natural Language Processing

The Natural Language Processing (NLP) is a technology developed by AI that allows the user to converse in natural language with the VA without fearing that the request will be misinterpreted (McLean and Osei-Frimpong, 2021). For this purpose, the system will start the process with tokenization. At this stage, the machine will break the query by associating each word of it with a smaller unit, called a token (Chapuzet, 2019). For example, in the question: "What time is it?" will probably be split by the machine into: "what/time/is/it/?" (Bourdois, 2023). Thus, this request comprises 5 tokens allowing the machine to better assimilate the request as well as its type (NLTK, 2023). Once each token has been identified, it will be necessary to determine their meaning. 4 methods can extract the meaning of the words spoken by the user (Bolaños, 2021). First, the lexical analysis identifies the nature of each word, namely whether it is a subject, a verb, a punctuation mark, and so on. Once this step has been done, the syntactic analysis aims to find the position of each word in the sentence (Chapuzet, 2019). Then follows the semantic analysis seeking to analyze the meaning of the tokens identified and their links in order to discover their influence (Zoomtech, 2018a). Finally, on the basis of all the previous steps, a pragmatic analysis is carried out in order to bring together everything that has been learned and to reconsider the context of the research from the beginning without the ambiguity caused by the natural language (Selig, 2022).

2.2.3. Text-to-speech

The last part of the process aims that VAs answer to the voice command, which has been previously turned into a textual form to facilitate the understanding of the request by the technology. Thus, the objective will be to transform again the result of the textual search into a sound that will be understandable for the user, namely a voice representing the VA and its personality (Chapuzet, 2019). This voice can be easily tailored to user preferences. For instance, Google allows the user to choose the voice of their VA based on their own audio recordings, or among more than 220 voices offered by the American company (Google Cloud, n.d.).

2.2.4. Artificial neural networks

Artificial neural networks and Deep Learning are two other important tools that enable VAs to identify the meaning of the words (Barnes, 2022). The purpose of artificial neural networks is to explore and analyze large and particularly complex datasets by using algorithms developed in data mining (Mariani, Perez-Vega and Wirtz, 2022). For instance, in VAs, artificial neural networks can be useful in the process from waking up the VA to it providing results to the user based on the request (Barnes, 2022). The user may ask: “Where is the nearest dog park?”. In this case, based on the first keyword "where", the VA can determine that the individual is looking for a place. Then, knowing that the user asked for a dog park, the machine will start working to understand what is requested and to try to provide the users with the results linked to their questions. Moreover, thanks to the voice commands of other users, the VA will even be able to provide the closest and best rated dog parks first (Barnes, 2022; Sanderson, 2021).

2.3.Advantages of VAs

VAs offer many advantages to their users. From a relational point of view, they are of great help for illiterate people, allowing them to be understood by those around them using only their voice. In addition, VAs can provide a constant presence for people with dementia (Hasan, Shams and Raman., 2021). Poushneh (2021) demonstrated that VA usage can lead people to feel happier, to be less depressed, to increase social relations and to develop their willingness to do more sports. As mentioned previously, VAs tend to look increasingly like real human beings by emulating some of their traits (Vimalkumar, Sharma, Singh and Dwivedi, 2021). The different companies with VAs on the market seem to try to make consumers feel that they are real people, notably by giving them the ability to perform specific tasks or by providing them human features. For example, VAs can replicate human interactions by speaking through the 'I' form with a humanized voice. They also answer to the users' requests using their names and memorize some relevant facts mentioned by them, making the conversation with the machine more pleasant (Mari, Mandelli and Algesheimer, 2020). This characteristic gives individuals the feeling of having developed a personal relationship with VAs, thus providing psychological and social benefits to them (Aldophs and Zaharia, 2021; Choi and Drumwright, 2021).

Additionally, the human characteristics of VAs coupled with their capacity to gather and exploit user data allow them to provide consumers with personalized answers. Therefore, the users will have the feeling to have a unique experience, tailored to their needs and past experiences through the data collected by the VA (Santos and Gonçalves, 2021). Lastly, the ability of VAs to understand natural language has also simplified the human-machine interaction by making it more spontaneous compared to the traditional use of a keyboard by consumers to transmit their request to the system (McLean and Osei-Frimpong, 2019; Vimalkumar et al., 2021).

2.4.Drawbacks of VAs

Despite the advantages offered by VAs, the development of this new technology is not without some reluctance from consumers. Indeed, three main reasons seem to discourage individuals from using VAs on a daily basis.

First, the process of data collection and processing appears to be unclear to individuals, leading them to develop concerns on privacy protection against VAs. In fact, some users fear that their data will be misused by the companies having launched VAs (Hasan et al., 2021). The recurring scandals regarding the handling of user data by the GAFA[2] seem to deter consumers to use their technologies. Despite the adoption of the General Data Protection Regulation (GDPR) in 2016, the access of new technologies to sensitive and private data remains a major point of tension today, particularly due to the increased risk of data loss or data breach (Hoy, 2018). The always-on mode of VAs, while useful for detecting user requests instantly, is a source of apprehension as well. As Ammari et al. (2019) revealed in their article, a home assistant owner does not feel comfortable talking about important topics with the device being in the same room.

Another point raised by Hasan et al. (2021) as well as Berriche and Benavent (2021) relates to the ease of use of VAs. As mentioned earlier, although increasingly intelligent and developed to analyse long requests, VAs still require the consumers to adapt themselves to the language accepted by them (Hasan et al., 2021). As a result, individuals tend to be reluctant towards the daily use of VAs fearing that the query will not be understood, and thus not be correctly processed by the system. This is particularly challenging in the context of voice commerce (cf. infra p.11). Consequently, the lack of trust in the technology also appears to be a key factor in the limited adoption of VAs by consumers (Schultz and Brüggemann, 2021).

A last issue brought up by Van Roey (2020) relates to the ability of the technology to understand voice commands in several languages at the same time. This issue is particularly relevant in Belgium which comprises 3 national languages. Some people might be fluent in 2 of these 3 languages and thus talk to their VAs using either of them. This requires VAs to understand voice commands in a language different from the one in which the VA has been set up, thus that the system is able to process several languages at the same time. Since 2018, Google Assistant can talk in 2 different languages among English, French, Spanish, German, Italian and Japanese, a feature also offered by Amazon Alexa in France since 2020 (Geeko, 2018).

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[2] GAFA, cf. glossary Appendix 1

2.5. Voice commerce

2.5.1. Definition

As described in the previous sections, VAs can perform a wide range of tasks from answering to a call to ordering a taxi. However, a new feature has attracted the attention of numerous companies, namely the ability to buy items via the VA, also known as voice commerce. This concept can be defined as the act of buying or selling products through a VA (Wolbers and Walter, 2021). According to Mari, Mandelli and Algesheimer (2020), this definition can be extended to include the ability of the VA to influence all stages of the consumer journey encompassing activities ranging from information search to leaving a review (cf. infra p.15).

2.5.2. Key figures and practical examples

According to Chevalier (2023), the number of transactions performed through voice commerce achieved \$4.6 billion in 2021 and this figure is expected to reach around \$19 billion in 2023. Another study conducted by Chevalier (2022) illustrates that the three main uses of VAs in the context of voice commerce in 2021 in the U.S.A are looking for new products (44.4%), searching for products (34.1%), followed by creating a shopping list (30.3%). Purchasing products is the 5th most used voice command, with 24.1% of U.S. respondents reporting that they use their VAs for this purpose. According to Wolbers and Walter (2021), the main products bought through voice commerce are groceries and household products. In fact, consumers are more inclined to make purchases through VAs for products that require little involvement and that are between \$20 and \$50, as opposed to purchases that are luxurious or that require them to have a visual representation of the good before purchasing it (Klaus and Zaichkowsky, 2022; Wolbers and Walter, 2021; Zaharia and Würfel, 2021)

Online purchases and online orders through VAs represented respectively only 2% and 4% of the overall use of this technology in 2019 in Belgium (Snoeck, 2019). However, 36% of the respondents surveyed demonstrated interest in making purchases through this channel (Snoeck, 2019). Moreover, some companies have started offering their services through VAs. For example, Colruyt, a Belgian discount supermarket chain, announced in 2019 the beginning of a partnership with Google's VA (Van Rompaey, 2019). The chain focused mainly on giving its customers the possibility to make a shopping list that they would be able to find on the Colruyt app (Van Campenhout, 2019). This allowed customers who already had a Colruyt account to connect it to their Google Assistant, which would then add their favourite products to the shopping list once they made their voice command (van Rompaey, 2019). However, the chain has announced the end of the partnership with Google (Colruyt, 2023).

Carrefour, a French retailer, has taken significant strides in developing voice commerce through a partnership with Google in 2018 (ActuRetail, 2020). In fact, since 2020 the French clients of Carrefour can do their grocery shopping entirely by voice (Carrefour, 2020). To avail this service, customers only need to connect their Carrefour accounts to the speaker (cf. Appendix 2). Several benefits linked to the use of VAs are put forward by the retailer (2020). One of the primary advantages lies in the ability for consumers to converse in natural language, as mentioned previously. Carrefour claims that the VA recognises product names, brands and generic names, contributing to a more intuitive and convenient shopping experience. Additionally, Carrefour offers users the opportunity to share their shopping lists through the VA. To enhance privacy and security, the voice match feature restricts access to the list solely to the user's voice (Carrefour, 2020). Lastly, the VA leverages data collected from consumers' previous purchases to provide personalized product recommendations. Drawing from this data, the VA tailors its suggestions to match users' preferences and interests. For first-time purchases, recommendations are made on the basis of the best available prices and sales (Carrefour, 2020). To address the potential lack of consumer trust in data usage by the VA, the chain commits to comply with the GDPR and guarantees users that they will be able to delete their accounts from the VA whenever they wish so (Carrefour, 2020).

2.5.3. Advantages of voice commerce

As discussed later in this thesis, anthropomorphism represents a considerable benefit for VAs over computers, tablets and phones. In fact, they provide a great help which is similar to that provided by a human in the same situation in the CJ. As explained above, a relationship will be built overtime between the consumer and the machine through its ability to provide individuals with useful information tailored to their voice commands thanks to Machine Learning (Lim et al., 2022). Overall, these features will make the shopping experience more unique and personal, as mentioned in the case of Carrefour (Carrefour, 2020; Rzepka, Berger and Hess, 2020). The convenience of the medium also seems to be a motivating factor to make purchases through VAs. Indeed, a study conducted by Couponfollow (2020) demonstrated that 56% of the American respondents in the research mentioned convenience as an enabler for voice purchases.

As Rzepka, Berger and Hess (2020) explain in their article, this ease stems from the fact that consumers do not have to use a keyboard to search, and that talking seems to be faster and easier for them. The ability for VAs to perform several tasks is fairly time saving for the users, as mentioned above. In fact, VAs can intervene in all stages of the consumer journey (cf. supra p.12). By using voice commerce, individuals no longer have to look for and compare products on different websites for hours, and the payment stage is also made simpler (Aw et al., 2022).

2.5.4. Disadvantages of voice commerce

One of the most apparent drawbacks for voice commerce currently lies in the overall lack of trust from the consumer in the voice technology, as presented previously (cf. supra p.10). More particularly, the fear that the VA misinterprets the command, leading to inaccurate orders appears as an important deterring factor for individuals (Wolbers and Walter, 2021). However, although mistakes allow the machine to learn and therefore to grow, which is the natural cycle of AI so that technologies can develop their skills, repeated mistakes seem to represent a lack of intelligence from the machine to some users, leading to an unwillingness from the latter to use it until it progresses and reaches their expectations (Chabria and Someya, 2020).

