Factors contributing to the adoption intention of the coronavirus tracking application

A better understanding of healthcare technology adoption by patients

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I – Preface

I believe my decision to register for the master of Innovation and Entrepreneurship has been a natural decision stemming from my interests I have developed in both my academic life studying International Business Administration at the Radboud University, as well as my personal interests outside of my academic life. However while making the decision to write my master thesis it was hard to exactly pinpoint what interested me the most, and what to spend a great deal of time writing about. I have always seen the value and been fascinated by the healthcare industry, while initially trying several things out within this subject, I finally felt that during the current ongoing pandemic of unprecedented scale in recent memory it would be most insightful to write and study this phenomenon. I finally decided that studying the coronavirus tracking application and what factors contribute to its adoption would be a subject interesting in both a practical sense as well as an academic one. I believe I have been able to create a master thesis that is therefore both relevant to governmental institutions willing to promote the use of such an application, as well as academics interested in learning about the healthcare technology acceptance with regards to patients.

I would like to specially thank my parents and friends who have supported me during this period of hard work, and late nights. Also I would like to thank my friends who have helped me in checking my work and providing advice and help when needed. This stressful period has been of personal importance as it is the end of my academic life, however the end of this stressful period does not just signify relief, but also a great pride in the work I have delivered.

Finally I would like to provide a special thanks to Dr. Robert A.W. Kok whose insight and support were a vital part of my ability to write this thesis. His patience with me and, and his advice with regards to my thesis were genuinely of great help, and for that I am thankful.

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II – Abstract

Contemporary healthcare technology acceptance literature has primarily focused on technology acceptance by healthcare professional instead of patients. In this paper we have focused on the healthcare technology adoption by patients, and in particular the coronavirus tracking application proposed by the Dutch government. Our goal has been to determine the various antecedent that play a role in the adoption intention of (potential) patients of the coronavirus. We have used the UTAUT2 model as a starting point for the range of antecedents to include, however we have also tested three alternative antecedents namely the social influence of governmental agencies and health institutions, the privacy concerns, and the role of media attention. For our study we have gathered a sample of n=163 and conducted both a confirmatory factor analysis, as well as a multiple regression analysis. Our findings show that the expected benefits from using the application, the convenience of the use of the application, the positive feelings related to using the application, as well as the social influence from governmental agencies and health institutions play a role in the adoption intention of (potential) patients of the coronavirus. These findings could provide useful in enhancing the ability of promoting the usage of the coronavirus tracking application for governmental agencies, particularly in The Netherlands.

Keywords: Technology acceptance, UTAUT2, corona application, corona tracking application, COVID-19, coronavirus, adoption intention, healthcare technology adoption, patient context, performance expectancy, convenience expectancy, hedonic motivation, legitimacy.

Inhoud

1 Introduction

In this first chapter we will discuss the main research problem, the objective of our study, and its relevance to both society and the academic world. We will discuss what has been researched about the topic, and the knowledge that is still lacking.

1.1 Problem description

In December 2019 the city of Wuhan in China became the centre of the world's attention due to an outbreak of pneumonia with an unknown origin. The cause of this outbreak has quickly been determined as a new zoonotic virus, which has been named the coronavirus, sometimes also referred to as COVID-19, or SARS-CoV-2 (Hui et. al., 2020). The virus quickly spread internationally infecting nearly three and a half million people in over 185 countries as of the 1st of May, with the actual number of active cases likely being much higher due to a lack of testing (John Hopkins University, 2020; RIVM, 2020). On February 27th the novel coronavirus reached the Netherlands with the first reported case of a 56 year old man in Loon op Zand, , with a strong possibility that the virus was already present in the Netherlands beforehand (''Eerste persoon in Nederland besmet met coronavirus'', 2020). The Dutch government responded on the 10th of March by banning events exceeding 1.000 people in the province of North-Brabant, followed by nationwide measure the next day, and the advice to social distance, as well as voluntary self-isolation (''Nederlandse aanpak en maatregelen tegen het coronavirus'', 2020). The same day of March 11th the World Health Organization declared the coronavirus a global pandemic (World Health Organization, 2020).

To combat the coronavirus pandemic several countries have implemented a coronavirus tracking app that includes features like following infected patients, and tracking symptoms of travellers. One of these countries is South-Korea who implemented the application among other measures to contain the virus, and has been relatively successful in their containment of the coronavirus (Kasulis, 2020). The tracking app is obligatory for all citizens and informs the users of the application about the whereabouts of currently infected patients. Furthermore travellers have to download the app and note their symptoms on a daily basis (Kasulis, 2020). Besides South-Korea, Australia has also developed a coronavirus tracking app, which works based on a Bluetooth signal measuring whether a person comes within 1.5 meter distance of another person. When someone has been exposed for over 15 minutes to someone with coronavirus the user of the app will be notified. While the app is not obligatory like in South-Korea, the Australian government urged that at least 40% of the country needs to make use of the app for it to be effective (''Million Australians download virus tracing app'', 2020).

The Dutch government has similar plans to implement a coronavirus tracking app, with goals to track down infected people and who they have been in contact with, as well as warning people that have been in contact with infected people (''Nederlandse aanpak en maatregelen tegen het coronavirus'', 2020). For the app to be effective a sufficient number of people need to download and use the app (''Apps moeten verspreiding coronavirus tegengaan, maar hoe zit het met privacy?'', 2020). Therefore it is important to know what drives people to accept and subsequently adopt the corona tracking app. Acceptance in this case refers to people deciding whether or not to use the applications (Rogers, 1995), while adoption refers to the subsequent prolonged use of the application (Van Biljon & Renaud, 2008).

When trying to predict what factors into the adoption of healthcare technology among patients we face the problem that scientific research into the healthcare technology adoption among patients has been relatively neglected compared to the healthcare technology adoption among healthcare professionals (Sun et al., 2013). Therefore in this study we will utilize technology adoption literature and in particular the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to predict what factors influence the adoption of the new coronavirus tracking app (Venkatesh et al., 2012). However Venkatesh et al. (2012) mention that the UTAUT2 model has not sufficiently been tested in different sectors and technologies, as the initial study focused on the mobile service sector for consumers in Hong Kong.

While the UTAUT2 model has been adapted to fit a consumer context it has not been tested in a patient level context (Venkatesh et al., 2012). The meaning of a consumer product is relatively broad, as it can be defined as a commodity or service used by a person or organization which leads us to the conclusion that the coronavirus tracking application is also a consumer product. However the question remains whether the UTAUT2 model is also applicable in patient level healthcare technology adoption, and in particular the adoption of the coronavirus tracking application.

1.2 Research objective and question

The goal of this research is to provide better insight in what drives the adoption of the new corona tracking app proposed by the Dutch government. To achieve this goal we will try to improve our understanding of adopting the coronavirus tracking application by utilizing the UTAUT2 model of technology acceptance. We hope that through this research governments will be able to implement the corona tracking application more efficiently or any other future health application targeted towards patients for that matter. By conducting this research our understanding of what drives patients in adopting a technology will hopefully improve:

'What factors influence the intention to adopt the new corona tracking app proposed by the Dutch government?'

1.3 Theoretical relevance

Within healthcare technology adoption literature the majority of studies look at the adoption of healthcare technology by healthcare professionals instead of healthcare technology by patients (Sun et al., 2013). Therefore this study tries to add to existing healthcare technology acceptance literature by looking at the technology acceptance among (potential) patients. We believe that this will provide a significant benefit to a body of academic literature that is currently severely lacking (Sun et al., 2013).

Venkatesh et al. (2012) mention that the UTAUT2 model currently has not been sufficiently tested in various contexts. Furthermore Holden and Karsh (2010) add that the healthcare technology acceptance environment has a very unique contextual environment that basic Technology Acceptance Models (TAM) may not fully capture. Therefore studying the use of the UTAUT2 model within patient technology acceptance will add to our understanding of to what extent the UTAUT2 model is generalizable to a healthcare context and more specifically a patient level context.

1.4 Practical relevance

As mentioned before, for the coronavirus application to be effective a sufficient number of people need to adopt it. This research hopes to provide governments and specifically the Dutch government with the necessary insights with regards to the adoption of a coronavirus tracking app. Knowing which factors contribute to either the acceptance or rejection of the coronavirus application will allow the government and the creators of such applications to better adjust the application to the public needs. While the corona app is specifically tailored to the coronavirus the knowledge gained from this research might also provide useful when creating an application for any future pandemic or virus, or even any other health related technology intended for the general public.

1.5 Scope

This study aims to analyse the general target of the coronavirus tracking application. We therefore want to interview both (potential) patients of the coronavirus as well as post-patients of the coronavirus. The primary target of the proposed corona tracking application is the general public of the Netherlands, therefore we will only interview people currently residing in the Netherlands.

2 Literature review

This chapter will provide knowledge about the main theories that we will be using in this study and how these are relevant, supplemented by the literature about adoption theory. Furthermore we will present a hypothesised conceptual model.

2.1 Technology acceptance and adoption

As this study is centred around the adoption of the coronavirus tracking application, it is important that we define technology adoption. With adoption we mean the prolonged use of a certain technology, or in this specific case a healthcare related application (Van Biljon & Renaud, 2008). The adoption of a technology can thus simply be defined as the use the use of a technology (Venkatesh el. al., 2012), however as the coronavirus tracking application is not currently in use in the Netherlands we are not capable of directly measuring who actually makes use of the app. Therefore within this study we will look at adoption intention which could be described as the willingness to use a technology rather than its actual use (Venkatesh el. al., 2012).

Furthermore within this study we will also utilize the term technology acceptance interchangeably with technology adoption. Technology acceptance can also be defined as the decision to make use of a technology (Venkatesh and Bala, 2008). Therefore the definition of both technology acceptance and technology adoption is blurred leading us to use both terminologies within this study.

2.2 Coronavirus tracking application

As the coronavirus tracking application is currently neither in use in the Netherlands nor being actively developed it can be very hard to comprehend what will be included. Therefore it is important that we determine what features the coronavirus tracking application will contain. As previously mentioned Australia and South-Korea both implemented a coronavirus tracking application however with slightly different methods (Kasulis, 2020; ‘’Million Australians download virus tracing app’’, 2020).

Within this study we will use the approach of the Australian government as the baseline for our study, as we assume that the Netherlands will likely have a similar approach being a western country as well. The coronavirus tracking application in Australia is called COVIDsafe and it is completely voluntary to use. Users can choose to download the application and are then asked to provide their name, age, postal code, and a phone number. The application then proceeds to track contact with other people who have downloaded the application as well, if they are within 1.5 meters for over 15 minutes. The data is then stored in your own phone within encrypted storage and can only be accessed by the government if you are tested positive for coronavirus and agree to provide them with access to the data (Long, 2020).

There might also be issues with how accurate the Bluetooth signals are in tracing the contact between users of the application, or concerns about the legality of tracking inhabitants, however these problems are beyond the confines of this specific study.

2.3 Adopting healthcare technologies

There are a significant amount of models that predict the acceptance and subsequent use of a certain technology. Among these are the Technology acceptance model (TAM) and its variations TAM2 and TAM3 (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008). Also the Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 2015) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Also there have been recent attempts to create a more unified model of all these variations with the creation of the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). However with the majority of these models the focus is primarily on technology acceptance within an organizational context (Venkatesh et al., 2012). This prompted Venkatesh et al. (2012) to create an adjusted model that is derived from the UTAUT model and that is more applicable in a consumer context. This study confirmed several factors that are antecedents of adoption of a technology in a non-organizational context, like hedonic motivation, price value, and habit (Venkatesh et al., 2012). However Venkatesh et al. (2012) do note that the UTAUT2 model has been insufficiently tested among different sectors and technologies, and might also not contain all factors that influence the acceptance and eventual use of a technology .

Determining a theoretical framework when trying to predict technology acceptance among patients provides us with two challenges. First of all a significant number of studies have applied technology acceptance models to the healthcare field (Chau et al., 2002; Liang et al., 2010; Moores, 2012), however these studies tend to analyse healthcare technology acceptance among healthcare professionals instead of patients (Sun et al., 2013). Secondly while TAM and its variations could almost be considered the standard measure for analysing technology acceptance, it was not made for the healthcare environment (Holden and Karsh, 2010). Therefore when TAM and its variations are used in its basic form it may not capture, or could even contradict the unique nature of the field of healthcare technology acceptance (Holden and Karsh, 2010). Current research does not provide direct evidence that the UTAUT2 model does not fit within a healthcare context.

In this specific study we have therefore made the decision to apply the UTAUT2 model (Venkatesh et al., 2012) to analyse the adoption of healthcare technology among patients. We have chosen the UTAUT2 model as it is a very recent model that unifies previous technology acceptance literature in one single model, with the addition of changing it to a consumer context. With the UTAUT2 model we believe that we have a model that provides a strong explanatory power in explaining which antecedents contribute to the adoption of a technology like the coronavirus tracking application (Venkatesh et al., 2012), especially since the UTAUT2 model is aimed at consumers instead of individuals within an organizational context (Davis, 1989). Furthermore the UTAUT2 model contains a larger range of antecedents or background factors compared to previous models (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008), which provides us a better understanding of what specific factors contribute to the adoption of a specific technology compared to solely providing us with an understanding of how a specific technology is adopted. One of the main factors is the inclusion of social influence which was not included in the TAM (Davis, 1989), and secondly the inclusion of factors like hedonic motivation that speak to healthcare technology adopters on a more personal level compared to the UTAUT model which is also aimed at explaining technology adoption in an organizational context (Venkatesh at al., 2003; Venkatesh et al., 2012).

The UTAUT2 model is however not as simple and clear cut as the Technology Acceptance Model by Davis (1989), it contains a significant number of additional factors that explain the adoption of a technology (Venkatesh et al., 2012). Both Bagozzi (2007) as well as Van Raaij and Schepers (2008) state that the UTAUT model and its extensions are becoming larger and more complicated without it being necessarily useful for the understanding of technology adoption. In our case however the additional antecedents included in the model are a benefit to our study, which is due to the reason that a more complete range of antecedents that contribute to the coronavirus tracking application will provide government policy makers as well as app developers with a better understanding of what specific factors contribute to the adoption of the coronavirus tracking application by patients. Furthermore the large range of factors contributing to consumer technology adoption are useful in serving as a foundation for our understanding of what range of factors contribute to the adoption of a consumer healthcare technology.

2.4 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

As mentioned before due to a large number of existing technology acceptance models Venkatesh et al. (2003) decided to unify these models into one single theory called the Unified Theory of Acceptance and Use of Technology (UTAUT). This theory however, is just like the theories it unifies, only applicable to an organizational context, which in our case would be healthcare professionals. Therefore to create a model that more accurately fits a consumer context Venkatesh et al. (2012) adapted the model to create UTAUT2. As Alvesson and Kärreman (2007) mention when a context is changed the relationships and the factors that were initially included in the model might change, adapt, or even be removed. Therefore the UTAUT2 model (Venkatesh et al., 2012) has several notable differences compared to existing technology acceptance models.

In the this section we will provide an overview of the UTAUT2 model that will be applied in this study, as well as the model which we can see represented in figure 1.

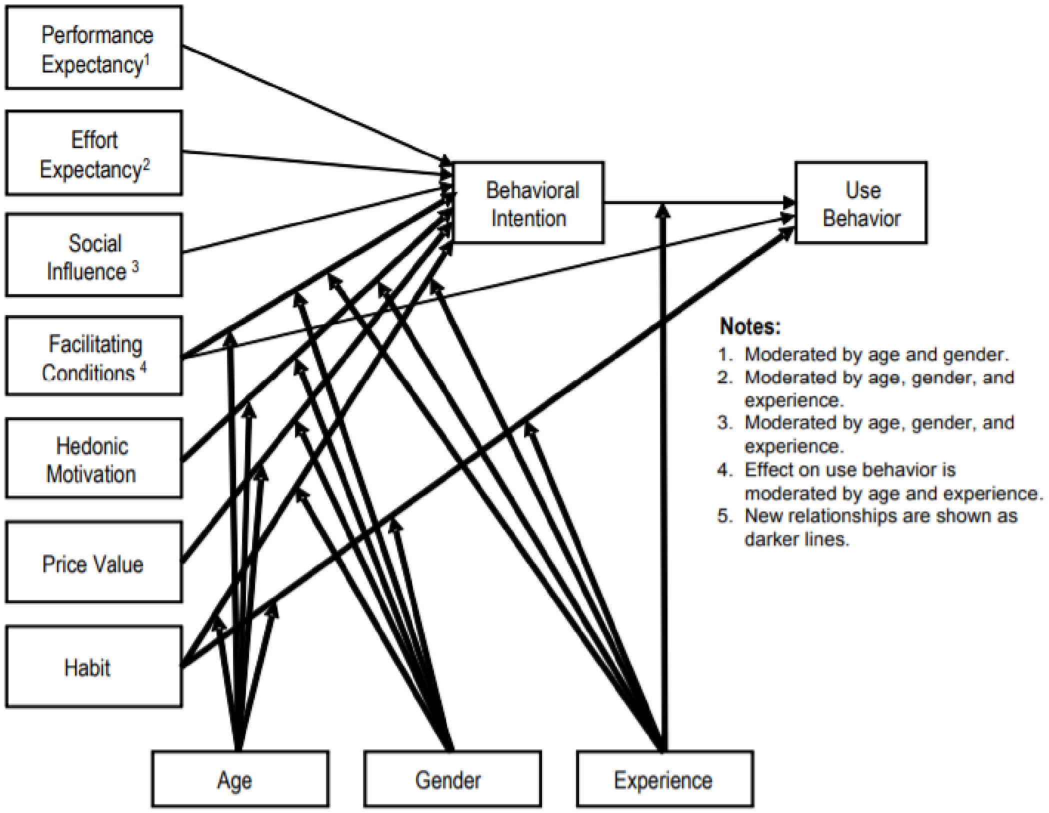

Figure 1: UTAUT2 model (Venkatesh et al., 2012, p. 160)

The UTAUT model by Venkatesh et al. (2003) consisted of four key constructs which have been taken and adopted to a consumer context to fit the UTAUT2 model (Venkatesh et al., 2012). Performance expectancy is defined as *''the degree to which using a technology will provide benefits to consumers in performing certain activities'',* which is moderated by age and gender (Venkatesh et al., 2012, p. 159). Effort expectancy on the other hand refers to how easy it is to make use of the new technology, and is moderated by age, gender, and experience (Venkatesh et al., 2012). Furthermore social influence is the influence that the social circle of the adopter has on the use of a new technology, and is moderated by age, gender, and experience (Venkatesh et al., 2012). Lastly facilitating conditions refers to the perception as to how well a new technology is supported, which is moderated by age and experience (Venkatesh et al., 2012).

