Smart voice assistant use and emotional attachment on reinforcement of filter bubble phenomenon towards the choice of acceptance of the new content: A quantitative research examining the moderating effects of brand trust and user satisfaction

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ABSTRACT

The explicit use of personalisation functions by voice assistants drives more and more companies to incorporate smart assistant technologies into their products. This means that companies must contend with the appearance of personalised filter bubbles – whether it is due to the companies' delivered content or otherwise - when it comes to facilitation of the new content via voice technologies, which might lie outside of the consumers' personalised preferences. However, according to the discussion among scholars, voice assistant users would be willing to receive more of new content if voice assistants sounded more human. As the implementation of natural language speech into voice assistants can produce emotional bonding or friendship connection on the users.

Therefore, the present study aims to offer the insights coming from empirical evidence on the phenomenon of the filter bubble and the ways emotional connections could possible reinforce filter bubble to foster the users' willingness to accept the new content. In addition, this research explores the extent to which user satisfaction, brand trust and filter bubble would moderate the effects of voice assistant use on acceptance of the new content. By conducting an online survey, insights into the different effects between the groups were obtained.

However, the findings of this study indicate that emotional attachment does not mediate the effect of voice assistant use on acceptance of the new content. It appeared that VA users experience less emotional attachment than other device users, as the voice assistant use had negative significant effect on emotional attachment. Also, voice assistant users experience less user satisfaction than device users. Brand trust had positive significant effect on emotional attachment. Yet, the most exiting finding of this research is that personalisation features of voice assistants lead to the increase of emotional attachment of voice assistant users, and emotional attachment in turn amplifies voice assistant user embeddedness in a filter bubble rather than mitigates. The both effects were positive and significant. Thus, it was found that emotional attachment is mingled with personalisation and embeddedness in a filter bubble and both leading to less acceptance of the new content. So more positive experience of voice assistant user with voice assistant makes one less likely to accept new content. The findings from this research can serve as a foundation for the future studies that aim to study the effectiveness of voice assistant use on acceptance of the new content.

KEYWORDS: *Smart voice assistant use, emotional attachment, acceptance of the new content, brand trust, user satisfaction*

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1. Introduction

"We are entering a new world. The technologies of machine learning, speech recognition, and natural language understanding are reaching a nexus of capability. The end result is that we'll soon have artificially intelligent assistants to help us in every aspect of our lives."
(Stapleton, 2015)

The developments in the sphere of artificial intelligence (AI) are quite profound as AI-driven machines have been impacting our daily lives with the prevailing technologies that can recognise and learn some aspects of humans' cognitive functions (Stanford University, 2016 & Smadi et al., 2015). One of the most sophisticated techniques of these machines is the deep learning of humans' language processing and recognition (Stanford University, 2016). Specifically, AI-innovations have improved users' interaction by introducing the voice recognition technology (Poola, 2017 & Drew, 2017). The first ever known voice recognition technology was IBM Shoebox, created by IBM in 1962 (Huang et al., 2015). It could perform mathematical manipulations with digits from 0-9 and recognize no more than 16 words (Huang et al., 2015). Once technology could recognise not just words, but word sequences, companies such as IBM, Apple, Microsoft and others started to build applications where this technology could be implemented (Huang et al., 2015). According to Mehta and McLoud (2003), voice recognition technology is based on the four main processes including speech recognition - the transfer of speech to text, speech synthesis – the transfer of text into speech, speaker identification, and natural language understanding. Also, the production of voice recognition technology has been based on the inclusion of certain types of datasets, which consist of machine-recognizable words and phrases (Pathak, 2010). When the user speaks into a microphone, the software tries to match the audio input with the corresponding features in the datasets (Pathak, 2010). The facilitation of the audio inputs happens through the integration of voice recognition functions and artificial intelligence features into digital devices such as mobile devices, smart speakers and personal computers (Prerana et al., 2015).

Voice assistants now have been integrated into the sophisticated operating systems of digital devices and have drawn massive opportunities in the sphere of human's interaction with technology (Mozer, 2013). According to Hoy (2018), voice assistants can be considered as the realisation of human's fictional dreams as these technologies enable natural speech communication and interaction with our digital devices. The pioneer in the voice recognition industry was Apple, integrating their voice recognition innovation - Siri - into their mobile device the iPhone in 2011. Eventually, other companies entered the market such as Google Now by Google, Alexa by Amazon, Cortana by Microsoft, Samsung with Bixby and Facebook with M by the end of 2016 (Pestanes & Gautier, 2017 & Terdiman, 2018). Smart voice assistants work through the replacement of the physical user interaction (typing), and allow users to perform many tasks such as web searches, managing schedules, ordering food delivery and many others in the form of human-like conversation (Prerana et al., 2015 & Kiseleva et al., 2016). The popularity and usage of smart voice assistants has been steadily growing by approximately 11 percent each year since 2016 (Jiang et al., 2015, Some, 2018 & Mozer, 2013), and the market of voice assistant technology has reached approximately 55 billion dollars at the beginning of 2019 and will reach around 1.8 billion voice assistants' users by the end of 2021 (Pestanes & Gautier, 2017). It is predicted that around 30 percent of human's interaction with technology will occur via natural language conversation by the end of 2020 (Kiseleva et al., 2016).

1.1. Problem background

AI-innovations have enabled voice assistants (VAs) to enhance our daily lives and advance in their sophistication by increasingly exploiting data about users' personal behaviour and preferences (Alepis & Patsakis, 2017 & Hoy, 2018). Hook et al. (2017) stated that more than 20 percent of online searches in Google already happen by voice, and this number will grow by 50 percent by the end of 2020. The gathered data allow VAs to execute users' tasks with a high level of personalisation (Armano, 2018, Hook et al. 2017 & Alepis & Patsakis 2017). According to Fan and Poole (2006), personalisation can be explained as a system that consists of multiple types of algorithms that identify interests, behaviour, preferences and users' goals in order to provide and address their individual needs. Therefore, the explicit use of personalisation functions by voice assistants drives more and more companies to incorporate smart assistant technologies into their products. The data on how consumers use these products can then be gathered and transformed into personalised experiences and advertising and consequently making them more attractive for purchase (Armano, 2018). According to Armano (2018), voice is one of the new channels for companies to connect with the consumers who look for specific type of information, content or products. Also, Olenski (2018), stated that approximately 87 percent of marketers in the business to customer sector consider AI technology such as voice assistants to be the one that will play a significant role in the customers' interaction processes by 2021. Also, Olenski (2018) states that voice assistants will provide customers with much more efficient, smooth, and simple access to more in-depth content with the use of voice in comparison to digital devices such as phones, laptops or tablets, which require typing or constant looking at the screen for accessing the new information. For instance, the BBC and Washington Post news companies integrate their news delivery via digital devices with VA technology such as Alexa, Google Home and Apple Home Pod to provide users with the access opportunity of more in-depth content just by asking their smart speakers (Hook et al., 2017). The New York Times announced that their listeners will be able to use the new features on their digital devices with the integration of voice assistants such as a daily flash briefing on the news and a daily news quiz, for recapping stories which they have already read (Prerez, 2019). In addition to news content and products becoming more personalised, around 30 percent of voice assistants' users agree to receive advertisements about new information as long as it is consistent with their personalised experience (Pestanes & Gautier, 2017). There are multiple marketing technics used of news content personalisation such as personalised emails, offers, real-time messaging and tailored recommendations that are based on users' previous searches (Bullock, 2018). According to Bullock (2018), the most effective and powerful way of news content personalisation is based on the data-drive approach. This data-driven approach offers companies the opportunity of gaining tremendously helpful and detailed insights about their users' preferences and consumption behaviour that could be used in order to increase efficiency of news content recommendations and enhance the experience for the users (Hassani et al., 2018). This means that companies must contend with the appearance of personalised filter bubbles – whether it is due to the companies' delivered content or otherwise - when it comes to facilitation of the new content via voice technologies, which might lie outside of the consumers' personalised preferences (Nagulendra & Vassileva, 2014).

1.2. Research question

Nagulendra and Vassileva (2014) explain the phenomenon of the filter bubble as:

"... referring to people getting encapsulated in streams of data such as news or social network updates that are personalized to their interests" (p. 61).

On the one hand, a filter bubble is beneficial for consumers as they require some protection from becoming overloaded by information that they consider to be irrelevant for them in terms of their personal viewpoints or familiarity (Nagulendra & Vassileva, 2014). On the other hand, there is a risk that the audience will remain unaware of new important or novel information or remain unexposed to multiple perspectives as alternative viewpoints can become filtered (Nagulendra & Vassileva, 2014).

Moreover, Pestanes and Gautier (2017) revealed that 57 percent of voice assistant users would be willing to receive more of new content if voice assistants sounded more human. Therefore, the producers of voice assistant technologies try to maintain capabilities of voice functions in smart assistants as human-like as possible (Stinson, 2018). These constant improvements in voice assistants happen because consumers expect more than just efficient tasks performance from voice machines, but they also want to be able to connect with them emotionally (Han & Yang, 2017, Berger & Calabrese, 1975 & Gavrilovska & Rakovic, 2016). The implementation of natural language speech into voice assistants can produce emotional bonding or friendship connection on the users (Han & Yang, 2017). Also, the implementation of AI-driven human-like features can create the conversation between the sophisticated technology and the users, which further fosters the appearance of the feeling of emotional connection (Bell et al., 2003). For example, it has been recently announced that smart voice assistants have names, genders and personalities to elicit users' interaction even more (Lacy, 2018). Furthermore, the more time the user spends interacting with personalised interactive technologies in the forms of natural dialogue, the stronger the feeling of engagement for the user (Han & Yang, 2017 & Liu & Karahanna, 2007). Hence, the research question will be:

To what extent does emotional attachment allow smart voice assistants to reinforce filter bubble phenomenon and foster the acceptance of the new content?

1.3. Academic relevance

On the one hand, recent studies about voice assistant technology focus on diverse research aspects, such as technical capabilities of natural language processing (Chang, Lee & Wang, 2016 & Armano, 2018), the adoption of voice recognition technology and users' perceptions on this technology (Von der Putten et al., 2010, Claessen et al., 2017), privacy risks of data-driven voice innovations (Chowdhury, 2018, Kiseleva et al., 2016, Alepis & Patsakis, 2017) and implementations of voice assistants' use in education and for health care services (Ahamed et al., 2006, Holden, 2018, Gregory & Smordal, 2003). There is also behavioural research on cognitive and behavioural elements that emerge during the human decision-making processes between users and personalised technologies (Mugge et al., 2008, Sandel, 2018 & Wu et al., 2016). However, the exploration of voice technology is still considered to be a niche area of scientific research. There are still very few data available about the outcomes of users' affective emotional attachment towards certain AI-driven technology, so voice assistant technology remains unexplored. Therefore, the research aims to address these gaps by conducting a quantitative research with the use of survey in order to provide more understanding about current perceptions and future potential of voice platforms, as well as classify the critical concepts and theories from the literature review. The research is also focused on the exploration of the phenomenon of the filter bubble and the ways emotional connections can reinforce personalised filter bubble in order to foster the users' willingness to accept the new content.

1.4. Societal relevance

The findings from this research will be valuable for broadcasting and media organizations and their quest for audience's engagement tactics (Pathak, 2010 & Rosen et al., 2013). Media and broadcasting organizations want people to be interested, to engage, to click on a link, follow their web pages and news content (Olenski, 2018 & Rosen et al., 2013). Thus, there is the need for an understanding of approaches to sustain the attention of an already existing audiences and also draw in new audience segments, through implementation and adoption of the voice recognition technology in their organisations (Armano, 2018 & Holden, 2018). These organizations should strategically exploit voice assistant technology in their communication and understand the kinds of narratives/stories or content in general work well (Tamborini et al., 2010), especially under the contexts of personalisation and also exposing the user to new content. The findings from this research will then be relevant not only for broadcasting and media organisations but also for such organisations in both public and private sectors. For example, the public medical health care sector and education sectors will benefit from this research in terms of deeper understanding of voice assistants' implementation, users' perceptions and attitudes (Ahamed et al., 2006, Holden, 2018 & Gregory & Smordal, 2003).

Moreover, the continuing growth of artificial intelligence (AI) is one of the world's most pressing and relevant questions that weigh heavily on organisations. The evolution of AI-driven technologies has been increasingly impacting our daily lives, technologies that can recognise and learn some aspects of humans' cognitive functions (Stanford University, 2016 & Smadi et al., 2015). The aforementioned literature has shown that personalisation features in voice assistants is one of the primary features that make voice technology so attractive for users' interaction (Armano, 2018). Thus, voice assistant technologies rapidly have been becoming the new channels of consumer preference and demand as they provide users with the new level of interaction and experience and consequently make more and more companies adopt smart assistant technologies in order to connect with the consumers who look for specific type of information, content or products (Armano, 2018). Approximately 87 percent of business organisations in private sector envisage voice assistant technology to play a central role in the user/technology interaction by the end of 2021 (Olenski, 2018). However, the organisations continue to face the problem of facilitating new content, and consequently new products, to the voice assistant users, given the typical resistance against receiving content outside of their personal preferences (Eskens, Helberger & Moeller, 2017).

Furthermore, there also loom larger issues behind personalization than just facilitation of the new content to users (Eskens, Helberger & Moeller, 2017). New content recommendation and filtering can exacerbate polarisation in our society; the continued reinforcing of established beliefs and preferences will likely lead to the increasing division, ideological or otherwise (Eskens, Helberger & Moeller, 2017). For example, some users will continue to select news items - listening to these through voice assistance - and stay up to date about political debates and thus learn even more every day about what is happening in society, while other users, who completely deselect the complex political news items with the help of personalisation function in VAs, may continue to remain outside of political discussion and knowledge (Eskens, Helberger & Moeller, 2017).

The goals of this thesis address this potential worsening of filter bubbles and polarisation, as there remains the possibility, as discussed above, that VA users might be more open for the new content facilitation if they experience an emotional connection to the voice technology ((Eskens, Helberger & Moeller, 2017). That audience receptivity may remain sensitive – due to emotional attachment - to new, yet personalised, content and recommendation issued through VA technology is still underexplored and investigated in this thesis.

1.5. Organisation cooperation

The research was carried out in collaboration with the Dutch Broadcasting Company – NPO, who started to employ voice assistants' technology into their audio programing such as news, radio and cooking skills programs. Hence, one of the immediate goals of NPO is to gather information on how voice assistants can help to enrich the facilitation of the new content for their audience. They seek insight into whether emotional bonding towards voice assistants can be one of the elements which could make voice assistant users to better accept the new content. This research will provide them with insight into how the phenomenon of the filter bubble and the ways emotional connections can reinforce personalised filter bubble in order to foster the users' willingness to accept the new content.

1.6. Thesis outline

This study will focus on the reasons for companies' adoption and implementation of voice assistants as well as their challenges for facilitation of the new content, because of the filter bubble phenomenon. The advantages and disadvantages of filter bubble will be addressed in more details with the connection to the appearance of emotional attachment of users to the voice technology.

Furthermore, the theoretical framework will include several key concepts that will be discussed and analysed within the thesis. Particularly, theoretical concepts are presented through first defining the combination of aspects in the Attachment theory and emotional attachment concept, followed by the Uses and Gratification theory, satisfaction concept, before focusing of the brand trust concept, personalisation concepts and filter bubble concept. Based on previous empirical findings related to the arguments, hypotheses will be proposed, as well as the conceptual model addressing the overall research problems. In order to test the hypothesis, the research design, choice of research method, operationalization and choice of data collection and analysis, validity and reliability will be explained in detail in the methodology chapter. The chapters of results and discussion will present the summery of the results as well as discus the implications of results.

Finally, the conclusion will present the final reflection on the research. Also, it will present the practical and scientific limitations of the research and the directions for the future research.

2. Theoretical framework

In this chapter, theoretical concepts are presented through first revealing the history of voice recognition technology and smart voice assistants, then defining Attachment theory and the concept of emotional attachment, followed by a discussion of Uses and Gratification, users' satisfaction and brand trust concepts, before focusing on the personalisation and filter bubble. Hypotheses are proposed based on previous empirical findings related to the arguments. Finally, a conceptual model addressing the overall research problems is presented.

2.1. Era of human-like voice assistant technology

Zumalt (2005) states that the enhancement of our everyday lives by services of voice recognition technologies has become so natural that one can wonder why the tech giants have only recently started bringing these voice recognition services to the public. However, the history of voice recognition technology revealed that speech recognition developments had started several decades ago. Modern pioneer in the voice recognition technology was the International Business Machines company (IBM) when it created the IBM Shoebox technology in 1962, which could recognise and understand up to 16 English spoken words and perform some mathematical manipulations with the digits from 0 to 9 (Huang et al., 2015). Thereafter, the first ever in the world voice recognition technology was called Dragon's NaturallySpeaking software and only created in 1997 (Zumalt, 2005). It could recognise 100 spoken words per minute without requiring from its users to pauses or speak slowly (Zumalt, 2005).

Furthermore, after the significant breakthroughs in the sphere of voice recognition technology, Google company combined the latest technology and incorporated cloud-based computing for data sharing, which improved the accuracy of speech recognition algorithms. However, it was the only Siri voice assistant technology by Apple in 2011, which first touched the imagination of the public by introducing the more human-like touch into the complex system of voice recognition technology (Boyd, 2018). Siri was followed by Cortana voice recognition technology, which was made by Microsoft, and Alexa by Amazon which was installed into Echo (speaker) that did not need activation buttons to press, just users' voice triggering commands (Boyd, 2018). Then other companies joined the battle for sophistication amongst voice recognition technology giants (Boyd, 2018).

As previously revealed (see Appendix 3 for the detailed history of voice technology), the developments in voice recognition technology brought the public considerable inventions into the intelligent smart voice assistants (Boyd, 2018). Now, smart voice assistant technology is not only able to recognise and understand the human speech, but also offers its users a new level of interaction via integrated personalisation and human-like features (Pestanes & Gautier, 2017). Voice assistants (VAs) are able to perform their owners' tasks with the perfectly individualistic suggestions and also offer recommendations, plus VAs are able to communicate with their owners by performing emotional imitation and traces of a certain gender features (Lacy, 2018). For example, it has been recently announced that smart voice assistants have been accompanied by gender and personality features in order to elicit even more user interaction (Lacy, 2018). Also, Google has recently demonstrated its intelligent voice assistant calling another real person and have a conversation without any suspicion of the (human) call receiver that he or she might be talking to AI machine (Vincent, 2018). Google's voice assistant was able to ask the right questions in order to make an appointment on behalf of the user, paused at the right moments and even was replicating the "mmm hmm" sounds for greater realism during the conversation (Vincent, 2018). Another example of voice assistants' showcasing their human-as-possible features was demonstrated during a presentation of Amazon's Alexa voice assistant (Goode, 2018). The Amazon executive whispered to Alexa the command, and Alexa responded by whispering back to him (Goode, 2018). Such human-like features as imitations of different voice tones and gender identifications as well as human-like emotions have allowed smart voice assistants to further create the feeling in the mind of their users of having a conversation with an actual person (Lacy, 2018).

Moreover, the research by Pestanes and Gautier (2017) states that approximately 57 percent of the VAs' users are keen on using these technologies due to the implemented these human-mimicking features. For example, Han and Yang (2017) stated that the implementation of natural language speech into voice assistants could produce emotional bonding or friendship connection on the users. Also, Bell et al. (2003) confirm that the implementation of AI-driven human-like features can create conversation between the sophisticated technology and its users, which further fosters the appearance of the feeling of emotional connection between them. According to Picard, Vyzas, and Healey (2001), users do not experience the feeling of an actual person presence and attachment to technology in the situations when technology is not able to respond towards their emotions in a human-like way. For example,

"Computers that repeatedly ignore human expressions of irritation toward them are likely to be significantly less liked as a product than those that respond intelligently to people under duress" (p. 3).