In addition, some consumers have expressed concerns about the lack of transparency from VAs in their purchasing process. Specifically, they are concerned by the VA's decision regarding the order in which results are presented in response to their requests (Rzepka, Berger, and Hess, 2020). This issue has been addressed by Carrefour, as mentioned earlier (cf. supra p.12), to mitigate these concerns and enhance user trust. Finally, consumers desire more detailed information about the products themselves and the ability to compare different products based on their specific features and attributes. In fact, individuals seek a more comprehensive and informative experience during their interactions with VAs (Rzepka, Berger, and Hess, 2020).

2.6.Future of VAs

Based on the information presented in this chapter, we assume that VAs will remain on the market in the long term. The consistent and progressive development of these technologies by companies underscores a promising future in this regard. Some authors already present a large number of examples of how VAs will be used in the future, such as by connecting them to smart home systems in order to allow the users to increase the temperature of the heating or to set the alarm simply on the basis of their voice and at any time (Jirík, 2022). Nevertheless, the development of this technology will only be likely if enhancements are made to address the most recurring issues that currently limit its widespread adoption. Many of these limitations have been presented previously and include trust in the technology, fear of loss or misuse of personal data, and fear of not being understood by the VA.

The aim of businesses is to establish a trustworthy relationship with the consumer. With the objective of developing the use of VAs by 2025, businesses could notably emphasize the technical prowess of VAs. It might enable these firms to demonstrate the skills and ease of use of this technology. Moreover, in the current economic environment, Gartner (2022) underlined the increasing search from Millennials[3] and Gen Zers[4] for discount coupons as well price comparison tools. In times of high inflation, one can imagine that consumers tend to lean toward private labels, which are usually cheaper. As a result, offering the possibility to individuals to choose between a number of options to be presented to them from the cheapest to the most expensive, as Carrefour claims to already perform, might be necessary in the future (cf. supra p.12). By doing so, individuals could make their purchases without having to worry if the results provided are the ones that will bring the most profit to the company selling its products through this medium.

Chapter 3: Consumer journey

3.1.Traditional consumer journey

The modern consumer journey (CJ) has been introduced by Court, Elzinga, Mulder and Vetvik in 2009. This CJ consists of 5 main stages between which the consumer moves, and during which one actively interacts with a number of businesses (Court et al., 2009). Thus, the CJ is defined by Lemon and Verhoef (2016, p.74) as: "(…) *the process that customers go through across all touchpoints and decision stages that add up to the customer experience*". The 5-step model introduced by Court et al. (2009) will be taken as a reference point in the following pages. However, the terms pre-purchase, purchase and post-purchase are used in thesis to represent the various stages that are part of these 3 terms.

First, the pre-purchase stage comprises the need of recognition, the initial consideration set and the active evaluation phase. The initial consideration set consists in the consumer having a

[3] Millennials, cf. glossary in Appendix 1
[4] Gen Zers, cf. glossary in Appendix 1

number of brands in mind in order to fulfil the need activated by internal or external triggers (Court et al., 2009). The brands considered by the consumers in this stage can either come from their insights on some brands or from their exposure to touchpoints that made some firms stand out (Zaharia and Würfel, 2021). Touchpoints are defined as "(…) *being direct and indirect episodes of contact with firms and products that are carried through channel mediums*" (Santos and Gonçalves, 2022, p.1). Overall, they are described as all points of contact between the consumer and the brands (Santos and Gonçalves, 2021; Magnus, 2022). Once the initial consideration set is built up, it will be expanded and/or reduced depending on the information they gathered to purchase products of the brand that is the most likely to fulfil their need (Santos and Gonçalves, 2021). This step is called the active evaluation or information search. Consumers might ask their relatives about the brands they have in mind and consult websites which will result in a list of brands to purchase the product they are looking for (Lambert, 2022).

Then, the purchase comprises any exchange between the consumer and the chosen brand (Lemon and Verhoef, 2016). For an online purchase, this includes namely the choice of delivery and payment method (Böhm et al., 2022). Lastly, the post-purchase is defined by the use of the purchased product and the commitment of the consumer to the brand after having started its use. According to Böhm et al (2022), this stage is essential for firms to build a long-term relationship with their consumers. Indeed, at this point it is necessary for companies to support the consumer in their purchase by providing them the required support in the event of a problem, notably through an efficient customer service that meets customers' expectations. If the consumers are satisfied, it is likely that they will purchase again products from the same brand without going through the pre-purchase stages. This process refers to the loyalty loop and is the basis for the development of the consumer's loyalty to the brand (Court et al., 2009).

3.2.The consumer journey and VAs

The emergence of VAs has created a significant shift in the CJ. In fact, through their functionalities and skills, VAs have considerably simplified the purchasing process of the consumers (Böhm et al., 2022). VAs exert a relatively strong influence at each stage, which are presented further below. Knowing that the reach, pace and interactivity of the touchpoints represent key factors for firms to increase the satisfaction through the CJ, VAs represent real assets for firms when consumers plan to place an order since they can shorten the overall purchasing process (Wolbers and Walter, 2021).

To be part of the initial consideration set, companies could rely on VAs to make ads. However, it is likely that consumers might perceive this functionality as too intrusive as highlighted in the study of Wolbers and Walter (2021). VAs can also rely on the data they have gathered on users to make suggestions for their following purchase (Santos and Gonçalves, 2022). These tailor-made recommendations aim at relating goods to consumers' preferences. This can take the form of notifying consumers when a brand is making some discounts for instance (Wolbers and Walter, 2021). VAs possess the capacity to offer a curated selection of choices, thereby alleviating cognitive burdens and affording individuals the mental space to focus on other matters. Consequently, this cognitive liberation is likely to engender improved decision-making, ultimately leading to heightened consumer satisfaction and increased loyalty (Mari, Mandelli and Algesheimer, 2020). Moreover, a distinctive aspect of VA interactions lies in the absence of visual access to precise shopping basket details, as one would have through a computer interface. This particular characteristic potentially paves the way for a greater occurrence of impulse purchases (Böhm et al., 2022).

After that, as for a normal purchase, VAs can be used by consumers in the active evaluation stage for information search. Nevertheless, VAs provide only the first results from the search. Accordingly, consumers have access to limited results compared to if they had looked for information through traditional search engines on physical devices (Böhm et al., 2022). The limited number of options presented to the consumers appears to be useful in the sense that it enables them to perform the information search more quickly and with less effort than if they had to browse the web and go on several websites for the same purpose (Böhm et al., 2022; Wolbers and Walter, 2021). This feature is particularly convenient for repeated and low-involvement purchases which require less search of information. However, the choice of the brands proposed as alternatives to the consumer by the algorithm remains unclear to most individuals, which represents a potential risk to its adoption in the population (cf. supra p.13) (Böhm et al., 2022). In addition, to some consumers, it would be easier to use their phones or computers for research especially because they think that the SEO functionality of VAs is underdeveloped and thus, not enough optimised for searches that involve the purchase of a product (Wolbers and Walter, 2021).

The purchase stage seems to be the one that has experienced the most changes through VAs. Consumers have the possibility to have their account linked to their VAs, making it easier for them to order products they have already purchased in the past through a voice command (Mari, Mandelli and Algesheimer, 2020). As mentioned above, individuals are more likely to use VAs for low-involvement purchases and for products that are relatively easy to buy such as groceries, food delivery, and so on (Wolbers and Walter, 2021). Most consumers are still reluctant to use a VA for more expensive products for reasons of trust in the technology. This trend was also demonstrated in a study conducted by PwC (2018). The research revealed that the respondents would use VAs to buy low-involvement products, but not piece of clothes. Nevertheless, unlike what Wolbers and Walter (2021) thought, the people interviewed in their article were not afraid of providing their personal and payment information, but rather that a mistake would be made when purchasing high-involvement products. Rzepka, Berger and Hess (2020) reached the same results when they noticed that the consumers they interviewed did not express any negative feelings related to potential privacy issues in voice commerce. As one respondent said, if needed, he can turn his VA off to avoid any leakage of personal data (Rzepka, Berger and Hess, 2020).

Still, VAs have access to considerable amounts of personal data and other studies have shown different results from those obtained by Wolber and Walter (2021). Indeed, Böhm et al. (2022) noted that voice commerce, according to some consumers, carries a great risk regarding the handling of personal data. The authors noticed that consumers tend to be afraid that their personal data could be used by hackers and thus, be leaked and misused. In addition to that, even though the payment process appears to be easier with a VA since there is no need to provide the card details again, the fact that the payment validation can only be done by voice seems to be problematic for some individuals, especially if they have children who could place an order without them knowing (PwC, 2018; Böhm et al., 2022).

Lastly, as mentioned above, VAs offer the opportunity to consumers to repurchase products they have already bought more easily, simply by granting their VAs access to their account (Wolbers and Walter, 2021). In this case, the link between the customer's account and the VA will allow the latter to go through the client's purchase history and add the last items purchased by them to their shopping list when they request it (De Brye, 2020). Besides, since VAs may appear as humans for some consumers, they might motivate them to use the product they have purchased but also support them when they start using the product (Böhm et al., 2022). VAs might also facilitate consumers' access to the after-sales service of the firm from which they have made a purchase since individuals can directly address their request to the VA (Grewal, Guha, Schweiger, Ludwig and Wetzels, 2022). Moreover, VAs are always available unlike most customer service departments (Wolbers and Walter, 2021). In fact, by saying "*Alexa, open Product Feedback*" or "*Alexa launch Product Feedback*" through Amazon's VA, consumers will be given the opportunity to leave a review on the product they have bought, easing the act of giving one's opinion after the purchase (Amazon, 2023).

Chapter 4: Conceptual framework

Various theories aim at studying the acceptance of technology such as the Technology Acceptance Model (TAM) as well as the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT-2 theory is the most recent and the most complete (Khan and Qudrat-Ullah, 2021). In fact, the UTAUT model draws upon 8 distinct theories including TAM, social cognition theory and Theory of Reasoned Action (TRA). By gathering these diverse perspectives, the UTAUT-2 is able to predict up to 74% of individuals' willingness to use technologies (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). For these reasons, we decided to study the intention to use VAs by Belgian Millennials in their CJ on the basis of the UTAUT-2.

4.1. Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2)

The UTAUT-2 comprises 7 core variables that aim to describe the behavioral intention to use (BIU) and the use of technologies by individuals (cf. Appendix 3). First, performance expectancy is defined as the extent to which one can experience benefits from using a technology to perform some activities (Venkatesh, Thong and Xu, 2012). In the case of VAs, it can relate to the degree to which using a VA can lead to higher performance and efficiency (Aw et al., 2022; García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). Zaharia and Würfel (2021) mentioned in their article that performance expectancy covers the convenience, the possibility to save time and to realise multiple tasks without having to use one's hands, enabling the experience to be effortless and the task to take less time. Then, effort expectancy is described as the easiness of use of a system for an individual (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). Applied to VAs, this factor refers to the degree of ease to learn using this technology and to start using it (Zaharia and Würfel, 2021).

Then, social influence relates to the degree to which individuals think that their relatives consider that they should use a specific technology (Venkatesh et al., 2012). It is likely that before making a decision, individuals tend to ask for the opinions of people close to them that might help them in determining what to do. For VAs, users might seek the approval of people important to them before starting using VAs to perform tasks and to make purchases on a daily basis (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). Then, another variable relates to the facilitating conditions. These can be associated to the access or support needed to perform some actions (Aw et al., 2022). Since the use of VAs may not be intuitive for some consumers, it is likely that they perceive they will need great help to start using this technology (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022).

The 3 last concepts are hedonic motivation, price value and habit. According to our research, few studies on VAs analyse the influence of any of these 3 factors. Nevertheless, we present them in order to have a first global understanding of the model. Hedonic motivation relates to an individual's enjoyment and satisfaction in using a technology (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). As a result, hedonic motivation takes the form of the consumer's perception that using a VA will be stimulating and entertaining (Zaharia and Würfel, 2021). When considering using a new technology, consumers are likely to assess the balance between the benefits and the costs brought by it, which is conceptualized under the term of the price value (Zaharia and Würfel, 2021; García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). Lastly, habit reflects the tendency for individuals to replicate behaviours spontaneously after having learned to do them on a regular basis (Venkatesh et al., 2012). For new technologies, it will be the basis for user engagement (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022).