The aforementioned constructs are all also present in the UTAUT model, however three notable constructs have been added to the UTAUT2 model that benefit its adaptation to the consumer context. The first construct included is hedonic motivation which is the pleasure or positive experience derived from using a particular technology (Venkatesh et al., 2012). Secondly there is the price value which refers to the influence pricing has on adopting a new technology (Venkatesh et al., 2012). And finally there is habit which is defined as the automatization of certain behaviours (Limayem et al., 2007).

The seven constructs in UTAUT2 are able to explain a significant portion of the variation in technology acceptance and actual use (Venkatesh et al., 2012), however as of yet they have not been sufficiently tested in a healthcare patient context. Through our study we aim to test the UTAUT2 model within healthcare context as well.

2.5 Applying UTAUT2 to the patient-level context

As mentioned before when a context of a certain model is changed the relationships and factors within this model change as well (Alvesson and Kärreman, 2007). This is even more so the case for a field with unique contextual factors like the field of healthcare technology acceptance (Holden and Karsh, 2010). However it is difficult to determine which antecedents influence the adoption of healthcare technology among patients as research regarding the acceptance of healthcare technologies by patients is rather scarce and studies predominantly focus on the acceptance of healthcare technologies by health professionals (Chau et al., 2001; Liang et al., 2010; Moores, 2012).

As the UTAUT2 model remains untested in the healthcare field we have decided to keep as many antecedents as possible within our study in order to be able to determine their effectiveness. However due to certain aspects of the coronavirus tracking application we are forced to remove two of the antecedents. First of all price value has been removed as the coronavirus tracking application is free of charge for everyone to download (Long, 2020). The second antecedent that has been removed is habit, this is due to the reason that the coronavirus tracking application is not an application that can be actively used but is rather an application that runs in the background (Long, 2020). Therefore it is impossible for users to compulsively use the application, rendering the antecedent habit obsolete.

Furthermore based on current literature we have supplemented the model with three more antecedents we believe will have an influence on the intent to adopt the coronavirus tracking application. These antecedents include privacy concerns, media attention, and legitimacy, which we will further explain and explore later in this chapter. Also in his Theory of Planned Behaviour (TPB) Ajzen (1991) divided his background factors into three separate categories being individual, social, and informational. Within our study we have decided for a similar approach which prompted us to divide the antecedents into individual factors and social factors. The individual factors are reliant on the personal concerns of the individual either being what they may benefit from using the application, or what the application may cost in effort, or privacy intrusion. The social factors on the other hand rely on factors that influence the individual either through their direct social circle, or through society at large like the media, the government, or health institutions.

These adaptations together have led us to create a preliminary conceptual model which you can see represented in figure 2.

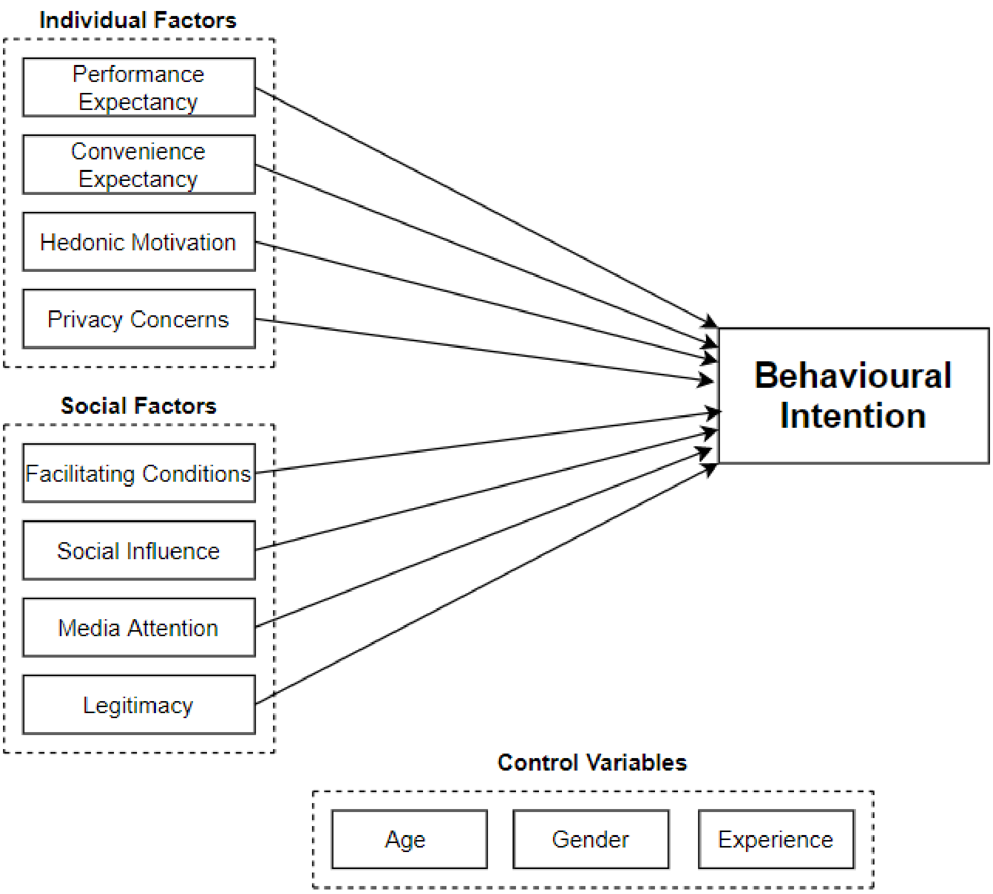

Figure 2: Preliminary conceptual model Technology acceptance coronavirus tracking application

2.5.1 Individual factors

As mentioned before we have divided the factors that influence the behavioural intention to use a technology into individual factors and social factors. We will start off by discussing what the individual factors consist of and which factors are included into this category. Individual factors in the specific case of our model refers to the factors that influence the adoption intention based on personal concerns rather than outside influence. It consists of three factors that were present in the previous UTAUT2 model which are performance expectancy, effort expectancy, and hedonic motivation (Venkatesh et al., 2012), as well as a newly added antecedent being privacy concerns. We do have to mention that we have chosen to rename the antecedent effort expectancy into convenience expectancy.

The initial model of UTAUT as well as UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012) consisted of the factor performance expectancy. Venkatesh et al. (2012) define this factor as the expected increase of performance due to the use of the new technology. In our study however the performance increase rather refers to more personal benefits like an expected prevention of being infected by the coronavirus, or alternative personal benefits provided through the service of the coronavirus tracking application. The possibility of returning to pre-corona regulations if the coronavirus tracking application would prove effective in controlling the virus could persuade individuals in downloading the application, especially individuals with professions significantly affected by the virus. We thus believe that the possible and perceived benefits of the coronavirus tracking application have an effect on the intention to utilize the application.

Hypothesis 1. Performance expectancy has a positive direct effect on behavioural intention

The second factor is effort expectancy, this factor is defined as *''the degree of ease associated with consumers' use of a specific technology''* (Venkatesh et. al., 2012, p.159), and in our specific case the coronavirus tracking application. This factor is also derived from the UTAUT and UTAUT2 models (Venkatesh et al., 2003; Venkatesh et al., 2012) and has been tested to have a significant effect when applied to a healthcare professional context (Liang et al., 2010), though it remains untested in a patient-level context. However a significant body of prior research (Davis, 1989; Liang et al., 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) indicates how an easier to use technology results in a higher adoption of said technology. We therefore also believe that in the specific case of the coronavirus tracking application this will hold true, as individuals that may perceive the use of the coronavirus tracking application as easy or convenient will be more likely to adopt the application. We do however believe that the term Effort expectancy is not an accurate descriptor of its actual meaning, as Effort expectancy seems to suggest a high effort when using a technology. We have therefore chosen to rename the term Effort expectancy into Convenience expectancy in our model while still retaining the same description of the antecedent, as we believe Convenience expectancy is a more accurate descriptor for *''the degree of ease associated with consumers' use of a specific technology''* (Venkatesh et. al., 2012, p.159).

Hypothesis 2. Convenience expectancy has a positive direct effect on behavioural intention

Hedonic motivation is the inclination of human beings to seek pleasurable or positive experiences (Gray, 1981). In the case of this study hedonic motivation is therefore the pleasure or positive experience that the user of a technology perceives from utilizing the technology. Van der Heijden (2004) and Thong et al. (2006) have found that there is a direct link between the pleasure derived from using a technology and its subsequent acceptance and use. As the coronavirus tracking application is not an application you can actively use, it is likely not enjoyable or pleasurable to the users of the app. However the user of the application may feel like they are doing something altruistic therefore evoking positive feeling in themselves, or alternative positive experiences like feeling safer. Since the coronavirus tracking application is intended for the public's health and safety, as well as individuals being able to contribute personally in keeping society healthier we believe that in fact hedonic motivation does affect the intention to adopt the coronavirus tracking application.

Hypothesis 3. Hedonic motivation has a positive direct effect on behavioural intention

The final factor privacy concerns has not been included in any previous technology acceptance models. Privacy concerns in our study refers to the personal concern of individuals to maintain their personal and/or intimate information as well as their concerns this personal and/or intimate information might leak or be distributed to third parties. Bélanger and Carter (2005) have found that trust in governmental agencies handling private data has an influence in citizens adopting e-government technologies. We believe that this type of privacy concern would also extend to governments tracking the whereabouts of citizens besides storing personal data. Furthermore Phelps et. al. (2000) have found that the majority of individuals (in the U.S.) want to limit the amount of information acquired by marketers and third parties. In the current digital age where large amounts of data is shared online people have an increased lack of confidence in online privacy (Malhotra et. al., 2004), and are thus more aware of their personal concerns with regards to issues involving online privacy. We thus believe that individuals who are more concerned with their online privacy will be less likely to adopt the coronavirus tracking application.

Hypothesis 4. Privacy concerns have a negative direct effect on behavioural intention

2.5.2 Social factors

The second group of factors consists of social factors which contrary to the individual factors influence the adopter of the technology from outside. These outside influences could include friends or family which are accounted for in both the UTAUT, and UTAUT2 models (Venkatesh et al., 2003;

Venkatesh et al., 2012), but also governmental/medical agencies or even the media. While the original Technology Acceptance Model (TAM) by Davis (1989) did not include social influences later technology acceptance models (Venkatesh & Davis, 2000; Venkatesh & Davis, 2003; Venkatesh & Bala, 2008; Venkatesh et al., 2012) have included the influence of the social circle on the technology adopter. However the coronavirus tracking application is implemented on a national scale involving more stakeholders than there are present within an organization. We are therefore of the belief that healthcare institutions like the RIVM or the government influence the decision of patients to adopt a technology. This has resulted in us including more antecedents addressing these outside influences which were absent in the baseline model of UTAUT2 (Venkatesh et al., 2012).

Facilitating conditions are influenced by both the own capacity of the adopter to support his or her use of the application, as well as any outside influence to aid in supporting the use of the new application. Facilitating condition can therefore be defined as the perception to how well the technology in question is supported (Venkatesh et al., 2012). Though while this antecedent has been tested to have an effect in a healthcare professional context and not a patient-level context (Liang et al., 2010), we assume that this factor will also remain of relevance in a patient level context.

Hypothesis 5. Facilitating conditions have a positive direct effect on behavioural intention

The factor of social influence has remained within the new conceptual model. Social influence is the effect people within the adopters social circle have on the decision to adopt a technology (Venkatesh et al, 2012). The idea that social influence plays a factor in technology acceptance has been tested among various models and contexts (Hung et al., 2012; Liang et al., 2010), resulting in a decision to keep this antecedent.

Hypothesis 6. Social Influence has a positive direct effect on behavioural intention

One of the newly added factors is legitimacy, by legitimacy we mean the *"acceptance by people of the need to bring their behaviour into line with the dictates of an external authority"* (Tyler, 1990, p. 25). We believe that certain sources that are seen as legitimate by citizens like the RIVM or possibly doctors could highly influence the adoption process of users. Sunshine and Tyler (2003) have found that citizens who consider the police as legitimate have a higher degree of complying with police. We assume therefore that when legitimate sources like the RIVM would advise people to adopt the new coronavirus application they would be more likely to adopt the application.

Hypothesis 7. Legitimacy has a positive direct effect on behavioural intention

Another newly added factor we believe is not addressed sufficiently within the UTAUT2 model (Venkatesh et al., 2012), is the antecedent of media attention. Kaplan and Haenlein (2010) note that especially new media and even traditional media influence the impressions people form. We extend this to our model as the impressions people form about the new coronavirus application due to information received by either traditional media like TV and radio, or even new media like Youtube and Twitter. Information received through these sources whether it is accurate or not could affect the decision of people to adopt the coronavirus tracking application. Furthermore in his Theory of Planned Behaviour Ajzen (1991) included media among the background factors that have an influence on behaviour of people, we believe that this would also extend to the adoption of healthcare technologies by patients.

Hypothesis 8. Media attention has a positive direct effect on behavioural intention

The extent of factors that influence healthcare technology adoption by patients is unknown due to the little attention this specific field of research receives (Sun et al., 2013). We believe that based on the existing literature these factors would largely explain the adoption of the coronavirus tracking application among (potential) patients, which could serve as a foundation to further our understanding of what factors contribute to healthcare technologies among patients in general. However we do have to be mindful that the results of a study based on single patient level healthcare technology might not necessarily be generalizable to the entire field of patient healthcare technology adoption.

3 Methodology

This chapter will provide an in depth view on the methodology used in this research. The type of research that will be conducted as well as the approach towards data collection, data analysis, and operationalization will be discussed in this chapter.

3.1 Quantitative research design

Despite the lack of studies done on the specific field of healthcare technologies adoption among patients we can still form a rough idea of what antecedents may influence adoption of a healthcare technology among patients based on the large body of research on technology adoption. Also while in qualitative research designs generating new information is the primary purpose (Mason, 2010), quantitative research designs are more aimed at testing preconceived relationships (Babbie, 2012). Therefore since we already have a preconceived idea of what the relationships might be, a quantitative research design would be more appropriate. Furthermore a quantitative research design would allow us to analyse a larger population compared to a qualitative design. This is done through the use of easier to process numerical data instead of linguistic data which is more used in qualitative research designs (Bleijenbergh, 2015). Also processing the amount of factors we have within our conceptual model through the use of linguistic data within our given time constraints was an impossible task, which therefore is another reason that lead us to prefer a quantitative design.

3.1.1 Survey

The specific quantitative method we applied in this study is the survey method. Babbie (2012) mentions that surveys are especially appropriate when individuals are the unit of analysis, as well as generating numerical data to test statistical relationships. In our case to indeed confirm that the antecedents or the independent variables have an effect on the behavioural intention or the dependent variable we would indeed need numerical data, which we can generate through the use of a survey. The survey respondents and units of analysis in our study will consist of people within the Netherlands that could either potentially become patients of the coronavirus or have previously already been patients of the coronavirus.

3.2 Operationalization of measures

Our measures are operationalized based on two separate studies, namely Venkatesh et. al. (2012), and Chismar and Wiley-Patton (2002). We primarily use Venkatesh et. al. (2012) since our study is in essence an extension of the UTAUT2 model to a patient healthcare technology environment, and the second study by Chismar and Wiley-Patton (2002) to better aid us in changing the UTAUT2 model survey questions to a healthcare environment. While Chismar and Wiley-Patton (2002) have not aimed their study at patients but rather at healthcare professionals, it still is useful in aiding us in adapting the questions to a healthcare environment. We have provided a copy of the operationalization of the measures including the original survey questions posed by Chismar and Wiley-Patton (2002), and Venkatesh et. al. (2012) below in *table 1,* we have also provided a translation of these items into Dutch in *appendix 1.* The studies we have based our survey on measure their constructs between 2-4 items, which is also the case within our survey. Both the independent variables and the dependent variable are measured with a 7-point Likert scale to provide respondents with a larger range to express their opinions.

3.2.1 Dependent variable

We have decided to use two items to measure the intention to use in our respondents. From the original survey of Venkatesh et. al. (2012) we have chosen one item, however we have decided not to include the other two items measuring intention to use. The items we dropped included ''I will always try to use the coronavirus tracking application in my daily life'' and '' I plan to continue to use the coronavirus tracking application frequently''. This is due to the fact that these items can only be used when referring to a technology that can be actively used unlike the coronavirus tracking application which cannot be actively used. Instead we have added one item from the survey of Chismar and Wiley-Patton (2002) which has led us to our dependent variable also being measured by two items.

3.2.2 Independent variables

From our eight independent variables three variables consist of items directly taken from the studies by Chismar and Wiley-Patton (2002), and Venkatesh et. al. (2012). The only necessary change when creating these items for our survey were changing the technologies that were mentioned in them for the coronavirus tracking application. These variables include performance expectancy, convenience expectancy, and social influence.

While the variables hedonic motivation and facilitating conditions were already present in the survey from Venkatesh et. al. (2012), we did however make the decision to make some adjustments we deem more fitting for our study. First of all hedonic motivation is, as mentioned in the previous chapter, the inclination of human beings to seek positive or pleasurable experiences (Gray, 1981). Therefore as the coronavirus tracking application is not an application you can use actively it would not particularly be pleasurable or enjoyable, however people can still have a positive experience from using the application by feeling safer or feeling they have done something altruistic. We have therefore framed the questions in a way that it would reflect the positive experience from using the application instead of the enjoyment from using the application. Besides this change the questions have largely remained the same. For facilitating conditions we have taken the items ‘’ I have the necessary resources to use the coronavirus tracking application’’, ‘’ I have the knowledge necessary to use the coronavirus tracking application’’, and ‘’ I can get help from others when I have difficulties using the coronavirus tracking application’’ directly from the study by (Venkatesh et. al., 2012). However we have added an additional item which replaced the social circle of the adopter as a facilitating condition with the government as a facilitating condition.

Besides the variables which were already present in previous technology acceptance models, we have also added three new variables which we believe will play a role in adopting the coronavirus tracking application. The variables of both legitimacy and media attention are phrased similarly to each other. While our intent was to phrase the items similarly to the items from the variable social influence this was not entirely possible. In the social circle of individual adopters of the coronavirus tracking application there might be varying views on whether the adopter should or should not adopt the application. However with health or governmental institutions (legitimacy) and new or traditional media (media attention) the application is most likely viewed favourably in particular because the application is being pushed by the government and health institutions in case it is released. Therefore we cannot phrase these items similarly to the items from the variable social influence leading us to make some adjustments. Furthermore for the variable privacy concerns we also did not have any reference on how to phrase them based on previous studies. We have however included three items we believe accurately measure the privacy concerns of individuals with regards to the coronavirus tracking application. These items are ‘’ I believe that the coronavirus tracking application would intrude my privacy’’, ‘’ I believe that when I use the coronavirus tracking application there is a serious chance my personal data would be leaked’’, and ‘’ I prefer not to provide personal data to the coronavirus tracking application’’.