2.2. Combining Attachment theory and emotional attachment concept

This section will look at the combination of both Attachment theory and emotional attachment as they are considered to be intermingled concepts. Attachment theory focuses on the explanation of the interpersonal relationships, while emotional attachment concept explains variations in emotional regulations in various contexts, not just interpersonal relationships (Gavrilovska & Rakovic, 2016). According to Jones et al. (2016), interpersonal relationship is a social connection which is based on the emotional bond between individuals. Emotions in the interpersonal relationships are based on the feeling of an assured foundation (Berger & Calabrese, 1975). People develop attachment relationships towards someone they receive care from, and then they tend to seek for this someone when stress, anxious, afraid or sick (Scharfe, 2017). The representation of the assured foundation feeling appears at the point when people experience stress and have expectations that particular someone or something will be there in the times of need (Bowlby, 1979). Liu and Karahanna (2007) confirm that if a person's relationship is based on pleasure or joy, then the feeling of attachment appears as the person wants to be near someone or something that brings comfort in time of distress. Moreover, when people do not receive the expected mental or physical support, they experience disappointment as a result, which leads to the appearance of dismissive attachment (Bowlby, 1979). Also, there is a difference in how strongly or weakly each person's attachment to the relationship can develop. The higher level of received care in the times of need will result into the strong attachment relationship or secure emotional attachment, while no care at all or the least care will result into the weak attachment relationship or dismissive emotional attachment (Scharfe, 2017). According to Jones et al. (2016), secure emotional attachment appears due to the repeated experience of having someone or something share your emotions, be available for you, understand you or respond appropriately to your unique situations and help you in the times of need. Dismissive attachment is then understood as repeated experience of rejection or disregard of the significance of person's attachment or connection to the relationship in the times of need (Mikulincer & Shaver, 2013). Emotional attachment is then understood as a relationship-based assemblage that considers emotional connection between an individual with either a material object or another human being (Bowlby, 1979).

In looking at the material object from the marketing perspective, there are three types of consumer needs towards any material objects: functional, symbolic and experiential (Wu et al., 2015). For example, a functional object is designed to solve externally generated consumption needs (Moon et al., 2017). Consumers will be motivated to buy and use functional objects in the situations where the product is viewed as addressing utilitarian needs (Moon et al., 2017). A symbolic object is designed to associate an individual with the desired group, enhancing self-concept through the consumption of goods as symbols (Moon et al., 2017). Experiential objects drive sensory interactions with consumers in all aspects from the emotional influence of consumers' preferences to active shaping their perceptions of an object (Moon et al., 2017). Particularly, hedonic values towards the material objects make people create expectations and refer to them in a time of need (Moon et al., 2017). As earlier explained by Bowlby (1979), this process of seeking and referring to the material objects while experiencing external stress situations builds an emotional attachment to the object. Park and Macinnis (2006) defined this process as:

"A consumer's emotional attachment to a consumption entity induces a state of emotion-laden mental readiness that influences his or her allocation of emotional, cognitive, and behavioural resources toward a particular target" (p. 17).

Smart voice assistants, in particular, can elicit both utilitarian and hedonic responses from their users. For example, voice assistants provide users with such utilitarian need as the replacement of the physical users' interaction (typing), which makes users' task performativity more efficient and convenient (Kiseleva et al., 2016). In terms of hedonics needs, voice assistants make users experience the presence of a close friend or the feeling of companionship via the implementation of natural language features (Terdiman, 2018). According to the report of Lacy (2018), Michael Horn said:

"When machines talk, people want to assume relationships, there is an innate human need to project emotions and attachments."

Also, voice assistants help their users to negotiate stressful external situations (Hoy, 2018). For instance, voice assistants can help the elderly to reinstate a sense of independence by setting medical reminders, new updates or even make the phone calls for them (Holden, 2018). Therefore, we can state that a relationship between an individual and a material object, such as voice assistants, is possible and it might develop into emotional attachment.

2.3. The Uses and Gratification theory in combination with user satisfaction

This section will look at the Uses and Gratification theory, which mainly focuses on how media and communication may fulfil the needs of the audience in order to lead them to the greater satisfaction of media use (Katz et al., 1974). According to Happer and Philo (2013), the media such as television, radio, press or online have a central role in communicating to the audiences about different types of information, events and experiences, which the public do not directly possess and therefore relies upon media. Furthermore, people experience social and mental needs, which make them develop expectations from media sources and lead them to various patterns of media use or the tendency of accepting certain media content or not (Mehrad & Tajer, 2016). The Uses and Gratification theory considers the audience to be active users rather than passive receivers of the media content, and therefore they use the media content to meet the audiences' needs and satisfy their interests (Katz et al., 1974). The main idea of this theory is based on the approach that the audiences know, which media content they want to use to fulfil their needs (Katz et al., 1974). This means that the audiences' needs influence their media content choice (Katz et al., 1974). Furthermore, user satisfaction is considered to be an essential construct in the studies regarding media effects, and it is commonly used in the uses and gratification studies (Tamborini et al., 2010). It is understood as a predictor of the public's media-related actions and behaviours (Zhu & Chen, 2015). Looking at the meaning of satisfaction from the industry perspective, one finds that it plays a central role in media institutions' ability successfully maintain the attention and engagement of their users, as satisfied users of media content are likely to stay loyal, while dissatisfied ones are likely to change to alternatives (Zhu & Chen, 2015).

Moreover, uses and gratifications poses the reasons for the audience's attraction to certain types of media as well as types of satisfaction, which media can provide to the audiences (Windahl et al., 2008). There are five different reasons such as information, entertainment, personal identity, social interaction and escapism for the audiences to decide what they want in terms of media (Choi et al., 2016). Firstly, information/education reason means that the audience desires to gain some knowledge from watching or listening to the particular media (Ruggiero, 2009). Secondly, entertainment reason suggests that the viewers want to enjoy and relax (Ruggiero, 2009). Thirdly, personal identity reason means that viewers can see role models that reflect similar values, characteristics, mimics to the ones they have (Ruggiero, 2009). Fourthly, integration and social interaction reasons mean that the ability for media products to produce a topic of conversation between people (Ruggiero, 2009). Finally, escapism reason indicates that the viewers want to have the ability to escape their real lives and imagine themselves in those situations the media shows (Ruggiero, 2009).

All this means that the audience's acceptance of recommended content, familiar or novel, will depend on the list of previously mentioned reasons, the relevance of which will vary depending on the individual's specific needs. Intertwined within these needs are the aforementioned utilitarian, hedonic, and symbolic needs (Wu et al., 2015). Therefore, we can suggest that the individuals' acceptance of content will depend on their referral to it as an immaterial object with the expectation that it will satisfy one or more of their needs (Bae, 2018). This means that in the case that new media content satisfies the needs of the individual, positive emotional attachment to that content will manifest and further the acceptance of it (Yonghwan et al., 2016). While if the content does not satisfy the needs of the audience, there will be the negative appearance of emotional attachment and no further acceptance of the recommended content, new or otherwise (Thomson et al., 2005).

Also, Hilchey and Hurych (1985) described user satisfaction as the state of people's mind, comfort and acceptability of the content and the system/channel for accessing the media content. Uses and Gratification links user satisfaction to the extent to which these information channels can provide the desired gratifications contributing to the satisfaction (Dobos, 1992). Gratifications sought represent the needs of the audience, while gratifications obtained is the actual fulfilment of the needs (Bae, 2018). Gratifications obtained and sought are socially constructed elements that lead to users' media satisfaction and satisfaction in the choice of the communication medium (Ruggiero, 2009). For example, the audiences can assign some proportion of their satisfaction feelings with verbal communication to expectations (gratifications sought) for interaction, such as "having conversation with voice assistant", and another part of their satisfaction feelings can be assigned to the actual fulfilment (gratifications obtained) of this need (Zhu & Chen, 2015). Also, people may assign some part of their satisfaction feelings to the particular communication medium (voice assistants or otherwise) with the expectation of interactive communication, and how well this medium will fulfil the needs (Dobos, 1992). As it is not clear from theory how the impact of satisfaction may intervene between the medium and consequential outcomes, such as acceptance of new content, the less complicated mechanism, i.e. moderation, is posed.

2.4. Brand trust

In connection with the Attachment theory and emotional attachment concept, consumer confidence in a certain brand can translate to the assurances about what individuals expect from it (Gavrilovska & Rakovic, 2016). Trust is considered to be one of the most important elements in the interpersonal relationship research (Nur et al., 2018). Also, trust has been defined as the willingness of one individual to rely on another with a strong sense of confidence. In addition, trust is defined as the award or consequence that can appear only in positive relationships and when there are emotional ties or connections between individuals or individual and material objects (Bowlby 1979 & Caroll & Ahuvia 2006). Furthermore, brand trust can be defined as the confident expectations of an individual that a certain type of brand will perform its stated functions (Lassoued & Hobbs, 2015). Trust is another construct regarded in this study as a consequent of love, passion, and positive evaluation and emotions of the brand. Moorman et al. (1992) define trust as: *"a willingness to rely on an exchange partner in whom one has confidence" (p. 82).* More specifically, Morgan and Hunt (1994) define trust as the perception of *"confidence in the exchange partner's reliability and integrity*" (p. 23). These definitions highlight the importance of confidence and reliability in the conception of trust. Trust exists between the two love partners implying that trust is a consequence of having feelings of love for a brand (Regan et al., 1998).

Furthermore, trust has been explored in the consumer-brand relationship in marketing research, and here, the "trustee" becomes a material object (Gavrilovska & Rakovic, 2016). Therefore, brand trust refers to the extent a brand (and its products) successfully performs functions which later result in the positive outcomes for the brand to appear as the relational partner for individuals (Gavrilovska & Rakovic, 2016). This means that in case a brand performs all the stated and expected functions, consumers will develop the greater sense of trust into the brand or brand trust, which will further get developed into positive emotional attachment (Fullerton, 2005 & Liu & Karahanna, 2007). Also, the consumers' brand trust can affect emotional attachment towards a certain brand negatively when brand does not perform its stated functions, which will consequently weaken the attachment between brand and individual (Fullerton, 2005 & Liu & Karahanna, 2007). The trust in a brand to perform functions towards solving the consumer's needs creates assurances for the consumers and develops the emotional attachment to the brand (Ballester et al., 2003). Also, the level of brand trust will evolve during the consumer and brand interaction process (Gavrilovska & Rakovic, 2016). The longer the consumers' experience, the more knowledge, interaction and later expectations they develop that the brand will provide the assured foundation (Bowlby 1979). While brand trust may have an effect on emotional attachment independent to the medium (e.g., voice assistant), the affective nature of both trust and voice assistants indicates that there is likely to be interplay between them for their effects.

2.5. Personalisation and the Filter bubble

Personalisation is a phenomenon embedded in every human activity such as decorating, modifications or tailoring objects, places, clothes, houses, workplaces, cars or software (Fan & Poole, 2006). Fan and Poole (2006) state that there are whole cultures based on personalisation, such as wine-tasting, fashion or car-modifications – to name a few - where people express their individualistic choices, preferences, tastes, attitudes and behaviours. Communication technology, for instance the smart voice assistant, is no exception as its products also harbour numerous personalisation features (Fan & Poole, 2006). According to Oulasvirta and Blom (2008), personalisation can be considered as the process in which specific changes in functionality and information content of the system are made according to an individual's preferences and needs. In other words, the personalisation system has been created in order to provide users or consumers with the experiences or interactions that speak directly to them and allow them to have more control over their choosing process of content or products (Lett, 2008).

Furthermore, there are different areas in the academic research that have been interested in the exploration of the personalisation phenomenon, for example, marketing, information science, social science, communication and many other sectors (Fan & Poole, 2006). Due to the variety of the different fields that studied the phenomenon of personalisation, there is a multiplicity in the definitions of this phenomenon (Fan & Poole, 2006). Marketing research studies explain personalisation as the ability to create the most relevant and useful experiences for the users or customers during their interaction with the system (Oulasvirta & Blom, 2008). Information science studies define personalisation as the process in which individuals are able to receive the most relevant and transformed information sources tailored to their needs (Oulasvirta & Blom, 2008). Social science studies describe personalisation as the technology that enhances social networks and re-affirms ideologies due to the provided experience (Wellman, 2002).

Moreover, there is a type of the implementation of personalisation in the systems such as option personalisation, programmed personalisation or customised personalisation (Kuruuzum, 2015). The option personalisation provides users with the ability to choose specific services from the already suggested list (Kuruuzum, 2015). The programmed personalisation is based on the provision of personalised services to the users through the encouragement of communication and interaction with the use of users' name or individual information (Kuruuzum, 2015). This programmed personalisation makes each user feel as a unique one and not just another user (Kuruuzum, 2015). Finally, customised personalisation provides users with the best possible options of content or products' advertisements, which match users' needs and preferences (Kuruuzum, 2015). According to Fan and Poole (2006), optional personalisation or customised personalisation have a positive effect on the user satisfaction while programmed personalisation had adverse effects. Also, personalisation has three dimensions of implementation choices such as initiator (to whom personalisation features are directed), type of product (content, user interface, channel) and level of personalisation (functionality) (Fan & Poole, 2006). Thus, personalisation can produce greater satisfaction in users through particular product/content and its medium (Berg, 2015).

As it was discussed earlier, personalisation is the process of altering recommendations and promotions of products or content towards the preferences and personal experiences and behaviours of users (Mugge et al., 2008). With the rise of the Internet and digitalisation, there are appeared many opportunities for the development of the personalisation functions (Lett, 2008). The main objective of the personalisation software is based on the collection of the relevant data about the users' preferences and interests, which can be gathered through the collaborative filtering analysis or data mining (shopping, social media activities etc.), sent personalised URL link, customer surveys to prepare the personalised plans for the users and many other marketing technics (Lett, 2008).

Also, there are multiple reasons why consumers experience personalisation through a product, including the product's ease of use, its reflection of personal identity and interests and recognition of the product as their own (Berg, 2015). Also, the digital age and the rise of the Internet use has allowed the audiences the easy access to the multiple content and information of their interests, but this convenience in access leads to the growing increase of the information load online. Therefore, more and more people started to inform themselves through the use of recommendation systems or personalisation services. As it was mentioned earlier, recommendation systems or personalisation provides users with the filtering of the irrelevant content sources to them. However, despite all the convenience and efficiency which personalisation can give the users, it also can lead them to filter bubbles (Nguyen et al., 2014 & Pariser 2012).

According to Moeller and Helberger (2018), the concept of the filter bubble was coined by Eli Pariser and defined as:

"unique, personal universe of information created just for you by this array of personalised filters. It's invisible, and it's becoming more and more difficult to escape" (p. 17).

Also, the filter bubble phenomenon is considered to be the encapsulation of audiences in the on-going process of tailoring content to the users' preferences, which leads to the isolation of and non-exposure to content that harbour alternative viewpoints and diversity (Nagulendra & Vassileva, 2014). On the one hand, a filter bubble is beneficial for consumers as they require some protection from becoming overloaded by the information that they consider to be irrelevant for them in terms of their personal viewpoints or familiarity (Nagulendra &

Vassileva, 2014). On the other hand, there is a risk that the audience will remain unaware of new important or novel information or remain unexposed to multiple perspectives as alternative viewpoints can become filtered (Nagulendra & Vassileva, 2014). Filtering can exacerbate polarisation in our society; the continued reinforcing of established beliefs and preferences will likely lead to the increasing division, ideological or otherwise (Eskens, Helberger & Moeller, 2017). For example, some users will continue to select news items - listening to these through voice assistance - and stay up to date about political debates and thus learn even more every day about what is happening in society, while other users - who completely deselect the complex political news items with the help of personalisation function in VAs - may continue to remain outside of political discussion and knowledge (Eskens, Helberger & Moeller, 2017). While there is a connection between emotional attachment and the choice of acceptance of the new recommended content – as mentioned earlier, if an individual is deeply embedded in their filter bubble there is a possibility that they will be resistant to new content outside of their filter bubble (Gavrilovska & Rakovic, 2016 & Bowlby, 1979). While the filter bubble alone can independently and negatively impact acceptance of new content, we can hypothesise that this could be countered by affective consequences of higher emotional attachment, given its influence on outcomes such as this acceptance.

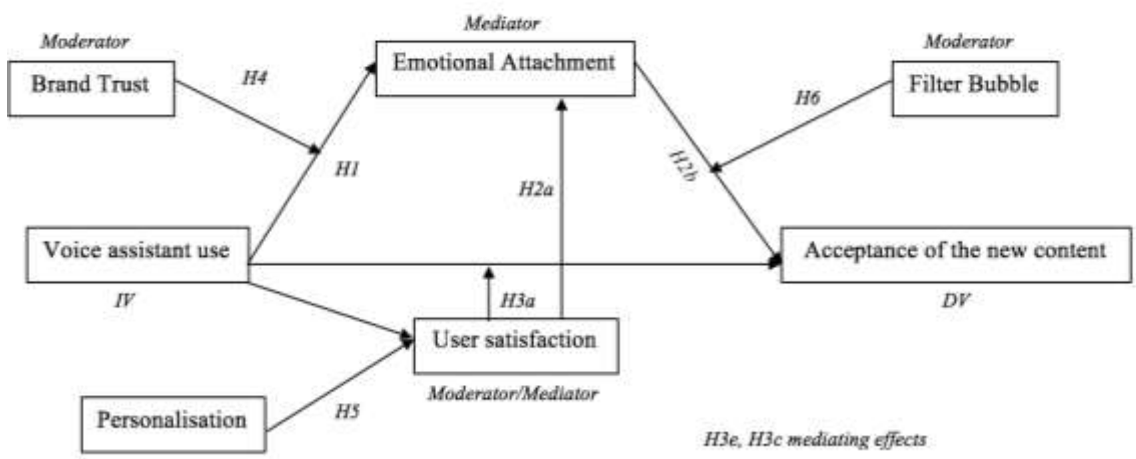
2.6. Hypotheses

Based on the previously done literature review, the following hypothesis are posed exploring the role of smart voice assistant use and emotional attachment on the choice of acceptance of the new recommended content and the mediating effects of user satisfaction as well as the moderation effects of brand trust, filter bubble and user satisfaction. Through a quantitative digital survey design, we can more precisely analyse the potentially casual chain between smart voice assistant use and emotional attachment on the choice of acceptance of the new recommended content. In addition, figure 2 will present the diagram of the conceptual theoretical framework model. A note to the reader: while it is not uncommon for hypotheses to be declared following its theoretical justification, the effects to be tested in this thesis are complex and intertwined. Thus, this thesis' author relegated their declaration to the end of this chapter.

H1: Voice assistant use for content consumption will positively influence the likelihood of emotional attachment.

H2a: The user satisfaction by content will positively influence the appearance of emotional attachment to new recommended content.
H2b: The appearance of emotional attachment will in turn positively influence the likelihood of the choice of acceptance of the new content.
H3a: The user satisfaction level will positively moderate the impact of voice assistant use on the acceptance of the new content, such that a high level of user satisfaction from voice assistant use will lead to a higher effect of voice assistant use on the acceptance of new content.
H3c: The user satisfaction will positively mediate the effect of voice assistant use on the emotional attachment.
H3e: The appearance of emotional attachment will positively mediate the effect of voice assistant use on the acceptance of the new content.
H4: Brand trust level will positively moderate the impact of voice assistants' use on emotional attachment, such that higher level of brand trust will lead to higher emotional attachment.
H5: The greater level of personalisation experienced will lead to the greater satisfaction of voice assistant use.
H6: The filter bubble will negatively moderate the relationship between emotional attachment and the choice of acceptance of the new recommended content, such that high emotional attachment will mitigate the effect of the filter bubble's reducing (negative effect) the likelihood of the choice of acceptance of the new content.