4.2.Additional factors

While the UTAUT-2 model is providing some guidance by determining the key variables related to the acceptance of new technologies, VAs present additional characteristics that also need to be studied and that have not been included in the model. We have decided to add 3 AI-related factors from the literature to the UTAUT-2 in order to make this model more relevant.

4.2.1. Perceived Anthropomorphism

Anthropomorphism is the tendency for individuals to associate characteristics, emotions or intentions traditionally carried by humans with nonhuman assistants (Kääriä, 2017; Wagner and Schramm-Klein, 2019). These characteristics include for instance the voice, appearance and personality (Wagner and Schramm-Klein, 2019). Overall, factors that can be used in anthropomorphism are either static, thus based on the image and sound, or dynamic, which includes namely the communication, verbal and non-verbal messages, and so on (Wagner and Schramm-Klein, 2019). Based on our research, this feature seems to be at the core of the spread of VAs. In fact, a great number of authors relied on this concept to determine whether it can facilitate the adoption of VAs among the population applied to voice commerce, as Kääriä (2017) as well as Wagner and Schramm-Klein (2019) have studied in their articles.

Perceived anthropomorphism confers many advantages to the adoption of VAs in the CJ. The humanoid characteristics of VAs facilitate the development of relationships akin to those with human beings. As a result, consumers would be more inclined to ask for the opinion of the machine and to trust them owing to these human features. VAs' capacity to offer personalized advice in a human voice further reinforces this association with a physical person, thereby increasing the likeliness of the creation of a relationship with them (Aw et al., 2022). Furthermore, as mentioned by Moriuchi (2021), the connection with the machine provides a greater likelihood for decision making given the natural character of the conversation with the consumer. Thus, providing VAs with human-like traits might pique users' interest and foster regular usage of this technology, as it bestows social and emotional benefits unlike traditional technologies lacking such features (Wagner and Schramm-Klein, 2019).

4.2.2. Perceived risk

Another point affecting the intention to use new technologies raised by several authors is the perceived risk for data privacy and data security. According to Vimalkumar et al. (2021), the perceived risk comprises 2 different types of risk, namely perceived privacy risk and perceived privacy concerns. Vimalkumar et al. (2021) stated that the difference between these two terms lies in the fact that perceived privacy risk refers to the likelihood that a company engages in behavior that could jeopardize consumer data. Perceived privacy concerns are associated to the fear that the firm might lose or misuse user data, while there might not be any explicit risk of it (Vimalkumar et al., 2021). For the average consumer, because the distinction between the 2 concepts is relatively small, we have decided to gather these 2 terms under perceived risk. Thus, perceived risk will be related to the risks that consumers might perceive that is related to data privacy and security.

Interestingly, there does not seem to be any concluding results from the different articles analyzed on this topic. In fact, Zaharia and Würfel (2021) found that the perceived risk can have a small but negative influence on the intention to use of the consumers they surveyed. However, Vimalkumar et al. (2021) highlighted that the privacy risk showed no significant influence on individuals' adoption of new technologies, as for perceived privacy concerns. As a result, we have decided to include this variable in our model to support either of the findings and to determine if this concept exerts an influence on the intention to use VAs.

While we cannot determine straight forward whether perceived risk influences somehow individuals' intention to use VAs, most studies have highlighted the fear of the loss of personal and confidential data perceived by the users and its negative influence on a consumer's willingness to adopt new technologies. Since VAs have an almost entire access to users' data once they have given their consent, they fear that their data can end up being misused, sold or hacked, limiting particularly the penetration of VAs in the European market (Buteau and Lee, 2021; Ewers, Baier and Höhn, 2020). Moreover, many people believe that data breach and security issues are core problems related to Internet of Things[5] tools such as VAs (Moriuchi, 2021). A worldwide study conducted by NortonLifeLock (2021) showed that 51% of the French respondents believe that it is not possible for them to protect their privacy. Yet, 56% of them said that they provide their data to have a more convenient life (NortonLifeLock, 2021).

4.2.3. Perceived trust

On the basis of the elements presented in the literature review and in the previous point, it also seemed important to us to consider the trust in technology and in the machine into our model. Indeed, as pointed out by Vimalkumar et al. (2021), the trust of consumers is impacted by their concern in the protection of their data. These 2 concepts, perceived trust and perceived risk, are thus intrinsically linked and both appear to affect the adoption of new technologies. Vimalkumar et al. (2021) add that perceived trust may thus be a mediating factor in the case of perceived risk towards the technology. Additionally, when shopping, online consumers tend to have access to less information than if they were shopping physically. Perceived trust can hence also be reflected in the confidence of the users that the VA will interpret their request correctly which, with regular use, will eventually encourage consumers to place orders through this medium (PwC, 2018). Therefore, perceived trust exhibits a link with PE as well.

[5] Internet of Things, cf. glossary in Appendix 1

Part II: Empirical analysis

Chapter 1: Frame of the research

1.1.Purpose of the thesis and problem background

As described in the literature review, the rise of VAs, their increasingly sophisticated features and their ability to perform various tasks instead of human beings make them a central topic in the current literature. Individuals seem to be attracted to these technologies for the convenience, time savings and the other advantages brought by VAs. However, some consumers are still sceptical about their daily use for a number of reasons provided before. Given this context, the study of the intention to use VAs requires the examination of numerous variables. Specifically, in light of the substantial proliferation of voice commerce, it is interesting to assess the extent to which a particular segment of the population is prepared to embrace voice commerce at any stage of the CJ. As a result, we seek to gain insights into the dynamics that underpin the adoption of VAs among users in the context of voice commerce.

Regarding the choice of the population in this thesis, we decided to target our research on Belgian Millennials for several reasons. First, we considered only Belgian inhabitants. As shown in the literature review, Belgian consumers seem to have developed a certain interest for voice commerce notably through the partnership between Colruyt and Google Assistant. Then, regarding the choice of Millennials, many authors have studied the adoption of VAs by comparing the results between genders and age groups. In particular, Fernandes and Oliveira (2021) noticed that Millennials are 4 times more likely to use a VA than Baby Boomers. In addition, although people in Generation Z seem to be prepared to use VAs more quickly than individuals in the other age groups, they are more reluctant to use them with firms (Fernandes and Oliveira, 2021). Instead, Millennials are using VAs more regularly. Finally, Ewers, Baier and Höhn (2020) have found that Millennials represent people in the age group most likely to develop trust issues with companies when it comes to the management and processing of their personal and private data, making people in this age group interesting to study.

The purpose of this thesis is thus to answer to the following question:

Which factors influence Belgian Millennials' intention to use a voice assistant in their consumer journey when grocery shopping?

Chapter 2: Hypotheses and model construction

This part of the thesis is dedicated to the presentation of the hypotheses that have been developed to answer the research question. The different hypotheses presented here below have been made on the basis of prior research detailed in the literature review, and more specifically on the part of the conceptual framework. From all these insights, we have then created our own model gathering the different variables that are the most relevant (cf. Appendix 4).

2.1.Hypotheses

First, even though effort expectancy (EE) is presented as a key variable influencing the behavioural intention to use (BIU) a technology in the population, the studies conducted on the theme of VAs highlight that this variable is only secondary in the sense that it has an indirect impact on the BIU. In fact, Zaharia and Würfel (2021) have discovered that the perception of the effort necessary to use VAs will have a positive impact on the image consumers have on the user-friendliness and performance of the technology. As a result, EE will influence positively the performance expectancy, another variable of the model. Vimalkumar et al. (2021) reached the same results in their article. Zaharia and Würfel (2021) went further in their research and noticed that EE also appears to be linked to hedonic motivation. In fact, the more complex and challenging the use of VA appears to be, the lesser the hedonic motivation is related to its use. This can be explained by the fact that since the users have to learn to use it, it will require them some time to become fully aligned with the technology, which in its turn can reduce the fun part related to its use (Zaharia and Würfel, 2021). Therefore, 2 hypotheses are provided:

H1: The effort expected has a negative influence on the hedonic motivation to use VAs.
H2: The effort expected has a positive influence on the expected performance of VAs.

After that, several research have highlighted that the humanoid characteristics attributed to the VAs enable these technologies to provide advice, hold a conversation and remember elements that were mentioned by the user as a real human would. Aw et al. (2022) have indicated in their study that when a VA has human-like features, it is likely that the users will consider them to be clever and skilled. Providing a VA with human characteristics would then encourage individuals to start using it to make their purchases. Overall, it can be summarized as the following process: if the VA possesses human-related features and that it is able to talk fluently with the users, it is considered to be able to better grasp the user's needs, which would then ease the purchasing process (Aw et al., 2022; Wagner and Schramm-Klein, 2019). Klaus and Zaichkowsky (2022) also mentioned that the human aspect of VAs might provide an additional reason to trust the machine. In fact, according to the authors, it is likely that individuals develop an attachment with the technology thanks to its human attributes and in consequence a certain trust in them (Klaus and Zaichkowsky, 2022).

H3: The human-like features attributed to VAs have a positive influence on their expected performance.
H4: The human-like features attributed to VAs have a positive influence on the trust in them.

As reported by Wolbers and Walter (2021), trust enables one to overcome the potential uncertainty when using a new technology. Even though the first VAs have been launched some years ago, most individuals still remain unfamiliar with their functionalities and characteristics, representing a potential barrier to their widespread acceptance in the population. In this thesis, the trust in the skills of the machine and in its capacity in keeping personal data carefully are 2 factors that individuals must overcome, and which might impact their vision of the performance of a VA. As a result, the perceived trust will tend to act as a variable between the perceived risk and the performance expectancy of VAs. The following hypothesis is formulated:

H5: The perceived trust in VAs has a positive influence on the expected performance of VAs.

The literature review has demonstrated that hedonic motivation appears to be important in the willingness for individuals to start using VAs in their CJ. An important characteristic to motivate people to use a VA lies in making sure that it appears as pleasant, fun and entertaining (Zaharia and Würfel, 2021). The various capabilities of VAs make them real playmates for some people, hence motivating them to learn using VAs as well as to actually use them for their friendly nature (García de Blanes Sebastián, Sarmiento Guede and Antonovica, 2022). As highlighted by García de Blanes Sebastián, Sarmiento Guede and Antonovica (2022), the more people think that using a technology will be amusing and fun, the more likely it is that they use it. Since the purpose of this thesis is to determine which factors influence Belgian Millennials' intention to use VAs for grocery shopping throughout the CJ, we have decided to make 3 different hypotheses for the 3 main steps of the CJ, namely:

H6a: The hedonic motivation has a positive influence on individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping.
H6b: The hedonic motivation has a positive influence on individuals' intention to use VAs in the purchase stage when doing grocery shopping.
H6c: The hedonic motivation has a positive influence on individuals' intention to use VAs in the post-purchase stage when doing grocery shopping.

Then, the performance expectancy of the system appears to have an important positive influence on the behavioural intention to use VAs as discovered by Adolphs and Zaharia (2021) in their study. In line with the hypotheses related to hedonic motivation, individuals are more likely to use VAs to purchase their groceries if they perceive the VA as a valuable tool to support their activities and if the underlying technology is considered suitable and effective for their needs (Adolphs and Zaharia, 2021; Zaharia and Würfel, 2021). If consumers believe that using VAs can enhance their performance and efficiency, it significantly influences their willingness to use a VA in their CJ for grocery shopping, as highlighted by García de Blanes Sebastián, Sarmiento Guede, and Antonovica (2022). This leads to the following hypothesis:

H7a: The expected performance has a positive influence on individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping.
H7b: The expected performance has a positive influence on individuals' intention to use VAs in the purchase stage when doing grocery shopping.
H7c: The expected performance has a positive influence on individuals' intention to use VAs in the post-purchase stage when doing grocery shopping.