3.2.3 Control variables

The control variables age, gender, and experience that we utilize are directly taken from the UTAUT2 model (Venkatesh et. al., 2012), while the original UTAUT model also included an additional control variable namely voluntariness of use (Venkatesh et. al., 2003). This does not apply in our case since the coronavirus tracking application is completely voluntary to use in Australia (Long, 2020), and will most certainly also be completely voluntary to use in the Netherlands. The inclusion of these control factors allows us to control for factors like age, gender, and experience. The items measuring the control variables can be found in *table 1.*

Age will be measured through a box in which the respondent can fill in their exact age. We prefer this method over categorizing the age of the respondent as our method indicates the exact age of the respondent.

For gender we have chosen to let the respondents select from two categories, male and female, with the reference category being male in our study. We acknowledge that indeed a number of people do not identify as either of these two gender categories, for which we would have liked to provide a third box for noting their gender as other. However from previous experience we have noted that a disproportionate amount of younger respondents selects the box other. Therefore we have chosen to provide respondents with just the two gender options to select.

Lastly there is the control variable experience, which in the study by Venkatesh et. al. (2012) has been measured by the usage of three different levels. Within our study we have used a similar approach letting respondents select from three different options of a low, a medium, and a high level of experience using mobile applications. Our approach differs from Venkatesh et. al. (2012) in the fact that they have chosen to measure experience in the length of time the individual has used said technology. We are however of the opinion that the length of time someone has used mobile applications does not necessarily accurately measure the adeptness at using mobile applications. This has resulted in our usage of a more self-report style subjective measurement of experience. We have dummy coded our results into two dummy variables with low experience being the reference category, and medium and high experience being combined into one category. We believe the only significant difference will be between the low experience category and the remainder of experience categories, hence our decision to dummy code into two instead of three dummy variables.

3.2.4 Factor rankings

We have also provided the respondents with an option to rank the factors that influenced their decision the most when adopting the coronavirus tracking application from most important to least important. However this is only meant as a measure to provide us with more insight in what respondents perceive they value the most. Our main conclusions will not be drawn from the data derived from the rankings, but rather we believe that these rankings could provide us with some interesting information. The rankings will be measured with a point system attributing a point matching the rank of the factor in question i.e. rank one scoring 8 points, while rank eight scores 1 point.

No.	Variables	No.	Items	Units	Categories	Original items	Source
Independent variables							
1.	Performance expectancy	**PE1.**	The use of the coronavirus tracking application seems useful to me.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	I find mobile Internet useful in my daily life.	(Venkatesh et. al., 2012)
		PE2.	I think the coronavirus tracking application would be beneficial to my health.			IHA could improve the quality of care that I deliver.	(Chismar and Wiley-Patton, 2002)
		PE3.	I think the coronavirus tracking application would prevent me from getting the coronavirus.			IHA could enhance my effectiveness.	
						IHA could be useful in my job.	
2.	Convenience expectancy	**CE1.**	Using the coronavirus tracking application seems easy to me.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	Learning how to use mobile Internet is easy for me.	(Venkatesh et. al., 2012)
						My interaction with mobile Internet is clear and understandable.	
		CE2.	The coronavirus tracking application seems understandable to me.			I find mobile Internet easy to use.	
		CE3.	Using the coronavirus tracking application would not require a lot of effort.			It is easy for me to become skillful at using mobile Internet.	
3.	Hedonic motivation	**HM1.**	Using the coronavirus tracking application would give me a positive feeling.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	Using mobile Internet is fun.	(Venkatesh et. al., 2012)
						Using mobile Internet is enjoyable.	
		HM2.	Using the coronavirus tracking application would make me feel safer.			Using mobile Internet is very entertaining.	
		HM3.	Using the coronavirus tracking application would make me feel better.				
4.	Privacy concerns	**PC1.**	I believe that the coronavirus tracking application would intrude my privacy.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	*We have created these items without basing it in pre-existing items, due to their absence from TAM-models.*	
		PC2.	I believe that when I use the coronavirus tracking application there is a serious chance my personal data would be leaked.				
		PC3.	I prefer not to provide personal data to the coronavirus tracking application.				
5.	Facilitating conditions	**FC1.**	I have the necessary resources to use the coronavirus tracking application.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	I have the resources necessary to use mobile Internet.	(Venkatesh et. al., 2012)
		FC2.	I have the knowledge necessary to use the coronavirus tracking application.			I have the knowledge necessary to use mobile Internet.	

		FC3.	I can get help from others when I have difficulties using the coronavirus tracking application.			I can get help from others when I have difficulties using mobile Internet.	
		FC4.	I can get help from the government when I have difficulties using the coronavirus tracking application.			Mobile Internet is compatible with other technologies I use.	
6.	Social influence	**SI1.**	People who are important to me would likely want me to use the coronavirus tracking application.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	People who are important to me think that I should use mobile Internet.	(Venkatesh et. al., 2012)
		SI2.	People who influence my behaviour would likely want me to use the coronavirus tracking application.			People who influence my behaviour think that I should use mobile Internet.	
		SI3.	People whose opinion that I value would likely want me to use the coronavirus tracking application			People whose opinions that I value prefer that I use mobile Internet.	
7.	Legitimacy	**L1.**	Health institutions (like the RIVM) influence my behaviour towards using the coronavirus tracking application.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	*We have created these items without basing it in pre-existing items, due to their absence from TAM-models.*	
		L2.	The government influences my behaviour towards using the coronavirus tracking application.				
		L3.	Healthcare practitioners (like your general practitioner) influence my behaviour towards using the coronavirus tracking application.				
8.	Media attention	**MA1.**	Media attention in general would influence my behaviour towards using the coronavirus tracking application.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	*We have created these items without basing it in pre-existing items, due to their absence from TAM-models.*	
		MA2.	New media (like twitter, youtube, facebook) influence my behaviour towards using the coronavirus tracking application.				
		MA3.	Traditional media (like the newschannels, news appers) influence my behaviour towards using the coronavirus tracking application.				

Dependent variable							
9.	Behavioural intention	**BI1.**	I intend to use the coronavirus tracking application.	7-point Likert scale	Scale: 1 Strongly disagree to 7 strongly agree	I intend to continue using mobile Internet in the future.	(Venkatesh et. al., 2012)
		BI2.	If significant barriers did not exist I would use the coronavirus tracking application.			If significant barriers did not exist, I predict I would use IHA.	(Chismar and Wiley-Patton, 2002)
Control variables							
10.	Age	**1.**	What is your age?	Open			
11.	Gender	**2.**	What is your gender?	Two categories	1.Male 2.Female		
12.	Experience	**3.**	How much experience do you have with mobile applications?	Three categories	1.Low 2.Medium 3.High / *level of experience*		

Table 1 Operationalisation of measures

3.3 Population and sample

Babbie (2012, p.115) defines a population within the context of scientific research as ‘’the group about whom we want to draw conclusions on’’. Within our study we aim to draw conclusions about potential adopters of the coronavirus tracking application, which consist of both potential patients of the coronavirus, as well as people who currently have the virus, or may have had the virus in the past. Since COVID-19 is capable of infecting any human being (Hui et. al., 2020), our population is limited to any citizen in the Netherlands who is capable of downloading the application. Since an entire population, even more so in our case, is impossible to study we have drawn a sample from the population which we collected data from and studied.

When we determined our sample size for our study our decision was based primarily on what analyses we would conduct. First of all we conducted a confirmatory factor analysis, to confirm whether our hypothesized constructs match the ones present within the dataset. Tabachnick and Fidell (2012) recommend a total of over 300 cases to conduct a proper factor analysis, while Hair et. al. (2010) recommends a much more conservative number of roughly 5 respondents per item, which in our case would equal to 150 respondents.

Additionally we conducted a multiple regression analysis to measure the effects of the constructs on an individual’s intention to adopt the coronavirus. According to Hair et. al. (2010) with multiple regression analyses we should always abide by a minimum of 5:1 sample size to predictor variable ratio, and preferably a 15:1 ratio . With our twelve predictor variables this would translate to at least a sample size of 60 while preferably having a sample size of 180 in our case. Therefore we aim to get as close to the 180 mark as possible, which we hope will allow us to conduct a proper multiple regression analysis.

When taking both the factor analysis and the multiple regression analysis into account we determined that a sample size of between 150 and 180 should suffice to properly conduct both analyses. We however aimed at a slightly larger sample size as we expected a certain number of incomplete surveys.

Among the total of 184 surveys 21 were deleted due to the fact that they were incomplete. This left us with a total of 163 usable surveys which is sufficient to conduct both analyses. In the following paragraph we will discuss the missing data as well as the deleted survey entries in depth.

3.4 Missing data analysis

We started off by cleaning up the survey responses through the deletion of specific cases that were missing a very significant amount of data points. As Field (2013) states missing data can sometimes be useful in determining whether respondents find certain questions sensitive or difficult to answer. However specific respondents that are missing too many data points can have a negative effect on the analyses that we will perform. Therefore to determine how many of the thirty data points are missing (excluding the ranking) from a specific respondent we have created a new variable which we have called ''Missing data''. This variable indicates how many data points are missing from each specific respondent, of which we have also created a frequency table (*see Appendix 3).*

We can see that out of a total of 184 respondents 150 respondents were missing no data, while 13 respondents were missing only between one to three data points. The remaining 21 respondents were however missing between 13 and 30 data points, and we have chosen to remove these specific respondents as they were missing roughly half of the required data from the survey. The removal of these respondents leaves us with 163 usable respondents which just surpasses our threshold of 160 respondents we deemed necessary for conducting our multiple regression analysis and factor analysis.

Of the 163 usable respondents we have to look whether there are specific items that were problematic to some extent. Field (2013) states that we need to look further into specific items that have more than five to ten percent of missing values. To be able to determine whether there are items missing more than five to ten percent of its values we have created a frequency table for the results of the usable 163 respondents. Due to the amount of items we have only included the items up till HM1, as the remainder of the items had no missing values. Among the missing values the only one that was somewhat problematic was the question regarding age, as the remainder of items were only missing one to two data points. The only problematic item age was missing 10 of its 163 values, which equals to roughly 6,13%. We assume that the missing values were caused by the fact that age is sometimes a sensitive subject for certain people, which resulted in these individuals not sharing this information. Therefore despite the fact that the item age is missing more than 5% of its values we have chosen not to remove the item.

3.5 Data collection

As mentioned before in this study we will be making use of a survey to gather the necessary data. To measure the variables we used a 7-point Likert-scale, as well as three items to measure age, sex, and experience. The survey questions from both Chismar and Wiley-Patton (2002) and Venkatesh et. al. (2012) have been used to create our own survey. The questions from the aforementioned studies have been adapted to be utilized with regards to the coronavirus tracking application. Additionally the survey contains an introductory paragraph explaining the coronavirus tracking application and its features, which allows respondents to better understand what the coronavirus tracking application contains. We have provided a copy of our survey in *Appendix 2.*

To create the survey and gather the necessary data we will be utilizing the free to use website Survey Hero, we will then distribute the survey through messaging software like WhatsApp. The use of messaging software like WhatsApp has several benefits to this study, first of all it ensures that the respondent is in the ownership of a smartphone which is also necessary to download the coronavirus tracking application, when and if it ever comes out. Secondly It allows us to reach a large population without having to be in direct contact with them. The sampling technique we will be using to approach respondents is snowball sampling. Snowball sampling is a sampling technique in which each respondent refers another respondent which then increasingly grows the sample size (Babbie, 2012). The benefit of this approach is that through low costs we can approach a large sample size necessary for this study, as well as the possibility to send the survey to a large population without having to come into direct contact with them. We do however have to acknowledge that non-probability sampling techniques like snowball sampling may not provide a sample that is fully representative of the entire Dutch population.

3.6 Assumptions

Within this section we will discuss both the assumptions for the confirmatory factor analysis and multiple regression analysis respectively.

3.6.1 Confirmatory factor analysis

We will first discuss the assumption test of the confirmatory factor analysis of which the SPSS output is provided in *appendix 5.* The assumption test has shown that our use of a confirmatory factor analysis is justified throughout the various iterations.

The first assumption to meet when conducting a factor analysis is to use an adequate sample size. Tabachnick and Fidell (2012) recommend a total of over 300 cases to conduct a proper factor analysis. This number is however unachievable for us due to both time constraints and lack of facilities to reach this size sample size. However Hair et. al. (2010) recommends a much more conservative number of roughly 5 respondents per item, which in our case would equal to 150 respondents, which we sufficiently surpass by having a total of 163 usable responses. While a larger sample size is preferable we believe that our sample size of 163 is sufficient. Additionally Field (2012) states that to properly conduct a factor analysis the Kayser-Meier-Olkin (KMO) test should surpass a threshold of 0.5 with a score closer to 1 being preferable. Additionally the Bartlett's test of sphericity should test significant. Both these assumptions have been met in our factor analysis with the KMO-test scoring a 0.909 and the Bartlett's test of sphericity testing significant with a ($p<.001$). After the first iteration we have removed item FC4, at which point we have to perform a second iteration and reconduct the assumption tests. In the second iteration the assumptions were met again with the KMO-test scoring an exceptionally high 0.913 and the Bartlett's test of sphericity testing significant with a ($p<.001$)

3.6.2 Multiple regression analysis

The results from the assumption tests indicate that our usage of a linear multiple regression analysis is justified for within our study, as the results indicate a linear relationship as well as the fact that all assumptions are met.

We have also conducted the assumption tests to determine whether a multiple regression analysis was an adequate regression model to utilize in our study *(see appendix 7).* The assumption tests have been conducted at both the variate and individual variable level. The first assumption to be met is that of a sufficient sample size. According to Hair et. al. (2010) a sample size should be at a minimum a 5:1 sample size to predictor variable ratio, and preferably 15:1. In our case with twelve predictor variables this translates to a sample size of at least 60 and ideally 180. With usable sample size of 163 we are at the upper range and thus we consider the assumption of sample size met. Furthermore the results from both the p-p plot and histogram indicate that the results are normally distributed . Additionally we have created a scatterplot by plotting the standardized predicted values on the X-axis against the standardized residuals on the Y-axis. Here our results are also sufficient with only one single outlier, however the remainder of point seem evenly distributed between the 3 and -3 points on both axes . The results therefore indicate that the data set is both linear and homoscedastic. The final assumption is that of the absence of multicollinearity. We have also provided a table of the collinearity statistics, here we can see that none of the independent variables have a VIF that exceeds a threshold of 10. Therefore we can consider the assumption for the absence of multicollinearity met. While all assumptions are met at the variate level we have still decided to conduct the assumption tests at the individual variable level as a control measure, however here all assumptions are also met without any single issue.

3.7 Data analysis

Our first step when analysing the data has been to get a better understanding of our results by analysing the descriptive statistics like the frequencies, modes, and means of our variables. We have looked at what data is missing, and deleted the respondents that are not usable. We continued by conducting a Confirmatory Factor Analysis (CFA) to measure whether our understanding of the constructs is in line with what items the constructs actually consists of. We have made use of a CFA as our factor analysis method as we already have a preconceived idea of which items the constructs consist of based on existing literature (Brown, 2015).

After the factor analysis we have also tested the reliability of our constructs through the use of the Cronbach's Alpha statistic. Furthermore we have also tested for the appropriateness to use a multiple regression analysis to test the relationships between the various independent variables and the dependent variable. Multiple linear regression is an ideal method when dealing with multiple independent variables and one dependent variable (Field, 2013), and according to our assumption testing this is an appropriate method to use. Contrary to other regression models, a multiple regression is useful in our instance as we make use of a 7-point Likert scale. Additionally as a control measure to provide us with extra information we have generated a ranking based on cumulative scores of all the personal rankings of the participants.

3.8 Sample distribution and representativeness

In this section we will discuss the age and gender distributions within our sample as well as to what extent these distributions are representative to the population we are studying, and what the consequences are for our study. In *appendix 4* we have compared both the gender as well as age distributions within our sample with the gender and age distributions within the population, as well as the number of respondents that did not reveal their age or gender. While the original item ''age'' within our survey was a continuous variable we have chosen to represent ''age'' as a category for clarity and simplification purposes. Therefore it is not clear from the table in *appendix 4* that the youngest respondent was aged 14, while the oldest respondent was aged 66.

First of all we can see there is a very significant overrepresentation of the age category 20-29. Furthermore while the age categories of 30-39, 40-49, 50-59, are somewhat representative of the population, the age categories of 10-19 and 60-69 are significantly underrepresented while categories 70-79 and 80+ are completely absent. Our assumptions for as what has caused these particular sample distributions is twofold. First of all our goal to reach a large enough sample size while simultaneously adhering to social distancing laws resulted in a use of a snowball sampling method as well as an overreliance on our personal network. This in turn has caused an overrepresentation of the age category 20-29. Secondly the underrepresentation of the groups 10-19, and 60+ could have been caused by the distribution method used in which these particular groups have a lack of facilitation conditions. For the groups of 60 and older WhatsApp might be an application they might not as frequently use or perhaps not even use at all, while for the age category 10-19 and in particular the ones closer to age 10 might not be in the ownership of a phone which also excludes them from our population. However luckily the age categories from 30-39, 40-49, 50-59 are quite representative. For gender we can see that the sample distribution is quite representative of the population.

Our sample does not include a significant portion of the elderly, and an overrepresentation of younger individuals aged 20-29. Therefore we have to be very careful when generalising the results of our study to the entire population.

3.9 Results confirmatory factor analysis

In this section and the following subsection we will use the abbreviations of the items of which the fully written counterparts are present in table 1.