Figure 2. Conceptual diagram of the theoretical framework



3. Methodology

Based on the developed conceptual model in the theoretical framework section, it is hypothesised that there is a moderated and mediated relationship of voice assistants' use, emotional attachment and acceptance of the new content. In order to test the hypotheses, the methodology, operationalisation and choice of data analysis are explained in details in this chapter. Finally, the issue of validity and reliability of this research is also justified and presented.

3.1. Choice of research method

The analysis of the study is based on quantitative methods. The objective of quantitative research is to verify and test the relationships amongst the variables (voice assistants use, the appearance of emotional attachment, the choice of acceptance of the new recommended content, brand trust, filter bubble, personalisation and user satisfaction) of the developed conceptual model in the theoretical framework section. The quantitative research in this thesis involves quantitative data which was collected through the use of the online survey.

3.1.1. Quantitative method

According to Fallon (2016), quantitative research is focused on the deductive approach which can be explained as the examination process of the previously done research and theories in order to provide the explanation of the particular phenomenon. This research includes the proposition of the hypotheses that are based on a critical assessment of prior literature, theories and empirical findings. The development of the theoretical model in this thesis was based on the independent, dependent, moderating and mediating variables, which can be statistically analysed in order to measure the relationships amongst the variables if using quantitative research method (Fallon, 2016). Also, a cause and effect connection between the variables can be inferred for those variables that have meaningful ordering, which makes the use of a quantitative research method the most suitable for arriving at the conclusions about the causality of the proposed hypotheses.

In particular, the survey research was chosen to be the most effective approach to provide the justification for precisely detecting relationships compared to other social research methods (Ho, 2014). According to Mathiyazhagan and Nandan (2010), survey research is considered to be a social scientific research that concentrates on people and their attitudes and behaviour. Also, the survey research method involves the collection the data samples to make inferences about a larger population of interest through the use of questionnaires (Nenty, 2009). In this research particularly, the online survey was used as it allowed for the collection of the data through quick distribution and quick response cycle rates (Andrews et al., 2003). Also, Andrews et al. (2003) stated that the use of the online survey is supported by the relatively inexpensive mechanism of their distribution online, in comparison to postal mail surveys, distribution of which increases the cost per response with the sample size increase. Furthermore, the online survey research method helps to provide reliable and valid information or characteristics of the desired population in the structured form for the ease at the stages of analysing and reporting (Ho, 2014).

3.2. Sampling

The sampling for this thesis was a mixture of a probability sampling and convenience sampling. The probability sampling means that all the items in a population will have an equal chance to be selected (Lumpur, 2016). The convenience sampling means that items are selected from the part of the population, which is easy to reach for the researcher because of their convenience accessibility (Lumpur, 2016). The use of the snowball method (type of convenience sampling) of the online survey distribution allowed the researcher to reach the broader sample beyond the limits of the individual network. The link of the survey was distributed amongst various social media communities and websites such as LinkedIn, Facebook, Twitter, Instagram and others, where participants were asked to fill out the survey. The researcher generated the QR code of the survey link and distribute it amongst participants with the greater convenience for them. In addition, respondents were asked to share and sent the link or QR code amongst their friends.

Furthermore, as the aim of the researcher was to obtain the representative sample, the Prolific tool was used (Lumpur, 2016). Prolific is the online survey distribution service for crowdsourcing and establishment of the cases before the facilitation of data analyses. The Prolific tool enabled the researcher to gather the desired sample through the generated by Qualtrics link, which was distributed amongst the participants all over the world (probability sampling). All the participants, who filled out the survey via Prolific received small monetary awards for their time and responses. Moreover, people who participated in the online surveys already allowed themselves to be contacted by Prolific tool, which means that they were a self-selected pool, hence not totally random. Therefore, the sampling was probability but also partly convenience sampling due to self-selected pool of survey participants (Lumpur, 2016). This research expected to obtain a sample that would consist of the voice assistant users and non-users (other device users). The non-users were needed for checking the impact of use/non-use of voice assistants and the acceptance of the new content such as User Satisfaction. According to Taherdoost (2016), the larger sample will reduce the likelihood of the biased findings from the obtained data.

The relatively larger sample of 786 participants was obtained in order to reduce the sampling error of estimators, obtain the representative sample, and reduce overfitting from the models with multiple covariates (Lumpur, 2016). During the period from the 5th of May to the 13th of May 2019, around 220 people solicited through the convenience sampling started the survey; however, around 30 of them did not finish the survey. Therefore, these respondents were not considered the active participants of the survey and were rejected from the sample. In order to increase the sample size, the Prolific crowdsourcing survey site was engaged to gather the representative sample, and an additional 593 respondents filled out the survey during the rest two day of data collection process the 14th of May and 15th of May 2019. After that, the division of the respondents on voice assistants' users and non-users was made. The more detailed descriptive statistics of the obtained sample will be presented in the results chapter.

3.2.1. Pre-test

After the survey were designed, a pre-test sample was conducted between 1 to 4 May 2019. The main objective of the pre-test was to improve survey questions, test and ensure participants' understanding of questions and clarity before the final execution of the questionnaire (Saunders et al., 2003). A total of 27 respondents were collected, two of them did not complete the survey and were removed from the study. Therefore, the pre-test included a sample size of 25 respondents. The final sample had a mean age of 23.02 years (SD = 2.84). The gender of the participants was not quite equally distributed, with 76% (n = 19) of female and 24% (n = 6) of male respondents. Since the participants were obtained based on the social network of the researcher, 64% (n = 16) of them were from Russia and the rest were respondents from the Netherlands 28% (n = 7) and a minority from India (n = 1) and Kazakhstan (n = 1).

3.2.2. Survey procedure

The quantitative data for this research was collected with the use of the online survey during the period of 10 days. The data collection process started on the 5th of May, shortly after the completion of the pre-tests and finished on the 15th of May. As it was mentioned earlier the survey was made with the use of the Qualtrics tool and adjusted for mobile phone, tablet, laptop and computer use, enabling participants to fill out the survey on the devices of their own choice. Qualtrics is the electronic survey generator program which is focused on the creation and managing of surveys (Snow, 2012). Ironically, Qualtrics does not yet provide a mechanism for allowing respondents to engage the survey on a voice assistant. Also, the creation of the digital survey on Qualtrics enabled the researcher to monitor the responses in progress and have access to the data straight after the participant's completion of the survey.

Furthermore, all the participants were asked to provide their consent before starting the survey for analysis of their data only for the purposes of this research. The consent form included the short explanations and definitions of voice assistants as an extra clarification for the participants. Also, the participants have been notified at the beginning of the survey that they were still eligible for the study if they did not have much of the knowledge about voice assistants. This has been done in order to gather responses from not only voice assistants' users, but other digital device users as well. All the question and statements of the online survey were presented in English. Finally, all the respondents filled out the survey on the basis of the anonymity requirements, which would ensure their privacy (Babbie, 2011).

3.3. Measurements and operationalisation

3.3.1. Scales and variables

Several measurements assessed the effect of voice assistant use on acceptance of the new content and the mediating effects of emotional attachment, which is the main objective of this study. This section will discuss measurements and of operationalization of dimensions developed in the conceptual model such as demographics, voice assistant use, user satisfaction, brand trust, personalisation, emotional attachment, filter bubble and acceptance of the new content. All the items of the listed dimensions were merged into one survey and tailored in Qualtrics. The factor analyses were conducted for the main variables and the rotated varimax factor loadings were reported for each set of variables. Also, the reliability of the survey was tested with the use of Cronbach's alpha test of reliability for each individual variable before proceeding to the actual statistical tests. The scales have been slightly adjusted in order to make them fit this study based on the reliability tests. The scales were five-point Likert scales where 1 is strongly agree, 2 is agree, 3 is neutral, 4 is disagree, and 5 is strongly disagree, and the abridged version of the items' scales can be seen below in the table 3.3 (Pai & Huang, 2010). Commonly used scales are seven-point Likert scales, but this research will use five-point Likert scales for the reduction of the respondents' confusion. Berdie (1994) stated that there is the appearance of the complexity and confusion among the respondents towards the seven-point Likert scales, while answering the questions. The use of seven-point Likert scale has the possibility to result in the more extended responses' rate or the mistakes in answers of respondents (Berdie, 1994). Also, the scales, which were used in the survey were in the reversed direction. Therefore, the scales of the reversed variables were unreversed in order to exclude the confusion on the stage of comparing these variables with normal direction variables.

Moreover, as it was mentioned earlier, respondents were identified as either voice assistant users or non-users. For VA users, their subsequent questions explicitly referred to their VA use, while for non-users, their questions regarded their most often device use. The overall survey consisted of 15 parts, where the first part consisted of demographic questions; the second part aimed to distinguish VA users from non-users (other device users). After the division, the participants were redirected to the remaining sections of the survey questions, which measured their user satisfaction, brand trust, emotional attachment, personalisation, embeddedness in a filter bubble and acceptance of the new content, accordingly with their identified type (VA users or non-users). Finally, the detail description of the scales and items can be found in Appendix 1 and survey design can be found in Appendix 2.

Table 3.3.1. Abridged version of the items' scales

Variable	Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
User's satisfaction	Overall I am satisfied with my experience with the voice assistant.	O	O	O	O	O
Brand trust	I trust in the brand(s).	O	O	O	O	O
Personalisation	This voice assistant makes me feel that I am a unique user.	O	O	O	O	O
Emotional attachment	I feel personally connected to this voice assistant.	O	O	O	O	O
Embeddedness in filter bubble	I like the selection of content/products recommended to me by this voice assistant.	O	O	O	O	O
Acceptance of the new content	I'm unlikely to change my interests in certain type of content once they're set.	O	O	O	O	O

3.3.2. Demographics

A number of control variable were included in order to check for alternative explanations. According to Hughes, Camden and Yangchen (2016), demographics play an essential role in sophisticated technology use in our case smart voice assistant use. Therefore, measures such as age, gender, highest educational degree, nationality, current country of living, employment status and income were obtained from respondents.

3.3.3. Voice assistant use versus device use

Voice assistant use was captured through two questions. The first one was asking the participants (e.g. "Do you use or have you ever tried to use any voice assistants?"). A second questions solicited the extent of their voice assistant use (e.g. "How often do you use voice assistants?"). Answers were appointed as 1) every day, 2) a few times a week, 3) about once a week, 4) about once a month, 5) less than once a month. If a respondent stated non-use (1^{st} question) or indicated voice assistant use, but less than once a month (2^{nd} question), they were identified as non-users and redirected to a section of the survey that will be in the context of their most used device. This differentiation was done based on the literature of technology usage and attitudes of Rosen et al., (2013). Each participant's assignment to voice assistant users/non-users was thus solicited through a set of items assessing participants' types of technology usage and their frequency of technology usage.

3.3.4. User satisfaction

For this research, user satisfaction was measured by using a subset of four items of the original satisfaction scale of Oliver (1980), which consisted of twelve items. Because the survey was quite long it was decided to use the validated scale from Anderson and Srinivasan (2003) research on user satisfaction, which was also used by Kuruuzum (2015). The items of the scale were slightly modified in order to ensure the better fit for this particular study and included the following items for measuring satisfaction of VA users and non-users: 1) overall I am satisfied with my experience with the voice assistant (device); 2) I am satisfied with my decision to use this voice assistant (device); 3) I think I did the right thing by using the services of this voice assistant (device); 4) I regret (feel bad) about my decision to use services of this voice assistant (device). These four items of user satisfaction were measured on a five-point Likert scale, where participants would have to choose from 1("Strongly agree"), 5 ("Strongly disagree"). In addition, the item 4) I regret (feel bad) about my decision to use services of this voice assistant (device), was reversed direction, therefore it was unreversed for both voice assistant and device user satisfaction scales.

Furthermore, the factor analysis was conducted in order to assess the appropriateness of the data. Four items which measured voice assistant and device user satisfaction were entered into factor analysis using Principal Components extraction with Varimax rotation based on Eigenvalues (> 1.00), $KMO = .77$, χ^2 (N = 786, 6) = 601.69, $p < .001$ for VA users; and Eigenvalues (> 1.00), $KMO = .78$, χ^2 (N = 786, 6) = 598.742, $p < .001$ for device users. The resultant model explained 63.1% of the variance in user satisfaction of VA users and

66.6% of the variance in user satisfaction of device users. The subsequent reliability analysis showed that these are reliable scales with a Cronbach's alpha of .84 for VA user satisfaction and Cronbach's alpha of .89 for device user satisfaction (Landis & Koch, 1977). We decided to call these variables *user satisfaction from voice assistant use* and *user satisfaction from device use.* The final measures consisted of an average of three items, as the results of Cronbach's alpha tests for both scales showed that if the question 4) I regret (feel bad) about my decision to use services of this voice assistant (device), were to be deleted, the Cronbach's alpha would be .84 for VA user satisfaction and .89 for device user satisfaction, which is considerably higher than the original Cronbach's alpha .79 for VA user satisfaction and .80 for device user satisfaction. The final Factor loadings of individual items onto one factor found are presented in Table 3.3.4.

Table 3.3.4. Factor loadings and reliability analysis for VA user satisfaction (N=650) and device user satisfaction (N=135)

Item	*User satisfaction from VA use*	*User satisfaction from device use*
Overall I am satisfied with my experience with the voice assistant (device).	**.819**	**.879**
I am satisfied with my decision to use this voice assistant (device).	**.876**	**.895**
I think I did the right thing by using the services of this voice assistant (device).	**.844**	**.889**
I regret (feel bad) about my decision to use services of this voice assistant (device).	**.612**	**.550**
R^2	63.1	66.6
Cronbach's α (p < 0.1)	.835	.888

3.3.5. Brand trust

For this research, brand trust was measured by using a subset of four items of the original brand trust scale of Chanduhuri and Holbrook (2001), which consisted of five items. Because the survey was quite long it was decided to use the validated scale from Matzler et al. (2008)

research on mediating role of brand trust, which was also used by Ahmed et al. (2014). The following items for measuring brand trust of VA users and non-users included: 1) I trust in the brand(s); 2) I rely on the brand(s); 3) This is an honest brand(s); 4) The brand(s) meets my expectations. These four items of brand trust were measured on a five-point Likert scale, where participants would have to choose from 1(“Strongly agree”), 5 (“Strongly disagree”).

Furthermore, the factor analysis was conducted in order to assess the appropriateness of the data. Four items which measured VA user and non-user brand trust were entered into factor analysis using Principal Components extraction with Varimax rotation based on Eigenvalues (> 1.00), $KMO = .74$, χ^2 (N = 786, 6) = 469.077, $p < .001$ for VA users; and Eigenvalues (> 1.00), $KMO = .66$, χ^2 (N = 786, 4) = 242.269, $p < .001$ for non-users. The resultant model explained 59.2% of the variance in brand trust of VA users and 67.01% of the variance in brand trust of device users. The subsequent reliability analysis showed that these are reliable scales with a Cronbach’s alpha of .77 for VA user brand trust and Cronbach’s alpha of .75 for device user brand trust (Landis & Koch, 1977). We decided to call these variables *brand trust from voice assistant use* and *brand trust from device use.* The final measures consisted of an average of four items. The final Factor loadings of individual items onto one factor found are presented in Table 3.3.5.

Table 3.3.5. Factor loadings and reliability analysis for VA user brand trust (N=650) and device user brand trust (N=135)

Item	*Brand Trust from VA use*	*Brand Trust from device use*
I trust in the brand(s).	**.842**	**.870**
I rely on the brand(s).	**.727**	**.794**
This is an honest brand(s).	**.826**	**.789**
The brand(s) meets my expectations.	**.668**	**.668**
R^2	59.2	67.01
Cronbach’s α ($\rho < 0.1$)	.767	.752

3.3.6. Personalisation

For this research, personalisation was measured by using a subset of six items of the original personalisation scale of Srinivasan, Anderson and Ponnavolu (2002), which was also used by Kuruuzum (2015) and consisted of nine items. The items of the scale were slightly modified based on the personalization literature Fan and Poole (2006) and Smith (2006), in order to ensure the better fit for this particular study and included the following items for measuring personalisation of VA users and non-users: 1)This voice assistant (device) makes product recommendations that match my needs; 2) This voice assistant (device) makes me feel that I am a unique user; 3) Overall, I like the idea of using the personalized product recommendations; 4) Personalised offerings provide time efficient experience for me; 5) The promotions that this voice assistant (device) offers to me are tailored to my preferences; 6) The promotions that this voice assistant (device) offers to me match my needs. These six items of personalisation were measured on a five-point Likert scale, where participants would have to choose from 1(“Strongly agree”), 5 (“Strongly disagree”).

Furthermore, the factor analysis was conducted in order to assess the appropriateness of the data. Six items which measured VA user and non-user personalisation were entered into factor analysis using Principal Components extraction with Varimax rotation based on Eigenvalues (> 1.00), $KMO = .84$, $\chi^2 (N = 786, 15) = 1087.62$, $p < .001$ for VA users; and Eigenvalues (> 1.00), $KMO = .79$, $\chi^2 (N = 786, 10) = 596.373$, $p < .001$ for non-users. The resultant model explained 58.9% of the variance in personalization of VA users and 58.7% of the variance in in personalization of device users. The subsequent reliability analysis showed that these are reliable scales with a Cronbach’s alpha of .86 for VA user personalisation and Cronbach’s alpha of .83 for device user personalisation (Landis & Koch, 1977). We decided to call these variables *personalisation from voice assistant use* and *personalisation from device use.* The final measures consisted of an average of six items for VA user personalisation and five items for device user personalisation. The results of Cronbach’s alpha test for device user personalisation showed that if the question 1) This device makes product recommendations that match my needs, were to be deleted, the Cronbach’s alpha would be .83, which is higher than the original Cronbach’s alpha .82. The final Factor loadings of individual items onto one factor found are presented in Table 3.3.6.

Table 3.3.6. Factor loadings and reliability analysis for VA user personalization (*N*=650) and device user personalisation (*N*=135)

Item	*Personalization from VA use*	*Personalization from device use*
This voice assistant (device) makes product recommendations that match my needs.	**.763**	**.604**
This voice assistant (device) makes me feel that I am a unique user.	**.666** **.766**	**.791** **.820**
Overall, I like the idea of using the personalized product recommendations.	**.778**	**.795**
Personalised offerings provide time efficient experience for me.	**.808**	**.799**
The promotions that this voice assistant (device) offers to me are tailored to my preferences.	**.815**	**.830**
The promotions that this voice assistant (device) offers to me match my needs.		
R^2	58.9	58.7
Cronbach's α (ρ < 0.1)	.856	.830

3.3.7. Emotional attachment

For this research, emotional attachment was measured by using a subset of seven items of the original attachment scale of Williams et al (1992), which was also used by Huigen, Haartsen and Folmer (2013), and consisted of twelve items. The items of the scale were slightly modified based on the research of Harmon-Jones et al. (2016) on emotions and attachments in order to ensure the better fit for this particular study and included the following items for measuring emotional attachment of VA users and non-users: 1) I feel personally connected to this voice assistant (device); 2) This voice assistant (device) means a lot to me; 3) I would like to spend more time interacting with this voice assistant (device);
4) I feel pleasure using this voice assistant (device); 5) It would be a struggle to give up using this voice assistant (device); 6) This voice assistant (device) is part of my personal life; 7) I would be disappointed if I could not use this voice assistant (device) when I need it. These

seven items of emotional attachment were measured on a five-point Likert scale, where participants would have to choose from 1("Strongly agree"), 5 ("Strongly disagree").