The perceived risk related to data protection and privacy has been greatly tackled in the articles consulted for this thesis. As explained in the literature review, no conclusive results have been achieved on the influence of perceived risk on the behavioral intention to use VAs. However, most studies have stressed the negative meaning associated with this type of perceived risk and the number of consequences it can have on the consumer such as loss, theft, and use of private data by third parties. As a result, from these insights, we decided to perceive perceived risk as having a negative influence on the behavioral intention to use VAs. Furthermore, it has been shown that perceived risk can also influence the perceived trust in VAs. Once again, studies have not been conclusive about its impact on perceived trust. However, based on the various articles, it seems that perceived risk negatively influences perceived trust, making a snowball effect potentially influencing the intention to use as well. Therefore, 2 hypotheses can be made from these insights:

H8: The perceived risk has a negative influence on the perceived trust in VAs.
H9a: The perceived risk has a negative influence on individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping.
H9b: The perceived risk has a negative influence on individuals' intention to use VAs in the purchase stage when doing grocery shopping.
H9c: The perceived risk has a negative influence on individuals' intention to use VAs in the post-purchase stage when doing grocery shopping.

2.2.Model for the thesis

The model we have developed comprises dependent and independent variables. The overall dependent variable is the intention of Belgian Millennials to use VAs in their CJ for grocery shopping. The independent variables are represented by the factors motivating or deterring Belgian Millennials for this purpose. While the UTAUT-2 theory includes moderating variables as well, namely the age, the gender and experience of the respondent, we decided not to include them in our model. In fact, since we are studying only one population gathering people from the same generation, namely Millennials, analysing whether the use of VAs could differ across age groups would not make sense, same goes for the gender and the experience.

Additionally, we have decided not to include habit, price value, social influence and facilitating conditions in our model. Our aim through this thesis is to study the intention to use VAs in the CJ, and not its actual use. Therefore, analyzing whether the habit would have an influence on this variable does not appear to be relevant. In fact, having developed a habit to a VA would require having used it on a regular basis, while we assumed that most of the respondents to our survey do not use this technology on a regular basis. Then, the price value appears once again as a variable that might have an impact on the behavioral intention to use only if individuals have already purchased a VA, which is not expected in this thesis. Besides, since VAs are still not very developed in Belgium, it seemed unlikely that anyone in the respondents' surrounding might have a significant influence on placing their orders online. In this case, a need for conformism might appear, but it was not intended to study this factor. Lastly, facilitating conditions did not appear to be relevant to consider here as well. Indeed, the facilitating conditions appeared be very close to effort expectancy and performance expectancy presented above in the case of the intent to use VAs for grocery shopping. As a result, including this variable would not have represented any added value when analyzing the intention to use VAs in the context of grocery shopping.

From all these insights, we have then developed our own model, which is provided in the Appendices (cf. Appendix 4).

Chapter 3: Methodology

3.1.Chosen methodology

The objective of this thesis is to determine the variables influencing the intention of Belgian Millennials to use VAs in their consumer journey when grocery shopping. In order to collect as many responses as possible and given the theme of the study, it seemed more appropriate to conduct a quantitative study through the development and distribution of an online questionnaire. The software Qualtrics has been chosen to implement the questionnaire and send the survey to several Belgian Millennials. After having gathered the answers to the questions, the analysis of the data has been performed through the SPSS software.

3.2.Data collection

As explained above, we used an online questionnaire as a cost-effective and quick method for data collection, in accordance with the observations made by Lambin and de Moerloose (2016). Online surveys offer immediate encoding of responses and real-time supervision (Lambin and de Moerloose, 2016). Additionally, they offer the advantage of reaching a larger and diverse audience, while mitigating interviewer bias.

To ensure the questionnaire's efficiency and suitability, a pre-test was conducted with 3 Millennials, namely one 28-year-old woman, one 34-year-old man and one 37-year-old woman. Based on their feedback, the questionnaire has been modified. After that, the final questionnaire has been published on various social networks, such as Facebook and LinkedIn, as well as in private conversation groups on Messenger and WhatsApp. To reach a larger number of Millennials, many different people have been contacted in this age group to share our questionnaire as much as possible. The survey was launched on the 7th of June and remained open until the 25th of June with the purpose of capturing as many perspectives as possible from the target population.

3.2.1. Questionnaire

The questionnaire consisted in 11 closed-ended and structured questions, of which 5 were 5-point Likert scales, 4 questions were multichotomic with single choice and the 2 last ones were dichotomic questions. The questionnaire was divided into 9 parts. As advised by Lambin and de Moerloose (2016) and Pleyers (2022), the survey started with a brief presentation of the research topic including the explanation of some words that may be difficult to understand for someone without any prior marketing knowledge. After that, some questions followed to determine the socio-demographic characteristics of the respondent such as one's age category, to ensure that the participants are in the studied age range, one's gender, and so on. Then, introductory questions about VAs were asked in order to get the respondent's attention, as suggested by Lambin and de Moerloose (2016). Lastly, the respondents were prompted to answer the questions in the 6 sections which are dedicated to more specific sub-questions on each variable that can influence the intention to use a VA in the CJ. The finalized questionnaire is provided in Appendix 5.

Regarding the measurement scales, they all followed the same structure. They were 5-point Likert scales and were always organized the same way. The scales were built from "strongly disagree" to "strongly agree" in order to avoid any confusion when the respondents would be directed from one part of the survey to the other. The participants also had to answer all questions to be able to move to the next section. More information on the measurement scales, the number of items and their source is provided in Appendix 6.

3.3.Data preparation

Before starting the analyses, we first proceeded to a clean-up of the answers to the questionnaire. In fact, 152 answers have been gathered. Even though it was explicitly mentioned that the questionnaire was only aimed at people aged between 26 and 43 years old, we have decided to add a question regarding the age group of the respondent. On this basis, any participants having responded that they belong to another age group have been automatically sent to the end page, and their answers have been deleted. Then, since the purpose is to determine the factors that might influence Belgian Millennials to use a VA in their consumer journey when doing grocery shopping, the answers from the respondents coming from another country than Belgium have also been deleted. Additionally, incomplete answers have been filtered out from the data. After this clean-up, 105 answers were usable for the analyses.

Chapter 4: Data analysis

4.1.Description of the sample

As mentioned above, a total of 105 valid answers have been gathered after proceeding to the clean-up of the data. Among them, 59 respondents are female (56%) and 46 are male (44%). 63 respondents have a master's degree (60%), 39 have a bachelor's degree (37%) and only 2 have their degree from their high school (2%). Then, regarding the living place of the participants, most of them come from Brussels (38%), followed by Wallonia (32%) and Flanders (30%). We also thought it would be appropriate to consider respondents' prior knowledge of VAs although this variable is purely informative and not exclusionary. We notice that a vast majority of the participants knew about VAs before this survey (83%) were and that most of them (37%) use VAs at least once per week or never (28%). Lastly, among those who have already used a VA, the majority have used Apple's VA, Siri (53%).

4.2.Factor analysis

The first part of the analysis consists in making a factor analysis to determine whether correlating variables can be grouped into a new variable that would encompass the items under this variable (Pleyers, 2022). A Principal Component Analysis (PCA) has been performed for this purpose, followed by an analysis of the Cronbach's alpha coefficient of the different variables to verify their internal consistency.

First, the KMO and Bartlett sphericity tests were carried out. For the results to be significant, the KMO had to be at least of 0.5 (Pleyers, 2022). In addition, the Bartlett sphericity test had to be statistically significant, namely the p-value had to be lower than 0.05. These 2 conditions were met for all our variables. Then, we analysed the communalities to determine which variables should be conserved on the basis of their degree of correlation. In this case, the variances had to be greater than 0.5 (Pleyers, 2022). Some of the variables under efficiency (Hedonic motivation and Performance) and perceived risk had a fairly low communality. However, since the results to the other tests were significant and conclusive, we have decided to keep the items to create a new variable.

Lastly, an internal consistency analysis has been performed using Cronbach's Alpha. The latter is a coefficient between 0 and 1. The closer the coefficient is to 1, the greater the degree of reliability in the questionnaire. In addition, it must be at least of 0.7 for the variables to be accepted (Pleyers, 2022). The Cronbach's Alpha for the new variables was higher than 0.7, indicating the reliability of these variables. However, the variable learning effort and efficiency (hedonic motivation) had a Cronbach's Alpha lower than 0.7. Nevertheless, since the variables had conclusive results to the previous tests, it seemed relevant to keep them while paying attention to the results that we could see in the upcoming analyses. Once all the analyses had been carried out, they were combined under a common variable by calculating the average of the items. The detailed analyses can be found in Appendix 7.

Chapter 5: Results

The objective of this chapter is to conduct an analysis of each hypothesis using SPSS. On the basis of the obtained results, we will be able to validate or refute each hypothesis.

5.1. Hypothesis testing

Before providing further details on the insights that have been gathered from the hypothesis testing, it is worth mentioning that each hypothesis has been tested using a simple linear regression model. In fact, all hypotheses comprised 2 quantitative variables. As a result, the simple linear regression represented the most suitable way to test the hypotheses and get meaningful insights from them.

H1: The effort expected has a negative influence on the hedonic motivation to use VAs.

In the analyses we carried out, we noticed first that the R squared value was very low (0,01). This indicated that less than 1% of the variance of the efficiency variable with hedonic motivation can be explained by the model. After that, the p-value is of 0,812 (>0.05). As a result, the null hypothesis indicating the variables are not correlated cannot be rejected and the model is not relevant. In addition, the β coefficient is positive. It has a low but positive value, which indicates the positive relationships between the variables. As a result, we cannot confirm that the expected effort has a negative influence on hedonic motivation for voice assistants. Therefore, this hypothesis is rejected.

H2: The effort expected has a positive influence on the expected performance of VAs.

The results indicate, once again, that less than 1% of the dependent variable, here the expected performance of VAs, can be explained by the model. Furthermore, the p-value is higher than 0.05 (0,530), indicating that the model is not relevant. Lastly, the β coefficient is positive, but has a low value. As a result, this hypothesis is rejected, and we cannot confirm that the effort expected to understand the use of this technology has a significant influence on the expected performance of VAs.

H3: The human-like features attributed to VAs have a positive influence on their expected performance.

The results to the analysis demonstrate in this case that the R square has a value of 0.095. Therefore, 9,5% of the variance of the expected performance can be explained by the model, which is fairly low. However, when considering the p-value, we can see that it is of ,001. Thus, we can say that the model is statistically significant. Lastly, the β coefficient is positive and has a value of 0.296. Therefore, we can affirm, with a 5% margin of error, that the expected performance of VAs is significantly influenced by the human-like features attributed to these devices. The hypothesis 3 is validated.

H4: The human-like features attributed to VAs have a positive influence on the trust in them.

On the basis of the analyses performed, we notice that the model is statistically significant since the p-value is < 0.05. Then, we could see that only 5% of the variance of the trust in VAs can be explained by the model, R square being 0.05. In addition, we notice that the relation between both variable is positive since the β coefficient is positive (0,265). As a result, we can affirm, with a 5% margin of error, that the trust in VAs is significantly influenced by the human-like features attributed to them. Thus, the hypothesis 4 is supported.

H5: The perceived trust in VAs has a positive influence on the expected performance of VAs.

For this hypothesis, the R square reaches 0,092, which indicates that 9,2% of the variance of the expected performance of VAs can be explained by the model. In addition, since the p-value is 0.002 (<0.05), we can say that the model is statistically significant. Lastly, the β coefficient is positive (0,245), demonstrating a positive relationship between both variables. Therefore, we can affirm, with a 5% margin of error, that the expected performance of VAs is significantly influenced by the trust that individuals put in VAs. Consequently, the hypothesis 4 is validated.

H6a: The hedonic motivation has a positive influence on individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping.