We have conducted a confirmatory factor analysis of which the results are depicted in *appendix 5*. Both the KMO-test and Bartlett's test of sphericity showed results that are more than adequate to conduct a factor analysis with scores of 0.909 and ($p<.001$) respectively. Nearly all communalities surpassed the threshold of .4 recommended by Field (2012), with the exception of the item FC4 with a value of .268. The factor analysis extracted a total of five factors having an eigenvalue of at least greater than one, these five factors cumulatively explain a total of 70.4 percent. While we did expect nine separate factors it is not unlikely that in a case like this where factors highly correlate with each other the data has been reduced to five factors. Since our factors correlate strongly with each other ranging between -.429 and .633 we believe that our use of an oblique rotation method is justified. When looking at the pattern matrix we can see that all the items measuring convenience expectancy cross load. Furthermore there were less factors with items intended to measure separate constructs grouped within the same factor than expected, however as explained before with items that are closely related to each other and correlating with each other it is not something surprising. We have therefore chosen to maintain the initial factors as long as the items load on the same factor with somewhat similar factor loadings. Based on this, we have decided to remove item FC4 as it did not load particularly strong on any factor and it had the by far the lowest communality among all items. The second iteration of our factor analysis was also adequate to perform a factor analysis and again extracted five factors cumulatively explaining 72.10 percent. However this time the results were satisfactory with high enough communalities and factor loadings, and we have thus decided to maintain the remaining items.

3.9.1 Results reliability analysis

In this subsection we discuss the Cronbach's Alpha (α) scores of the factors that were determined in the previous section, of which the SPSS output can be found in *appendix 6*. According to Field (2013) a Cronbach's Alpha is sufficient if it surpasses a threshold of .7, preferably exceeding a level of .8, though this is not a necessity. An item can be removed if we believe that it sufficiently improves the reliability score of the construct. The first construct behavioural intention had a high reliability score (α=.933), no items could be removed as the construct only consisted of two items. The second construct performance expectancy also had a high reliability score (α=.915), with none of the items removal improving its reliability score. Convenience expectancy also had a sufficient reliability score (α=.894), removal of any of the items could not improve the reliability score. Hedonic motivation scored an exceptionally high reliability score of (α=.968), of which the reliability could not be improved. Privacy concerns scored a reliability score of (α=.852) of which the reliability score could not be improved. For the construct facilitating conditions we have already removed the item FC4 as a result of the factor analysis. The construct facilitating conditions scored a sufficient reliability score of (α=.849), the removal of item FC3 could slightly improve the reliability score however we do not believe the increase is high enough to justify the removal of the item. The construct social influence scored a high reliability score (α=.950), of which the reliability score could not be improved. The construct legitimacy scored a high reliability score of (α=.914), of which the reliability could not be improved. Finally the construct media attention scored a high reliability score of (α=.903), while the reliability could be improved through the removal of item MA2 we believe it is not a sufficient increase to justify removal.

According to the reliability analysis all constructs are sufficiently reliable to utilize in a multiple regression analysis. The only removal of an item has been item FC4 as a result of the factor analysis conducted in the previous section.

Construct and Item list	1	2	3	4	5	α
(a) Behavioural Intention						.933
BI1	.762	-.125	.124			-
BI2	.734		.161			-
(b) Performance expectancy						.915
PE1	.626		.147	-.129		.898
PE2	.706				.162	.825
PE3	.713	.118			.150	.906
(c) Convenience expectancy						.894
CE1	.500			-.552		.850
CE2	.511			-.431		.844
CE3	.577			-.373		.854
(d) Hedonic motivation						.968
HM1	.794				.107	.956
HM2	.853			.112	.165	.953
HM3	.722		.153		.163	.948
(e) Privacy concerns						.852
PC1		.779				.817
PC2		.863				.742
PC3	-.193	.785				.822
(f) Facilitating conditions						.849
FC1				-.754	.178	.748
FC2				-.846		.740
FC3	-.101		.128	-.660		.864
(g) Social influence						.950
SI1					.906	.924
SI2					.884	.920
SI3					.882	.934
(h) Legitimacy						.914
L1	.246		.516		.107	.848
L2	.285		.484			.894
L3	.280		.570		.111	.884
(i) Media attention						.903
MA1			.943			.812
MA2			.702			.913
MA3			.891			.854
Eigenvalue	12.88	2.62	1.83	1.59	1.17	
% of variance	49.53	10.07	7.04	6.10	4.50	
Cumulative Percent	49.54	59.61	66.65	72.76	77.26	

Note1: The table is representative of the final iteration of the factor analysis.
Note2: The Cronbach's Alpha scores are representative of the factors used in the study not the ones extracted by SPSS, the Cronbach's Alpha scores next to the constructs is the one of the construct while the ones next to the items indicate what the score would be if said item is deleted.
Note3: Factor loadings between .1 and -.1 are suppressed.

Table 2 Confirmatory factor analysis and reliability analysis

3.10 Research ethics

In this research it is important that we maintain ethical standards both prescribed to us by the university of Radboud Nijmegen, as well as the ethical standards we prescribe to ourselves. As researchers we have the duty to maintain integrity and honesty about the results of our study, and refrain from abusing our status as a member of an academic profession. Therefore we have ensured that we did not plagiarise, and fabricate or manipulate any data, imagery, or consent forms. Furthermore we correctly referenced all sources that were used, and also ensured that the sources and information we use were not misrepresented to unjustly support our narrative. To our respondents we have the duty that the information is fully anonymized, and not shared to third parties without their permission. Additionally during this ongoing pandemic we have the duty to maintain the health of our respondents as well, therefore we have made the decision to not gather information face-to-face but rather through either the phone or any other method which allows us to refrain from direct contact with the respondent. We maintained this approach for the entirety of our study. Lastly any allegation of misconduct towards this research will be taken into full consideration, there will be no act of retaliation from our part.

4 Results

This chapter will provide and discuss the results of the descriptive statistics, as well as the results from the multiple regression analysis. In the final section we will also briefly discuss how the various factors have been ranked by the respondents.

4.1 Descriptive statistics and correlations

Below in table 3 we have summarized both the descriptive statistics as well as the correlations with the dependent variable behavioural intention, of which the raw data is presented in *appendix 8*. As there are various descriptions of what is a strong, moderate, and weak relationship we have determined that in our case 0.3 to -0.3 are weak correlations, between 0.6 and -0.6 are moderate correlations, and any correlation exceeding 0.6 and -0.6 is a strong correlation. The test presented is a Spearman's Rho two-tailed test due to the inclusion of categorical variables like Gender and Experience.

When we look at the data we can see that there are significant correlations across the board. First of all, when looking at the dependent variable Behavioural intention we can see It correlates significantly with all other variables with the exception of two control variables namely Age and Gender, which is in line with our expectations. Behavioural intention correlates strongly with the variables Performance expectancy, Convenience expectancy, Hedonic motivation, Social influence, and Legitimacy (respectively .782, .640, .788, .603, .643). Additionally Behavioural intention correlates moderately with Facilitating conditions, Media attention , and Experience (respectively .380, .526, .309). Finally Behavioural intention has a weak relationship of -.224 with the variable Privacy concerns. These results are very much in line with our expectations prior to conducting this research.

When we take a look at our control variables we can see that gender has no significant correlations as expected. Age, on the contrary, has a moderate relationship with both Convenience expectancy and Facilitating conditions (respectively -.399, -.345). Furthermore Experience correlates moderately with the variables Behavioural intention, Convenience expectancy, Facilitating conditions, Age (respectively .309, .397, .350, -.386), as well as a weak correlation with Performance expectancy and Hedonic motivation (respectively .283, .271).

Additionally, as expected, established factors contributing to technology acceptance like Performance expectancy, and Convenience expectancy correlated strongly with several other variables. Performance expectancy correlates strongly with Convenience expectancy, Hedonic motivation, Social influence and Legitimacy (respectively .701, .843, .675, .674). Furthermore Convenience expectancy correlates strongly with Hedonic motivation .668. Additional strong relationships are Hedonic motivation with Social influence and Legitimacy (respectively .679, .622), as well as a strong correlation between Media attention and Legitimacy (.603), this is also an expected result as both variables rely on the individuals acceptance of outside information to make a decision.

When we look at the means of the variables there are only a few variables that stand out. Facilitating conditions had by far the highest mean (5,413) indicating that individuals on average believed they had the means and knowledge to download and utilize the coronavirus application. Secondly Privacy concerns (5,149) also had a high mean indicating that on average people indicated concerns when it comes to their online privacy. On the lower end we have the variable Media attention (3,546) meaning individuals on average did not believe the media has an influence on their decision to adopt the application.

Finally for the dummy variable of Experience the valid percentage recorded indicated that the respondents have an average to high experience with utilizing mobile applications. This percentage is 84 percent indicating that the vast majority of respondents perceive themselves as adequately experienced when it comes to utilizing mobile applications. While this percentage is quite sizeable it is not entirely unexpected that the majority of the respondents are somewhat experienced with mobile applications, as over 87 percent of the Dutch citizens aged between 16-75 currently own a smartphone (Centraal Bureau voor Statistiek, 2019), furthermore the average age of the respondents is quite low which is an additional factor causing the high experience with mobile application usage.

N.	Variable	n	Mean	s.d	1	2	3	4	5	6	7	8	9	10	11	12
1	Behavioural Intention	163	3,963	1,972	1											
2	Performance Expectancy	163	4,317	1,739	.782***	1										
3	Convenience Expectancy	163	4,763	1,590	.640***	.701***	1									
4	Hedonic Motivation	163	3,746	1,812	.788***	.843***	.668***	1								
5	Privacy Concerns	163	5,149	1,400	-.224**	-.090	-.048	-.229**	1							
6	Facilitating Conditions	163	5,413	1,459	.380***	.508***	.642***	.384***	.033	1						
7	Social Influence	163	4,047	1,545	.603***	.675***	.561***	.683***	-.172*	.460***	1					
8	Legitimacy	163	4,065	1,748	.643***	.674***	.561***	.648***	-.111	.410***	.589***	1				
9	Media Attention	163	3,546	1,570	.526***	.512***	.391***	.541***	-.168*	.311***	.473***	.636***	1			
10	Age	153	34,50	13,168	-.123	-.109	-.399***	-.123	-.069	-.345***	-.144	-.086	-.096	1		
N.	**Variable**	**n**	**Percent**	**s.d.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
11	Gender	161	50,9	0,501	-.019	-.093	-.016	.026	-.021	-.015	.002	-.089	-.090	.037	1	
12	Experience	162	84,0	0,367	.309***	.283***	.397***	.271***	-.089	.350***	.144	.129	.139	-.386***	.008	1

Note1: *** is significant at the 0.001 level, ** is significant at the 0.01 level, and * is significant at the 0.05 level.

Note2: The categorical variable correlations are tested for a Spearman's Rho two-tailed test, while the metric variable correlations are tested for a Pearson two-tailed test.

Note3: All decimals are rounded at three decimals.

Note4: Percentages are shown for the dummy/dichotomous variables. For the variable Gender the percentage of females is valid, while the males are the reference category. For the variable Experience the percentage of average or higher experience is valid, while low experience is the reference category.

Table 3 Spearman's Rho and Pearson correlation coefficients and descriptive statistics

4.2 Multiple regression analysis results

In this section we will provide the results for the multiple regression analysis with behavioural intention as the dependent variable, and test our hypotheses. The results have been summarized in *table 4* as well as non-summarized version in *appendix 9.* As our hypotheses are one-sided the p-values have been divided by two.

We have generated two separate models with model 1 including only the control variables (adjusted R^2=.103, p<.001), and model 2 including both the control variables and independent variable (adjusted R^2=.673,p<.001). As we can see model 2 explains a relatively large amount of the variance within the model, namely 67,3 percent which is a good sign.

At first glance when taking a look at model 1 where the control variables were tested, the model seems to indicate that the control variable Experience plays a role in the adoption process, while Gender and Age do not. In model 1 the control variable Experience, which has been dummy coded and includes the categories medium and high level of mobile application use experience has a positive strong effect of (β=.354,p<.001), which indicates that individuals with medium to high experience in mobile application usage have a higher intention to adopt the coronavirus tracking application compared to people with low experience in mobile application usage, which in our model was the reference category. After including the remainder of independent variables we can see that among the control variables only Experience still tested statistically significant (β=.141,p<.01), however the observed effect is moderate instead of strong. The control variables of both Age and Gender remain statistically unsignificant in model 2 as well. While this is what we expected for the control variable Gender, for the control variable Age we have to keep in mind that the sample did not include a representative amount of elderly.

The first independent variable Performance expectancy has a positive direct effect on the dependent variable behavioural intention (β=.352,p<.001). The effect we have found is fairly strong and is statistically significant, which fully supports our H1 hypothesis, which stated that Performance expectancy has a positive direct effect on Behavioural intention. The strong positive direct effect is very much in line with our expectations as the antecedent of Performance expectancy is quite established within Technology acceptance literature (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008).

For our second independent variable we have again found a statistically significant effect, the positive direct effect is of moderate strength (β=.149,p<.05). Our H2 hypothesis stated that Convenience expectancy has a positive direct effect on Behavioural intention, which based on the data is supported. The results are again very much in line with our expectations as Convenience expectancy is also an established antecedent within Technology acceptance literature (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008).

For our third variable Hedonic motivation we have found a moderate positive direct effect ($\beta=.221, p<.05$). Our H3 hypothesis stated that Hedonic motivation has a positive direct effect on Behavioural intention, which our data fully supports.

Furthermore for our fourth independent variable Privacy concerns we have not found a statistically significant effect. Based on these results we have no support for our H4 hypothesis. This result is rather surprising as, based on the factor rankings in *table 5,* respondents valued Privacy concerns the most in their decision to adopt or reject the coronavirus tracking application. While this could have multiple causes, we assume that respondents in general do value Privacy concerns the most, however the remainder of antecedents collectively outweigh the effects of the antecedent Privacy concerns. Therefore people could choose to adopt the coronavirus tracking application because of the expected returns from it or for altruistic reasons, while also valuing Privacy concerns resulting in a statistically unsignificant effect. Another possible explanation is that respondents have a perception that they need to care about Privacy concerns due to outside influence, while in reality Privacy concerns do not influence their final decision to adopt or reject the coronavirus application.

For the independent variable Facilitating conditions we have quite unexpected results. While the effect is in fact significant, contrary to our H5 hypothesis stating that Facilitating conditions has a positive direct effect on Behavioural intention, the effect found in our model is a moderate negative direct effect ($\beta=-.129, p<.05$). Based on this result we have no support for our H5 hypothesis. We think this result might have been caused by the fact that our respondents largely believed that they did have the proper facilities to use the coronavirus tracking application indicated by the very high average mean of Facilitating conditions in *table 3.* This results in a dataset where even the people that did not want to adopt the coronavirus tracking application. believed that they possessed the right facilities to use the coronavirus tracking application.

Our next independent variable Social influence did not measure a significant effect. This results in us not being able to support our H6 hypothesis that Social influence has a positive direct effect on Behavioural intention. Our explanation for this result is that while respondents might possibly have valued the opinions of others within their social circle, they might not have been fully aware what the opinion of people within their social circle was towards the coronavirus tracking application. Another possibility is that people within the social circle of the respondents did not have a strong opinion when it comes to influencing other to adopt or reject the coronavirus tracking application.

For the independent variable Legitimacy we found a moderate positive direct effect ($\beta=.137, p<.01$). This result is fully in line with our H7 hypothesis stating that Legitimacy has a positive direct effect on Behavioural intention, which is thus supported.

Finally we have our last independent variable Media attention for which we did not find a significant effect, therefore our H8 hypothesis that states Media attention has a positive direct effect on Behavioural intention is not supported. For the antecedent Media attention we can see it had the lowest mean among the independent variables as well as ranking at the bottom in the factor ranking in *table 5*. We therefore believe that people do not value the media when it comes to decision making, but rather see it solely as a source of information.

Dependent variable: Behavioural intention				
	Model 1		**Model 2**	
Variable	**B (SE)**	**Β**	**B (SE)**	**β**
Constant	2.408 (.714)		-.004 (.719)	
Control variables				
Age	.003 (.013)	.024	.005 (.008)	.033
Gender	-.140 (.300)	-.036	.051 (.189)	.013
Experience	1.924 (.458)***	.354	.766 (.308)**	.141
Independent variables				
Performance expectancy	-	-	.394 (.121)***	.352
Convenience expectancy	-	-	.185 (.109)*	.149
Hedonic motivation	-	-	.240 (.111)*	.221
Privacy concerns	-	-	-.105 (.068)	-.076
Facilitating conditions	-	-	-.169 (.093)*	-.129
Social influence	-	-	.058 (.094)	.045
Legitimacy	-	-	.154 (.082)*	.137
Media attention	-	-	.081 (.078)	.065
Model statistics				
	Model 1		**Model 2**	
R square	.120		.696	
Adjusted R square	.103		.673	
R square change	.120***		.576***	
F	F(6.79)=6.79***		F(29.39)=33.44***	

Note1: P-values have been divided by two as all tests conducted are one-tailed.
Note2: B (SE) is the unstandardized coefficient with the standard error in the brackets, β is the standardized coefficient.
Note3: *** is significant at the 0.001 level, ** is significant at the 0.01 level, and * is significant at the 0.05 level.

Table 4 Multiple regression analysis results

4.3 Factor rankings

We have also generated an output of which factors respondents valued most in their adoption of the coronavirus tracking application. The results from the ranking are not particularly surprising in combination with the results from the multiple regression analysis. Variables that tested significant ended up in the higher end of the table, while variables that tested non-significant ended at the lower end of the table. The only exception is the variable of Social influence which ranked at a fourth place despite testing non-significant. Additionally it is rather surprising that the variable Privacy has been ranked disproportionally as the most important factor determining a respondents decision to adopt the coronavirus tracking application, while only measuring a weak effect.

Rank	Choice	Distribution	Score	Times Ranked
1.	Privacy		640	126
2.	De verwachte maatschappelijke en persoonlijke voordelen die de app brengt		569	113
3.	Het geven van een positief/veilig gevoel		514	114
4.	Invloed uit mijn sociale cirkel		486	115
5.	Invloed vanuit gezondheidsinstellingen en/of regering		483	113
6.	De middelen en kennis voor het gebruik van de app bezitten		454	120
7.	Gebruiksvriendelijkheid		403	117
8.	Media aandacht		356	111
		Lowest – Highest		

Note1: Scores are based on the place the factors ranked i.e. lowest rank awarding 1 point, while the highest ranking awards 8 points.

Note2: The colours represent how often the factor has been ranked at a specific position. Red being the lowest and progressively getting greener for higher rankings.

Table 5 Independent factor rankings

5 Conclusion

This chapter will provide the conclusion of this study as well as an in depth discussion about the results found in chapter 4. Furthermore we will discuss both the theoretical and practical implications the results of this study has. And finally we will discuss the limitations of this study, as well as possible future research on the subject.