Furthermore, the factor analysis was conducted in order to assess the appropriateness of the data. Seven items which measured VA user and non-user emotional attachment were entered into factor analysis using Principal Components extraction with Varimax rotation based on Eigenvalues (> 1.00), $KMO = .88$, $\chi^2 (N = 786, 21) = 1562.104$, $p < .001$ for VA users; and Eigenvalues (> 1.00), $KMO = .84$, $\chi^2 (N = 786, 21) = 935.061$, $p < .001$ for non-users. The resultant model explained 60.4% of the variance in emotional attachment of VA users and 52.2% of the variance in emotional attachment of device users. The subsequent reliability analysis showed that these are reliable scales with a Cronbach's alpha of .89 for VA user personalisation and Cronbach's alpha of .85 for device user personalisation (Landis & Koch, 1977). We decided to call these variables *emotional attachment from voice assistant use* and *emotional attachment from device use.* The final measures consisted of an average of seven items for VA user emotional attachment and six items for device user emotional attachment. The results of Cronbach's alpha test for device user emotional attachment showed that if the question 3) I would like to spend more time interacting with this device, were to be deleted, the Cronbach's alpha would be .85, which is higher than the original Cronbach's alpha .84. The final Factor loadings of individual items onto one factor found are presented in Table 3.3.7.

Table 3.3.7. Factor loadings and reliability analysis for VA user emotional attachment (N=650) and device user emotional attachment (N=135)

Item	*Emotional attachment from VA use*	*Emotional attachment from device use*
I feel personally connected to this voice assistant (device).	**.650**	**.766**
This voice assistant (device) means a lot to me.	**.738**	**.836**
I would like to spend more time interacting with this voice assistant (device).	**.563**	**.677**
I feel pleasure using this voice assistant (device).	**.544**	**.686**
It would be a struggle to give up using this voice assistant (device).	**.640**	**.761**
	.643	

This voice assistant (device) is part of my personal life.	**.450**	**.789**
I would be disappointed if I could not use this voice assistant (device) when I need it.		**.691**
R^2	60.4	52.2
Cronbach's α (ρ < 0.1)	.888	.854

3.3.8. Filter bubble

For this research, filter bubble was measured by using a subset of four items of the original scale of Matt et al. (2014) on users' acceptance of novelty and filter bubble, which consisted of twelve items. The items of the scale were slightly modified based on the research in order to ensure the better fit for this particular study and included the following items for measuring embeddedness in a filter bubble of VA users and non-users: 1) The voice assistant (device) provides me with surprising recommendations that helped me discover new content/products that I wouldn't have found elsewhere; 2) The voice assistant (device) provides me with recommendations that were a pleasant surprise to me because I would not have discovered them somewhere else; 3) I like the selection of content/products recommended to me by this voice assistant (device); 4) The selection of content/products recommended to me by this voice assistant (device) coincide with my personal preferences. These four items of filter bubble were measured on a five-point Likert scale, where participants would have to choose from 1("Strongly agree"), 5 ("Strongly disagree").

Furthermore, the factor analysis was conducted in order to assess the appropriateness of the data. Four items which measured VA user and non-user embeddedness in a filter bubble were entered into factor analysis using Principal Components extraction with Varimax rotation based on Eigenvalues (> 1.00), KMO = .81, χ^2 (N = 786, 6) = 898.446, p < .001 for VA users; and Eigenvalues (> 1.00), KMO = .77, χ^2 (N = 786, 6) = 725.367, p< .001 for non-users. The resultant model explained 73.4% of the variance in extent of embeddedness in filter bubble of VA users 73.5% of the variance in extent of embeddedness in filter bubble of device users. The subsequent reliability analysis showed that these are reliable scales with a Cronbach's alpha of .88 for VA user filter bubble and Cronbach's alpha of .88 for device user filter bubble (Landis & Koch, 1977). We decided to call these variables *filter bubble from voice assistant use* and *filter bubble from device use.* The final measures consisted of an average of four items. The final Factor loadings of individual items onto one factor found are presented in Table 3.3.8.

Table 3.3.8. Factor loadings and reliability analysis for VA user filter bubble (*N*=650) and device user filter bubble (*N*=135)

Item	*Filter Bubble from VA use*	*Filter Bubble from device use*
The voice assistant (device) provides me with surprising recommendations that helped me discover new content/products that I wouldn't have found elsewhere.	**.855**	**.879**
The voice assistant (device) provides me with recommendations that were a pleasant surprise to me because I would not have discovered them somewhere else.	**.855**	**.855**
I like the selection of content/products recommended to me by this voice assistant (device).	**.863**	**.863**
The selection of content/products recommended to me by this voice assistant (device) coincide with my personal preferences.	**.851**	**.832**
R^2	73.3	73.5
Cronbach's α (ρ < 0.1)	.877	.877

3.3.9. Acceptance of the new content

For acceptance of the new content, this study aimed to measure user acceptance of the new content outside and within their interest. First, the five items were constructed and measured the extent to which the participants were willing to accept the novelty (newness) of new recommended information/content. The items were inspired by a similar study of Shimpock-Vieweg, (1996), who reviewed the validated Change Readiness Scale by Kriegel and Brandt (1996), which consisted of 35 items. Because the survey was quite long it was decided to use only five items of the Change Readiness Scale, which were also slightly modified to ensure the better fit for this particular study and included the following items for acceptance of the new content outside of VA users and non-users interest: 1) I'm unlikely to change my interests in certain type of content once they're set; 2) I'm inclined to establish routines in terms of content consumption and stay with them; 3) I can make any new content/ information work for me; 4) I prefer consuming certain type of content that is familiar and within my comfort zone; 5) Once I've made up my mind, I don't easily change it. These five items of acceptance of the new content were measured on a five-point Likert scale, where participants would have to choose from 1("Strongly agree"), 5 ("Strongly disagree"). In addition, the item 4) I regret (feel bad) about my decision to use services of this voice assistant (device), was reversed direction, therefore it was unreversed for both scales of VA users and device users.

Moreover, user acceptance of the new content within their interest consisted of the single question for only VA users and asked the participants (e.g. 'What is generally your first reaction when you receive the new information regarding the interests you indicated before?'). Answers were appointed as 1) very positive, 2) positive, 3) neutral, 4) negative, 5) very negative. The construction of this single question regarding user acceptance of the new content within their interests was based on the literature of audience attitude towards new content acceptance by Moeller and Helberger (2018). In addition, the answers of this single question were unreversed for VA users.

Furthermore, the factor analysis was conducted in order to assess the appropriateness of the data. Four items which measured VA user and non-user acceptance of the new content outside of their interest were entered into factor analysis using Principal Components extraction with Varimax rotation based on Eigenvalues (> 1.00), $KMO = .71$, χ^2 ($N = 786$, 10) = 218.651, $p < .001$ for VA users; and Eigenvalues (> 1.00), $KMO = .70$, χ^2 ($N = 786$, 6) = 275.560, $p < .001$ for non-users. The resultant model explained 59.4% of the variance in acceptance of the new content outside of VA users interest and 55.3% of the variance in acceptance of the new content outside of device users interest. The subsequent reliability analysis showed that the acceptance of the new content outside of device users interest is reliable scale with a Cronbach's alpha of .73 (Landis & Koch, 1977). However, the results for acceptance of the new content outside of VA users interest showed that if the question 3) I can make any new content/ information work for me, were to be deleted, the Cronbach's alpha would be .650, which is considerably higher than the original alpha of .58. After taking the closer look at the other questions in the scale, it was found that question 3) I can make any new content/ information work for me, was the only reversed question in the scale and it was unreversed. To conclude, Cronbach's alpha of acceptance of the new content outside of VA users interest was .650, which was still not higher than .70 and made this variable less reliable, but it was still be used in the analyses. Therefore, the reliability result of this variable should be taken into account when interpreting the results.

Finally, the variables were called *acceptance of the new content outside of VA users interest, acceptance of the new content outside of device users interest and acceptance of the new content within VA users interest and acceptance of the new content within devices users interest.* The final measures consisted of an average of five items for both VA and device user acceptance of the new content outside of their interest. The final Factor loadings of individual items onto one factor found are presented in Table 3.3.9.

Table 3.3.9. Factor loadings and reliability analysis for VA user filter bubble (*N*=650) and device user filter bubble (*N*=135)

Item	*Acceptance of new content from VA use*	*Acceptance of new content from device use*
I'm unlikely to change my interests in certain type of content once they're set.	**.742**	**.755**
I'm inclined to establish routines in terms of content consumption and stay with them.	**.691**	**.776**
I can make any new content/ information work for me.	**.985**	**.728**
I prefer consuming certain type of content that is familiar and within my comfort zone.	**.699**	**.715**
Once I've made up my mind, I don't easily change it.	**.665**	**.665**
R^2	*59.4*	*55.3*
Cronbach's α (ρ < 0.1)	*.650*	*.727*

3.4. Data analysis

The collected data on Qualtrics was first loaded into SPSS software for statistical data analysis. In order to increase the validity of this research, the data was cleaned by removing the incomplete samples from the data set. Composite measures of scales were created through averaging of their items, per scale. As respondents were divided into users and non-users (based on either non-use at all of VAs or infrequent use), the variables for user satisfaction, brand trust, personalisation, emotional attachment, filter bubble and acceptance of the new content, describe the respondents for their respective device use (either VA or non-VA, other device use). As this thesis is concerned with general relationships among the variables as well as those relationships specific to VA use, each of the hypothesis will be tested for non-VA users (other device users) and VA users. For H1 stating the relationship between voice assistant use and emotional attachment, a linear regression was performed to see if independent binary variable voice assistant use could predict the dependent continuous variable emotional attachment in the conceptual model. Also, this hypothesis H1 will be tested on the often voice assistant use variable in order to see if there is difference in the effect on emotional attachment between VA use and more often VA use, as supplementary/exploratory analysis. The often VA use variable is technically ordinal; however, in order to test mediation/moderation effects, this variable will be treated as non-ordinal; hence, any findings from this variable will be mildly tentative.

Furthermore, a linear regression analyses were used to examine the hypotheses H2a and H2b in order to see if independent continuous variable user satisfaction could predict dependent continuous variable emotional attachment. And in the case of H2b if dependent continuous variable emotional attachment could predict dependent continuous variable acceptance of the new content. The additional comparison of liner regression tests was conducted to see if there is a difference in the effect on emotional attachment depending on user satisfaction variable of VA users and device users. Also, another comparison of liner regression tests was conducted to see if there is a difference in the effect on acceptance of the new content depending on emotional attachment variable of VA users and device users. Moreover, a linear regression analyses were also used to examine the hypotheses H5, in order to see if independent continuous variable personalisation could predict dependent continuous variable user satisfaction. Also, additional exploratory analysis of liner regression tests were conducted to see if there is a difference in the effect on user satisfaction depending on personalisation variable of VA and device users.

The Hayes PROCESS macro add-on (version 3.3) to SPSS program was installed to conduct the test for measuring the moderation and mediation effects alongside the main effects. Hayes PROCESS model 4 (see figure 3.4.2 below) for simple mediation was used to test H3e and Hayes PROCESS model 1 (see figure 3.4.1 below) for simple moderation analysis was used to test the hypothesis H3a, H3c, H4, H6. According to Hayes (2012), PROCESS unlike other tools is used to test the combination of the direct and indirect effects of moderation and mediation with 95 percent confidence intervals. Also, Hayes (2012) states that PROCESS is used to test the combination of the effects of moderated mediation for conditional process modelling. According to Hayes (2017), the traditional mediation analysis can occur in the model 4 if following conditions are met. First path c of the model 4 says that there should be significant total direct effect between IV independent variable (X) and DV dependent variable (Y). Secondly, path a of the model 4 states that there should be the significant direct effect between IV independent variable (X) and the mediator (M_i) (Hayes, 2017). Also, the path b of the model 4 states that there should be significant effect between mediator (M_i) and dependent variable (Y) when independent variable (X) and mediator (M_i) predict dependent variable (Y) together (Hayes, 2017). Finally, the path c' of the model 4 states that the effect of independent variable (X) on dependent variable (Y) needs to be no longer significant when the mediator variable (M_i) included in the model (Hayes, 2017).

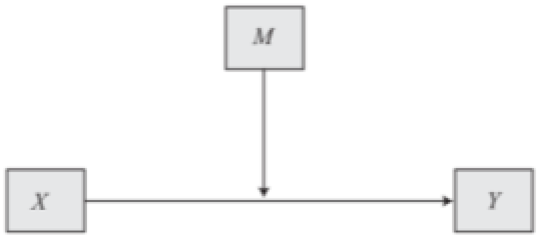


Figure 3.4.1. Conceptual diagram of the PROCCESS model 1-Simple moderation

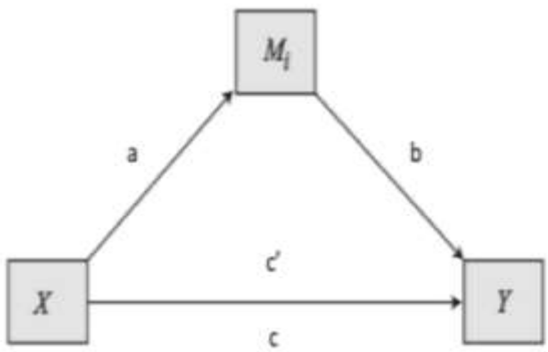


Figure 3.4.2. Conceptual diagram of PROCESS model 4 - Simple mediation

3.5. Validity and reliability

There are several steps were taken to in order to ensure and strengthen the validity and reliability of this research. Neuman (2014) stated that validity of the research was referred to the truthfulness of the research findings of the measured phenomenon. Schriesheim et al. (1993) revealed the steps for checking content validity such as first manage a list of developed items for measuring constructs plus their definitions, to participants. A pre-test of the survey was conducted to verify participants' understanding of questions and clarity before the final execution of the questionnaire (Saunders et al., 2003). Nenty (2009) stated that the use of quantitative deductive approach with the use of the online survey will ensure the content validity of the final scale. Also, the validity of the research method for this study has been ensured by using the established scales which were derived from the already existing literature and validated by previously done studies (see Appendix 1) (Pallant, 2010). As it was mentioned earlier, the sampling for this thesis was a mixture of a probability sampling and convenience sampling. While convenience sampling to obtain participants for the first part of the data collection process might lack generalizability of findings, random selection of respondents was also chosen through the use of Prolific tool, as probability sampling could most likely lead to the general population (Neumen, 2014).

Furthermore, the data cleaning through removing the incomplete samples and outliers was performed to ensure the internal reliability. Also, the factor analyses were conducted for each item of the scales in order to ensure orthogonality and strengthen reliability. Cronbach's alpha test of reliability ensured the relevance of the collected data derived from the survey as well as the internal consistency of the scales (Pallant, 2010). The results of Cronbach's alpha tests of reliability are presented in table 3.5; these display the final alpha, after scale adjustments through appropriately deleting an item when necessary (see below).

Table 3.5. Cronbach's alpha reliability tests

	Cronbach's Alpha	*Mean*
User satisfaction from VA use	.835	2.07
Brand trust from VA use	.767	2.37
Personalisation features from VA use	.856	2.95
Emotional attachment from VA use	.888	3.51
Filter bubble from VA use	.877	3.08
Acceptance of the new content outside of VA user interest	.650	2.40

	Cronbach's Alpha	*Mean*
User satisfaction from device use	.888	2.33
Brand trust from device use	.752	2.43
Personalisation features from device use	.830	2.99
Emotional attachment from device use	.854	2.47
Filter bubble from device use	.877	2.80
Acceptance of the new content outside of device user interest	.727	2.56

4. Results

This chapter will present the tests and results of the hypotheses with the use of different quantitative analyses. First, descriptive statistics will be presented and discussed. Thereafter, the types of analysis will be presented for each individual hypothesis, followed by an explanation if the hypothesis is rejected or supported.

4.1. Descriptive statistics

Before testing the hypothesis, it is important to discuss descriptive statistic of the obtained sample such as age, gender, nationality, employment status, monthly income and current place of location, in order to understand the diversity of the obtained group. After data cleaning, N= 786 were included in further analyses. The final sample comprised both (N=317, 40.3%) women while the majority was men (N=468, 59.5%). The other 0.1% (N=1) preferred not to indicate gender. These participants were included for reliability testing but excluded for further analyses in order to be able to include sex as a binary variable in regression analyses. Also, participants were varied in age from 18 years old to 59 years old, and the average age was 23 (SD= 5.33). Due to the international nature of the approached groups, the sample obtained a total of around 70 different nationalities most prominent being Portuguese (15.2%), Polish (13.1%) and British (8.8%). The most named highest education level was Bachelor degree (39.8%), followed by high school degree (36.4%), and Master degree (19.5%). The most named monthly income was less than 1000 euros per month (37.0%), followed by from 1000 to 2500 euros per month (24.6%), and no income at all (15.1%). The participants were varied in terms of employment status, the most prominent being students (45.0%), followed by full-time employed participants (33.0%), and part-time employed (8.9%).

The participants who were considered to be often voice assistants' users were (N=650, 86.3%). Furthermore, the most used voice assistants' technology was Google Now by Google (42.6%), Siri by Apple (41.0%) and Alexa by Amazon (17.8%). Also, the most common voice assistants' use was via mobile phone (47.3%), followed by smart speaker (16.3 %) and laptop/computer (9.9%). The longest use of the voice assistants was about 1 to 3 years (41.6%), 6 months to 1 year (30.0%) and less than 6 months (17.7%). The most common purpose of voice assistants' use was asking questions (45.5%), followed by checking weather (32.8%) and calling someone (26.8%). The most common interest which has been identified by voice assistants' users was music (43.6%), films/cinema (38.9%) and news/current affairs (29.2%). The participants identified that they tend to use the most often the following sources and platforms for receiving their information of interest: social media on mobile phone (44.0%), social media on a computer/laptop (37.1%), other internet sources on a computer/laptop/netbook/tables (including apps you've downloaded and those automatically loaded onto your device, e. g. voice assistants) (32.1 %).

There were *N*=135 (17.3%) participants who never tried or do not use voice assistants. The most commonly used digital devices were mobile phones (40.2%), laptops/computers (28.9%) and tablet computers (6.9%). The most often use of the indicated digital devices was every day (96.3%). The longest use of the indicated digital devices was more than 5 years (38.6%), followed by 1 to 3 years (32.5%) and 6 months to 1 year (10.9%). The most common purpose of devices' use was calling someone (35.0%), messaging or emailing someone (34.5%) and setting an alarm (32.1%). The most common interests of the device users were music (31.8%), film and cinema (29.0%) and news and current affairs (23.4%). The device users identified that they tend to use the most often the following sources and platforms for receiving their information of interest: social media on mobile phone (32.2 %), social media on computer/laptop/netbook/tablet (29.4%) and other internet sources on a computer/laptop/netbook/tables (including apps you've downloaded and those automatically loaded onto your device, e. g. voice assistants) (20.9%).

4.2. Voice assistant use and emotional attachment

As mentioned in the Research Design chapter, this study had two different variables which measured the *voice assistant use*. The first variable measured if a participant ever tried to use or use voice assistants, which was *voice assistant use* variable. The second variable measured the frequency of voice assistant use, which was *often voice assistant use* variable. The mean of *voice assistant use* variable is .83, meaning the proportion of respondents who used VA at all was 83%. The distribution of *often voice assistant use* variable is 2.75.

Furthermore, this study had three different variables which measured emotional attachment. The first variable of emotional attachment was measured through the survey on the participants who were considered voice assistant users. The second variable of emotional attachment was measured on the participants who were non-users (device users). Therefore, in order to answer hypothesis H1, the third variable emotional attachment for all users was created as the combination of the two variables emotional attachment of voice assistant and device users. The means of all emotional attachment variables were calculated. The mean of *emotional attachment from voice assistant use* variable was 2.49. The mean of the *emotional attachment from device use* variable was 3.53. The mean of *emotional attachment* variable was 2.93.