The test demonstrated that the R square is 0.054. Thus, only about 5% of the variance of the intention to use VAs in the pre-purchase stage is explained by the model. However, the p-value is lower than 0.05, indicating that the model is statistically significant. In addition, the β coefficient is positive (0,240). As a consequence, we can affirm, with a 5% margin of error, that the intention to use VAs in the pre-purchase stage when doing grocery shopping is significantly influenced by the hedonic motivation that individuals might have to use VAs. The hypothesis 6a is thus supported.

H6b: The hedonic motivation has a positive influence on individuals' intention to use VAs in the purchase stage when doing grocery shopping.

For this hypothesis, the R square is 0.037, demonstrating that only about 4% of the variance of the intention to use VAs in the purchase stage when doing grocery shopping can be explained by the model. Then, the p-value is 0,049. Thus, just below the point of 0.05. However, we can still say from this result that the model is statistically significant. Then, the β coefficient is positive (0,197), showing a positive relationship between both variables. Therefore, we can confirm, with a 5% margin of error, that the intention to use VAs in the purchase stage when doing grocery shopping is significantly influenced by the hedonic motivation that individuals might have to use VAs. The hypothesis 6b is thus confirmed.

H6c: The hedonic motivation has a positive influence on individuals' intention to use VAs in the post-purchase stage when doing grocery shopping.

The tests performed for this hypothesis show that 3% of the variance of the intention to use VAs in the post-purchase stage when doing grocery shopping is explained by the model through the R square. Nevertheless, the p-value is 0.072 (>0.05). Therefore, the model is not statistically significant. From these insights, the hypothesis is rejected, and we cannot confirm that the hedonic motivation has a significant influence on the intention to use VAs in the post-purchase stage when doing grocery shopping.

H7a: The expected performance has a positive influence on individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping.

When considering the results of this test, we notice that the R square is 0,183. Thus, 18% of the variance of the intention to use VAs in the pre-purchase when doing grocery shopping can be explained by this model. Then, the p-value is lower than 0.001 (<0.05). Therefore, we can affirm that the model is statistically significant. Lastly, the β coefficient is positive (0,416), as well as the p-value associated (<0,001). As a consequence, we can confirm, with a 5% margin of error, that the intention to use VAs in the pre-purchase stage when doing grocery shopping is significantly influenced by the expected performance that individuals might have about VAs. The hypothesis 7a is validated.

H7b: The expected performance has a positive influence on individuals' intention to use VAs in the purchase stage when doing grocery shopping.

This test informs us that the R square is 0.109, indicating that about 11% of the variance of the intention to use VAs in the purchase stage when doing grocery shopping can be explained by the model. The model is also statistically significant since its p-value is lower than 0.001 (<0.05). The β coefficient is positive (0.317), meaning that there is a positive relationship between both variables. We can confirm, with a 5% margin of error, that the intention to use VAs in the purchase stage when doing grocery shopping is significantly influenced by the expected performance that individuals might have about VAs. The hypothesis 7b is validated.

H7c: The expected performance has a positive influence on individuals' intention to use VAs in the post-purchase stage when doing grocery shopping.

The results to this test indicate first that the R square reaches 0.091. This means that around 9% of the variance of the intention to use VAs in the post-purchase stage when doing grocery shopping can be explained by the model. Then, the p-value associated to this test is 0.002 (<0.05). As a result, this model is statistically significant. Then, the β coefficient is positive (0.314) confirming the existence of a positive relationship between both variables. Therefore, we can confirm, with a 5% margin of error, that the intention to use VAs in the post-purchase stage when doing grocery shopping is significantly influenced by the expected performance that individuals might have about VAs. The hypothesis 7c is supported.

H8: The perceived risk has a negative influence on the perceived trust in VAs.

The results to this test show that the R square is 0.012, indicating that only 1% of the variance of the perceived trust in VAs can be explained by the model. Then, when analysing the p-value, it is 0.022 (<0.05). Thus, the model is statistically significant. We notice that the β coefficient is negative (-0.147), meaning that there is indeed a negative relationship between both variables. Even though the R square is very low, the other results were conclusive. As a result, we can confirm, with a 5% margin of error, that the perceived risk has a negative influence on the perceived trust in VAs. The hypothesis 8 is validated.

H9a: The perceived risk has a negative influence on individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping.

The results to the tests carried out for this hypothesis are somewhat contradictory with it. The R square is 0.082, meaning that slightly above 8% of the variance of the individuals' intention to use VAs in the pre-purchase stage when doing grocery shopping is explained by the model. The p-value is 0.003 (<0.05), thus the model is statistically significant. However, the β coefficient is positive, while it was assumed that there was a negative relationship between the perceived risk and the intention to use VAs in the pre-purchase stage when doing grocery shopping. As a result, we cannot confirm that the perceived risk has a negative influence on the intention to use VAs in the pre-purchase stage when doing grocery shopping. Therefore, the hypothesis 9a is rejected.

H9b: The perceived risk has a negative influence on individuals' intention to use VAs in the purchase stage when doing grocery shopping.

Once again, the results to the test demonstrate that the R square is 0.116. In addition, the p-value is <0.001 (<0.05). Thus, the model is statistically significant. However, as for hypothesis 9a, the β coefficient is positive while it was also hypothesised that there was a negative relationship between both variables. Yet, the results demonstrate another conclusion. Therefore, we cannot confirm that the perceived risk has a negative influence on the intention use VAs in the purchase stage when doing grocery shopping. The hypothesis 9b is thus rejected.

H9c: The perceived risk has a negative influence on individuals' intention to use VAs in the post-purchase stage when doing grocery shopping.

Finally, the R square is 0.121, meaning that 12% of the variance of the intention to use VAs in the post-purchase stage when doing grocery shopping can be explained by the model. The p-value is <0.001 (<0.05), thus the model is statistically significant. Nevertheless, the β coefficient is positive, as for the 2 previous hypotheses. Therefore, although we have assumed that there was a negative relationship between the perceived risk and the intention to use VAs in the post-purchase stage when doing grocery shopping, the results seem to indicate the existence of a positive relationship between the variables. Consequently, we cannot confirm that the perceived risk has a negative influence on the intention use VAs in the post-purchase stage when doing grocery shopping. The hypothesis 9c is rejected.

Chapter 6: Discussion

This chapter compares the results obtained to the previous chapter to the potential factors of influence highlighted in the literature review.

First, the literature review underlined that the required effort to learn to use a VA may have a negative impact on the perception of enjoyment and entertainment related to using a VA due to the time required to become accustomed to this technology. However, the analysis of this hypothesis did not reveal any significant correlation between the 2 variables in our research. Surprisingly, despite the initial effort needed, the pleasure and entertainment associated with the VA does not seem to be reduced, which is inconsistent with the findings of Zaharia and Würfel (2022). In addition, it could not be demonstrated that there was a positive influence between the effort expectancy and the expected performance of the VA. After that, we considered the perceived anthropomorphism. We have noticed that this variable has a positive influence on both the perceived trust and the expected performance of the systems. This aligns with the findings of Aw et al. (2022), Wagner and Schramm-Klein (2019) and Klaus and Zaichkowsky (2022) in their respective studies. The more human features are provided to VAs, the more likely Belgian Millennials will be to develop trust towards them and to have an increased expected performance of this technology due to the ability of VAs to talk as humans.

Similarly, if we consider the trust consumers have in VAs, we notice that this variable is also affected by the risk perceived by individuals. Although the results on the perceived risk in the literature review presented opposite views, our study showed that the risk of personal data breach expected by Belgian Millennials influences negatively the trust they have in VAs. However, as Vimalkumar et al. (2021) have pointed out, the perceived risk did not appear in our study as having a negative impact on the intention to use a VA at any stage of the CJ for grocery shopping. Therefore, these results are interesting as they suggest that consumers may have varying perceptions of risks when they intend to use a VA compared to the trust they have in this technology. In fact, we can assume from these insights that despite the perceived risk of data breach, Belgian Millennials tend to accept this risk to have a more convenient life, which was also highlighted in the study of NortonLifeLock (2021). Our analysis revealed as well that the more trust Belgian Millennials have in VAs, the higher their expectation in the performance of the systems, which aligns with the findings of Wolbers and Walter (2021).

After that, we aimed to determine the factors that would influence the intention to use VAs at any stage of the CJ, and how these factors may impact the different stages of the CJ. First, we examined the influence of the hedonic motivation related to VAs on their intended usage in the CJ. Interestingly, the results demonstrate that the more pleasure and enjoyment related to the VA, the higher the respondents' intention to use a VA for the pre-purchase and purchase. These findings are consistent with the study conducted by García de Blanes Sebastián, Sarmiento Guede and Antonovica (2022). Nevertheless, the analyses performed for the post-purchase stage did not enable us to arrive at conclusive results, thus the hypothesis has been rejected.

Then, we moved on to the analysis of the expected performance of VAs. We observed that the expected performance has a positive influence on all the stages of the CJ. Our conclusion is in line with the research realised by Adolphs and Zaharia (2021) and Zaharia and Würfel (2022). As a result, if Belgian Millennials increasingly perceive VAs as being skilled to accomplish certain tasks, they will be more inclined to use them in the various stages of their CJ for grocery shopping. Overall, our thesis sheds light on the importance of hedonic motivation and perceived performance as influential factors, unlike the perceived risk, in shaping the intention to use VAs in the different phases of the CJ for grocery shopping among Belgian Millennials.

Part III: Conclusions

1. Main conclusion

The purpose of this dissertation was to address the following research question: "*Which factors influence Belgian Millennials' intention to use a voice assistant in their consumer journey when grocery shopping?*". Therefore, we investigated and analyzed the various factors that motivate or deter Belgian Millennials' intention to use a VA when grocery shopping.

We started this thesis by assessing the interest of Belgian Millennials in VAs. From the literature review, it seemed that this population is interested in new technologies. VAs indeed represent an easy way of simplifying the consumer journey. It can be mostly attributed to their ability to talk fluidly with the consumer, to retain data in memory and to be relatively easy to use. However, these elements come with certain other factors which are currently limiting their use and development. We may list among these reasons notably the lack of trust in VAs, the level of data protection they ensure and the fact that setting up a VA tailored to the consumer's needs is relatively burdensome. Consequently, although a future may have been promised in a number of articles, we wanted to contribute to the literature to compare this thinking to a real-life example by analyzing the case of Belgium. For this purpose, we carried out a quantitative study, focusing exclusively on Belgian Millennials. The questionnaire gathered 105 valid responses which we analyzed in order to confirm or refute our hypotheses.

The most striking results concerning the factors directly impacting the intention to use a VA, as highlighted by the reviewed articles, relate to the perceived risk. In fact, our analyses failed to identify any negative relationship between perceived risk and any of the 3 stages in the consumer journey. Nevertheless, our analyses showed that the more Belgian Millennials expect VAs to be able to perform tasks, the more they will want to use them in the various stages of their purchasing process. The pleasure and entertainment associated with VAs also proved to be important for both pre-purchase and purchase, confirming the need for Belgian Millennials to feel pleasure when considering using VAs in these two stages. However, our analysis did not allow us to determine whether this is the case for post-purchase. Another interesting point relates to the human characteristics attributed to VAs. Many articles focus on this aspect, which seems to play a major role in the factors influencing people's intention to use a VA. In the dissertation, we observed that the more human attributes VAs possess, the more Belgian Millennials will perceive them as being able to perform several tasks, and will entrust them to do so. Lastly, our analysis showed that perceived risk has a negative influence on the trust in VAs. As a result, the greater the risk of data loss from the point of view of Belgian Millennials, the less trust they are likely to have in the systems.

The literature review and our quantitative analysis provided the key factors which influence Belgian Millennials' intention to use VAs in their consumer journey for grocery shopping. Overall, our research has identified 2 variables that exert a direct positive influence on the different steps of the CJ, namely the hedonic motivation and the expected performance. However, no significant relationship has been found in the data between the perceived risk and the intention to use a VA in the different steps of the CJ when grocery shopping.