5.1 Conclusion and discussion

We will start off by summarizing the answer to our main research question: *''what factors influence the intention to adopt the new corona tracking app proposed by the Dutch government?''* . This study has been able to determine that the antecedents Performance expectancy, Convenience expectancy, Hedonic motivation, and Legitimacy effect the intention to adopt the coronavirus tracking application. The remaining antecedents of Privacy concerns, Facilitating condition, Social influence, and Media attention were not in line with our preconceived hypotheses. We have provided a visual overview of the hypothesis outcomes below in *table 6.*

Variable	Behavioural intention
Direct effect	
Performance expectancy	H1: Yes
Convenience expectancy	H2: Yes
Hedonic motivation	H3: Yes
Privacy concerns	H4: No
Facilitating conditions	H5: No
Social influence	H6: No
Legitimacy	H7: Yes
Media attention	H8: No

Note: Yes, there is a significant effect. No, there is not a significant effect.

Table 6 Overview of all hypothesis outcomes

Among our eight antecedents five have been derived from previous Technology Acceptance Models namely Performance expectancy, Convenience expectancy, Hedonic motivation, Facilitating conditions, and Social influence (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008). The remaining three antecedents have not been derived from previous models but were rather added by us namely Privacy concerns, Legitimacy, and Media attention.

Among the antecedents derived from previous Technology Acceptance Models we have been able to determine that there is in fact an effect of Performance expectancy, Convenience expectancy, and Hedonic motivation on the intent to adopt the coronavirus tracking application. These results are thus very much in line with our expectations. It is however rather surprising that we have not been able to find similar support for the antecedents Facilitating conditions and Social influence, as these antecedents have also been derived from well-established Technology Acceptance literature (Venkatesh et al., 2003; Venkatesh & Bala, 2008).

We will start off by discussing the antecedent of Facilitating conditions. When looking at the questions regarding Facilitating conditions we can see it measured whether respondents believed they possessed the knowledge and tools to utilize the coronavirus tracking application, as well as whether they believed they could receive help within their social circle in case they did not. The mean of the variable Facilitating conditions was the highest among the independent variables, indicating that respondents on average believed they did in fact possess the skills and knowledge to utilize the coronavirus tracking application. Further data supports this idea as 84 percent of respondents perceived themselves as possessing average or higher experience in mobile application usage. Facilitating conditions also ranked sixth among the factor rankings (*table 5*) indicating that respondents did not value this antecedent as much compared to other antecedents in their decision to adopt the coronavirus tracking application. We therefore believe that Facilitating conditions did not play a role in the intent to adopt the coronavirus tracking application in our case due to the overwhelming access to the knowledge and tools to use the coronavirus tracking application. We have to keep in mind however that this study did not include a representative amount of elderly who potentially might not possess the tools and knowledge to utilize the coronavirus tracking application.

Social influence is another antecedent that has been derived from previous Technology acceptance literature, but we were still unable to find a significant effect. It is interesting that despite the lack of a significant effect Social influence ranked fourth among the other factors, which is a relatively high position. Our assumption as to what caused this contradiction is that individuals do in fact value the opinions of people within their social circle however they are uncertain what this opinion might be without openly discussing it. Furthermore individuals scoring high on Social influence could still either accept or reject the coronavirus tracking application based on the opinion of individuals within their social circle. Scoring high on Social influence does therefore not have to unequivocally mean that intent to adopt the coronavirus tracking application is higher, due to the fact that the usefulness of the app might be contested. These points are merely our speculation since we cannot determine the exact cause without directly asking the respondents, which is not a part of this study.

Of our three newly added antecedents Privacy concerns, Legitimacy, and Media attention we were only able to find a significant effect on the intent to adopt with the antecedent Legitimacy. This result is not particularly surprising when it comes to the antecedent Media attention, due to several reasons. First of all Media attention had the lowest average mean among the independent variables, meaning that respondents on average did not think that media had an influence on their intent to adopt. The factor ranking supports this as well, as Media attention scored at the very bottom of the ranking. We therefore believe that Media is simply not used as a source of decision making when it comes to adopting the coronavirus tracking application.

The fact that we did not measure a significant effect for the antecedent Privacy concerns is quite surprising. Especially since Privacy concerns ranked at the first place of the factor ranking, as well as a high average mean indicating an on average there were high concerns when it comes to privacy. This potentially could have a variety of causes. Privacy issues are currently a very relevant subject, with a large scale privacy issue in 2018 where Cambridge Analytica harvested the data of over fifty million Facebook users to provide to clients (New Yorker, 2018). We therefore believe it is possible that a sizeable portion of the respondents care about their Privacy regardless of their intent to adopt the coronavirus tracking application. We however also believe it is possible that there is a certain degree of social desirability effect going on, effectively meaning that people state they care a lot about Privacy issues because it seems the right response to give, while in reality they do not take Privacy concerns into consideration within their decision making. Finally it is also possible that people do in fact care about privacy however the positive sides of the coronavirus tracking application outweigh its negative sides like Privacy concerns.

Among the significant effects we have found Performance expectancy to be by far the strongest effect, as well as a moderate effect of both Convenience expectancy and Hedonic motivation. These results are somewhat in line with the study of Venkatesh et.al. (2012). While there are some similarities, the range of effects has changed somewhat. As Alvesson and Kärreman (2007) state it is not surprising that the relationships change when the context of those relationship is changed, as is the case in our situation. Our study has also been able to find a new antecedent influencing the intention to adopt the coronavirus tracking application previously absent from Technology Acceptance literature, namely Legitimacy. It is interesting to compare the antecedent of Legitimacy with the antecedent of Social influence as both rely on an outside influence to effect the respondent in their decision making. We believe the reason that Legitimacy did test significant contrary to Social influence is that the attitude of governmental agencies and health institutions is clear and positive towards the use of the coronavirus tracking application, while the attitude of individuals within a social circle towards the use of the coronavirus tracking application is uncertain and could vary.

As a final point we would like to discuss the differences between the social antecedents, as well as the individual antecedents. Within our conceptual model we have made the distinction between social and individual factors, while this is not a central focus of our study we do believe it is important to discuss. We can see that three of the four individual antecedents tested significant, while only one of the four social antecedents tested significant. This result could be an indication that individuals value individual factors a greater deal compared to social factors. We do have mention that this outcome could be coincidental, and solely be caused by the range of antecedents we have included in this analysis. We therefore believe that we should not make conclusive statements about whether individual factors or social factors weigh greater, but our data does suggest an inclination towards individual factors being valued more.

5.2 Theoretical implications

In chapter 1 we discussed how current healthcare technology acceptance literature focused on technology adoption by healthcare professionals rather than patients (Sun et al., 2013). Which resulted in us wanting to be able to add to this lacking body of research. We had chosen the UTAUT2 model by Venkatesh et. al. (2012) as a starting point, which we believed would be most useful in aiding us to determining which antecedents influenced the intention to adopt the coronavirus tracking application.

First of all we believe that we have definitely been able to demonstrate which antecedents play a role in the intent to adopt the coronavirus tracking application, however we do have to mention that the antecedents we have been able to find that play a role in the intent to adopt the coronavirus tracking application namely Performance expectancy, Convenience expectancy, Hedonic motivation, and Legitimacy might not necessarily be transferable to alternative healthcare technologies adopted by patients. Our study focused on a single healthcare technology and thus we believe it is not possible to make generalized statements about the adoption of all healthcare technologies when it comes to patients. Regardless we believe that this study does provide useful information to this body of research by demonstrating how pre-existing technology acceptance models like the UTAUT2 model (Venkatesh et. al., 2012) do not fully capture which antecedents play a role in patient technology adoption. Performance expectancy, Convenience expectancy, and especially Hedonic motivation, which is relatively unique to the UTAUT2 model, are directly derived from the UTAUT2 model, which confirms our idea that the UTAUT2 model was an adequate starting point for this study. We have also been able to demonstrate how the opinions of healthcare institutions and governments play a role in healthcare technology adoption, which is absent from previous technology adoption literature. Also the results from the factor ranking indicate that data privacy concerns might play a role in healthcare technology adoption, however we have not been able to determine a significant effect in our particular study.

5.3 Practical implications

Besides the theoretical contributions of our study, we also aim to contribute in a more practical manner. This subsection will discuss how our findings can translate to practical contributions in the promotion of the coronavirus tracking application.

As we have stated before the coronavirus tracking application can only be effective if a sufficient amount of people have downloaded the application (''Apps moeten verspreiding coronavirus tegengaan, maar hoe zit het met privacy?'', 2020). To ensure that people download the application it is important to first understand what influences their decision to download such an application. We have been able to find that Performance expectancy, Effort expectancy, Hedonic motivation, and Legitimacy play a role in the adoption. Therefore when promoting the coronavirus tracking application to the citizens of the Netherlands the promotional material should address these elements. We will provide an example of how each antecedent can be used within promotional material. With regards to Performance expectancy promotional material could address the potential long term societal benefits of using the application on a large scale, as well as the personal benefits the application could have. Secondly for Convenience expectancy the promotional material could address how acquiring and using the coronavirus tracking application does not require a lot of effort. For Hedonic motivation promotional material could address how combatting the coronavirus is a collective effort where everyone can participate, playing into the sense of altruism of people. Finally with regards to Legitimacy the promotional material could state how it has been reviewed and recommended by a respected and well-known health institution like the RIVM. We believe that these practical implications of the findings of our study should provide useful to governmental agencies, as well as healthcare institutions that would promote the use of the application.

During the final stages of study the Dutch government released some promotional material with regards to the newly released Corona Melder which is the current form of the coronavirus tracking application (Ministerie van Volksgezondheid, Welzijn en Sport, 2020). While the promotional video primarily focusses on how the application works, it does put a focus on privacy and how data is used and stored within the application. It does not seem to address how much effort it is to download and use the application or any recommendation by a health institution. However at the very end they do provide the statement '*Only together we can beat corona*' (Ministerie van Volksgezondheid, Welzijn en Sport, 2020), which does seem to play in a collective sense of altruism, as well as suggesting that the application is a tool to beat the virus. This suggests that the government is, to some extent, aware of what antecedents play a role when it comes to the adoption of the coronavirus tracking application.

5.4 Limitations

In this subsection we will discuss the various limitations present within our study.

First of all we have to discuss how the data sample used is not fully representative of the Dutch population with regards to Age. We can see that up until 60 years of Age all age categories are fairly well represented, however there is a severe lack of respondents over the age of 60 and a complete absence of any respondents over the age of 70. A consequence of this is that our results are not fully generalizable to the Dutch population. We believe that the lack of representativeness of the data sample can be attributed to the distribution method used. Due to our limited capacity and time we have used a convenience sampling technique which does not ensure representativeness. Additionally we have distributed the survey through WhatsApp to prevent direct contact with respondents during this ongoing pandemic, which might have resulted in excluding elderly who might not utilize WhatsApp. While we do believe our choice was the right ethical choice to make, we do have to keep in mind we cannot generalize our results to the entire population due to a lack of representativeness.

Also while our quantitative study has been able to determine which factors play a role in the intent to adopt the coronavirus tracking application, a qualitative study would have been more appropriate to answer the questions as to why these factors play a role, and why certain ones do not. However do to time constraints we have not been able to include qualitative elements within our study, which would have provided interesting results.

Furthermore in hindsight we realized that while we have measured whether participants were influenced by their social circle, we did not measure what participants thought the opinion of their social circle was. If we would have measured the type of social influence group the participant had we believe we would have been much more capable of determining a significant effect. We believe that we could have also expanded on other antecedents in a similar way, as our conceptual model has been rather straightforward and simplistic. We are however of the opinion that our approach has been justified given our time constraints, as well as the fact that including a larger range of antecedents is more appropriate in answering our main research question.

Another limitation of our study is the fact that we measure intent to adopt rather than actual adoption of the coronavirus application. This choice was made as the coronavirus application was not yet released during the start of this research, nor was it certain when this would be the case. The reason we believe this is a limiting factor is due to the fact that we believe there might be the possibility of a potential discrepancy between the intent to adopt the coronavirus tracking application and its actual adoption.

An extension of this limitation is that our study is fully dependent on self-report type survey questions, which thus enhances the problems the dependency on these type of questions brings with it. Podsakoff and Organ (1986) state that respondents' consistency motive, momentary mood states, and social desirability might affect the results of the survey. We believe that with such a debated application like the coronavirus tracking application these factors could have potentially played a role, and even had a large impact.

Another minor point when it comes to our survey is that it does not include reverse coded items in combination with regular items. We have performed a check to remove respondent with consistently the same answer to questions, and we do believe that we have removed all the cases where ingenuine answers were given. But due to the fact we have not included reverse coded items our capability to identify these ingenuine respondents has been limited, allowing for the potential that we might have missed a small number of ingenuine respondents.

5.5 Future research

Future research on the subject of the coronavirus tracking application could study actual adoption rates of the application and what antecedents contribute to this, now that the Corona Melder has been released, which was not a possibility within our research. This type of research could possibly even contradict our results as there might indeed be a significant discrepancy between the intent to adopt and the actual adoption of the application. Additionally this research could test for a larger range of antecedents than in our case. While we have tested for three different antecedents lacking in previous Technology Acceptance literature, of which one tested significant, future research could expand this range. While Bagozzi (2007) claims that including a larger range of antecedents only complicates Technology Acceptance models without significantly adding to them, we are of the contrary opinion that adding more antecedents only adds to our understanding of technology acceptance as well as providing practical solutions to problems with regards to technology acceptance.

Furthermore we are of the belief that more research is needed on the subject of patient level healthcare technology adoption to provide us with a better understanding of this subject. While we have been able to contribute to this subject we have only tested a single technology with quite unique context and situation. As Alvesson and Kärreman (2007) state a unique context might significantly change the relationships factors present within a model. Therefore to get a better understanding of patient level healthcare technology adoption, different technologies within different contexts should be tested for a better understanding.

As our study has been conducted in The Netherlands with Dutch citizens, our results are only applicable in The Netherlands. Another possible avenue of research could therefore be to conduct a similar research in various countries and cultural zones in the world. It would be possible to measure different cultural attitudes towards the coronavirus tracking application, and with the possibility of combining this data with the five cultural dimensions of Hofstede (1984). This would provide us with deeper insight in how cultures differ in their adoption of healthcare technologies.

Also we believe that future research on the subject would benefit from using qualitative research elements like interviews to determine why certain factors play a role. Our study has only been able to determine which factors play a role in the intent to adopt the coronavirus tracking application, resulting in a large number of questions remaining which could be answered through the use of qualitative data.

Lastly, as mentioned before, among our limitations we noted that our study only measured whether someone was influenced by their social circle, which is a similar approach to previous technology acceptance studies (Venkatesh et al., 2003; Venkatesh & Bala, 2008: Venkatesh et. al., 2012). However we believe now that it is also vital to note the type of perception the social influence group has, as this could be positive, negative, or neither. Therefore future studies could expand on the antecedent Social influence, or possibly even other antecedents to provide us with a more complete picture of the healthcare technology adoption process.

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Appendix list

APPENDIX 1 – Item translations to Dutch

Below we have provided a table containing the translations of our items into Dutch.

No.	Dependent variable	Item no.	Original items	Dutch item translations
1	Behavioural intention	BI1.	I intend to use the coronavirus tracking application.	Ik ben van plan om de coronavirus tracking applicatie te gebruiken.
		BI2.	If significant barriers did not exist I would use the coronavirus tracking application.	Ik verwacht gebruik te maken van de coronavirus tracking applicatie indien er geen grote barrières in het gebruik van de app zijn.
No.	**Independent variables**	**Item no.**	**Original items**	**Dutch item translations**
2	Performance expectancy	PE1.	The use of the coronavirus tracking application seems useful to me.	Het gebruik van de coronavirus tracking applicatie lijkt mij nuttig.
		PE2.	I think the coronavirus tracking application would be beneficial to my health.	Ik denk dat de coronavirus tracking applicatie voordelig is voor mijn gezondheid.
		PE3.	I think the coronavirus tracking application would prevent me from getting the coronavirus.	Ik denk dat de coronavirus tracking applicatie helpt met het voorkomen van besmet raken met het coronavirus.
3	Convenience expectancy	CE1.	Using the coronavirus tracking application seems easy to me.	Het gebruik maken van de coronavirus tracking applicatie lijkt mij makkelijk.
		CE2.	The coronavirus tracking application seems understandable to me.	De coronavirus tracking applicatie klinkt begrijpelijk.
		CE3.	Using the coronavirus tracking application would not require a lot if ideas.	Het kost geen moeite om gebruik te maken van de coronavirus tracking applicatie.
4	Hedonic motivation	HM1.	Using the coronavirus tracking application would give me a positive feeling.	Gebruik maken van de coronavirus tracking applicatie zal mij een positief gevoel geven.
		HM2.	Using the coronavirus tracking application would make me feel safer.	Gebruik maken van de coronavirus tracking applicatie zal mij een veilig gevoel geven.
		HM3.	Using the coronavirus tracking application would make me feel better.	Gebruik maken van de coronavirus tracking applicatie zal mij een beter gevoel geven.
5	Privacy concerns	PC1.	I believe that the coronavirus tracking application would intrude my privacy.	Ik ben van mening dat de coronavirus tracking applicatie mijn privacy schendt.
		PC2.	I believe that when I use the coronavirus tracking application there is a serious chance my personal data would be leaked.	Ik geloof dat er bij het gebruik van de coronavirus tracking applicatie er een serieuze kans is dat mijn persoonlijke data wordt gelekt.
		PC3.	I prefer not to provide personal data to the coronavirus tracking application.	Ik verstrek liever niet mijn persoonlijke data voor het gebruik van de coronavirus tracking applicatie.