In order to answer the hypothesis H1, a linear regression with *emotional attachment* score as the dependent variable (DV) and *voice assistant use* (binary variable) as the predictor (IV) was conducted. The model was found to be significant, $F(1, 750) = 91.09$, $p<.001$. The regression model is thus useful for predicting *emotional attachment* from *voice assistant use*, but the predictive power is weak: 11% percent of the variance in *emotional attachment* can be explained by voice assistant use ($R^2 = .11$). *Voice assistant use* had a strong negative significant influence on *emotional attachment* (B=-0.848, $p < .001$). Thus, a unit increase in the range of VA usage contributes to -.848 decrease of EA. This means that hypothesis H1 was not supported.

Furthermore, device use is just the opposite of voice assistant use which means that device use variable coefficients will be the negative of the coefficient of voice assistant use (the H1) model. Therefore, the non-VA users are more emotionally attached to their respective devices than voice assistant users by .848 points in the emotional attachment scale.

4.2.1. Often voice assistant use and emotional attachment

A linear regression with *emotional attachment from often VA use* score as the dependent variable (DV) and *often voice assistant use* as a predictor (IV) was conducted. The model was found to be significant, $F(1, 428) = 46.189$, $p< .001$. The regression model is thus useful for predicting *emotional attachment* from *often voice assistant use*, but the predictive power is weak: 10% percent of the variance in *emotional attachment from often VA use* can be predicted based on ($R^2 = .10$). *Often voice assistant use* had weak positive significant influence on *emotional attachment from often VA use* (B=0.258, $p< .001$). Thus, a unit increase in the range of VA usage frequency contributes to .258 increase of emotional attachment. Finally, the hypothesis H1 with often voice assistant use on emotional attachment was supported.

4.2.2. Often device use and emotional attachment

A linear regression with *emotional attachment from often device use* as the dependent variable (DV) and *often device use* as predictor (IV) was conducted. The model was found to be positive significant, $F(1, 316) = 20.460$, $p< .001$. The regression model is thus useful for predicting *emotional attachment* from *often device use*, but the predictive power is weak: 6% percent of the variance in *emotional attachment from often device use* can be predicted based on ($R^2 = .06$). *Often device use* had weak positive significant influence on *emotional* *attachment from device use* (B=0.280, p<.001). Thus, a unit increase in the range of device usage frequency contributes to .280 increase of emotional attachment. Therefore, the hypothesis H1 with often device use on emotional attachment was supported**.**

4.2.3. Comparison often voice assistant versus often device use on emotional attachment

In comparing the effect of *often voice assistant use* and *often device use* on *emotional attachment*, unstandardized coefficients are required for this comparison. The difference between the unstandardized coefficients (B _often_useDev = 0.280, B_often_useVA =0.258), accounting for their S.E. (SE_often_useDev =.062, SE_often_useVA=.038) is insignificant (z = 0.302, $p = 0.62$). That is, the effect of frequency of use on emotional attachment is similar for users of VA and users of other devices.

4.3. User satisfaction and emotional attachment

This study had three different variables which measured *user satisfaction*. The first variable measured the participants' satisfaction who were voice assistant users, which was called *user satisfaction from voice assistant use*. The second variable measured the participants' satisfaction, who were device users, which was called *user satisfaction variable from device use*. The third variable was called *user satisfaction* and measured satisfaction of all participants. The mean of *user satisfaction from voice assistant use* variable is 3.88. The mean of *user satisfaction from device use* variable is 4.26. And the mean for called *user satisfaction* variable is 4.04.

Furthermore, this study had three different variables which measured emotional attachment. The first variable of emotional attachment was measured through the survey on the participants who were considered the voice assistant users. The second variable of emotional attachment was measured on the participants who were device users. Therefore, in order to answer hypothesis H2a, the third variable emotional attachment for all users was created as the combination of the two variables emotional attachment of voice assistant and device users. The means of all emotional attachment variables were calculated. The mean of *emotional attachment from voice assistant use* variable was 2.49. The mean of *emotional attachment from device use* variable was 3.53. The mean of *emotional attachment* variable was 2.93.

In order to answer the hypothesis H2a, a linear regression with *emotional attachment* score as the dependent variable (DV) and *user satisfaction* as predictor (IV) was conducted. The model was found to be significant, F(1, 742) = 152.26, p<.001. The regression model is thus useful for predicting *emotional attachment* from *user satisfaction*, but the predictive power is weak: 17% percent of the variance in *emotional attachment* can be predicted based on ($R^2 = .17$). *User satisfaction* had moderate significant positive influence on *emotional attachment* (B=0.572 p<.001). Thus, a unit increase in the range of user satisfaction contributes to .572 increase of the appearance of emotional attachment. Therefore, the hypothesis H2a was supported.

4.3.1. User satisfaction and emotional attachment (VA users)

A linear regression with *emotional attachment from VA use* score as the dependent variable (DV) and *user satisfaction from VA use* as predictor (IV) was conducted. The model was found to be significant, $F(1, 425) = 37.798$, $p<.001$. The regression model is thus useful for predicting *emotional attachment from VA use* from *user satisfaction from VA use*, but the predictive power is weak: 8% percent of the variance in *emotional attachment from VA use* can be predicted based on (R^2=.08). *User satisfaction from VA use* had moderate positive significant influence on *emotional attachment from VA use* (B=0.379, p<.001). Thus, a unit increase in the range of user satisfaction from VA use contributes to .379 increase of the appearance of emotional attachment from voice assistant use. Therefore, the hypothesis H2a with user satisfaction from VA use on emotional attachment from VA use was supported.

4.3.2. Users satisfaction and emotional attachment (device users)

A linear regression with *emotional attachment from device use* as the dependent variable (DV) and *user satisfaction from device use* as predictor (IV) was conducted. The model was found to be significant, $F(1, 315) = 53.106$, p<.001. The regression model is thus useful for predicting *emotional attachment from device use* from *user satisfaction from device use*, but the predictive power is weak: 14% percent of the variance in *emotional attachment from device use* can be predicted based on (R^2=.14). *User satisfaction from device use* will have moderate significant positive influence on emotional attachment from devices' use (B=0.402, p <.001). Thus, a unit increase in the range of user satisfaction by content from device use contributes to .402 increase of the appearance of emotional attachment from device use. Therefore, the hypothesis H2a with user satisfaction from device use and emotional attachment from device use was supported.

4.4. Emotional attachment and acceptance of the new content

This study had three different variables which measured the user *acceptance of the new content* outside of their interest and one variable which measured the user *acceptance of the new content* within their interest. The first two variables measured all the participants who were VA users, which was called *acceptance of the new content outside of VA user interest* and *acceptance of the new content within of VA users interest.* The second variable measured all the participants who were device users, which was called *acceptance of the new content outside of device users interest.* The third variable was called *acceptance of the new content outside of user interest*, which was a combination of the two variables *acceptance of the new content outside of VA and device user interest.* The mean of *acceptance of the new content outside of VA user interest* variable is 3.40. The mean of *acceptance of the new content outside of device user interest* variable is 3.44. And the mean of *acceptance of the new content outside of user interest* variable is 3.42. The mean of *acceptance of the new content within VA user interest* variable is 3.88.

In order to answer the hypothesis H2b, a linear regression with *acceptance of the new content outside of user interest* score as the dependent variable (DV) and *emotional attachment* (the combined variable of both VA and other device users) as predictor was conducted. The model was found to be significant, $F(1, 743) = 30.328$, $p<.001$. The regression model is thus useful for predicting *the acceptance of the new content* from *emotional attachment*, but the predictive power is weak: 4% percent of the variance in *acceptance of the new content* can be predicted based on ($R^2=.04$). *Emotional attachment* had significant weak negative influence on *acceptance of the new content outside of user interest* ($B=-0.136$, $p< .001$). Thus, a unit increase in the range of emotional attachment contributes to -.136 points decrease of acceptance of the new content outside of user interest.
Therefore, the hypothesis H2b was not confirmed.

4.4.1. Emotional attachment and acceptance of the new content (VA users)

A linear regression with *acceptance of the new content outside of VA user interest* as the dependent variable (DV) and *emotional attachment from VA* use as predictor (IV) was conducted. The model was found to be significant, $F(1, 428) = 13.379$, $p<.001$. The regression model is thus useful for predicting *acceptance of the new content outside of VA user interest* from *emotional attachment from VA use*, but the predictive power is weak: 3% percent of the variance in *acceptance of the new content outside of VA user interest* can be predicted based on ($R^2=.03$.) *Emotional attachment from VA use* will have weak significant negative influence on their *acceptance of new content outside of VA user interest* (B=-0.132, p<.001). Thus, a unit increase in the range of emotional attachment from VA use contributes to -.132 decrease of the likelihood of the choice of acceptance of the new content outside of VA user interest. Therefore, the hypothesis H2b with emotional attachment from VA use on acceptance of the new content outside of VA user interest was not confirmed.

4.4.2. Emotional attachment and acceptance of the new content within VA user interest

A linear regression with *acceptance of the new content within of VA user interest* as the dependent variable (DV) and *emotional attachment from VA* use as predictor (IV) was conducted. The model was found to be significant, $F(1, 428) = 17.584$, p<.001. The regression model is thus useful for predicting *acceptance of the new content within of VA user interest* from *emotional attachment from VA use*, but the predictive power is weak: 6% percent of the variance in *acceptance of the new content within VA user interest* can be predicted based on (R^2=.06.) *Emotional attachment from VA use* will have moderate significant positive influence on their *acceptance of new content within VA user interest* (B=0.338, p<.001). Thus, a unit increase in the range of emotional attachment from VA use contributes to .338 increase of the likelihood of the choice of acceptance of the new content within VA user interest. Therefore, the hypothesis H2b with emotional attachment from VA use on acceptance of the new content within VA user interest was confirmed.

4.4.3. Emotional attachment and acceptance of the new content for (device users)

A linear regression with *acceptance of the new content outside of device user interest* as the dependent variable (DV) and *emotional attachment from device use* as predictor (IV) was conducted. The model was found to be significant, $F(1, 317) = 14.168$, p<.001. The regression model is thus useful for predicting *acceptance of the new content outside of device user interest* from *emotional attachment from device use*, but the predictive power is weak: 4% percent of the variance in *acceptance of the new content outside of device user interest* can be predicted based on (R^2=.04). *Emotional attachment from device use* will have weak negative significant influence on *the acceptance of new recommended content outside of device user interest* (B=-0.191, p <.001). Thus, a unit increase in the range of emotional attachment from device use contributes to -.191 decrease of the likelihood of the choice of acceptance of the new content outside of device user interest. Therefore, the hypothesis H2b with emotional attachment from device use on acceptance of the new content outside of device user interest was not supported.

4.4.4 Comparison of user satisfaction on emotional attachment for VA and device users

In comparing the effect of *user satisfaction from VA use* and *user satisfaction from device use* on *emotional attachment for VA and device users*, the difference between the unstandardized coefficients (*B*_Sat_VA = 0.379, *B* _Sat_Dev =0.402), accounting for their S.E. (SE_Sat_VA =.062, SE_Sat_Dev=.055) is insignificant (z = 0.278, $p = .78$). That is, the effect of user satisfaction on EA is similar for users of VA and users of other devices.

4.4.5. Comparison of emotional attachment from VA and device use on acceptance of the new content of VA and device users

In comparing the effect of *emotional attachment from VA* and *device use* on *acceptance of the new content from VA* and *device use*, the difference between the unstandardized coefficients B*b* _EA_VA = -.132, *B*_EA_Dev =-0.191), accounting for their S.E. (SE_EA_VA =0.036, SE_EA_Dev=.051) is insignificant (z = 0.945, $p = .34$). That is, the effect of emotional attachment on the acceptance of the new content outside of user interest is similar for users of VA and users of other devices.

4.5. Personalisation and user satisfaction

This study had three different variables which measured *personalisation*. The first variable measured the participants' attitude towards personalisation who were voice assistant users, which was called *personalisation from VA use*. The second variable measured the participants' attitude towards personalisation, who were device users, which was called *personalisation from device use*. The third variable was called *personalisation* and measured attitudes towards personalisation of all participants. The mean of *personalisation from voice assistant use* variable is 3.05. The mean of *personalisation from device use* variable is 3.1. And the mean for *personalisation* variable is 3.07.

In order to answer the hypothesis H5, a linear regression with *user satisfaction from VA use* score as the dependent variable (DV) and *personalisation* as predictor (IV) was conducted. The model was found to be significant, $F(1, 423) = 29.683$, $p<.001$. The regression model is thus useful for predicting *user satisfaction from VA use* from *personalisation*, but the predictive power is weak: 6% percent of the variance in *user satisfaction from VA use* can be predicted based on (R^2=.06). *Personalisation* will have weak positive significant influence on *user satisfaction from VA use* (*B*=0.230, p<.001). Thus, a unit increase in the range of personalisation contributes to .230 increase in user satisfaction from voice assistant use. Therefore, the hypothesis H5 was supported.

4.5.1. Personalisation and user satisfaction (device users)

A linier regression with *user satisfaction from device use* as the dependent variable (DV) and *personalisation* as predictor (IV) was conducted. The model was found to be significant, $F(1, 318) = 7.795$, $p<.05$. The regression model is thus useful for predicting *user satisfaction from device use* from *personalisation*, but the predictive power is weak: 2% percent of the variance in *user satisfaction from device use* can be predicted based on (R^2=.02). Personalisation will have weak positive significant influence on the user satisfaction for device users (B=0.173, p<.05). Thus, a unite increase in the range of personalisation contributes to .173 increase of user satisfaction from device use. Therefore, the regression model of personalisation on user satisfaction from device use was supported.

4.5.2. Comparison of personalisation on user satisfaction from VA and device use

In comparing the effect of personalisation on *user satisfaction from VA use* and *device use,* the difference between the unstandardized coefficients (B _Sat_VA = .225, B _EA_Dev =.138), accounting for their S.E. (SE_Sat_VA =.041, SE_Sat_Dev=.049) is insignificant (z = 1.362, $p = .91$). That is, the effect of personalisation on user satisafction is similar for users of VA and users of other devices.

4.5.3. Personalisation and filter bubble (VA users)

A linier regression with *filter bubble from VA use* as the dependent variable (DV) and *personalisation* as predictor (IV) was conducted. The model was found to be significant, $F(1, 418) = 428.768$, $p<.001$. The regression model is thus useful for predicting *filter bubble from VA use* from *personalisation*, but the predictive power is strong: 51% percent of the variance in *filter bubble from VA use* can be predicted based on (R^2=.51). Personalisation will have strong positive significant influence on *filter bubble from VA use* (B=0.800, p<.001). Thus, a unite increase in the range of personalisation contributes to .800 increase of *filter bubble from VA use*. Therefore, the regression model of personalisation on *filter bubble from VA use* was supported.

4.5.4. Personalisation and emotional attachment (VA users)

A linier regression with *emotional attachment from VA use* as the dependent variable (DV) and *personalisation* as predictor (IV) was conducted. The model was found to be significant,

$F(1, 412) = 140.493$, $p<.001$. The regression model is thus useful for predicting *emotional attachment from VA use* from *personalisation*, but the predictive power is moderate: 25% percent of the variance in *emotional attachment from VA use* can be predicted based on (R^2=.25). Personalisation will have moderate positive significant influence on *emotional attachment from VA use* (B=0.580, p<.001). Thus, a unite increase in the range of personalisation contributes to .580 increase of *emotional attachment from VA use*. Therefore, the regression model of personalisation on *emotional attachment from VA use* was supported.

4.6. Moderation user satisfaction (VA users)

PROCESS model 1 was run to test H3a. The model was found to be significant, $F(3, 753)$ = 4.75, ρ=.0027. The main effect of *voice assistants use* on *acceptance of the new content outside of user interest* had negative but insignificant effect, controlling for the moderation (B =-0.38, $t(753)$ = -.84, ρ=.401, 95% CI [-1.25, 0.50]. *User satisfaction* had negative significant effect on *acceptance of the new content* outside of user interest B =-0.20, $t(753)$ = -2.12, p=.035, 95% CI [-0.39, -0.01], such that a unit decrease in the *user satisfaction* range contributes to B =-0.20 of *acceptance of the new content outside of user interest*. Also, the interaction term was positive insignificant (B=0.09, $t(753)$ =.81, p=.421, 95% CI [-0.12, 0.28] and thus *user satisfaction* does not moderate *voice assistant use* effect on *acceptance of the new content*. However, this models suffers from high and unavoidable multicollinearity as the interaction term and VA use has strong, significant correlation (r = .922, p < .001). Therefore, H3a was not supported. In fact, the positive effect of the moderation, despite its being insignificant, does not run counter to what was hypothesized and so higher user satisfaction in fact increases the effect of VA use on acceptance of the new content outside of user interest. See the moderation analysis in table 4.6.

4.6.1. Moderation user satisfaction (often device users)

PROCESS model 1 was run to test the moderation of often device use (IV) on the choice of acceptance of the new content outside of device user interest (DV) and user satisfaction from device use (W). The model was found to be not significant, $F(3, 320)$ = 1.61, p=.186. The main effect of *often device use* on *acceptance of the new content outside of device user interest* had positive and insignificant effect, not controlling for the moderation (B = 0.43, $t(320)$ = 1.57, p=.118, 95% CI [-0.11,0.97]. And now, *user satisfaction from device use* had positive insignificant effect on *acceptance of the new content outside of device user interest* B =0.51, $t(320)$ = 1.17, p=.242, 95% CI [-0.35, 1.38]. Also, the interaction term was negative insignificant (*B* = -0.12, *t*(320) =-1.40, *p*=.162, 95% CI [-0.30, 0.05] and thus and thus *user satisfaction from device use* does not moderate *often device use* effect on *acceptance of the new content outside of device user interest*. Therefore, the moderation model of often device use on the choice of acceptance of the new content outside of device user interest was not supported. In fact, the negative effect of the moderation, despite its being insignificant, runs counter to what was hypothesized and so higher user satisfaction from device use in fact reduces the effect of frequent device use on acceptance of the new content outside of device user interest. See moderation analysis in table 4.6.

Table 4.6. Moderation analysis for (VA, device, often VA and often device) use on acceptance of the new content outside of their interest (unstandardized coefficients)

Outcome:	*B*	*SE*	*t*	*p*
Acceptance of the new content				
Voice assistant use	-.38	.45	-.84	.401
User Satisfaction	-.20*	.10	-2.12	.034
Voice assistant use × User Satisfaction	.08	.10	.80	.420
Outcome :	*B*	*SE*	*t*	*p*
Acceptance of the new content from device use				
Often devices' use	.43	.27	1.57	.118
User Satisfaction from devices' use	.51	.44	1.17	.242
Often device use × User Satisfaction from device use	-.12	.09	-1.40	.162

Note:

Significance level: * $p < .05$, ** $p < .01$, *** $p < .001$.

4.7. Moderation brand trust (VA users)

PROCESS model 1 was run to test the moderation of the hypothesis H4. The model was found to be significant, $F(3, 743) = 59.49$, $p < .001$. We see that the main effect of *voice assistant use* on *emotional attachment* remains negative and significant ($B = -0.88$, $t(743) = -2.12$, $p = .035$, 95% CI [-1.69, -0.06] as seen earlier in H1, controlling for the moderation, such that a unit increase in the *voice assistant use* range contributes to $B = -0.88$ decrease of *emotional attachment. Brand trust* also had positive significant effect on *emotional attachment* $B = 0.38$, $t(743) = 3.84$, $p < .001$, 95% CI [0.18, 0.57] such that a unit increase in *brand trust* range contributes to $B = 0.38$ increase in *emotional attachment.* However, the interaction effect was found to be positive insignificant ($B = 0.01$, $t(743) = 0.13$, $p = .897$, 95% CI [-0.20, 0.23] and thus *brand trust* does not moderate *voice assistant use* effect on *emotional attachment.* Therefore, the hypothesis H4 was not supported. In fact, the positive effect of the moderation, despite its being insignificant, does not run counter to what was hypothesized and so higher level of brand trust in fact increases the effect of VA use on the appearance of emotional attachment. See moderation analysis in the table 4.7.