2. Managerial implications

Our research and analyses have revealed a number of points of attention which shall be considered by retail and technology companies which wish to launch a grocery shopping offer through VAs in order to fine-tune their offer to Belgian Millennials.

First, this thesis has enabled us to realize that selling goods through voice commerce is very much different than in physical stores or on the retailers' website. It requires to consider different aspects related to the technology acceptance and usage that retailers might not take into account before offering their services through a VA. In fact, we note that expected performance plays in the current case a strong influence. Accordingly, market actors should emphasize on the performance of VAs. This includes, in particular, their ability to understand several languages and to be useful in the various stages of the CJ, by notably easing the buying process. In addition, we observed that the joy and entertainment of using a VA positively influences the intention of Belgian Millennials to use it for grocery shopping. Therefore, communicating on the user-friendly, fun and playful nature of the technology might encourage an increasing number of consumers to recourse to a VA in the future.

Our research has also highlighted that the perceived risk of data breach or leakage did not appear to be a significant factor in the intention to use VAs for grocery shopping. Nevertheless, in the current environment, we recommend companies to remain transparent with consumers. In fact, while no direct link can be established between the perceived risk and the intention to use in this thesis, we did note that the perceived risk has a negative impact on individuals' trust in VAs, which in turn can also influence the expected performance of these systems. As a result, we recommend firms to reassure individuals about the data privacy issues by demonstrating them the way their data is handled, stored and protected. Communicating on the fact that the data can be deleted at any time, as required by the GDPR, might also foster a greater sense of trust among individuals interested in VAs.

Lastly, despite recent studies suggesting that VAs have a promising future, the penetration rate of this technology remains limited in Belgium. However, in the light of the results analysed we consider that we can expect several players in the retail market to embrace this technology as soon as one of them has developed it, as it was the case in France. The fact remains that, with the arrival of ChatGPT, it is highly likely that business interest will diversify into other new technologies too. Still, in view of current market developments and the data presented to us, it seems worthwhile for companies to consider the development of voice commerce first. To ensure the successful expansion of their activities, retailers need to adapt their communications on the launch of this service to a group of individuals who are most likely to use VAs, appreciate them and talk about voice commerce to their relatives afterwards. In this case, the primary objective for companies will be to identify the early adopters[6] among Belgian Millennials, namely individuals who are most likely to try out grocery shopping through a VA and to influence other people to do the same.

3. Limitations and future research

Our thesis also comprises some limitations relating to our study and analyses, which will be discussed below. Some piece of advice is also provided for future research.

First, the sample comprised 105 valid answers. The purpose of this thesis was to study the intention to use VAs by Belgian Millennials, thus already limiting the scope of the sample to a specific part of the population. However, we are aware that the number of answers gathered is not fully representative of the aggregate viewpoint of Belgian millennials' intention to use VAs. This has also impacted the results to the analyses performed. In fact, we assume that some of the hypotheses rejected were due to the lack of responses to the survey, which then impacted our statistical analyses. Therefore, researchers should try to make sure that a higher number of Belgian Millennials answer to their survey in order to increase the representativeness of their

[6] Early adopters, cf. glossary in Appendix 1

results. This may be done by incentivising people to answer the survey through a discount code or by sharing it in a way that would attract their attention.

Then, it has been often reported that the questionnaire was relatively long and took some time to answer. In fact, as mentioned previously, the questionnaire comprised 9 different parts and has been written in English to facilitate the understanding by both French and Dutch speaking Belgian Millennials. It was thus assumed that the respondents understood the English language well enough to answer our questionnaire, which might have deterred some people to take part in our survey. Therefore, it might be more appropriate to prepare 2 questionnaires in future research, in Dutch and in French, in order to make it easier for respondents to understand the questions and the choices proposed to them.

Additionally, although many people know VAs such as Siri or Alexa, the terminology used might have been a source of trouble for some respondents. In fact, we noticed that when asking the participants to provide us another brand of VA that they are aware of, some individuals answered the followings: Connected watch, Samsung TV and Mercedes. These 3 answers are interfaces on which a VA has been integrated and are thus not VAs themselves. For this reason, in future research, researchers should ensure that all the words are correctly defined by the respondents before launching the test to make sure that they understand exactly the context of the research and respond as accurately as possible.

Lastly, the scope of this research was limited to grocery shopping primarily because the literature review indicates that individuals are more inclined to purchase low-involvement and daily products than luxury goods in the context of voice commerce. Therefore, in this thesis, we found it more interesting and appropriate to study whether Belgian Millennials would be likely to use a VA for grocery shopping, which involves the purchase of daily products. As a result, future research might focus on the willingness or the likeliness of Belgian Millennials to purchase high-involvement products with voice commerce. Understanding how individuals perceive and respond to voice commerce in the context of more significant and higher-involvement purchases could unveil additional factors that shape the adoption of VAs in different domains of consumer behaviour.

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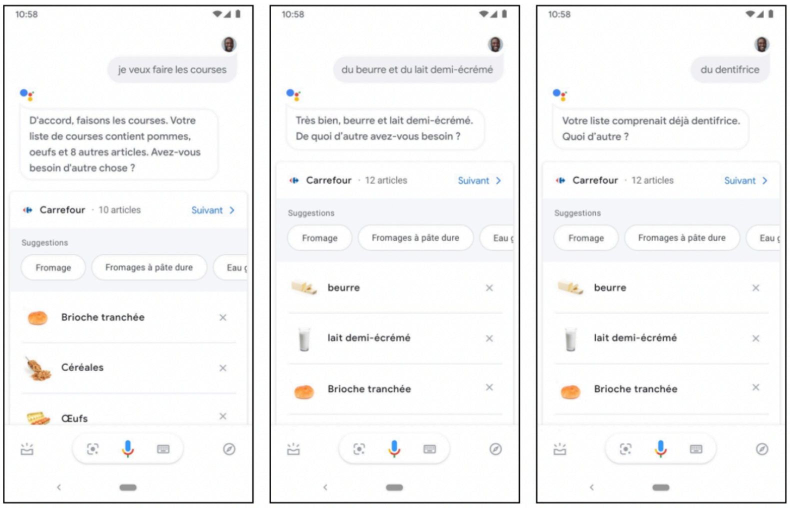
Appendices

Appendix 1: Glossary

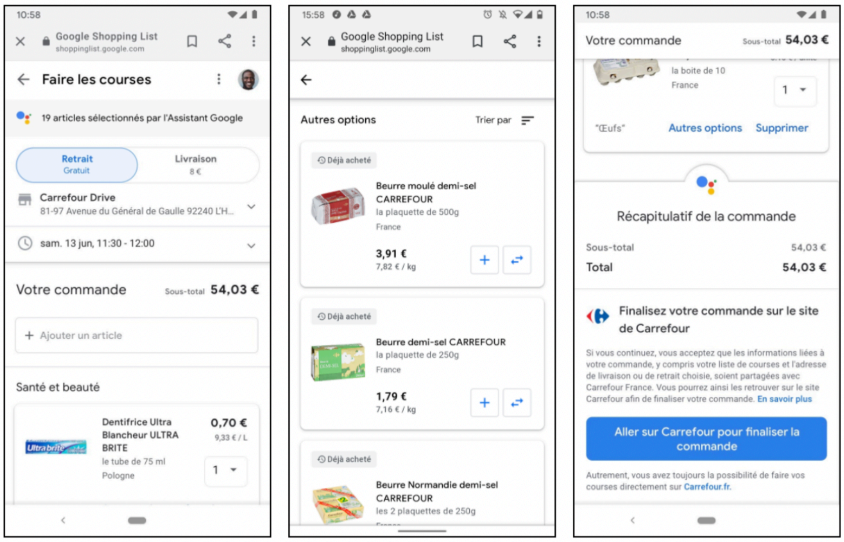
- Driverless cars: Also called autonomous or self-driving vehicles, driverless cars are vehicles that can navigate autonomously, without requiring any input from an individual (GCF Global, n.d.).
- Early adopters: They are opinion leaders and determine the success or failure of a new technology once they have tried it and compared it to other similarly systems. They can easily reduce the uncertainty related to the launch of new products and are thus essential to convince other groups of people to try them as well (Wani and Ali, 2015).
- GAFA: Also written GAFAM in some cases, is an acronym for Google, Amazon, Facebook and Amazon. This acronym stands for the most powerful firms active in the tech and Internet industry (Van Roey, 2018).
- Gen Zers: Refer to people in the Generation Z, i.e., individuals born between 1998 and 2010 (Dimock, 2019).
- Internet of Things: Encompasses various technologies, such as smart thermostats and smartwatches, that comprise sensors, software and that are connected through networks. These smart objects can communicate with each other and centralized systems through this mean (IBM, n.d.c).
- Millennials: Also called Generation (Gen) Yers, Millennials are individuals born from 1980 to 1997 (Dimock, 2019).

Appendix 2: Voice grocery shopping with Carrefour through Google



Il vous suffit de dire « Ok Google je veux faire les courses » pour commencer votre expérience d'achat par la voix. © Google.

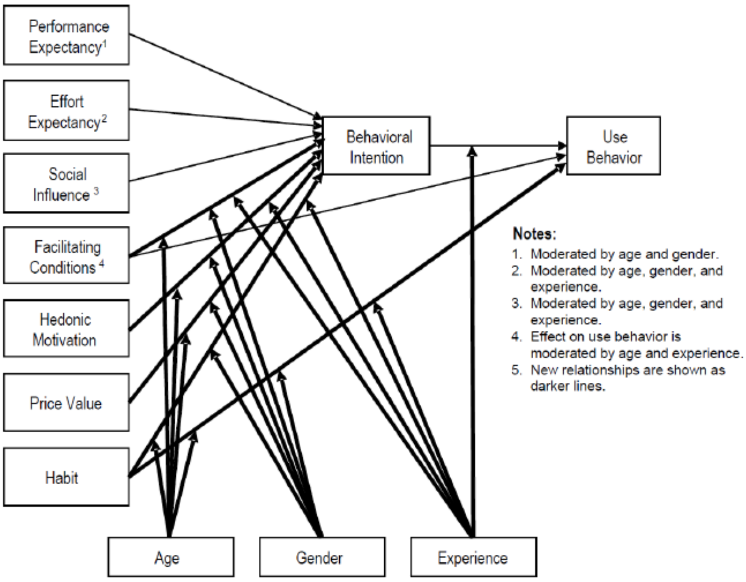
Source: Coëffé, T. (2020). *"Ok Google, je veux faire les courses » : l'achat alimentaire à la voix arrive sur l'Assistant Google*. Blog du Modérateur. Retrieved from https://www.blogdumoderateur.com/ok-google-je-veux-faire-les-courses/



Vous retrouvez vos produits demandés à l'oral sur Google Shopping List. © Google.