6	Facilitating conditions	FC1.	I have the necessary resources to use the coronavirus tracking application.	Ik heb de benodigde middelen om gebruik te maken van de coronavirus tracking applicatie.
		FC2.	I have the knowledge necessary to use the coronavirus tracking application.	Ik heb de benodigde kennis om gebruik te maken van de coronavirus tracking applicatie.
		FC3.	I can get help from others when I have difficulties using the coronavirus tracking application.	Ik kan hulp krijgen van anderen als ik moeite heb met het gebruiken van de coronavirus tracking applicatie.
		FC4.	I can get help from the government when I have difficulties when using the coronavirus tracking application.	Ik ben van mening dat ik hulp zal krijgen van de regering als ik moeite heb met het gebruiken van de coronavirus tracking applicatie.
7	Social influence	SI1.	People who are important to me would likely want me to use the coronavirus tracking application.	Mensen die belangrijk voor mij zijn zouden (waarschijnlijk) willen dat ik de coronavirus tracking applicatie gebruik.
		SI2.	People who influence my behaviour would likely want me to use the coronavirus tracking application.	Mensen die invloed hebben op mijn gedrag zouden (waarschijnlijk) willen dat ik de coronavirus tracking applicatie gebruik.
		SI3.	People whose opinion I value would likely want me to use the coronavirus tracking application.	Mensen van wie ik de mening waardeer zouden (waarschijnlijk) willen dat ik de coronavirus tracking applicatie gebruik.
8	Legitimacy	L1.	Health institutions (like the RIVM) influence my behaviour towards using the coronavirus tracking application.	Gezondheidsinstanties (zoals het RIVM) hebben invloed op mijn keuze om gebruik te maken van het coronavirus tracking applicatie.
		L2.	The government influences my behaviour towards using the coronavirus tracking application.	De regering heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken.
		L3.	Health care practitioners (like your G.P.) influence my behaviour towards using the coronavirus tracking application.	Gezondheidsprofessionals (zoals uw huisarts) hebben invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken.
9	Media attention	MA1.	Media attention in general would influence my behaviour towards using the coronavirus tracking application.	Media aandacht voor de coronavirus tracking applicatie heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken.
		MA2.	New media (like Twitter, Youtube, Facebook) influence my behaviour towards using the coronavirus tracking application.	Nieuwe media (zoals Twitter, Youtube, Facebook) heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken.
		MA3.	Traditional media (like newschannels, newspapers, radio) influence my behaviour towards using the coronavirus tracking application.	Traditionele media (zoals het nieuws, kranten, radio) heeft invloed op mijn keuze om de coronavirus tracking applicatie te gerbuiken.
No.	**Control variables**	**Item no.**	**Original items**	**Dutch item translations**
10	Age	1.	What is your age?	Wat is uw leeftijd?
11	Gender	2.	What is your gender?	Wat is uw geslacht?
12	Experience	3.	How much experience do you have with mobile applications?	Hoeveel ervaring heeft u in het gebruik van mobiele applicaties?

Appendix 2 – Survey

Vragenlijst over het gebruik van de coronavirus tracking applicatie

De Nederlands regering heeft het idee om een applicatie in te voeren om individuen besmet met het coronavirus te volgen. De applicatie is vrijwillig om te downloaden en gebruikers moeten hun naam, telefoon, leeftijd en adres opgeven. De tracking applicatie werkt doormiddel van het gebruik van een bluetooth systeem om te tracken of een persoon voor meer dan 15 minuten binnen 1,5 meter van een andere gebruiker van de app zit. Deze data wordt opgeslagen en vergrendeld in de telefoon van de gebruiker van de applicatie. De informatie kan alleen gebruikt worden door de regering als je positief test voor het coronavirus en vervolgens toegang geeft aan de regering om gebruik te maken van de opgeslagen data.

Wij hebben enkele vragen over het gebruik van de coronavirus tracking applicatie. De vragenlijst bestaat uit meerkeuze vragen en duurt ongeveer 5 minuten. Alvast bedankt voor uw deelname aan dit onderzoek.

Age: Wat is uw leeftijd?

Gender: Wat is uw geslacht? (Man/ Vrouw)

Ervaring: Hoeveel ervaring heeft u met het gebruik van mobiele applicaties?

Behavioural intention

BI1: Ik ben van plan om de coronavirus tracking applicatie te gebruiken

BI2: Ik verwacht gebruik te maken van de coronavirus tracking applicatie indien er geen grote barrières in het gebruik van de app zou zijn

Performance expectancy

PE1: Het gebruik van de coronavirus tracking applicatie lijkt mij nuttig

PE2: Ik denk dat de coronavirus tracking applicatie voordelig is voor mijn gezondheid

PE3: Ik denk dat de coronavirus tracking applicatie helpt met het voorkomen van besmet raken met het coronavirus

Convenience expectancy

CE1: Het gebruik maken van het de coronavirus tracking applicatie lijkt mij makkelijk

CE2: De coronavirus tracking applicatie klinkt begrijpelijk

CE3: Het kost geen moeite om gebruik te maken van de coronavirus tracking applicatie

Hedonic motivation

HM1: Gebruik maken van de coronavirus tracking applicatie zal mij een goed gevoel geven

HM2: Gebruik maken van het coronavirus tracking applicatie zal mij een veilig gevoel geven

HM3: Gebruik maken van het coronavirus tracking applicatie zal mij een beter gevoel geven

Privacy concerns

PC1: Ik ben van mening dat de coronavirus tracking applicatie mijn privacy schendt

PC2: Ik geloof dat er bij het gebruik van de coronavirus tracking applicatie er een serieuze kans is dat mijn persoonlijke data wordt gelekt

PC3: Ik verstrek liever niet mijn persoonlijke date voor het gebruik van de coronavirus tracking applicatie

Facilitating conditions

FC1: Ik heb de benodigde middelen om gebruik te maken van de coronavirus tracking applicatie

FC2: Ik heb de benodigde kennis om gebruik te maken van de coronavirus tracking applicatie

FC3: Ik kan hulp krijgen van anderen als ik moeite heb met het gebruiken van de coronavirus tracking applicatie

FC4: Ik ben van mening dat ik hulp zal krijgen van de regering als ik moeite heb met het gebruiken van de coronavirus tracking applicatie

Social Influence

SI1: Mensen die belangrijk voor me zijn zouden (waarschijnlijk) willen dat ik de coronavirus tracking applicatie gebruik

SI2: Mensen die invloed hebben op mijn gedrag zouden (waarschijnlijk) willen dat ik de coronavirus tracking applicatie gebruik

SI3: Mensen van wie ik de mening waardeer zouden (waarschijnlijk) willen dat ik de coronavirus tracking applicatie gebruik

Legitimacy

L1: Gezondheidsinstanties zoals het RIVM hebben invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken

L2: De regering heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken

L3: Gezondheidsprofessionals zoals mijn huisarts hebben invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken

Media attention

MA1: Media aandacht voor de coronavirus tracking applicatie heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken

MA2: Nieuwe media zoals Twitter, Youtube en Facebook heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken

MA3: Traditionele media zoals het nieuws, de krant en de radio heeft invloed op mijn keuze om de coronavirus tracking applicatie te gebruiken

Ranking factoren

Kunt U noteren welke factoren het belangrijkste zijn in u keuze om de coronavirus tracking applicatie wel of niet te adopteren (nummer 1 is het belangrijkste, nummer 8 is het minst belangrijk).

1. Gebruiksvriendelijkheid
2. Media aandacht
3. Invloed uit mijn sociale cirkel
4. Invloed vanuit gezondheidsinstellingen en/of regering
5. Het geven van een positief/veilig gevoel
6. De middelen en kennis voor het gebruik van de app bezitten
7. Privacy
8. De verwachte maatschappelijke en persoonlijke voordelen die de app brengt

Appendix 3 – Missing data

Statistics

Missing Data

N	Valid	184
	Missing	0

Missing Data

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	150	81.5	81.5	81.5
	1.00	11	6.0	6.0	87.5
	2.00	1	.5	.5	88.0
	3.00	1	.5	.5	88.6
	13.00	1	.5	.5	89.1
	16.00	3	1.6	1.6	90.8
	19.00	1	.5	.5	91.3
	22.00	3	1.6	1.6	92.9
	23.00	2	1.1	1.1	94.0
	25.00	2	1.1	1.1	95.1
	27.00	7	3.8	3.8	98.9
	28.00	1	.5	.5	99.5
	30.00	1	.5	.5	100.0
	Total	184	100.0	100.0	

Statistics

		Age	Gender	Experience	BI1	BI2	PE1	PE2	PE3	CE1	CE2	CE3	HM1
N	Valid	153	161	162	163	163	162	162	163	163	163	163	162
	Missing	10	2	1	0	0	1	1	0	0	0	0	1

APPENDIX 4 - Sample representativeness

The population data below has been derived from the Centraal Bureau voor Statistiek (CBS), and is accurate as of January 1st 2020. The original source additionally states the age category of 0-9 years old, however we have chosen to delete this category since we do not study this group, therefore it is not part of our study population.

Age

Age	Sample		Population	
	Frequency	Valid Percent	Frequency	Valid Percent
10-19 years old	13	8,50%	2.014.491	13,09%
20-29 years old	64	41,83%	2.174.938	14,14%
30-39 years old	22	14,38%	2.078.145	13,51%
40-49 years old	28	18,30%	2.307.135	15,00%
50-59 years old	20	13,07%	2.491.356	16,19%
60-69 years old	6	3,92%	2.079.275	13,51%
70-79 years old	0	0,00%	1.460.665	9,49%
80+ years old	0	0,00%	778.914	5,06%
Age not stated	10	n/a	n/a	n/a
Total:	153	100%	15.385.919	100%

Source for population distributions: *Centraal Bureau voor Statistiek (CBS)*

Gender

Gender	Sample		Population	
	Frequency	Valid Percent	Frequency	Valid Percent
Male	78	48,45%	7.606.518	49,44%
Female	83	51,55%	7.779.401	50,56%
Gender not stated	2	n/a	n/a	n/a
Total:	161	100%	15.385.919	100%

Source for population distributions: *Centraal Bureau voor Statistiek (CBS)*

APPENDIX 5 – Results confirmatory factor analysis

We have used abbreviations for the items namely: Behavioural Intention (BI), Performance Expectancy (PE), Convenience Expectancy (CE), Privacy Concerns (PC), Hedonic Motivation (HM), Social Influence (SI), Facilitating Conditions (FC), Legitimacy (L), and Media Attention (MA).

Confirmatory factor analysis

Our first step when conducting the confirmatory factor analysis was to determine whether the data was adequate to conduct a factor analysis. The Kaiser-Meyer-Olkin test scored a 0.909 which is exceptionally high and more than adequate to conduct a factor analysis. Furthermore a Bartlett's test for sphericity was conducted with a (p<.001) which is sufficient to conduct a factor analysis. Additionally nearly all communalities scored over a value of >.4 which is a good sign that a sufficient portion of the variance in the items can be explained by the factors, the only exception was item FC4 which scored .268. Furthermore multiple factors correlate strongly with each other over a value of >|3|, which justifies our usage of the oblique rotation method. There are a total of five separate factors extracted which is lower than the expected nine, and they cumulatively explain 70 percent of the variance. Within the pattern matrix we can see that various items preconceived to belong to different factors have loaded strongly on the same factors, furthermore there are also several crossloadings present. This is however to be expected as there is a strong correlation in between the factors and items. However the items preconceived to belong in the same factors did score at similar rates on the same factors. These results has led us to the decision the maintain the preconceived factor names and the items within them for content validity reasons. The only exception however has been the item FC4 which has scored by far the lowest communality with .268 not surpassing the threshold of .4, as well as the fact that item FC4 did not clearly load strong on any one factor or with the other items intended to measure Facilitating Conditions. This has led us to remove the item FC4.

For the second iteration we have reconducted the factor analysis, after which the KMO-test scored a sufficient .913. Also the Bartlett's test of sphericity (p<.001) indicated a result which was adequate to perform a factor analysis. After the deletion of the item FC4 the remainder of the items have stayed largely the same and do not require any deletion or adjustment.

First Iteration Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.909
Bartlett's Test of Sphericity	Approx. Chi-Square	4284.406
	df	351
	Sig.	.000

Communalities

	Initial	Extraction
BI1	.836	.710
BI2	.862	.760
PE1	.804	.720
PE2	.842	.795
PE3	.755	.684
CE1	.729	.671
CE2	.753	.672
CE3	.709	.612
HM1	.904	.837
HM2	.910	.884
HM3	.910	.827
PC1	.617	.628
PC2	.679	.736
PC3	.610	.652
FC1	.734	.692
FC2	.742	.782
FC3	.563	.490
FC4	.436	.268
SI1	.854	.866
SI2	.867	.887
SI3	.815	.846
L1	.786	.575
L2	.759	.593
L3	.802	.691
MA1	.828	.808
MA2	.667	.559
MA3	.784	.765

Extraction Method: Principal Axis Factoring.

Factor Correlation Matrix

Factor	1	2	3	4	5
1	1.000	-.094	.538	-.445	.611
2	-.094	1.000	-.152	-.107	-.147
3	.538	-.152	1.000	-.313	.509
4	-.445	-.107	-.313	1.000	-.383
5	.611	-.147	.509	-.383	1.000

Extraction Method: Principal Axis Factoring.

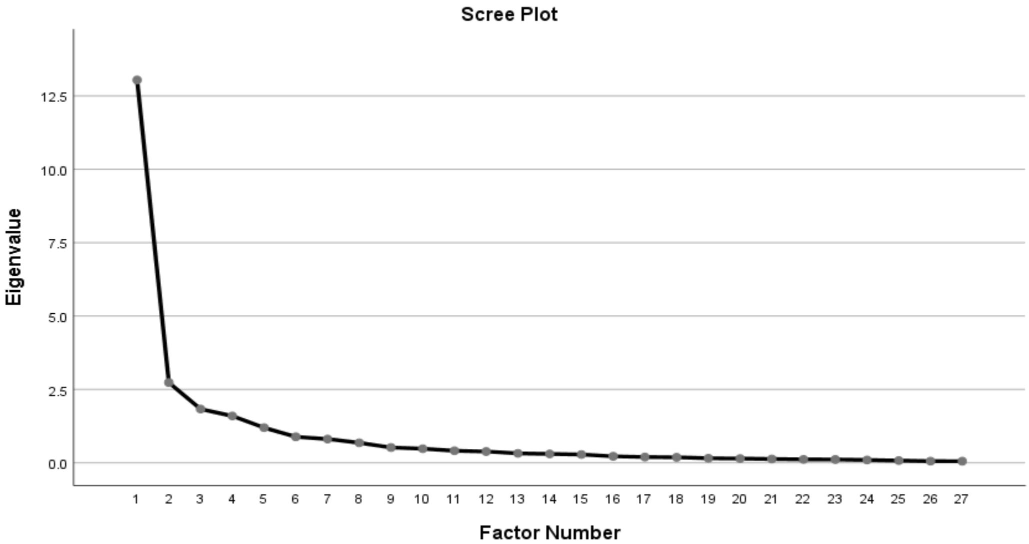
Rotation Method: Oblimin with Kaiser Normalization.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	13.041	48.301	48.301	12.778	47.327	47.327	10.818
2	2.733	10.122	58.423	2.399	8.884	56.211	2.380
3	1.831	6.781	65.204	1.523	5.641	61.852	7.831
4	1.594	5.905	71.109	1.297	4.804	66.656	5.820
5	1.195	4.427	75.536	1.013	3.753	70.409	8.351
6	.884	3.274	78.811				
7	.809	2.995	81.806				
8	.681	2.523	84.329				
9	.521	1.928	86.257				
10	.479	1.773	88.030				
11	.408	1.513	89.543				
12	.383	1.419	90.962				
13	.321	1.191	92.153				
14	.302	1.117	93.270				
15	.281	1.040	94.309				
16	.220	.816	95.125				
17	.197	.728	95.854				
18	.186	.688	96.541				
19	.155	.574	97.115				
20	.143	.531	97.646				
21	.129	.477	98.123				
22	.115	.427	98.550				
23	.112	.414	98.963				
24	.096	.354	99.317				
25	.076	.280	99.597				
26	.056	.206	99.803				
27	.053	.197	100.000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.



Pattern Matrix[a]

	Factor				
	1	2	3	4	5
BI1	.756	-.130	.128		
BI2	.722		.164		
PE1	.607		.147	-.118	.126
PE2	.694				.177
PE3	.708	.117			.149
CE1	.472			-.552	
CE2	.486			-.425	
CE3	.555			-.373	
HM1	.789		.104		.114
HM2	.851			.105	.168
HM3	.718		.160		.165
PC1		.789			
PC2		.848			
PC3	-.209	.786			
FC1				-.754	.198
FC2				-.855	
FC3	-.119		.124	-.693	
FC4	.232	.172		-.319	
SI1					.893
SI2				-.100	.875
SI3					.882
L1	.243		.522		
L2	.280		.490	-.106	
L3	.268		.572		.123
MA1			.944		
MA2			.705		
MA3			.893		

Extraction Method: Principal Axis Factoring.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 8 iterations.

Second Iteration Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.913
Bartlett's Test of Sphericity	Approx. Chi-Square	4207.846
	df	325
	Sig.	.000

Communalities

	Initial	Extraction
BI1	.835	.710
BI2	.862	.762
PE1	.797	.727
PE2	.842	.797
PE3	.751	.678
CE1	.726	.679
CE2	.753	.683
CE3	.706	.615
HM1	.903	.836
HM2	.909	.884
HM3	.910	.827
PC1	.588	.611
PC2	.671	.757
PC3	.603	.652
FC1	.734	.701
FC2	.741	.782
FC3	.529	.463
SI1	.853	.868
SI2	.867	.888
SI3	.811	.840
L1	.781	.570
L2	.747	.588
L3	.788	.694
MA1	.828	.810
MA2	.667	.559
MA3	.784	.767

Extraction Method: Principal Axis Factoring.

Factor Correlation Matrix

Factor	1	2	3	4	5
1	1.000	-.134	.537	-.429	.633
2	-.134	1.000	-.180	-.060	-.151
3	.537	-.180	1.000	-.296	.516
4	-.429	-.060	-.296	1.000	-.396
5	.633	-.151	.516	-.396	1.000

Extraction Method: Principal Axis Factoring.