Table 4.7. Moderation analysis for model 1 of voice assistants use on emotional attachment (unstandardized coefficients)

Outcome:	*B*	*SE*	*t*	*p*
Emotional Attachment				
Voice assistant use	-.88*	.41	-2.12	.034
Brand Trust	.38***	.10	3.84	.000
Voice assistant use × Brand Trust	.01	.11	.13	.897

Note:

Significance level: * $p < .05$, ** $p < .01$, *** $p < .001$.

4.8. Moderation filter bubble

PROCESS model 1 was run to test the moderation of the hypothesis H6. The model was found to be not significant $F(3, 736) = 12.91$, $p < .001$. We see that the main effect of *emotional attachment* on *acceptance of the new content* outside of user interest remains positive insignificant (*B*=0.03, *t*(736) = .36, *p*=.716, 95% CI [-0.14, 0.20], as seen earlier in the hypothesis H2b, not controlling for the moderation. And now, *filter bubble* also has insignificant positive effect on *acceptance of the new content outside of user interest* (*B*=0.05, *t*(736) = .55, *p* =.581, 95% CI [-0.11, 0.21]. Also, the interaction term is negative insignificant (*B* =-0.05, *t*(736) =-1.66, *p*=.097, 95% CI [-0.10, 0.01], and thus *filter bubble* does not moderate *emotional attachment* effect on *acceptance of the new content outside of user interest*. Therefore, the hypothesis H6 was not supported. A separate regression with just the main effects of emotional attachment and filter bubble verifies that filter bubble's significant negative effect on ACN (*B* = -0.08, *b** = -.101, *p* < .05), albeit weak. See moderation analysis in the table 4.8.

4.8.1 Moderation filter bubble (VA users)

PROCESS model 1 was run to test the moderation of the model. The model was found to be significant *F*(3, 420) = 5.76, *p*<.001. We see that the main effect of *emotional attachment from VA use* on *acceptance of the new content outside of VA use*r interest remains positive insignificant (*B* =0.00, *t*(420) = .01, *p*=.995, 95% CI [-0.27, 0.27], , not controlling for the moderation. And now, *filter bubble from VA use* also has insignificant negative effect on *acceptance of the new content* outside of *VA user interest* (*B* =-0.02, *t*(420) = -.20, *p*=.842, 95% CI [-0.23, 0.19]. Also, the interaction term is negative insignificant (*B*=-0.02, *t*(420) =-0.70, *p* =.485, 95% CI [-0.11, 0.05], and thus *filter bubble from VA use* does not moderate *emotional attachment from VA use* effect on *acceptance of the new content outside of VA user interest*. Therefore, the model was not supported. In fact, the negative effect of the moderation, despite its being insignificant, does not run counter to what was hypothesized and so higher level of emotional attachment will mitigate the effect of the filter bubble's reducing (negative effect) the likelihood of the choice of acceptance of the new content outside of user interest. See moderation analysis in the table 4.8.

4.8.2 Moderation filter bubble (device users)

PROCESS model 1 (see figure 3.1) was run to test the moderation of emotional attachment (IV) on acceptance of the new content (DV) and filter bubble from device use (W). The model was found to be significant F(3, 316) = 6.86, *p* <.001. We see that the main effect of emotional attachment from device use on acceptance of the new content from device use remains positive insignificant (*B*=0.19, t(316) = 1.11, =.267, 95% CI [-0.15, 0.54], not controlling for the moderation. Filter bubble from device use has insignificant positive effect on acceptance of the new content from device use (*B*=0.34, t(316) = 1.70, =.090, 95% CI [-0.05, .073]. However, the interaction term is negative significant (*B* =-0.11, t(316) =-2.13, =.034, 95% CI [-0.21, -0.01], and thus filter bubble from device use does moderate emotional attachment from device use effect on acceptance of the new content from device use. However, despite the significance of the term, the fact that earlier we observed that emotional attachment from device use having a negative impact (main effect) on acceptance of the new content can mean that the negative interaction here worsens (makes less likely) acceptance of the new content and does so significantly. However, the main effects here are positive, yet rendered insignificant, strongly suggesting possible multicollinearity. What is most likely occurring is that emotional attachment from device use and filter bubble from device use amplify (rather than mitigate) one another's negative effect on acceptance of the new content. Thus, H6a is not supported.

From Table 4.8, one can see that in general, the moderation is negative while earlier we observed that EA for both VA and devices have a negative effect on ACN. Hence, the general pattern is that the negative effects of EA are amplified by FB rather than a positively effecting EA mitigating FB's negative effect (as stipulated by H6).

Table 4.8. Moderation analysis of model 1 of emotional attachment on acceptance of the new content outside of user interest (unstandardized confidents)

Outcome:	*B*	*SE*	*t*	*p*
Acceptance of the new content				
Emotional Attachment	.03	.09	.36	.716
Filter Bubble	.05	.08	.55	.581
Emotional attachment × Filter Bubble	-.04	.03	-1.66	.097

Outcome:	*B*	*SE*	*t*	*ρ*	**Outcome:**	*B*	*SE*	*t*	*p*
Acceptance of the new content from VA use					**Acceptance of the new content from device use**				

Emotional Attachment from VA use	.00	.14	.01	.995	Emotional attachment from devices use	.19	.18	1.11	.269
Filter Bubble from VA use	-.02	.11	-.20	.842	Filter Bubble from Device use	.34	.20	1.70	.070
Emotional attachment from VA use × Filter Bubble from VA use	-.03	.04	-.70	.486	Emotional Attachment from device use × Filter Bubble from device use	-.11*	.05	-2.13	.034

Note:

Significance level: * $p < .05$, ** $p < .01$, *** $p < .001$.

4.9. Mediation voice assistant use, emotional attachment and user satisfaction

The PROCESS mediation model 4 was run and the model was found to be significant (see table 4.9). The total direct effect between (IV) voice assistant use X and DV emotional attachment (Y) was found to be negative significant (B =-0.65, $t(744)$ =-7.63, p<.001, 95% CI [-0.82, -0.48]. The direct effect between (IV) voice assistant use X and the mediating variable user satisfaction (M_i) was found to be negative significant (B =-0.40, $t(744)$ =-5.91, p<.001, 95% CI [-0.53, -0.26]. The positive significant relationship between the mediating variable user satisfaction (M_i) and (DV) emotional attachment Y was found (B=.50, $t(744)$ =10.90, p<.001, 95% CI [0.41, 0.59], verifying the findings of H2a. The effect of (IV) voice assistant use X on (DV) emotional attachment Y was found to be negative significant (B =-0.85, $t(744)$ =-9.44, p=.000, 95% CI [-1.02, -0.67]. Therefore, as the effect of voice assistant use on emotional attachment drops from -.85 to -.65, it is partially mediated by user satisfaction. Thus, hypothesis H3c is partially supported.

Table 4.9. Mediation analysis of voice assistants use on acceptance of the new content outside of user interest and user satisfaction (unstandardized coefficients)

Outcome:	*B*	*SE*	*t*	*p*	*CI (lower)*	*CI(upper)*
User Satisfaction (path a)						
Constant	4.38***	.06	71.44	.000	4.26	4.50
Voice assistant use	-.40***	.07	-5.91	.000	-.53	-.26
Outcome:	*B*	*SE*	*t*	*p*	*CI (lower)*	*CI(upper)*

Emotional Attachment (path c)						
Constant	3.64***	.08	44.30	.000	3.48	3.80
Voice assistant use	-.85***	.09	-9.45	.000	-1.02	-.67
Outcome:	*B*	*SE*	*t*	*p*	*CI (lower)*	*CI(upper)*
Emotional Attachment (path b and c')						
Constant	1.46***	.21	6.81	.000	1.04	1.88
User satisfaction	.50***	.05	10.90	.000	.40	.59
Voice Assistant use	-.65***	.09	-7.63	.000	-.82	-.49

Note:

Significance level: * $p < .05$, ** $p < .01$, *** $p < .001$.

4.10. Mediation voice assistant use, emotional attachment and acceptance of the new content outside of VA user interest

The PROCESS mediation model 4 was run and the model was found to be significant (see table 4.9). The total direct effect between (IV) voice assistant use X and DV acceptance of the new content outside of user interest (Y) was found to be negative insignificant (B =-0.10, $t(749)$ =-1.47, p=1.41, 95% CI [-0.23, 0.03]. The direct effect between (IV) voice assistant use X and the mediating variable emotional attachment (M_i) was found to be negative significant (B =-0.85, $t(749)$ =-9.51, p<.001, 95% CI [-1.03, -0.68], verifying the hypothesis H1. The negative significant relationship between the mediating variable emotional attachment (M_i) and (DV) acceptance of the new content outside of user interest Y was found (B=-0.15, $t(749)$ =-5.67, p<.001, 95% CI [-0.20, -0.10]. The effect of (IV) voice assistant use X on (DV) acceptance of the new content Y was found to be negative insignificant (B =-0.10, $t(749)$ =-1.47, p=.141, 95% CI [-0.23, 0.33]. Thus, hypothesis H3e is not supported.

Table 4.10. Mediation analysis of voice assistants use on acceptance of the new content outside of user interest and emotional attachment (unstandardized coefficients)

Outcome:	*B*	*SE*	*t*	*p*	*CI (lower)*	*CI(upper)*

Emotional attachment (path a)						
Constant	3.65***	.08	44.42	.000	3.49	3.81
Voice assistant use	-.85***	.09	-9.51	.000	-1.03	-.68
Outcome:	*B*	*SE*	*t*	*p*	*CI (lower)*	*CI(upper)*
Acceptance of the new content outside of user interest (path c)						
Constant	3.65***	.08	44.42	.000	3.49	3.81
Voice assistant use	-.10	.07	-1.47	.141	-.23	.03
Outcome:	*B*	*SE*	*t*	*p*	*CI (lower)*	*CI(upper)*
Acceptance of the new content outside of user interest (path b and c')						
Constant	3.14***	.11	27.98	.000	2.92	3.36
Emotional Attachment	-.15***	.03	-5.67	.000	-.20	-.10
Voice Assistant use	-.10	.07	-1.47	.141	-.23	.03

Note:

Significance level: * $p < .05$, ** $p < .01$, *** $p < .001$.

4.11. Moderation voice assistant use, emotional attachment and user satisfaction

After completion of the moderation model 1 analysis, it was observed that user satisfaction appears to be the moderator of voice assistant use effect on emotional attachment. As only partial mediation was observed among these effects, a moderation analysis may shed more light on the effects. Therefore, additional PROCESS moderation analysis of model 1(see figure 3.1) of voice assistant use (IV), emotional attachment (DV) and user satisfaction (W) has been conducted. The model was found to be significant $F(3, 744) = 76.50$, $p<.001$. We see that the main effect of *voice assistant use* on *emotional attachment* remains negative significant (B=-2.05, $t(744) = -3.50$, $p<.001$, 95% CI [-3.20, -0.90], controlling for the moderation, such that a unit increase in the *voice assistant use* range contributes to B =-2.05 decrease of *emotional attachment.* And now, *user satisfaction* has positive insignificant effect on *emotional attachment*, (B =.22, t(744) = 1.76, p=.079, 95% CI [-0.03, 0.46]. However, the interaction term is positive significant (B =0.32, t(744) =2.42, p=.016, 95% CI [0.06, 0.59], and thus *user satisfaction* does moderate *voice assistant use* effect on *emotional attachment.* That is, the negative effect of being a VA user on EA is further mitigated through high satisfaction. These findings in fact corroborate the findings from the mediation. Therefore, the moderation model 1 of voice assistant use (IV) on emotional attachment (DV) and user satisfaction (W) was supported. See moderation analysis in the table 4.10.

4.11.1. Moderation device use, emotional attachment and user satisfaction

The PROCESS moderation analysis of model 1 of device use (IV), emotional attachment (DV) and user satisfaction (W) has been conducted. The model was found to be significant F(3, 744) = 91.21, p<.001. We see that *user satisfaction* has positive significant effect on *emotional attachment*, (B=0.44, t(744) = 3.82, p<.001, 95% CI [0.21, 0.66]. However, the interaction term is positive insignificant (B =0.02, t(744) =.63, p=.529, 95% CI [-0.04, 0.07], and thus *user satisfaction* does moderate *device use* effect on *emotional attachment.* Therefore, the moderation model 1 of device use (IV) on emotional attachment (DV) and user satisfaction (W) was not supported. See moderation analysis in the table 4.10.

4.11.2. Often voice assistant use, emotional attachment and user satisfaction

The PROCESS moderation analysis of model 1 of often voice assistant use (IV), emotional attachment (DV) and user satisfaction (W) has been conducted. The model was found to be significant F(3, 426) = 22.38, p<.001.However, the moderation model 1 of often voice assistant use (IV) on emotional attachment (DV) and user satisfaction (W) was not supported. See moderation analysis in the table 4.10.

4.11.3. Often device use, emotional attachment and user satisfaction

The PROCESS moderation analysis of model 1 (see figure 3.1) of often device use (IV), emotional attachment (DV) and user satisfaction (W) has been conducted. The model was found to be significant F(3, 314) = 21.22, p<001. We see that the main effect of *often device use* on *emotional attachment* remains positive significant (B=0.61, t(314) = 2.23, p<.05, 95% CI [0.07, 1.16], controlling for the moderation, such that a unit increase in the *often device use* range contributes to B=0.61 increase of *emotional attachment. Users satisfaction* has positive significant effect on *emotional attachment*, (B=1.06, t(314) = 2.38, p=.018, 95% CI [0.18, 1.94]. However, the interaction term is negative insignificant (B =-0.14, t(314) =-1.61, *p*=.108, 95% CI [-0.32, 0.03], and thus *user satisfaction* does not moderate *often device use* effect on *emotional attachment.* Therefore, the moderation model 1 of often device use (IV) on emotional attachment (DV) and user satisfaction (W) was not supported. See moderation analysis in the table 4.10.

Table 4.11. Moderation analysis for model 1 of (VA, device, often VA and often device use) on emotional attachment (unstandardized coefficients)

Outcome:	*B*	*SE*	*t*	*p*	**Outcome:**	*B*	*SE*	*t*	*p*
Emotional Attachment					**Emotional attachment**				
Voice assistants' use	-2.03***	.59	-3.50	.000	Devices' use	.11	.12	.92	.359
Users' Satisfaction	.22	.12	1.76	.079	Brand Trust	.44***	.11	3.82	.000
Voice assistants' use × Users' Satisfaction	.32*	.13	2.42	.016	Devices' use × Brand Trust	.02	.03	.63	.529
Outcome:	*B*	*SE*	*t*	*p*	**Outcome:**	*B*	*SE*	*t*	*p*
Emotional Attachment from VA use					**Emotional Attachment from devices' use**				
Often voice assistants' use	.04	.21	.21	.836	Often devices' use	.61*	.28	2.23	.026
Users' Satisfaction from VA use	.13	.20	.63	.528	Users' Satisfaction from devices' use	1.06*	.45	2.38	.018
Often VA use × Users' Satisfaction from VA use	.04	.05	.78	.439	Often devices' use × Users' Satisfaction from devices' use	-.15	.09	-1.61	.108

Note:

Significance level: * $p < .05$, ** $p < .01$, *** $p < .001$.

4.12. Summary of the analysis and hypothesis testing results

By combining results from all the conducted analysis, (table 4.12. below) present the table of the hypothesis tests results with their coefficients and significances levels.

Table 4.12. An overview of the hypothesis testing results with coefficients and significance level

Hypothesis for voice assistants users (VA users)	**Hypothesis for devices users**	**Outcome**	**Unstandardized Coefficients/ Significance levels**
H1		Not supported	-0.848***
	H1	Supported	0.848***
H1 (often VA users)		Supported	0.258***
	H1 (often device users)	Supported	0.280***
H2a (general relationship)		Supported	0.572***
H2a		Supported	0.379***
	H2a	Supported	0.402***
H2b (general relationship)		Not supported	-0.136***
H2b (ANC outside of their interest)		Not supported	-0.132***
H2b (ANC within of their interest)		Supported	0.338***
	H2b (ANC outside of their interest)	Not supported	-0.191***
H3a		Not supported	0.09
	H3a (often device users)	Not supported	-0.12
H3c		Partly supported	-.65***
H3e		Not supported	-.85***
H4		Not supported	0.01
H5		Supported	0.230***

	H5	Supported	0.173***
H6 (general relationship)		Not supported	-0.05
H6 (ANC outside of their interest)		Not supported	-0.02
	H6 for device users	Not supported	-0.11

5. Discussion and Conclusion

Voice assistants bring the massive opportunities in the sphere of human's interaction with technology (Mozer, 2013). Such AI-innovations as personalisation features have enabled voice assistants (VAs) to enhance our daily lives and become more advanced by using provided users' data about their personal behaviour and preferences (Alepis & Patsakis, 2017 & Hoy, 2018). Therefore, the explicit use of personalisation functions by voice assistants drives more and more companies to incorporate smart assistant technologies into their products. This means that companies must contend with the appearance of personalised filter bubbles – whether it is due to the companies' delivered content or otherwise - when it comes to facilitation of the new content via voice technologies, which might lie outside of the consumers' personalised preferences (Nagulendra & Vassileva, 2014). Moreover, Pestanes & Gautier (2017) revealed that voice assistant users would be willing to receive more of new content if voice assistants sounded more human. As the implementation of natural language speech into voice assistants can produce emotional bonding or friendship connection on the users (Han & Yang, 2017). Therefore, the present study aimed to offer the insights from empirical evidence on the phenomenon of the filter bubble and the ways emotional connections can reinforce personalised filter bubble in order to foster the users' willingness to accept the new content. As a result, the main objective of this research was to answer the following research questions: *To what extent does emotional attachment allow smart voice assistants to reinforce filter bubble phenomenon and foster the acceptance of the new content?* In addition, this research aimed to explore the extent to which user satisfaction, brand trust and filter bubble would moderate the effects of voice assistant use on acceptance of the new content. By conducting an online survey, insights into the different effects between the groups were obtained.

5.1. Theoretical and practical implications of the main findings

5.1.1. Voice assistant and device use on emotional attachment

The first hypothesis (**H1**) stated that the usage of voice assistants would increase emotional attachment of the users. Also, this hypothesis (**H1)** was tested for device users, often VA users and often device users. Voice assistant use negatively and significantly predicted emotional attachment of users and thus did not induce emotional attachment (refuting **H1**). However, device use was the opposite of VA use in prediction of emotional attachment (supporting **H1** for device users). The negative coefficient only means that VA users experienced less emotional attachment in comparison to device users.

These results can be explained by the research of Bowlby (1979), who states that there is a difference in how strong or weak each person's attachment relationship can develop. The higher level of received care in the times of need will result into the strong attachment relationship or secure emotional attachment, while no care at all or the least care will result into the weak attachment relationship or dismissive emotional attachment (Scharfe, 2017). Dismissive attachment is then understood as repeated experience of rejection or disregard of the significance of person's attachment or connection to the relationship in the times of need (Mikulincer & Shaver, 2013). We can assume that VA users repeatedly did not receive the expected level of care from voice assistants in the times of need and therefore did not develop secure emotional attachment relationships, but developed the opposite so called dismissive emotional attachment. Another possible explanation of these results could be that voice assistant is considered to be quite new technology to symbolically and functionally operate the way the other devices do (Pestanes & Gautier, 2017). Also, VAs has not been around long enough for people to become emotionally attached, meaning that the process for a society overall to become "attached" to material objects may require the device to become much more encultured than VAs are now (Terdiman, 2018).