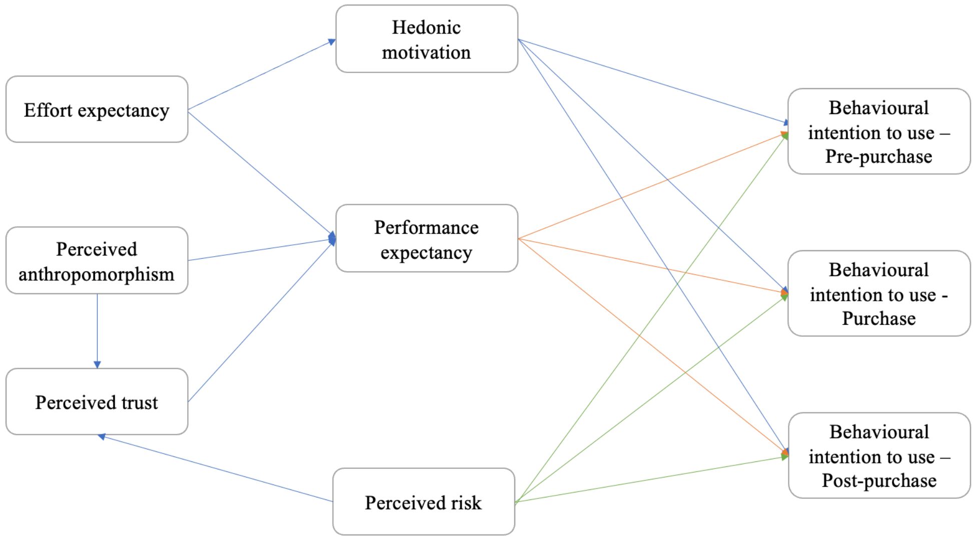
Source: Coëffé, T. (2020). *"Ok Google, je veux faire les courses » : l'achat alimentaire à la voix arrive sur l'Assistant Google*. Blog du Modérateur. Retrieved from https://www.blogdumoderateur.com/ok-google-je-veux-faire-les-courses/

Appendix 3: Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) model



Source : Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), p.160. https://doi.org/10.2307/41410412

Appendix 4: Adapted model of the UTAUT-2 for this thesis



Source: Personal realisation

Appendix 5: The survey

Beginning: Introduction

Dear Sir or Madam,

Thank you for taking the time to answer this survey!

The latter is conducted as part of my studies in business management at the Louvain School of Management, and more specifically in the case of my thesis for my master's degree. The objective of my thesis is to determine the factors influence the intention to use voice assistants in your purchasing process when doing grocery shopping.

Attention: The questionnaire is only intended for people aged between **26 and 43 years old**. Please answer **ALL** questions, although some of them may seem similar to you. Your answers are recorded **confidentially** and **anonymously**.

If you have any questions about this survey or would like more information about it, please contact me: juliette.cordier@student.uclouvain.be

Once again, thank you for contributing to my master's thesis!

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To help you better understand the subject of this questionnaire, here are some further explanation of terms that may be used in future steps:

- Voice Assistant: A voice assistant is a technology with which you can have a conversation in order to perform various tasks including setting an alarm clock, playing music, ordering a meal on Uber Eats, etc. The most known voice assistants are Siri from Apple, Google Assistant from Google and Alexa from Amazon.

- The consumer journey represents the different steps that consumers go through before using a product. They include the pre-purchase (characterized by the search for information), the purchase (including payment and choice of delivery in the case of an online purchase), and the post-purchase (comprising the contact with the customer service and the use of the purchased product).

Saut de page

Q1 What gender do you identify yourself with?

- Woman (1)
- Man (2)
- X (3)
- Prefer not to say (4)

Q2 How old are you?

- Less than 18 (1)
- Between 19 - 25 (2)
- Between 26 - 43 (3)
- Between 44 - 56 (4)
- Above 57 (5)

Passer à : Fin de l'enquête Si How old are you? != Between 26 - 43

Q3 What is your highest education level?

- Elementary school (école primaire/basisonderwijs) (1)
- High school (école secondaire/secundaire onderwijs) (2)
- Bachelor's degree (3)
- Master's degree (4)
- PhD (5)
- Other (6)

Q4 Where do you live?

- ◯ Brussels (1)
- ◯ Flanders (2)
- ◯ Wallonia (3)
- ◯ Other: (4) ____________________

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Q5 Did you know what were voice assistants before this survey?

- ○ Yes (1)
- ○ No (2)

Q6 How often do you use a voice assistant?

- ○ Never (1)
- ○ Once per week (2)
- ○ 2 to 3 times per week (3)
- ○ 4 to 6 times per week (4)
- ○ Everyday (5)

Q7 If you have already used one, which brand of voice assistant did you use?

- ☐ Siri (Apple) (1)
- ☐ Google Assistant (Google) (2)
- ☐ Alexa (Amazon) (3)
- ☐ Cortana (Microsoft) (4)
- ☐ Other: (5) ____

Saut de page

Q8 To what extent do you (dis)agree with the following sentences?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Learning to use a voice assistant seems to be easy to me (1)	○	○	○	○	○
Because learning to use a voice assistant seems to be easy to me, I expect the voice assistant to be very **convenient** for grocery shopping (2)	○	○	○	○	○
The effort needed to understand the way of working of voice assistants **decreases** my motivation to use it (3)	○	○	○	○	○

Saut de page

Q9 To what extent to do you (dis)agree with the following sentences?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Knowing that voice assistants can have the voice of a human being make them more **trustful** to me (1)	○	○	○	○	○
Voice assistants appear as intelligent and skilled at performing tasks to me because they have a voice similar to that of a human being (2)	○	○	○	○	○
Knowing that voice assistants can have the voice of a human being make them more **convenient** to me (3)	○	○	○	○	○
Voice assistants' ability to talk with a human being voice make them more **friendly** and **pleasant to use** (4)	○	○	○	○	○

Saut de page

Q10 To what extent do you (dis)agree with the following sentences?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
I trust voice assistants because I consider them to be able to understand all my queries perfectly (1)	○	○	○	○	○
I trust voice assistants because I believe they are enough developed to be used in my daily life (2)	○	○	○	○	○

Saut de page

Q11 To what extent do you (dis)agree with the following sentences?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
I perceive using a voice assistant as fun and entertaining (1)	○	○	○	○	○
I believe that using a voice assistant might increase my chance to fulfill the different tasks I have to do in a day (2)	○	○	○	○	○
I believe the technologies in which voice assistants are embedded (mobile phone, smart speaker, car, etc.) are easy to use when **looking for some information** for grocery shopping (3)	○	○	○	○	○
I believe the technologies in which voice assistants are embedded (mobile phone, smart speaker, car, etc.) are easy to use to **purchase** my groceries (4)	○	○	○	○	○

I believe the technologies in which voice assistants are embedded (mobile phone, smart speaker, car, etc.) are easy to use to contact the **aftersales service** and/or **leave a review** after shopping my groceries (5)	○	○	○	○	○

Saut de page

Q12 To what extent do you (dis)agree with the following sentences?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
I am afraid of sharing my personal data (e.g., baking and financial data) to the voice assistant fearing that they end up being sold or breached by a third party when **looking for some information** for grocery shopping (1)	○	○	○	○	○
I am afraid of sharing my personal data to the voice assistants fearing that they end up being sold or breached by a third party when **purchasing** my groceries (2)	○	○	○	○	○
I am afraid of sharing my personal data to the voice assistant fearing that they end up being sold or breached by a third party when contacting the **aftersales service** and/or **leaving a review** after my groceries (3)	○	○	○	○	○

The lack of clarity regarding the handling of my personal data **reduces** my **trust** in voice assistants (4)	○	○	○	○	○

Fin de bloc: Voice assistants usage

Appendix 6: Summary of the measurement scales, items and sources

Investigated variable	Measurement scale	# of items	Sources
Performance expectancy	5-point Likert scale	5	Adapted from Venkatesh et al. (2012)
Effort expectancy	5-point Likert scale	3	Adapted from Venkatesh et al. (2012)
Hedonic motivation	5-point Likert scale	2 (combined with the performance expectancy)	Adapted from Venkatesh et al. (2012)
Perceived anthropomorphism	5-point Likert scale	4	Developed by myself on the basis of the literature
Perceived risk	5-point Likert scale	4	
Perceived trust	5-point Likert scale	2	

Appendix 7: Factor analyses

1. KMO test and sphericity test of Bartlett

We conducted KMO and Bartlett's sphericity tests to determine whether the items making up the various variables could be grouped together to form a new variable. All the variables obtained significant results in each of the tests, i.e., for the KMO test, a result greater than 0.5 and for Bartlett's sphericity test, a p-value lower than 0.05.

1. Learning effort

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,500
Bartlett's Test of Sphericity	Approx. Chi-Square	6,492
	df	1
	Sig.	,011

2. Anthropomorphism

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,614
Bartlett's Test of Sphericity	Approx. Chi-Square	103,681
	df	6
	Sig.	<,001

3. Trust

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,500
Bartlett's Test of Sphericity	Approx. Chi-Square	30,039
	df	1
	Sig.	<,001

4. Efficiency: hedonic motivation

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,649
Bartlett's Test of Sphericity	Approx. Chi-Square	91,711
	df	6
	Sig.	<,001

5. Efficiency: performance

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,680
Bartlett's Test of Sphericity	Approx. Chi-Square	108,908
	df	6
	Sig.	<,001

6. Perceived risk

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,694
Bartlett's Test of Sphericity	Approx. Chi-Square	79,134
	df	6
	Sig.	<,001

2. Communalities of the variables

To be valid, all the items composing the variables have a communality higher than 0.5. This indicates that above 50% of each of the variables' variance can be explained by the chosen component. It is the case for the different variables analyzed here, except for the 1st item under efficiency (hedonic motivation) and 2nd item under efficiency (performance). The 1st and 4th item of the perceived risk also had a communality lower than 0.5. Nevertheless, we have decided to keep the items since the results to the other analyses were significant and because deleting these items would not have improved the results to the communality.

1. Learning effort

Only the 1st and the 3rd item have been included in the making of the new variable. In fact, the 2nd item was not relevant to include in the new variable for the study of the 1st hypothesis. Therefore, the purpose was to create a new variable only on the basis of the 1st and 3rd items.

Communalities

	Initial	Extraction
Learning_Item1	1,000	,624
Learning_Item3	1,000	,624

Extraction Method: Principal Component Analysis.

2. Anthropomorphism

Communalities

	Initial	Extraction
HBvoice_Item1	1,000	,517
HBvoice_Item2	1,000	,539
HBvoice_Item3	1,000	,573
HBvoice_Item4	1,000	,579

Extraction Method: Principal Component Analysis.

3. Trust

Communalities

	Initial	Extraction
Trust_Item1	1,000	,776
Trust_Item2	1,000	,776

Extraction Method: Principal Component Analysis.

4. Efficiency: Hedonic motivation

Communalities

	Initial	Extraction
Efficiency_Item1	1,000	,183
Efficiency_Item3	1,000	,575
Efficiency_Item4	1,000	,756
Efficiency_Item5	1,000	,614

Extraction Method: Principal Component Analysis.

5. Efficiency: Performance

Communalities

	Initial	Extraction
Efficiency_Item2	1,000	,414
Efficiency_Item3	1,000	,598
Efficiency_Item4	1,000	,715
Efficiency_Item5	1,000	,578

Extraction Method: Principal Component Analysis.

6. Perceived risk

Communalities

	Initial	Extraction
Privacy_Item1	1,000	,410
Privacy_Item2	1,000	,628
Privacy_Item3	1,000	,659
Privacy_Item4	1,000	,417

Extraction Method: Principal Component Analysis.

3. Total variance explained

Then, on the basis of the results to the previous tests, we aimed to determine the number of components that we should keep to represent the different variables. For this purpose, we applied the Kaiser rule which sets that only the components with an Eigenvalue higher than 1 should be preserved in the model. For this test, each of the values that had significant results to the previous tests can be grouped together under a single component.

1. Learning effort

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,248	62,387	62,387	1,248	62,387	62,387
2	,752	37,613	100,000			

Extraction Method: Principal Component Analysis.

2. Anthropomorphism

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,209	55,216	55,216	2,209	55,216	55,216
2	,961	24,022	79,238			
3	,490	12,258	91,495			
4	,340	8,505	100,000			

Extraction Method: Principal Component Analysis.

3. Trust

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,552	77,583	77,583	1,552	77,583	77,583
2	,448	22,417	100,000			

Extraction Method: Principal Component Analysis.

4. Efficiency: Hedonic motivation

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2,127	53,176	53,176	2,127	53,176	53,176
2	,905	22,613	75,789			
3	,637	15,920	91,709			
4	,332	8,291	100,000			

Extraction Method: Principal Component Analysis.

5. Efficiency: performance

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2,306	57,642	57,642	2,306	57,642	57,642
2	,791	19,775	77,417			
3	,577	14,436	91,853			
4	,326	8,147	100,000			

Extraction Method: Principal Component Analysis.