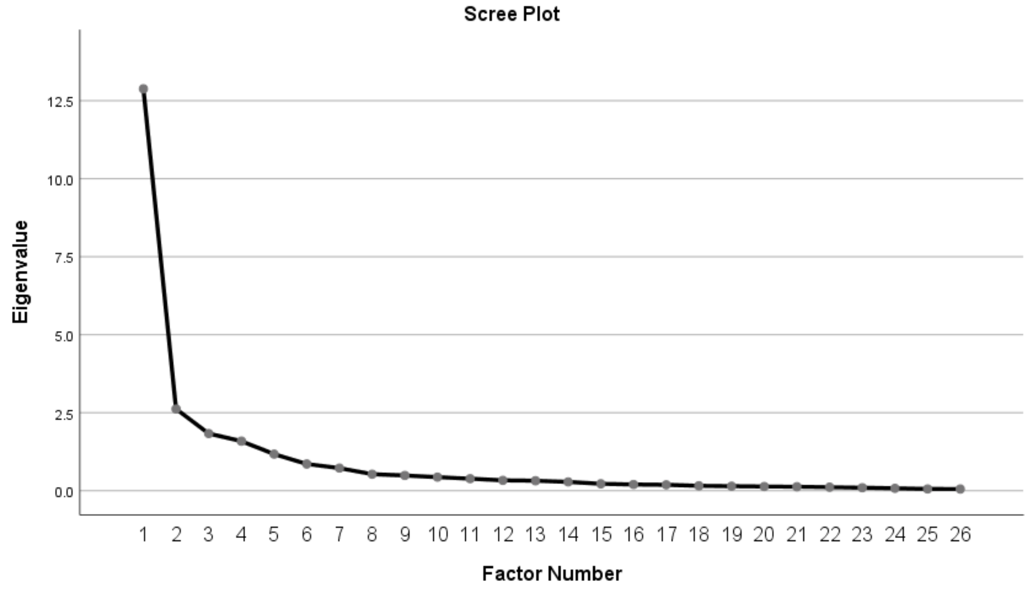
Rotation Method: Oblimin with Kaiser Normalization.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	12.880	49.538	49.538	12.624	48.554	48.554	10.795
2	2.619	10.072	59.610	2.307	8.873	57.426	2.459
3	1.831	7.041	66.651	1.524	5.862	63.288	7.687
4	1.587	6.104	72.755	1.290	4.961	68.249	5.494
5	1.172	4.507	77.262	1.001	3.850	72.099	8.455
6	.855	3.289	80.551				
7	.724	2.784	83.334				
8	.529	2.034	85.368				
9	.488	1.875	87.244				
10	.436	1.676	88.919				
11	.384	1.476	90.396				
12	.331	1.272	91.668				
13	.319	1.229	92.897				
14	.281	1.082	93.979				
15	.221	.851	94.830				
16	.199	.764	95.594				
17	.190	.731	96.325				
18	.156	.602	96.927				
19	.143	.551	97.478				
20	.133	.513	97.991				
21	.128	.492	98.483				
22	.113	.433	98.916				
23	.096	.368	99.284				
24	.077	.295	99.579				
25	.056	.217	99.796				
26	.053	.204	100.000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.



Pattern Matrix[a]

	Factor				
	1	2	3	4	5
BI1	.762	-.125	.124		
BI2	.734		.161		
PE1	.626		.147	-.129	
PE2	.706				.162
PE3	.713	.118			.150
CE1	.500			-.552	
CE2	.511			-.431	
CE3	.577			-.373	
HM1	.794				.107
HM2	.853			.112	.165
HM3	.722		.153		.163
PC1		.779			
PC2		.863			
PC3	-.193	.785			
FC1				-.754	.178
FC2				-.846	
FC3	-.101		.128	-.660	
SI1					.906
SI2					.884
SI3					.882
L1	.246		.516		.107
L2	.285		.484		
L3	.280		.570		.111
MA1			.943		
MA2			.702		
MA3			.891		

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 8 iterations.

APPENDIX 6 – Results reliability analysis

Below we have provided the SPSS output of the Cronbach's Alpha tests conducted on all the factors utilized in this study.

Behavioural intention Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.933	2

Item-Total Statistics

	Statistics			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BI1	4.10	4.077	.875	.
BI2	3.83	4.217	.875	.

Performance expectancy Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.915	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PE1	8.47	13.376	.804	.898
PE2	8.70	11.948	.891	.825
PE3	8.83	12.570	.796	.906

Convenience expectancy Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.894	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CE1	9.45	10.410	.792	.850
CE2	9.52	10.511	.797	.844
CE3	9.61	11.018	.787	.854

Hedonic motivation Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.968	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
HM1	7.47	13.406	.925	.956
HM2	7.59	13.572	.930	.953
HM3	7.41	13.324	.936	.948

Privacy concerns Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.852	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PC1	10.29	8.666	.697	.817
PC2	10.34	8.363	.779	.742
PC3	10.26	8.217	.696	.822

Facilitating conditions Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.849	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FC1	10.68	8.885	.761	.748
FC2	10.93	8.130	.770	.740
FC3	10.87	10.471	.635	.864

Social influence Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.950	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SI1	8.07	9.804	.897	.924
SI2	8.13	9.483	.903	.920
SI3	8.09	10.091	.883	.934

Legitimacy Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.914	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
L1	8.15	12.312	.860	.848
L2	8.27	12.816	.804	.894
L3	7.98	13.111	.816	.884

Media attention Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.903	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
MA1	6.91	9.615	.863	.812
MA2	7.34	10.756	.746	.913
MA3	7.03	10.623	.818	.854

APPENDIX 7 – Assumption testing multiple regression analysis

In this appendix the assumption tests of the multiple regression analysis will be depicted at the variate level and the individual variable level. While all assumptions are met at the variate level we have still conducted the assumption test at the individual variable level as a control measure. Both at the variate and individual level all assumptions are met.

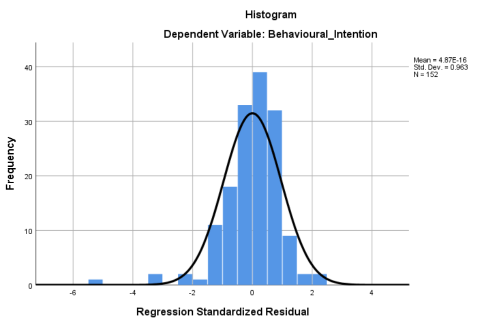
Variate level assumptions

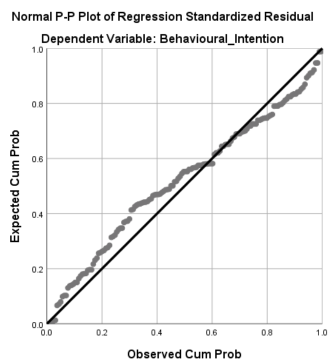
Sample Size

According to Hair et. al. (2010) to conduct a proper multiple aggression analysis we need at least a sample size ratio of 5:1 with a preferable ratio of 15:1. In our case with twelve predictor variables the recommended sample size would range from 60 to 180. We have a total of 163 usable responses and are therefore on the upper range of the recommended sample size to conduct a proper multiple regression analysis, which we deem more than sufficient.

Assumption of normality

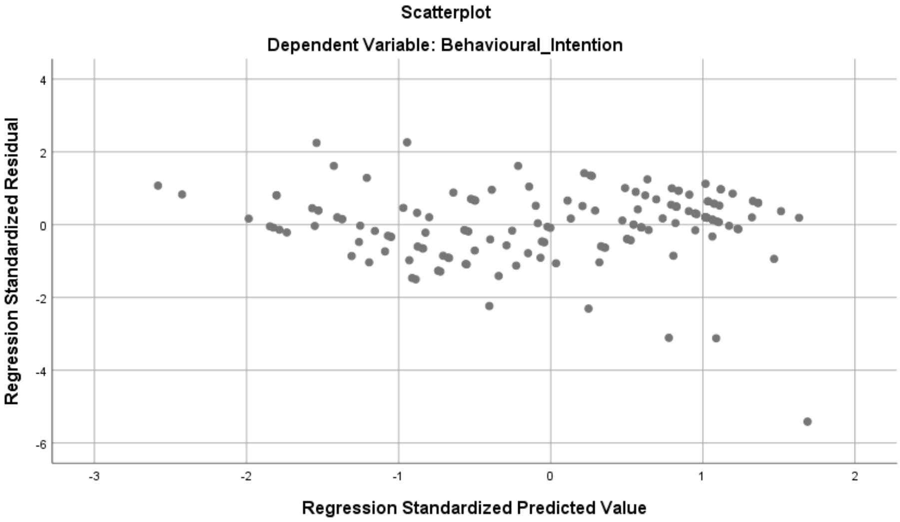
We first started off by checking all assumptions on the variate level and determine whether the results are within an acceptable range. The first assumption of normality can be checked by taking a look at the p-p plots as well as the histogram(Hair et. al., 2010). We preferably want results that are approximately normally distributed, which we can see in the p-p plot. As long as it does not deviate drastically from the line this assumption will be met. We can see that this is most definitely the case despite it deviating slightly from the line, also the histogram is showing adequate normally distributed results.





Assumption of homoscedasticity and linearity

To check for this assumption we will plot the standardized predicted values of the regression model on the X-axis against the standardized residuals on the Y-axis. We ideally want a random pattern not exceeding the 3 or -3 values on either axis. In our model the results seem adequate despite a single outlier. Ideally we would want a more random pattern, however the points are relatively evenly distributed between the 3 and -3 values on both axes. The scatterplot also indicates that the relationship between the dependent and independent variables is linear.



Assumption for the absence of multicollinearity

The final assumption is that for the absence of multicollinearity, for this assumption to be met the VIF of each independent variable should be below 10. As shown in the table below none of the independent variables exceeds a VIF of 10. Therefore also this assumption is considered met.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.408	.714		3.374	.001					
	Age	.003	.013	.024	.279	.780	-.123	.023	.021	.829	1.207
	GenderID_Female	-.140	.300	-.036	-.466	.642	-.038	-.038	-.036	.995	1.005
	Experience_MH	1.924	.458	.354	4.199	.000	.344	.325	.323	.832	1.201
2	(Constant)	-.004	.719		-.006	.995					
	Age	.005	.008	.033	.583	.561	-.123	.049	.027	.685	1.461
	GenderID_Female	.051	.189	.013	.271	.787	-.038	.023	.013	.907	1.102
	Experience_MH	.766	.308	.141	2.482	.014	.344	.205	.115	.670	1.493
	Performance_Expectancy	.394	.121	.352	3.247	.001	.780	.264	.151	.184	5.448
	Convenience_Expectancy	.185	.109	.149	1.693	.093	.635	.141	.079	.279	3.582
	Hedonic_Motivation	.240	.111	.221	2.168	.032	.772	.180	.101	.207	4.822
	Privacy_Concerns	-.105	.068	-.076	-1.544	.125	-.203	-.129	-.072	.881	1.135
	Facilitating_Conditions	-.169	.093	-.129	-1.824	.070	.395	-.152	-.085	.430	2.327
	Social_Influence	.058	.094	.045	.613	.541	.620	.052	.028	.396	2.526
	Legitimacy	.154	.082	.137	1.872	.063	.635	.156	.087	.403	2.480
	Media_Attention	.081	.078	.065	1.032	.304	.521	.087	.048	.550	1.819

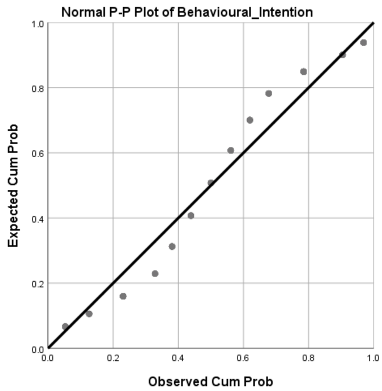
a. Dependent Variable: Behavioural_Intention

Individual variable level assumptions

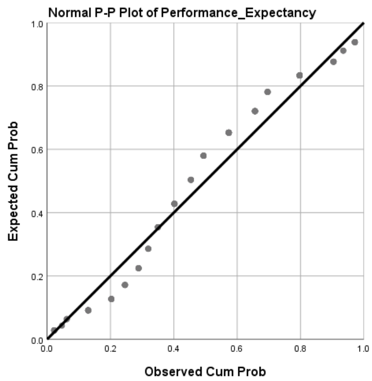
Assumption of normality

Below we have provided the p-p plots of each individual variable. To have a normally distributed variable the points should approximately follow the indicated line. As depicted in the p-p plots below we can see that is most certainly the case for all the variables. While they are not perfectly normally distributed we belief it is definitely sufficient for the multiple regression.

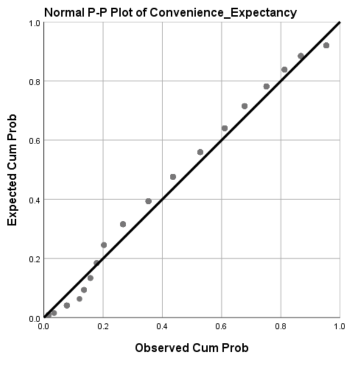
Behavioural intention



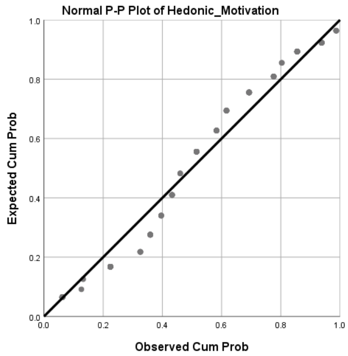
Performance expectancy



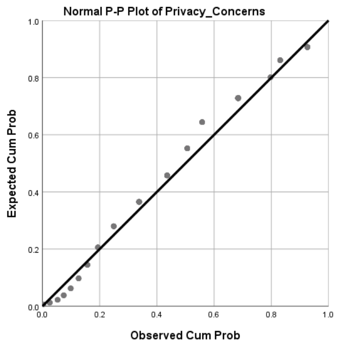
Convenience expectancy



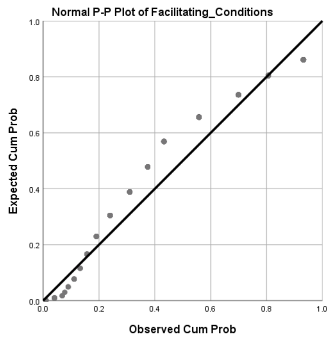
Hedonic motivation



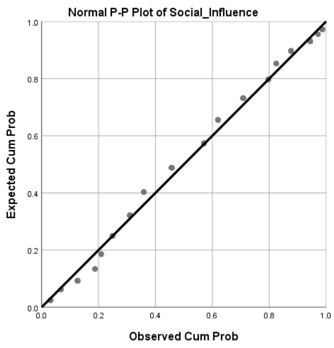
Privacy concerns



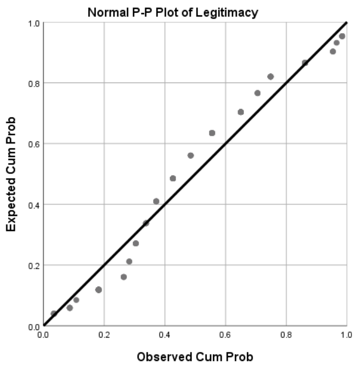
Facilitating conditions



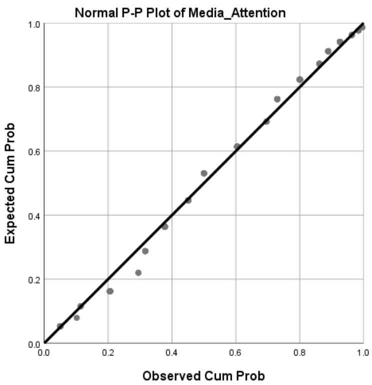
Social influence



Legitimacy



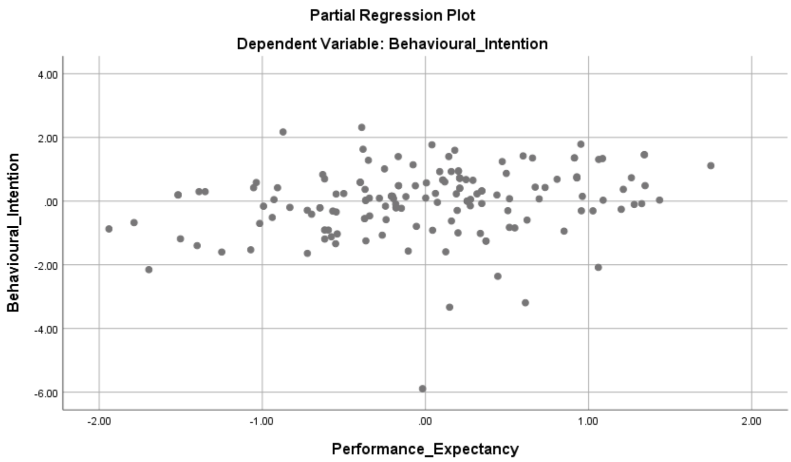
Media attention



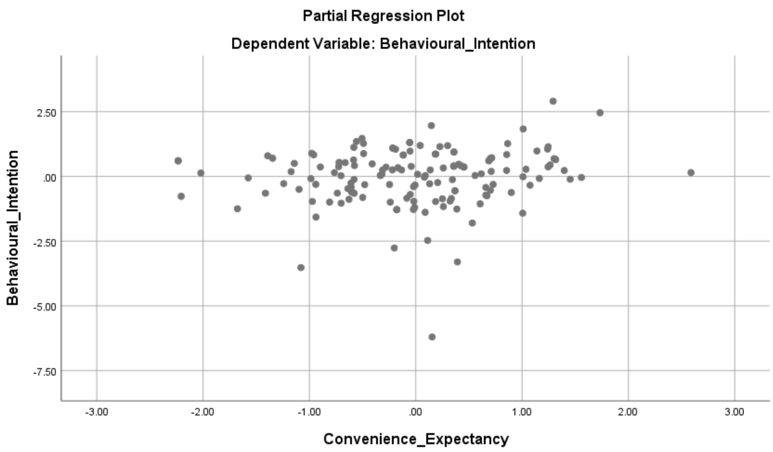
Assumption of homoscedasticity and linearity

As mentioned before ideally when looking at the scatterplot we would want the points relatively evenly spread among the values of -3 to 3 on both axes on no distinct pattern. When creating the regression plot we have additionally created partial regression plots for each individual variable. Here we can see the results are again homoscedastic and linear. While at first glance the partial regression plot of the individual variable of hedonic motivation seems heteroscedastic on closer inspection we can see that this has been caused by a single outlier.