Moreover, when people do not receive the expected mental or physical support in our case from voice assistant use, they experience disappointment, which translates into the negative emotional attachment (Bowlby, 1979). For example, the study of emotional responses of VAs users by Sensum (2018) revealed that users felt frustrated and disappointed from voice assistants use in cases when they did not receive the expected outcome to a simple question from VAs or when VAs failed to deliver the expected outcome. Also, our study has indicated that the most common use of voice assistants by the respondents was searching for answers or asking question. Kleber (2018) stated that the internet search which is programmed in voice assistants tends to be the most appreciated function by VA users due to the high level of convince and efficiency. This means that the respondents might have an experience of not receiving the expected efficiency or convenience during their search from VAs, which resulted in disappointment. However, Sensum (2018) states that the feeling of disappointment still results in the elevated heart rate, which indicates that users produce emotional responses towards voice assistants, but these responses are negative. Therefore, we can assume that voice assistant users experienced disappointment from the use of VAs, which further resulted in their decrease in emotional attachment or dismissive emotional attachment, while device users experience joy and pleasure from the use, which resulted in increase of emotional attachment or secure emotional attachment.

5.1.1.1. Often VA and often device use on emotional attachment

As it was mentioned above the hypothesis (**H1**) was also tested with often VA use and often device use. Often voice assistants and device use positively and significantly predicted emotional attachment (supporting **H1** for often VA and often device users). After the conduction of comparison of often VA use with often device use, the effect of frequency of use on emotional attachment was found to be similar for users of VA and users of other devices.

According to Scharfe, (2017), people develop emotional attachment towards someone or something they receive care from, and then they tend to seek for this someone or something more frequently when stressed, anxious, afraid or sick (Scharfe, 2017). The findings of this research showed that most of the respondents were international students, who currently live and study abroad. According to Diehl et al. (2018), international students, who are away from the familiar environment, family and friends, experience the certain changes in their lives, which may lead to many opportunities, but also cause some negative consequences such as being alone in the new environment, missing family and old friends, which might lead to loneliness. Loneliness is defined as anxious feelings about the lack of emotional connection or communication with both people in the current environment and the close ones, family, friends, who might be far away (Diehl et al., 2018). Also, Kleber (2018) stated that voice assistants are programmed with the tasks to help their users alleviate the feeling of loneliness due to the targeted emotional learning system, which recognises and interprets the emotional results of users, and make adequate adjustments to outcomes. The implementation of AI-driven human-like features can create the conversation between the sophisticated technology and the users, which further fosters the appearance of the feeling of emotional connection (Bell et al., 2003). Therefore, we can assume that often voice assistant users as well as often device users seek for VAs use or their other devices more frequently when they experience the feeling of loneliness or anxiety, because they may have previously received the expected care from Vas or devices, which in turn have been influencing further increase in their emotional attachment (Bowlby, 1979).

5.1.2. User satisfaction and emotional attachment

The hypothesis (**H2a**) stated that the user satisfaction by content would positively increase emotional attachment. This hypothesis was also tested for VA and device users. User satisfaction by received content positively significantly predicted emotional attachment and thus induced the level of emotional attachment (supporting **H2a**). Also, user satisfaction by received content from both VAs and devices positively significantly predicted emotional attachment and thus induced the level of emotional attachment for both VA and device users (supporting **H2a**). The hypothesis (**H3c)** stated that the user satisfaction would positively mediate the effect of voice assistant use on emotional attachment. The user satisfaction partially mediated of the effect of voice assistant use on emotional attachment (partly supporting **H3c**). Essentially, the negative impact of VA use (vs. other traditional devices) is mitigated by higher satisfaction; a finding corroborated by the additional moderation model.

Moreover, these findings can be explained by the list of five different reasons of the audience's attraction and attachment to certain types of media such as information, entertainment, personal identity, social interaction and escapism (Choi et al., 2016). This means that the audiences' attraction and further emotional attachment and acceptance of the newly recommended content will depend on the list of previously mentioned reasons, which will vary depending on the type of the individuals' needs. Intertwined within these needs are the aforementioned hedonic needs towards the material objects, which make people create expectations and refer to them in a time of need (Moon et al., 2017). As earlier explained by Bowlby (1979), this process of seeking and referring to the material objects while experiencing external stress situations builds an emotional attachment to the object. Therefore, we can suggest that the individuals' attraction/attachment and further acceptance would depend on their referral to voice assistants as an immaterial object with expectations that it would aim to satisfy one or more of their needs (Bae, 2018). Furthermore, according to Yonghwan et al. (2016) in the case that new media content satisfies the needs of the individual, positive emotional attachment to that content will manifest and further the acceptance of it. Conversely, if the content does not satisfy the needs of the audience, it will negatively impact emotional attachment and no further acceptance of the new recommended content (Thomson et al., 2005).

These findings also can be explained by Bae (2018) who stated that there were two types of satisfaction such as gratifications sought, which was the needs of the audience and gratifications obtained, which was the actual fulfilment of the needs (Bae, 2018). This study found that voice assistant users were mostly interested in music, films and cinema, which means that their needs (gratifications sought) were related to the entertainment type of media content. Also, their attraction towards the entertainment content meant that VAs users were seeking for (gratifications obtained) or fulfilment of enjoyment and relaxation from VAs use (Ruggiero, 2009). Therefore, in particular case the respondents' attraction/attachment to the content depended on whether they received the content related to entertainment accompanied with the feeling of enjoyment and relaxation. According to the results, the respondents experienced the satisfaction of their individual content needs (gratifications sought), such as received entertainment content from voice assistants, and therefore further developed the appearance of emotional attachment.

5.1.3. Emotional attachment and acceptance of the new content

The hypothesis (**H2b**) stated that emotional attachment would in turn positively influence the likelihood of the choice of acceptance of the new content. The appearance of emotional attachment negatively yet significantly predicted the likelihood of the choice of acceptance of the new content outside of user interest for both VA and device users (fully refuting **H2b** with an opposing significant effect). However, the hypothesis **H2b** showed that the appearance of emotional attachment in turn positively influence the likelihood of the choice of acceptance of the new content within user interest for VA users (supporting H2b for VA user if the new content within their interest). The hypothesis **H3e** stated that emotional attachment would positively mediate the effect of voice assistant use on the acceptance of the new content. The emotional attachment would not mediate the effect of voice assistant use on the acceptance of the new content. Also, the hypothesis (**H3a**) stated that the user satisfaction level would moderate the effect of voice assistant use on the choice of acceptance of the new content, such that the high level of user satisfaction from VA use would lead to the higher acceptance of the new content outside of VA user interest. The main effect negatively and insignificantly predicted acceptance of the new content outside of VA user interests, verifying H2a. However, user satisfaction from VA use had negative insignificant effect on acceptance of the new content outside of their interest. The interaction term for VA users was positive insignificant and thus user satisfaction from VA use does not moderate voice assistant use effect on acceptance of the new content outside of VA user interest. In fact, the positive effect of the moderation, despite its being insignificant for VA users, runs counter to what was hypothesized and so higher user satisfaction from (often)VA use in fact reduces the effect of (often) VA use on acceptance of the new content outside of VA user interest.

The additional model was run to explain these findings and showed that user satisfaction had positive significant effect on the filter bubble. This means the more level of satisfaction and emotional attachment of VA or devices user experience the more his/her level of embeddedness in the filter bubble (causal direction uncertain) and thus less acceptance of the new content. Therefore, this additional analysis explains the negative coefficient of the effect of user satisfaction on acceptance of the new content. This finding could be explained by Pestanes and Gautier (2017) who stated that, because news content and products becoming more personalised around 30 percent of voice assistant users agree to receive new information content as long as it is consistent with their personalised experience. To explain this finding, also the additional test was run and showed that emotional attachment positively and significantly predicts filter bubble. This means that more increase in emotional attachment from VA use will lead to greater embeddedness of VA users in filter bubble and the less likely they will be willing to accept the content outside of their interest, but rather only new content within their interest.

5.1.4. Brand trust

The hypothesis (**H4**) stated that the brand trust would moderate the relationship between voice assistant use and emotional attachment, such that higher brand trust would lead to higher emotional attachment. Brand trust positively insignificantly predicted the moderation effect on the relationship between voice assistant use and emotional attachment (refuting **H4**). Also, the effect of voice assistant use negatively and significantly predicted emotional attachment, as discussed earlier in the hypothesis H1. However, brand trust positively significantly predicted emotional attachment. This finding can be explained by Gavrilovska & Rakovic (2016), who stated that in case a brand performs all the stated and expected functions, consumers will develop the greater sense of trust into the brand or brand trust, which will further get developed into positive emotional attachment (Fullerton, 2005 & Karahanna, 2007). The trust in a brand to performs functions towards solving the consumer's needs creates assurances for the consumers and develops the emotional attachment to the brand (Ballester et al., 2003). However, brand trust is observed to not impact VA use effect on emotional attachment. Also, the longer the experience of consumers, the more knowledge, interaction and later expectations they develop that the brand will provide or not the assured foundation (Bowlby,1979). Therefore, we can assume that VA users had more knowledge and experience in use of the VAs' brand and developed a sense that the brand would provide the assured foundation. The findings of this study showed that the most used brands of VAs by the respondents was Google Now by Google and Siri by Apple and Alexa by Amazon. According to Oremus (2019), such brands as Google, Amazon and Apple have assured their smart voice assistants users that their products can be trusted in terms of privacy. Also, it has been proven that smart voice assistants do not constantly record and listen to the conversations when they are not supposed to, unless the unlock command word has been said by VA users (Oremus, 2019).

5.1.5. Personalisation

The hypothesis (**H5**) stated that the greater level of personalisation experienced would lead to the greater satisfaction of voice assistant use. Personalisation positively and significantly predicted user satisfaction from VA use (supporting **H5**). According to Fan & Poole (2006), personalisation can be explained as a system that consists of multiple types of algorithms which identify interests, behaviour, preferences and users' goals in order to provide and address their individualistic needs. This finding can be explained Oulasvirta & Blom (2008), who stated that personalisation services increase user satisfaction as they receive individualistic changes in functionality and information content of the system are accordingly with their individualist preferences and needs. According to Scharfe (2017), people develop feeling of satisfaction towards someone or something they receive care from, and then they tend to seek for this someone or something more frequently when stressed. The digital age and the rise of the Internet use has allowed the audiences the easy access to the multiple content and information of their interests, but this convenience in access leads to the growing increase of the information overload online, stress and frustration (Berg, 2015). Therefore, more and more people started to inform themselves through the use of personalisation services in order to increase their satisfaction of internet search (Lett, 2008). There are multiple reasons why consumers experience satisfaction from personalisation services through a product, including the product's ease of use, its reflection of personal identity and interests and recognition of the product as their own (Lett, 2008). Communication technology, for instance, smart voice assistants, are no exception as there are also the implemented personalisation features in them (Fan & Poole, 2006). Therefore, we can assume that our respondents experienced the satisfaction from personalisation services of voice assistants due to the fact that it satisfied their individualistic needs and which in turn influenced their more often voice assistants' use.

5.1.6. Filter bubble

The hypothesis **(H6)** stated that filter bubble would moderate the relationship between emotional attachment and the choice of acceptance of the new recommended content outside of user interest, such that high emotional attachment would mitigate the effect of the filter bubble's reducing the likelihood of the choice of acceptance of the new content. Also, this hypothesis was tested for VA and device users. The main effect of emotional attachment insignificantly predicted acceptance of the new content outside of user interests (same for VA users and device users), as discussed earlier H2b. Also, filter bubble insignificantly predicted the effect on acceptance of the new content outside of user interest for both VA and device users. Filter bubble negatively and insignificantly predicted the moderation effect of emotional attachment on acceptance of the new content only for VA users. In fact, the negative effect of the moderation, despite its being insignificant for VA users, does not run counter to what was hypothesized and so higher level of emotional attachment will mitigate the effect of the filter bubble's reducing (negative effect) the likelihood of the choice of acceptance of the new content outside of VA user interest. However, filter bubble negatively and significantly predicted the moderation effect of emotional attachment on acceptance of the new content outside of device users interest. What is most likely occurring is that emotional attachment from device use and filter bubble from device use amplify (rather than mitigate) one another's negative effect on acceptance of the new content outside of device user interest. Thus, the hypothesis H6 for device users not supported.

Furthermore, these findings can be explained by Gavrilovska & Rakovic (2016) & Bowlby (1979), while there is a connection between emotional attachment and the choice of acceptance of the new recommended content – as mentioned earlier, if an individual is deeply embedded in their filter bubble there is a possibility that they will be resistant to new content outside of their filter bubble (Gavrilovska & Rakovic, 2016; Bowlby, 1979). However, the main effects here are positive, yet rendered insignificant, strongly suggesting possible multicollinearity. One can see that in general, the moderation is negative while earlier we observed that EA for both VA and devices have a negative effect on ACN. Hence, the general pattern is that the negative effects of EA are amplified by FB rather than a positively effecting EA mitigating FB's negative effect (as stipulated by H6).

5.2. Discussion for further research and limitations

Although this research offers interesting finding, some limitations should be noted during the results' interpretation.

Firstly, at the beginning if the study the research planned to accomplish the mix method of the research such as conduct additional qualitative interviews in order to understand the context of a phenomenon of filter bubble and VA users perception on acceptance of the new content in depth. However, due to the time limitations, it was decided to concentrate on only quantitative research method with the use of online survey, which made difficult to understand context of the phenomenon because of the lack of robust enough data. Also, the collected quantitative data did not allow fully shed the light on complexity of voice assistant user experiences and perceptions.

Secondly, the study had such limitations as causality or causal inference uncertainties, which refer to analysis of the potential casual model in the future under changing conditions. It was found that voice assistant users experience less emotional attachment than device users. The possible explanation of these results could be that voice assistant is considered to be quite new technology to symbolically and functionally operate the way the other devices do (Pestanes & Gautier, 2017). Also, VAs has not been around long enough for people to become emotionally attached, meaning that the process for a society overall to become "attached" to material objects may require the device to become much more encultured than VAs are now (Terdiman, 2018). Another limitation of this research was to find a representative enough sample of voice assistant users as this technology is still quite new and most of the respondents were not eligible to participate. Therefore, a longitudinal study is suggested for the future research, as it allows to gather the data continuously or repeatedly over a certain period of time (Ployhart and Vandenberg, 2010).

Thirdly, it was found that the voice assistant use did not lead to acceptance of the new content. This can be explained by an interplay among lack of VA's maturity, which leads to less emotional attachment, as discussed above, as well as the relatedness of personalisation and emotional attachment and filter bubble. After conduction of additional tests, it was found that personalisation leads to the increase of emotional attachment from VA use as well as increase of VA user embeddedness in a filter bubble as the both effects were positive and significant. Thus, suggesting that emotional attachment is mingled with personalisation and VA user embeddedness in a filter bubble both leading to less acceptance of the new content.

Also, it was found that user satisfaction from VA and device use increases emotional attachment but as tested earlier, emotional attachment in turn instead of mitigation of the effect of filter bubble predicts amplification of it and therefore users are less likely to accept the new content. Thus, suggesting that emotional attachment is mingled with user satisfaction from personalisation and VA user embeddedness in a filter bubble both leading to less acceptance of the new content. So more positive experience of user with the device or VA makes one less likely to accept new content.

Furthermore, this research had the limitations in terms of the occurrence of multicollinearity during the moderation PROCESS analysis of the results, which lead to the poor estimations of the results. According to Gruber and Kockläuner (1984), multicollinearity can refer to the situation when independent variables in a model are correlated or when one independent variable in a model can be predicted from the other variables in the model with a high degree of accuracy. Unfortunately, there were steps to avoid the multicollinearity even in PROCESS, but the researcher wasn't aware of it until the end. Therefore, it is important for the future research to avoid the multicollinearity by click 'mean centre for construction of product' under Options command in SPSS (Hayes, 2017). Also, for the future research a structural equation modelling would be more appropriate rather than just mediation/moderation models. As Reisinger and Mavondo (2007) state that structural equation modelling allows the researcher to test and analyse structural relationships between measured variables and constructs that cannot be measured directly (e.g. voice assistants use and emotional attachment), with the combination of both factor and multiple regression analysis.

Finally, ironically, Qualtrics does not yet provide a mechanism for allowing respondents to engage the survey on a voice assistant, but allows it on any other devices. The possible explanation of this could be that voice assistant is considered to be quite new technology to symbolically and functionally operate the way the other devices do (Pestanes & Gautier, 2017).

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Appendix 1: Classifications of survey's variables and validated scales

Construct	*Question*	*Source*
Demographic questions	Gender, age, educational level, nationality, monthly income, current location	Hughes, Camden & Yangchen, (2016).
Voice assistant usage	Do you use or have you ever tried to use any voice assistants? How often do you use a voice assistant(s)?	Rosen et al., (2013).
User Satisfaction voice assistants	Overall I am satisfied with my experience with the voice assistant. I am satisfied with my decision to use this voice assistant. I think I did the right thing by using the services of this voice assistant. I regret (feel bad) about my decision to use services of this voice assistant. [deleted].	Chang & Chen (2008); Oliver, (1980); Kurruuzum (2015).
Brand Trust voice assistants	I trust in the brand(s). I rely on the brand(s). This is an honest brand(s). The brand(s) meets my expectations.	Matzler et al, (2008); Chanduhuri & Holbrook (2001); Ahmed et al., (2014).

Personalisation voice assistants	This voice assistant makes product recommendations that match my needs. This voice assistant makes me feel that I am a unique user. Overall, I like the idea of using the personalized product recommendations. Personalised offerings provide time efficient experience for me. The promotions that this voice assistant offers to me are tailored to my preferences. The promotions that this voice assistant offers to me match my needs.	Fan & Poole, (2006); Srinivasan, Anderson & Ponnavolu, (2002); Smith, (2006); Kurruuzum (2015).
Emotional Attachment voice assistants	I feel personally connected to this voice assistant. This voice assistant means a lot to me. I would like to spend more time interacting with this voice assistant. I feel pleasure using this voice assistant. It would be a struggle to give up using this voice assistant. This voice assistant is part of my personal life. I would be disappointed if I could not use this voice assistant when I need it.	Huigen, Haartsen & Folmer, (2013); Harmon-Jones et al., (2016); Williams et al., (1992).
Filter Bubble voice assistants	The voice assistant(s) provides me with surprising recommendations that helped me discover new content/products that I wouldn't have found elsewhere.	Matt et al., (2014).

	The voice assistant(s) provides me with recommendations that were a pleasant surprise to me because I would not have discovered them somewhere else. I like the selection of content/products recommended to me by this voice assistant. [deleted]. The selection of content/products recommended to me by this voice assistant coincide with my personal preferences.	
Acceptance of new content voice assistants	I'm unlikely to change my interests in certain type of content once they're set. I'm inclined to establish routines in terms of content consumption and stay with them. I can make any new content/ information work for me. I prefer consuming certain type of content that is familiar and within my comfort zone. Once I've made up my mind, I don't easily change it.	Shimpock-Vieweg, (1996); Kriegel and Brandt (1996); Moeller and Helberger (2018)
Device usage	Which of the following devices do you currently use the most? How often do you use the device(s) you just indicated before?	Rosen et al., (2013).
User Satisfaction devices	Overall I am satisfied with specific experience with the device. I am satisfied with my decision to use this device. I think I did the right thing by using the services of this device. I regret (feel bad) about my decision to use services of this device. [deleted].	Chang & Chen (2008); Oliver, (1980); Kurruuzum (2015).