6. Perceived risk

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2,127	53,182	53,182	2,127	53,182	53,182
2	,763	19,071	72,253			
3	,712	17,799	90,052			
4	,398	9,948	100,000			

Extraction Method: Principal Component Analysis.

4. Correlation between the component and the original variables

1. Learning effort

Component Matrix[a]

	Component 1
Learning_Item1	,790
Learning_Item3	,790

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

2. Anthropomorphism

Component Matrix[a]

	Component 1
HBvoice_Item4	,761
HBvoice_Item3	,757
HBvoice_Item2	,734
HBvoice_Item1	,719

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

3. Trust

Component Matrix[a]

	Component 1
Trust_Item1	,881
Trust_Item2	,881

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

4. Efficiency: Hedonic motivation

Component Matrix[a]

	Component 1
Efficiency_Item1	,427
Efficiency_Item3	,758
Efficiency_Item4	,869
Efficiency_Item5	,783

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

5. Efficiency: Performance

Component Matrix[a]

	Component 1
Efficiency_Item2	,644
Efficiency_Item3	,773
Efficiency_Item4	,846
Efficiency_Item5	,760

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

6. Perceived risk

The results found at the step of the communalities is aligned with the results of the component matrix that are provided here below. In fact, as mentioned above, both the first and fourth item had low communalities with the component. In this table, we can see that it is indeed the case since neither of the items correlate strongly with the axis, compared to the third item for instance.

	Component
	1
Privacy_Item1	,630
Privacy_Item2	,794
Privacy_Item3	,821
Privacy_Item4	,653

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

5. Cronbach's Alpha

The last part of this factor analysis consists in performing the test with the Cronbach's Alpha coefficient to determine the internal consistency of the scales. The Cronbach's Alpha of most of the variables is higher than 0.7. Therefore, we can say that these variables are internally consistent. Despite the Cronbach alpha coefficient being lower than 0.7 for the variable of the learning effort and efficiency (hedonic motivation), the results to the other tests as part of the PCA were conclusive and significant. Therefore, we have decided to keep both variables while knowing that we should pay attention to the analyses carried out afterwards.

1. Learning effort

Reliability Statistics

Cronbach's Alpha	N of Items
,374	2

2. Anthropomorphism

Reliability Statistics

Cronbach's Alpha	N of Items
,729	4

3. Trust

Reliability Statistics

Cronbach's Alpha	N of Items
,711	2

4. Efficiency: Hedonic motivation

Reliability Statistics

Cronbach's Alpha	N of Items
,689	4

5. Efficiency: performance

Reliability Statistics

Cronbach's Alpha	N of Items
,750	4

6. Perceived risk

Reliability Statistics

Cronbach's Alpha	N of Items
,703	4

Appendix 8: Hypothesis testing

Before carrying out the analyses, we checked, for each of the hypotheses involving the use of simple linear regression, that they positively met the conditions necessary before carrying out the tests. These conditions are the homogeneity of variances, the normal distribution and the independence of residuals.

1. Hypothesis 1

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,024[a]	,001	-,009	,67752

a. Predictors: (Constant), Learning_Effort

b. Dependent Variable: Efficiency_HM

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,026	1	,026	,057	,812[b]
	Residual	47,281	103	,459		
	Total	47,307	104			

a. Dependent Variable: Efficiency_HM

b. Predictors: (Constant), Learning_Effort

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2,914	,336		8,663	<,001
	Learning_Effort	,022	,092	,024	,239	,812

a. Dependent Variable: Efficiency_HM

2. Hypothesis 2

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,062[a]	,004	-,006	,72186

a. Predictors: (Constant), Learning_Effort

b. Dependent Variable: Efficiency_Perfo

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,207	1	,207	,397	,530[b]
	Residual	53,672	103	,521		
	Total	53,879	104			

a. Dependent Variable: Efficiency_Perfo

b. Predictors: (Constant), Learning_Effort

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2,593	,358		7,235	<,001
	Learning_Effort	,062	,098	,062	,630	,530

a. Dependent Variable: Efficiency_Perfo

3. Hypothesis 3

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,309[a]	,095	,087	,68787

a. Predictors: (Constant), Anthropomorphism

b. Dependent Variable: Efficiency_Perfo

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,142	1	5,142	10,867	,001[b]
	Residual	48,737	103	,473		
	Total	53,879	104			

a. Dependent Variable: Efficiency_Perfo

b. Predictors: (Constant), Anthropomorphism

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1,925	,278		6,925	<,001
	Anthropomorphism	,296	,090	,309	3,297	,001

a. Dependent Variable: Efficiency_Perfo

4. Hypothesis 4

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,223[a]	,050	,041	,87316

a. Predictors: (Constant), Anthropomorphism

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,129	1	4,129	5,415	,022[b]
	Residual	78,528	103	,762		
	Total	82,657	104			

a. Dependent Variable: Trust

b. Predictors: (Constant), Anthropomorphism

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2,260	,353		6,406	<,001
	Anthropomorphism	,265	,114	,223	2,327	,022

a. Dependent Variable: Trust

5. Hypothesis 5

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,303[a]	,092	,083	,68919

a. Predictors: (Constant), Trust

b. Dependent Variable: Efficiency_Perfo

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,956	1	4,956	10,434	,002[b]
	Residual	48,923	103	,475		
	Total	53,879	104			

a. Dependent Variable: Efficiency_Perfo

b. Predictors: (Constant), Trust

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2,066	,241		8,560	<,001
	Trust	,245	,076	,303	3,230	,002

a. Dependent Variable: Efficiency_Perfo

6. Hypothesis 6a

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,232[a]	,054	,045	,910

a. Predictors: (Constant), Efficiency_Item1

b. Dependent Variable: Efficiency_Item3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,850	1	4,850	5,851	,017[b]
	Residual	85,379	103	,829		
	Total	90,229	104			

a. Dependent Variable: Efficiency_Item3

b. Predictors: (Constant), Efficiency_Item1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,082	,355		5,858	<,001
	Efficiency_Item1	,240	,099	,232	2,419	,017

a. Dependent Variable: Efficiency_Item3

7. Hypothesis 6b

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,193[a]	,037	,028	,907

a. Predictors: (Constant), Efficiency_Item1

b. Dependent Variable: Efficiency_Item4

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3,275	1	3,275	3,979	,049[b]
	Residual	84,782	103	,823		
	Total	88,057	104			

a. Dependent Variable: Efficiency_Item4

b. Predictors: (Constant), Efficiency_Item1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,059	,354		5,814	<,001
	Efficiency_Item1	,197	,099	,193	1,995	,049

a. Dependent Variable: Efficiency_Item4

8. Hypothesis 6c

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,176[a]	,031	,022	,987

a. Predictors: (Constant), Efficiency_Item1

b. Dependent Variable: Efficiency_Item5

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3,223	1	3,223	3,308	,072[b]
	Residual	100,339	103	,974		
	Total	103,562	104			

a. Dependent Variable: Efficiency_Item5

b. Predictors: (Constant), Efficiency_Item1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,169	,385		5,630	<,001
	Efficiency_Item1	,196	,108	,176	1,819	,072

a. Dependent Variable: Efficiency_Item5

9. Hypothesis 7a

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,428[a]	,183	,176	,846

a. Predictors: (Constant), Efficiency_Item2

b. Dependent Variable: Efficiency_Item3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16,552	1	16,552	23,140	<,001[b]
	Residual	73,676	103	,715		
	Total	90,229	104			

a. Dependent Variable: Efficiency_Item3

b. Predictors: (Constant), Efficiency_Item2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,769	,252		7,018	<,001
	Efficiency_Item2	,416	,087	,428	4,810	<,001

a. Dependent Variable: Efficiency_Item3

10. Hypothesis 7b

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,330[a]	,109	,101	,873

a. Predictors: (Constant), Efficiency_Item2

b. Dependent Variable: Efficiency_Item4

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,616	1	9,616	12,627	<,001[b]
	Residual	78,441	103	,762		
	Total	88,057	104			

a. Dependent Variable: Efficiency_Item4

b. Predictors: (Constant), Efficiency_Item2

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1,870	,260		7,190	<,001
	Efficiency_Item2	,317	,089	,330	3,553	<,001

a. Dependent Variable: Efficiency_Item4

11. Hypothesis 7c

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,302[a]	,091	,082	,956

a. Predictors: (Constant), Efficiency_Item2

b. Dependent Variable: Efficiency_Item5

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,442	1	9,442	10,333	,002[b]
	Residual	94,120	103	,914		
	Total	103,562	104			

a. Dependent Variable: Efficiency_Item5

b. Predictors: (Constant), Efficiency_Item2

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1,982	,285		6,960	<,001
	Efficiency_Item2	,314	,098	,302	3,214	,002

a. Dependent Variable: Efficiency_Item5

12. Hypothesis 8

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,109[a]	,012	,002	,89048

a. Predictors: (Constant), PRisk

b. Dependent Variable: Trust

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,984	1	,984	1,241	,022[b]
	Residual	81,673	103	,793		
	Total	82,657	104			

a. Dependent Variable: Trust

b. Predictors: (Constant), PRisk

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,576	,474		7,547	<,001
	PRisk	-,147	,132	-,109	-1,114	,022

a. Dependent Variable: Trust

13. Hypothesis 9a

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,286[a]	,082	,073	,873

a. Predictors: (Constant), Privacy_Item4

b. Dependent Variable: Privacy_Item1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6,982	1	6,982	9,152	,003[b]
	Residual	78,580	103	,763		
	Total	85,562	104			

a. Dependent Variable: Privacy_Item1

b. Predictors: (Constant), Privacy_Item4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,199	,465		4,733	<,001
	Privacy_Item4	,364	,120	,286	3,025	,003

a. Dependent Variable: Privacy_Item1

14. Hypothesis 9b

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,340[a]	,116	,107	,899

a. Predictors: (Constant), Privacy_Item4

b. Dependent Variable: Privacy_Item2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,909	1	10,909	13,492	<,001[b]
	Residual	83,281	103	,809		
	Total	94,190	104			

a. Dependent Variable: Privacy_Item2

b. Predictors: (Constant), Privacy_Item4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,797	,478		3,756	<,001
	Privacy_Item4	,455	,124	,340	3,673	<,001

a. Dependent Variable: Privacy_Item2

15. Hypothesis 9c

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,348[a]	,121	,112	,980

a. Predictors: (Constant), Privacy_Item4

b. Dependent Variable: Privacy_Item3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,603	1	13,603	14,165	<,001[b]
	Residual	98,911	103	,960		
	Total	112,514	104			

a. Dependent Variable: Privacy_Item3

b. Predictors: (Constant), Privacy_Item4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,300	,521		2,493	,014
	Privacy_Item4	,508	,135	,348	3,764	<,001

a. Dependent Variable: Privacy_Item3

Executive summary:

Emerging technologies, together with Artificial Intelligence have grown considerably over the past half-century. This advancement has generated new means of communication, such as chatbots like ChatGPT and voice assistants including Siri, Alexa and Google Assistant. These technologies have not only reshaped cognitive processes and decision-making patterns among individuals but have also revolutionized consumer behaviours. A noteworthy addition to these new technologies is the advent of voice commerce, recently developed by voice assistants-owning firms.

To explore the adoption of these new technologies, an extensive array of models has been developed in the literature. For this thesis, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) model has been selected and extended to encompass the factors that may influence the intention to use voice assistants in the context of voice commerce in Belgium. Therefore, the primary objective of this dissertation is to identify the factors impacting the intention to use a voice assistant in the consumer journey when grocery shopping, applied to the case of Belgian Millennials. Based on the literature review, the UTAUT-2 model and the various variables added, as well as our quantitative research through an online questionnaire targeted at Belgian Millennials, several conclusions and recommendations have been drawn in relation to this subject matter to offer retailers interesting insights for the future.

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