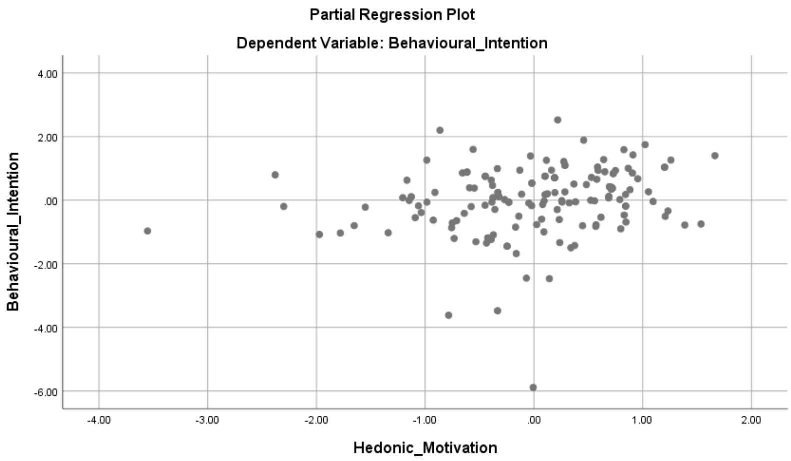
Performance expectancy



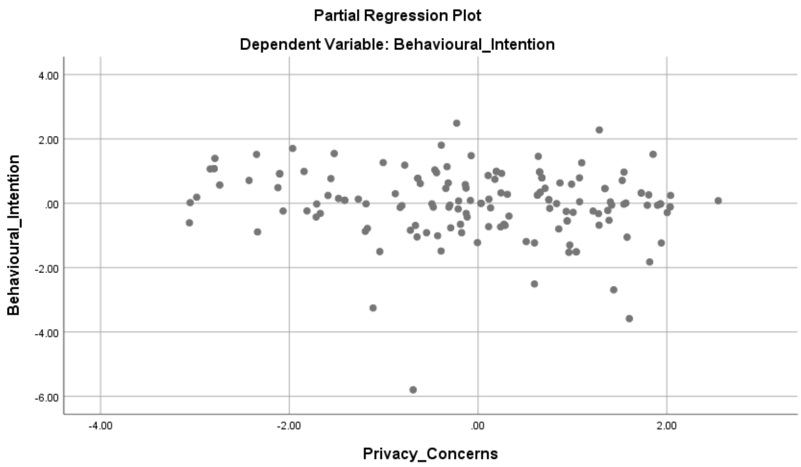
Convenience expectancy



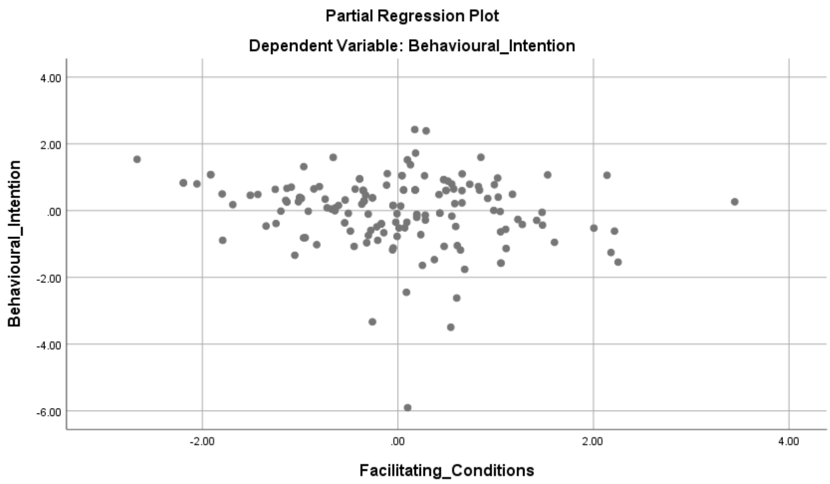
Hedonic motivation



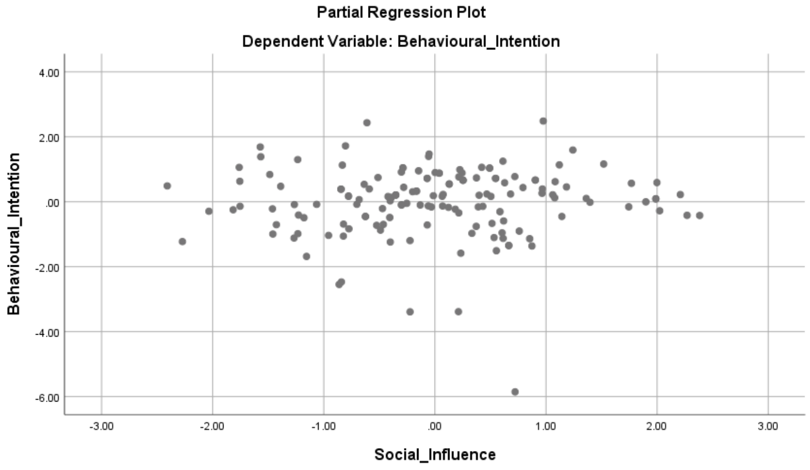
Privacy concerns



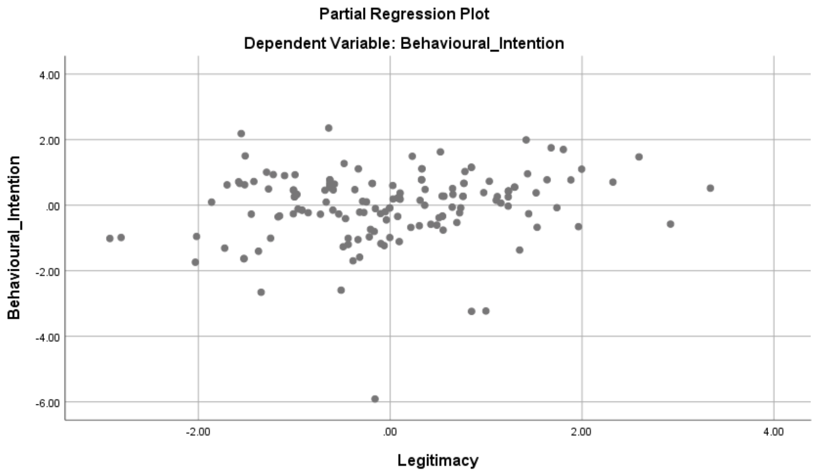
Facilitating conditions



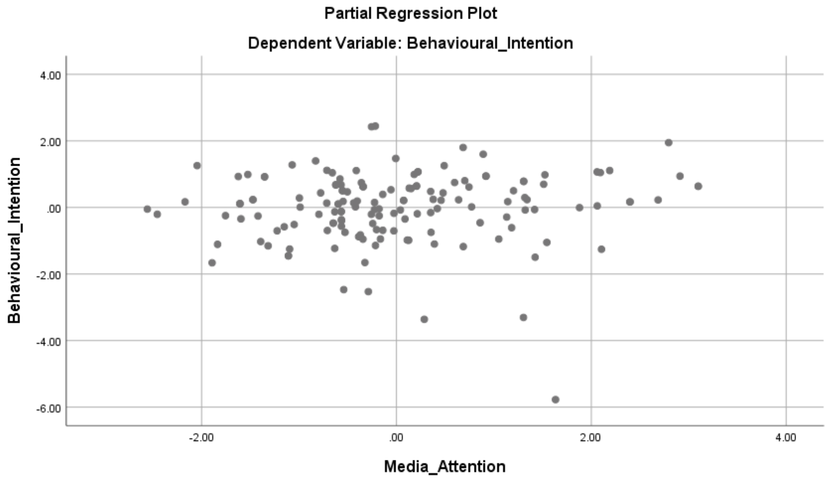
Social influence



Legitimacy



Media Attention



APPENDIX 8 – Descriptive statistics and correlation table

Experience

Experience_MH (experience level average or above)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	26	16.0	16.0	16.0
	Yes	137	84.0	84.0	100.0
	Total	163	100.0	100.0	

Gender

GenderID_Female (respondent identifies as female)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	80	49.1	49.1	49.1
	Yes	83	50.9	50.9	100.0
	Total	163	100.0	100.0	

Descriptive statistics

Descriptive Statistics

	N	Mean	Std. Deviation
Age	153	34.50	13.168
Behavioural_Intention	163	3.9632	1.97168
Performance_Expectancy	163	4.3170	1.73948
Convenience_Expectancy	163	4.7628	1.58989
Hedonic_Motivation	163	3.7464	1.81248
Privacy_Concerns	163	5.1493	1.39966
Facilitating_Conditions	163	5.4131	1.45948
Social_Influence	163	4.0470	1.54533
Legitimacy	163	4.0654	1.74776
Media_Attention	163	3.5460	1.56952
Experience_MH	163	.8405	.36728
GenderID_Female	163	.5092	.50146
Valid N (listwise)	153		

Correlations Spearman's Rho two-tailed

Correlations

			Age	Behavioural_Intention	Performance_Expectancy	Convenience_Expectancy	Hedonic_Motivation	Privacy_Concerns	Facilitating_Conditions	Social_Influence	Legitimacy	Media_Attention	GenderID_Female	Experience_MH
Spearman's rho	Age	Correlation Coefficient	1.000	-.093	-.082	-.311**	-.112	-.022	-.314**	-.154	-.091	-.077	.037	-.386**
		Sig. (2-tailed)	.	.250	.316	.000	.168	.787	.000	.058	.265	.341	.649	.000
		N	153	153	153	153	153	153	153	153	153	153	153	153
	Behavioural_Intention	Correlation Coefficient	-.093	1.000	.793**	.662**	.799**	-.237**	.374**	.615**	.616**	.532**	-.019	.309**
		Sig. (2-tailed)	.250	.	.000	.000	.000	.002	.000	.000	.000	.000	.813	.000
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Performance_Expectancy	Correlation Coefficient	-.082	.793**	1.000	.710**	.848**	-.120	.467**	.678**	.662**	.501**	-.093	.283**
		Sig. (2-tailed)	.316	.000	.	.000	.000	.126	.000	.000	.000	.000	.240	.000
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Convenience_Expectancy	Correlation Coefficient	-.311**	.662**	.710**	1.000	.670**	-.049	.576**	.563**	.555**	.403**	-.016	.397**
		Sig. (2-tailed)	.000	.000	.000	.	.000	.537	.000	.000	.000	.000	.838	.000
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Hedonic_Motivation	Correlation Coefficient	-.112	.799**	.848**	.670**	1.000	-.255**	.343**	.679**	.622**	.531**	.026	.271**
		Sig. (2-tailed)	.168	.000	.000	.000	.	.001	.000	.000	.000	.000	.741	.000
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Privacy_Concerns	Correlation Coefficient	-.022	-.237**	-.120	-.049	-.255**	1.000	.016	-.165*	-.084	-.177*	-.021	-.089
		Sig. (2-tailed)	.787	.002	.126	.537	.001	.	.838	.036	.285	.023	.793	.256
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Facilitating_Conditions	Correlation Coefficient	-.314**	.374**	.467**	.576**	.343**	.016	1.000	.425**	.353**	.300**	-.015	.350**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.838	.	.000	.000	.000	.854	.000
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Social_Influence	Correlation Coefficient	-.154	.615**	.678**	.563**	.679**	-.165*	.425**	1.000	.550**	.457**	.002	.144
		Sig. (2-tailed)	.058	.000	.000	.000	.000	.036	.000	.	.000	.000	.984	.067
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Legitimacy	Correlation Coefficient	-.091	.616**	.662**	.555**	.622**	-.084	.353**	.550**	1.000	.603**	-.089	.129
		Sig. (2-tailed)	.265	.000	.000	.000	.000	.285	.000	.000	.	.000	.259	.101
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Media_Attention	Correlation Coefficient	-.077	.532**	.501**	.403**	.531**	-.177*	.300**	.457**	.603**	1.000	-.090	.139
		Sig. (2-tailed)	.341	.000	.000	.000	.000	.023	.000	.000	.000	.	.251	.077
		N	153	163	163	163	163	163	163	163	163	163	163	163
	GenderID_Female	Correlation Coefficient	.037	-.019	-.093	-.016	.026	-.021	-.015	.002	-.089	-.090	1.000	.008
		Sig. (2-tailed)	.649	.813	.240	.838	.741	.793	.854	.984	.259	.251	.	.919
		N	153	163	163	163	163	163	163	163	163	163	163	163
	Experience_MH	Correlation Coefficient	-.386**	.309**	.283**	.397**	.271**	-.089	.350**	.144	.129	.139	.008	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.256	.000	.067	.101	.077	.919	.
		N	153	163	163	163	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

<u>Correlations Pearson two-tailed</u>

Correlations

		Age	Behavioural_Intention	Performance_Expectancy	Convenience_Expectancy	Hedonic_Motivation	Privacy_Concerns	Facilitating_Conditions	Social_Influence	Legitimacy	Media_Attention	GenderID_Female	Experience_MH
Age	Pearson Correlation	1	-.123	-.109	-.399**	-.123	-.069	-.345**	-.144	-.086	-.096	.066	-.409**
	Sig. (2-tailed)		.128	.182	.000	.128	.394	.000	.075	.292	.240	.418	.000
	N	153	153	153	153	153	153	153	153	153	153	153	153
Behavioural_Intention	Pearson Correlation	-.123	1	.782**	.640**	.788**	-.224**	.380**	.603**	.643**	.526**	-.025	.333**
	Sig. (2-tailed)	.128		.000	.000	.000	.004	.000	.000	.000	.000	.755	.000
	N	153	163	163	163	163	163	163	163	163	163	163	163
Performance_Expectancy	Pearson Correlation	-.109	.782**	1	.701**	.843**	-.090	.508**	.675**	.674**	.512**	-.094	.286**
	Sig. (2-tailed)	.182	.000		.000	.000	.253	.000	.000	.000	.000	.232	.000
	N	153	163	163	163	163	163	163	163	163	163	163	163
Convenience_Expectancy	Pearson Correlation	-.399**	.640**	.701**	1	.668**	-.048	.642**	.561**	.561**	.391**	-.041	.432**
	Sig. (2-tailed)	.000	.000	.000		.000	.545	.000	.000	.000	.000	.602	.000
	N	153	163	163	163	163	163	163	163	163	163	163	163
Hedonic_Motivation	Pearson Correlation	-.123	.788**	.843**	.668**	1	-.229**	.384**	.683**	.648**	.541**	.021	.267**
	Sig. (2-tailed)	.128	.000	.000	.000		.003	.000	.000	.000	.000	.793	.001
	N	153	163	163	163	163	163	163	163	163	163	163	163
Privacy_Concerns	Pearson Correlation	-.069	-.224**	-.090	-.048	-.229**	1	.033	-.172*	-.111	-.168*	-.024	-.085
	Sig. (2-tailed)	.394	.004	.253	.545	.003		.675	.028	.160	.032	.761	.278
	N	153	163	163	163	163	163	163	163	163	163	163	163
Facilitating_Conditions	Pearson Correlation	-.345**	.380**	.508**	.642**	.384**	.033	1	.460**	.410**	.311**	-.056	.435**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.675		.000	.000	.000	.479	.000
	N	153	163	163	163	163	163	163	163	163	163	163	163
Social_Influence	Pearson Correlation	-.144	.603**	.675**	.561**	.683**	-.172*	.460**	1	.589**	.473**	.011	.158*
	Sig. (2-tailed)	.075	.000	.000	.000	.000	.028	.000		.000	.000	.885	.044
	N	153	163	163	163	163	163	163	163	163	163	163	163
Legitimacy	Pearson Correlation	-.086	.643**	.674**	.561**	.648**	-.111	.410**	.589**	1	.636**	-.073	.129
	Sig. (2-tailed)	.292	.000	.000	.000	.000	.160	.000	.000		.000	.351	.102
	N	153	163	163	163	163	163	163	163	163	163	163	163
Media_Attention	Pearson Correlation	-.096	.526**	.512**	.391**	.541**	-.168*	.311**	.473**	.636**	1	-.076	.138
	Sig. (2-tailed)	.240	.000	.000	.000	.000	.032	.000	.000	.000		.337	.080
	N	153	163	163	163	163	163	163	163	163	163	163	163
GenderID_Female	Pearson Correlation	.066	-.025	-.094	-.041	.021	-.024	-.056	.011	-.073	-.076	1	.008
	Sig. (2-tailed)	.418	.755	.232	.602	.793	.761	.479	.885	.351	.337		.919
	N	153	163	163	163	163	163	163	163	163	163	163	163
Experience_MH	Pearson Correlation	-.409**	.333**	.286**	.432**	.267**	-.085	.435**	.158*	.129	.138	.008	1
	Sig. (2-tailed)	.000	.000	.000	.000	.001	.278	.000	.044	.102	.080	.919	
	N	153	163	163	163	163	163	163	163	163	163	163	163

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX 9 – Multiple regression analysis output

Model summary

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.347[a]	.120	.103	1.84773	.120	6.787	3	149	.000	
2	.834[b]	.696	.673	1.11595	.576	33.436	8	141	.000	1.994

a. Predictors: (Constant), Experience_MH, GenderID_Female, Age

b. Predictors: (Constant), Experience_MH, GenderID_Female, Age, Privacy_Concerns, Legitimacy, Facilitating_Conditions, Media_Attention, Social_Influence, Hedonic_Motivation, Convenience_Expectancy, Performance_Expectancy

c. Dependent Variable: Behavioural_Intention

ANOVA table output

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	69.516	3	23.172	6.787	.000[b]
	Residual	508.703	149	3.414		
	Total	578.219	152			
2	Regression	402.626	11	36.602	29.391	.000[c]
	Residual	175.593	141	1.245		
	Total	578.219	152			

a. Dependent Variable: Behavioural_Intention

b. Predictors: (Constant), Age, GenderID_Female, Experience_MH

c. Predictors: (Constant), Age, GenderID_Female, Experience_MH, Privacy_Concerns, Legitimacy, Facilitating_Conditions, Media_Attention, Social_Influence, Hedonic_Motivation, Convenience_Expectancy, Performance_Expectancy

Coefficients output

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.408	.714		3.374	.001					
	Age	.003	.013	.024	.279	.780	-.123	.023	.021	.829	1.207
	GenderID_Female	-.140	.300	-.036	-.466	.642	-.038	-.038	-.036	.995	1.005
	Experience_MH	1.924	.458	.354	4.199	.000	.344	.325	.323	.832	1.201
2	(Constant)	-.004	.719		-.006	.995					
	Age	.005	.008	.033	.583	.561	-.123	.049	.027	.685	1.461
	GenderID_Female	.051	.189	.013	.271	.787	-.038	.023	.013	.907	1.102
	Experience_MH	.766	.308	.141	2.482	.014	.344	.205	.115	.670	1.493
	Performance_Expectancy	.394	.121	.352	3.247	.001	.780	.264	.151	.184	5.448
	Convenience_Expectancy	.185	.109	.149	1.693	.093	.635	.141	.079	.279	3.582
	Hedonic_Motivation	.240	.111	.221	2.168	.032	.772	.180	.101	.207	4.822
	Privacy_Concerns	-.105	.068	-.076	-1.544	.125	-.203	-.129	-.072	.881	1.135
	Facilitating_Conditions	-.169	.093	-.129	-1.824	.070	.395	-.152	-.085	.430	2.327
	Social_Influence	.058	.094	.045	.613	.541	.620	.052	.028	.396	2.526
	Legitimacy	.154	.082	.137	1.872	.063	.635	.156	.087	.403	2.480
	Media_Attention	.081	.078	.065	1.032	.304	.521	.087	.048	.550	1.819

a. Dependent Variable: Behavioural_Intention