Brand Trust devices	I trust in the brand(s). I rely on the brand(s). This is an honest brand(s). The brand(s) meets my expectations.	Matzler et al, (2008); Chanduhuri & Holbrook (2001); Ahmed et al., (2014).
Personalisation devices	This device makes me feel that I am a unique user. [deleted]. Overall, I like the idea of using the personalized product recommendations. Personalised offerings provide time efficient experience for me. The promotions of services/products, which my device offers to me are tailored to my preferences. The promotions of services/products, which my device offers to me match my needs.	Fan & Poole, (2006); Srinivasan, Anderson & Ponnavolu, (2002); Smith (2006); Kurruuzum (2015).
Emotional Attachment Devices	I feel personally connected to this device. This device means a lot to me. I would like to spend more time interacting with this voice device. I feel pleasure using this device. It would be a struggle to give up using this device. This device is part of my personal life.	Huigen, Haartsen & Folmer, (2013); Harmon-Jones et al., (2016); Williams et al., (1992).

	I would be disappointed if I could not use this device when I need it.	
Filter bubble devices	The device provides me with surprising recommendations that helped me discover new content/products that I wouldn't have found elsewhere. The device provides me with recommendations that were a pleasant surprise to me because I would not have discovered them somewhere else. I like the selection of content/products recommended to me by this device. The selection of content/products recommended to me by device coincide with my personal preferences.	Matt et al., (2014).
Acceptance of new content Devices	I'm unlikely to change my interests in certain type of content once they're set. I'm inclined to establish routines in terms of content consumption and stay with them. I can make any new content/ information work for me. I prefer consuming certain type of content that is familiar and within my comfort zone. Once I've made up my mind, I don't easily change it.	Shimpock-Vieweg, (1996); Kriegel and Brandt (1996); Moeller and Helberger (2018)

Appendix 2: Survey Design

Dear respondent,

You are invited to participate in a research about smart voice assistants, which is part of my master thesis. This questionnaire will take you about 10 minutes to finish.

A voice assistant is an intelligent personal assistant such as Siri by Apple, Google Assistant by Google, Alexa by Amazon, Cortana by Microsoft, Bixby by Samsung and others, which use voice recognition to supply users with information and perform basic tasks with verbal commands (such as emailing, to-do list, ordering food, calendars, calls).

You can also participate in the survey even if you do not know much about voice assistants or do not use voice assistants.

This study is anonymous and all data will be treated confidentially. Further, your responses will not be shared with any third party . Also, your participation is voluntary. You can stop your participation at any time if you do not want to continue and your answers will be discarded.

If you have any questions on this study or the outcome, feel free to email me at 480005mk@eur.nl

Maria Krupnik

Student in Media and Business at Erasmus University Rotterdam

Please consent if you agree to participate in this survey:

- ○ I have read the above information carefully and I agree to consent
- ○ I do not consent

Demographic questions (Part 1)

Please indicate your gender.

- ○ Male
- ○ Female
- ○ Prefer not to answer

Please indicate your age in numbers.

____

What is the highest educational degree you have received?

- ○ Less than high school degree
- ○ High school degree or equivalent
- ○ Bachelor degree
- ○ Master degree
- ○ PhD

What is your nationality?

____

What country are you currently living in?

____

What is your employment status?

- ○ Student
- ○ Full- time employed
- ○ Part-time employed
- ○ Unemployed
- ○ Retired
- ○ Homemaker
- ○ Self-employed
- ○ Unable to work
- ○ Other (please specify) ________________________________

What is your monthly income?

- ○ less than 1000 euros
- ○ from 1000 to 2500 euros
- ○ from 2500 to 5000 euros
- ○ more than 5000 euros
- ○ I do not have income
- ○ I do not know
- ○ Prefer not to answer

Voice Assistant use questions (Part 2)

Do you use or have you ever tried to use any voice assistants?

- ○ Yes
- ○ I have never tried

Which of the following voice assistants do you use the most?

- ☐ Alexa by Amazon
- ☐ Siri by Apple
- ☐ Cortana by Microsoft
- ☐ Google Now by Google
- ☐ Bixby by Samsung
- ☐ Other (please specify) ____

How often do you use a voice assistant(s)?

- ○ Every day
- ○ A few times a week
- ○ About once a week
- ○ About once a month
- ○ Less than once a month

How long have you been using a voice assistant(s)?

- ○ Less than 6 months
- ○ 6 months to 1 year
- ○ About 1 to 3 years
- ○ About 3 to 5 years
- ○ 5 years or more

What devices do you normally use for the voice assistant(s)?

- ☐ Mobile phone
- ☐ Smart Speaker (e. g. Google Home, Amazon Echo)
- ☐ Laptop or computer
- ☐ Other (please specify) ________________________________

What do you use the voice assistant(s) for?

- ☐ Ask a question
- ☐ Check the weather
- ☐ Listen to radio
- ☐ Listen to news/ sports
- ☐ Listen to podcasts or other talk formats
- ☐ Check traffic/ direction
- ☐ Access my calendar
- ☐ Call someone
- ☐ Message/ email someone
- ☐ Make a purchase
- ☐ Control smart home devices
- ☐ Find a recipe or cooking instructions
- ☐ Set an alarm
- ☐ Set a timer
- ☐ Listen to streaming music service
- ☐ Find a place to eat
- ☐ Other (please specify) ___________________________

User Satisfaction for VA users (Part 3)

How well does voice assistant(s) you use meets your needs?

- ○ Extremely well
- ○ Well
- ○ Moderately well
- ○ Slightly well
- ○ Not well at all

Please indicate how strongly you agree with the following statements considering your satisfaction with the voice assistant(s) of your use. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
Overall I am satisfied with my experience with the voice assistant.	○	○	○	○	○
I am satisfied with my decision to use this voice assistant.	○	○	○	○	○
I think I did the right thing by using the services of this voice assistant.	○	○	○	○	○
I regret (feel bad) about my decision to use services of this voice assistant.	○	○	○	○	○

Brand Trust for VA users questions (Part 4)

Please indicate how strongly you agree with the following statements considering your trust in the brand(s) of voice assistant you indicated before.

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
I trust in the brand(s).	○	○	○	○	○
I rely on the brand(s).	○	○	○	○	○
This is an honest brand(s).	○	○	○	○	○
The brand(s) meets my expectations.	○	○	○	○	○

Personalisation for VA users questions (Part 5)

Which of the online personalization features appear on the voice assistant(s) you use?

- ☐ None
- ☐ Personalized content/product recommendations
- ☐ Personalized promotions
- ☐ Both of them
- ☐ I do not know

Please indicate how strongly you agree with the following statements considering the personalisation features of the voice assistant(s) you indicated before. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
This voice assistant makes product recommendations that match my needs.	○	○	○	○	○
This voice assistant makes me feel that I am a unique user.	○	○	○	○	○
Overall, I like the idea of using the personalized product recommendations.	○	○	○	○	○
Personalised offerings provide time efficient experience for me.	○	○	○	○	○
The promotions that this voice assistant offers to me are tailored to my preferences.	○	○	○	○	○
The promotions that this voice assistant offers to me match my needs.	○	○	○	○	○

Emotional attachment for VA users questions (Part 6)

Please indicate how strongly you agree with the following statements considering the voice assistant(s) you indicated before. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
I feel personally connected to this voice assistant.	○	○	○	○	○
This voice assistant means a lot to me.	○	○	○	○	○
I would like to spend more time interacting with this voice assistant.	○	○	○	○	○
I feel pleasure using this voice assistant.	○	○	○	○	○
It would be a struggle to give up using this voice assistant.	○	○	○	○	○
This voice assistant is part of my personal life.	○	○	○	○	○
I would be disappointed if I could not use this voice assistant when I need it.	○	○	○	○	○

Filter Bubble for VA users questions (Part 7)

Please indicate how strongly you agree or disagree with the following statements regarding the recommendation system of the voice assistant(s) you indicated before. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
The voice assistant(s) provides me with surprising recommendations that helped me discover new content/products that I wouldn't have found elsewhere.	○	○	○	○	○
The voice assistant(s) provides me with recommendations that were a pleasant surprise to me because I would not have discovered them somewhere else.	○	○	○	○	○
I like the selection of content/products recommended to me by this voice assistant.	○	○	○	○	○
The selection of content/products recommended to me by this voice assistant coincide with my personal preferences.	○	○	○	○	○

We would like to know about some of your interests. Which of the following are you interested in?

- ☐ News and Current affairs
- ☐ Sports
- ☐ Film and Cinema
- ☐ Books
- ☐ Music
- ☐ Politics
- ☐ Business
- ☐ Cars/motoring
- ☐ Holidays/travel
- ☐ Cooking
- ☐ Fashion
- ☐ None of these
- ☐ Other (specify)____

Which of the following sources or platforms do you tend to go most often for receiving information regarding your interests nowadays?

- ☐ Television
- ☐ Newspapers (printed)
- ☐ Radio
- ☐ Social media on a computer/laptop/netbook/tablet
- ☐ Social media on a mobile phone
- ☐ Other internet sources on a computer/laptop/netbook/tablet (including apps you've downloaded and those automatically loaded onto your device, e. g. voice assistants).
- ☐ Other internet sources on a mobile phone (including apps you've downloaded and those automatically loaded onto your phone e. g. voice assistants).
- ☐ Magazines
- ☐ Word of mouth (family / friends / colleagues) – in person/by phone/email
- ☐ Smart speaker (e.g. Google Home, Amazon Echo)
- ☐ None of these
- ☐ Other (please specify)____

How often do you look for information regarding the interests you indicated before?

- ○ Once a day
- ○ 2-3 times a day
- ○ Several times a day
- ○ About once a week
- ○ Every 2 weeks
- ○ About once a month
- ○ Do not know

Acceptance of the new content for VA users questions (Part 8)

What is generally your first reaction when you receive the new information regarding the interests you indicated before?

- ○ very positive
- ○ positive
- ○ neutral
- ○ negative
- ○ very negative

Please indicate how strongly you agree with the following statements considering your attitude towards changes in the way you receive the new information, that is not aligned with your interests. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
I'm unlikely to change my interests in certain type of content once they're set.	○	○	○	○	○
I'm inclined to establish routines in terms of content consumption and stay with them.	○	○	○	○	○
I can make any new content/ information work for me.	○	○	○	○	○
I prefer consuming certain type of content that is familiar and within my comfort zone.	○	○	○	○	○
Once I've made up my mind, I don't easily change it.	○	○	○	○	○

Device use questions (Part 9)

Which of the following devices do you currently use the most?

- ☐ Mobile phone
- ☐ Laptop or netbook computer
- ☐ Tablet Computer e.g. iPad or Samsung Galaxy
- ☐ Personal assistant e.g. Amazon Echo/Dot, Google Home
- ☐ E-book Reader e.g. Kindle or Kobo
- ☐ None of these
- ☐ Do not know
- ☐ Other (please specify)____

How often do you use the device(s) you just indicated before?

- ○ Every day
- ○ A few times a week
- ○ About once a week
- ○ About once a month
- ○ Less than once a month

How long have you been using the current device you indicated before?

- ○ Less than 6 months
- ○ 6 months to1 year
- ○ About 1 to 3 years
- ○ About 3 to 5 years
- ○ More than 5 years

What do you use the device for you indicated before?

- ☐ Ask a question
- ☐ Check the weather
- ☐ Listen to radio
- ☐ Listen to news/sports
- ☐ Listen to podcasts or other talk formats
- ☐ Check traffic/direction
- ☐ Access my calendar
- ☐ Call someone
- ☐ Message/email someone
- ☐ Make a purchase
- ☐ Control smart home devices
- ☐ Find a recipe or cooking instructions
- ☐ Set an alarm
- ☐ Set a timer
- ☐ Listen to streaming music services
- ☐ Find a place to eat
- ☐ Other (please specify) ____

Device users satisfaction questions (Part 10)

How well does the device you use the most meets your needs?

- ○ Extremely well
- ○ Well
- ○ Moderately well
- ○ Slightly well
- ○ Not well at all

Please indicate how strongly you agree with the following statements considering your satisfaction with the device you use the most. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
Overall I am satisfied with specific experience with the device.	○	○	○	○	○
I am satisfied with my decision to use this device.	○	○	○	○	○
I think I did the right thing by using the services of this device.	○	○	○	○	○
I regret (feel bad) about my decision to use services of this device.	○	○	○	○	○

Device users Brand Trust questions (Part 11)

Please indicate how strongly you agree with the following statements considering your trust in the brand(s) of the device(s) you indicated you use the most. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
I trust in the brand(s).	○	○	○	○	○
I rely on the brand(s).	○	○	○	○	○
This is an honest brand(s).	○	○	○	○	○
The brand(s) meets my expectations.	○	○	○	○	○

Personalisation device users questions (Part 12)

Which of the online personalization features appear on the device(s) you use?

- ○ None
- ○ Personalized content/product recommendations
- ○ Personalized promotions
- ○ Both of them
- ○ I do not know

Please indicate how strongly you agree with the following statements considering the personalisation features of the device you indicated you use the most. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
This device makes me feel that I am a unique user.	○	○	○	○	○
Overall, I like the idea of using the personalized product recommendations.	○	○	○	○	○
Personalised offerings provide time efficient experience for me.	○	○	○	○	○
The promotions of services/products, which my device offers to me are tailored to my preferences.	○	○	○	○	○
The promotions of services/products, which my device offers to me match my needs.	○	○	○	○	○

Emotional attachment for device users questions (Part 13)

Please indicate how strongly you agree with the following statements considering the device you indicated you use the most. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
I feel personally connected to this device.	○	○	○	○	○
This device means a lot to me.	○	○	○	○	○
I would like to spend more time interacting with this device.	○	○	○	○	○
I feel pleasure using this device.	○	○	○	○	○
It would be struggle to give up using this device.	○	○	○	○	○
This device is part of my personal life.	○	○	○	○	○
I would be disappointed if I could not use this device when I need it.	○	○	○	○	○

Filter Bubble for device users questions (Part 14)

Please indicate how strongly you agree or disagree with the following statements regarding the recommendation system of the device you indicated you use the most. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
The device provides me with surprising recommendations that helped me discover new content/products that I wouldn't have found elsewhere.	○	○	○	○	○
The device provides me with recommendations that were a pleasant surprise to me because I would not have discovered them somewhere else.	○	○	○	○	○
I like the selection of content/products recommended to me by this device.	○	○	○	○	○
The selection of content/products recommended to me by this device coincide with my personal preferences.	○	○	○	○	○

We would like to know about some of your interests. Which of the following are you interested in?

- ☐ News and Current affairs
- ☐ Sports
- ☐ Film and Cinema
- ☐ Books
- ☐ Music
- ☐ Politics
- ☐ Business
- ☐ Car/motoring
- ☐ Holiday/travel
- ☐ Cooking
- ☐ Fashion
- ☐ None of these
- ☐ Other (specify)____

Which of the following sources or platforms do you tend to go most often for receiving information regarding your interests nowadays?

- ☐ Television
- ☐ Newspapers (printed)
- ☐ Radio
- ☐ Social media on a computer/laptop/netbook/tablet
- ☐ Social media on a mobile phone
- ☐ Other internet sources on a computer/laptop/netbook/tablet (including apps you've downloaded and those automatically loaded onto your device, e. g. voice assistants).
- ☐ Other internet sources on a mobile phone (including apps you've downloaded and those automatically loaded onto your phone e. g. voice assistants)
- ☐ Magazines
- ☐ Word of mouth (family / friends / colleagues) – in person/by phone/email
- ☐ Smart speaker (e.g. Google Home, Amazon Echo)
- ☐ None of these
- ☐ Other (please specify) ____

How often do you look for information regarding the interests you indicated before?

- ○ Once a day
- ○ 2-3 times a day
- ○ several times a day
- ○ About once a week
- ○ Every 2 weeks
- ○ About once a month
- ○ Do not know

Device users acceptance of the new content questions (Part 15)

Please indicate how strongly you agree with the following statements considering your attitude towards changes in the way you receive the new information, that is not particularly aligned with your interests. (1= Strongly Agree, 3= Neutral, 5=Strongly Disagree).

	Strongly Agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly Disagree (5)
I’m unlikely to change my interests in certain type of content once they’re set.	○	○	○	○	○
I’m inclined to establish routines in terms of content consumption and stay with them.	○	○	○	○	○
I prefer consuming certain type of content that is familiar and within my comfort zone.	○	○	○	○	○
Once I’ve made up my mind, I don’t easily change it.	○	○	○	○	○

Appendix 3: History of voice recognition technology

Voice recognition technology is quite a recent invention that has made public become fascinated by software that can understand human language commands and perform tasks accordingly (Zumalt, 2005). According to Huang et al. (2015), a person, in general, is able to speak around 150 words per minute, which makes a big difference in comparison to approximately 50 words, which a person is able to type during the minute. Zumalt (2005) states that the enhancement of our everyday lives by services of voice recognition technologies has become so natural that one can wonder why the tech giants have only recently started bringing these voice recognition services to the public. However, the history of voice recognition technology revealed that speech recognition developments had started several decades ago, back to the 18th century, when Wolfgang von Kempelen created the Acoustic Mechanical Speech Machine in 1784 (Boyd, 2018). Unfortunately, the rate of developments of this technology did not affect much the level of interest in the topic back at that time, but Wolfgang von Kempelen became the basis for later developments (Huang et al., 2015). Thomas Edison created the dictation machine in 1879, which could record the human speech and was very popular amongst people who had to take many notes in their particular occupations in the late 19th century (Gomes, 2007). Soon after, Bell Labs created Aundrey technology which could recognise digits when they were spoken by its creator with approximately 90 percent of accuracy, and with about 75 percent of accuracy when another people spoke with this machine (Gomes, 2007).

Then, until the beginning of 1960, there was not much of the progress in voice technology production, to the extent that it could not only record spoken words but also interpret them (Gomes, 2007). Modern pioneer in the voice recognition technology was the International Business Machines company (IBM) when it created the IBM Shoebox technology in 1962, which could recognise and understand up to 16 English spoken words and perform some mathematical manipulations with the digits from 0 to 9 (Huang et al., 2015). Thereafter, another voice recognition technology was created by scientists Alexander Waibel at Carnegie Mellon University in 1970 (Huang et al., 2015). It was called Harpy, and it could recognise no more than 1000 spoken words (Huang et al., 2015). Then the IBM Tangora voice recognition technology was created and named by its creator Albert Tangora in 1986 (Gomes, 2007). This voice recognition machine could interpret up to 20000 English spoken words and recognise some full sentences (Gomes, 2007). And even though IBM Tangora's users still required to speak slowly and clearly and use the machine, then there was no background noise (Gomes, 2007).

The first ever in the world voice recognition technology was called Dragon's NaturallySpeaking software and only created in 1997 (Zumalt, 2005). It could recognise 100 spoken words per minute without requiring from its users to pauses or speak slowly (Zumalt, 2005). After the significant breakthroughs in the sphere of voice recognition technology, Google company combined the latest technology and incorporated cloud-based computing for data sharing, which improved the accuracy of speech recognition algorithms. Then Google launched the Google Voice Search app in 2006, and further implemented the personalisation features into its software with the use of Hummingbird algorithms for even more accurate recognition of speech in 2008 (Boyd, 2018). However, it was the only Siri voice assistant technology by Apple in 2011, which first touched the imagination of the public by introducing the more human-like touch into the complex system of voice recognition technology (Boyd, 2018). Siri was followed by Cortana voice recognition technology, which was made by Microsoft. Further, Amazon introduced Alexa which was installed into Echo (speaker) that did not need activation buttons to press, just users' voice triggering commands, and then other companies joined the battle for sophistication amongst voice recognition technology giants (Boyd, 2018).