# How does information technology influence the behavior intention to use nutrition *e-Health* services?

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Dissertation submitted in partial fulfilment of requirements for the MSc in Management with Specialization in Strategic Marketing, at the Universidade Católica Portuguesa, April 2022

**ABSTRACT**

Covid-19 is an enable factor of new *e-Health* technology data-driven services which catalyzes the development of virtual personalized people-driven and preventive digital services model integrated into daily life. The access to individuals' data provides solutions that ensure the safest health information technology. However, people still feel their data is at risk.

The present paper aims to examine the key factors affecting health information technology as a strategy to improve the usage of smart nutrition services in the online environment. The study was conducted to assess the impact of IT towards storing and sharing individuals` health data and influencing their judgments about trust and behavioral intention to use *e-Health* apps in comparison with face-to-face consultation services.

The technology acceptance model has been extended by introducing new factors (perceived risk, security, data privacy and behavioral intention to use the service) that allow to study the online consumer behavior and perceived threat associated with the type of data stored and shared**.** Findings revealed that health IT increased consumers` perceptions about perceived risk of data sharing and trust regarding the type of data stored and shared. However, it decreased consumers `perceptions about *e-Health* nutrition services related to perceived utility, data safety, trust, risk and behavioral intention to use these services.

This research will help to empirically explore and test the suggested model in terms of social influence factors and the acceptance of using technology on health services in an emerging research area.

**Title:** How does information technology influence the behavior intention to use nutrition *e-Health* services?

**Author:** Madalena Reinas de Sá Lourenço

**Keywords:** Health Information Technology (IT); Technology Acceptance; *E-Health* services; Data Privacy; Perceived Risk; Behavioral Intention; Online consumer behavior; Psychological Distance

**SUMÁRIO**

A covid-19 é um fator impulsionador de novos serviços digitais personalizados e preventivos através do uso de dados de tecnologia de informação de saúde. O acesso aos dados permite assistir as pessoas no seu dia-a-dia, garantindo o uso mais seguro da tecnologia. Porém, as pessoas continuam a sentir que seus dados pessoais estão em risco.

A presente dissertação pretende avaliar os principais fatores que afetam o uso da tecnologia de informação de saúde como uma estratégia de aperfeiçoamento dos serviços de nutrição "inteligentes" no contexto online. O impacto da tecnologia relativamente ao armazenamento e compartilhamento de dados avalia a forma como os consumidores são influenciados pela confiança e intenção comportamental de uso de serviços *e-Saúde* comparativamente às consultas de nutrição presenciais.

O modelo de aceitação da tecnologia foi alargado com a introdução de novos fatores (risco percebido, segurança e privacidade de dados), permitindo estudar o comportamento do consumidor no contexto online e a sua perceção de ameaça associada ao tipo de dados. Os resultados revelaram que a tecnologia aumentou as perceções dos consumidores sobre o risco percebido do uso de dados pessoais e a confiança em relação aos dados armazenados e compartilhados. Todavia, diminuiu as perceções relativamente à utilidade percebida, segurança, confiança, risco e intenção comportamental de uso dos serviços *e-Saúde.*

O presente estudo ajudará a explorar e testar empiricamente o modelo sugerido relativamente a fatores de influência social, bem como melhorar a aceitação do uso de tecnologia em serviços de saúde em uma área de pesquisa emergente.

**Título:** Como a tecnologia da informação influencia a intenção comportamental de usar serviços de nutrição *e-Saúde*?

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**Palavra – Chave:** Tecnologia de Informação da Saúde (TI); Aceitação de Tecnologia; Serviços de e-*Saúde*; Privacidade de Dados; Risco Percebido; Intenção Comportamental; Comportamento online do consumidor; Distância Psicológica

**ACKNOWLEDGEMENTS**

This journey has been challenging, especially, during these pandemic times because dissertation seminars and the whole process of writing the thesis moved to an online context. Consequently, it increased the physical distance between students and supervisors. Thankfully, I have been surrounded by inspiring and helpful people that supported me during my dissertation semester.

First, I would like to thank to my supervisor Sofia Jacinto for her guidance and availability to encourage and support me to do an excellent thesis. Apart from giving me useful and important insights, she was always patient and resilient to my doubts whether via Zoom or email.

Furthermore, I would like to express my gratefulness to my dissertation seminar colleagues – Duarte Pinto Gonçalves, Inês Rodrigues, Nadja, Raquel Sousa and Sandra Caetano. The mutual help between each other was extremely important to make the path less stressful, anxious and also to become possible to achieve greater successes.

Then, my gratefulness will be to my closest friends who always encouraging me to write a dissertation thesis with passion and motivation about the chosen topic and to not lose my focus or do not feel stressful during the process. A special thanks to Beatriz Carvalho, Franscisca Resende, Joana Pontes, Manuel Rodrigues and Margarida Ponte.

An absolute gratitude to Inês Grosso, an amazing friend that I made at Católica - Lisbon during my bachelor and that follow her master studies in the same specialization as I follow – master's in management with specialization in Strategic Marketing. Inês was involved in the entire process of my thesis which made this semester to seemed less lonely and stressful period of my life. There are no words to thank for all the support that she gave me.

Lastly, a special thanks to my family. More precisely, to my parents and brother who always believe in me and support me personally, emotionally and financially. They always encourage me to believe in myself, to follow my dreams and to never give up of anything in life.

*Thank you all.*

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# CHAPTER 1: INTRODUCTION

## 1.1. Background, Problem Statement and Relevance

The healthcare industry has been marked by an increasingly transformation and rapid growth of the internet of things technology. Specifically, in the nutrition health services, new opportunities enhance personalized solutions to manage eating habits and to support consumers on regulating their calories.

Covid-19 is an enable factor of health information technology associated to consumers` acceptance of using smart digital nutrition apps. Several studies aimed to examine the impact of technology as a strategy to identify changes in consumer behaviour and educational knowledge towards the usage of *e-Health* apps (Ling, L. P., & Yazdanifard, R., 2014).

The evolution of telemedicine's technology services to mobile platforms driven by information technology significantly helped individuals to change their healthy eating habits through the possibility of having access to their personal health data on nutrition mobile apps (DiFilippo, K. N., Huang, W. H., Andrade, J. E., & Chapman-Novakofski, K. M., 2015).

However, health IT turns consumers more reluctant towards accepting and using *e-Health* services due to risk perception (Kumar, D., & Dange, U., 2012; Papa, A., Mital, M., Pisano, P., & Del Giudice, M., 2020; Wu, J. H., & Wang, S. C., 2005).

Consumers `risk perception and the lack of affordable and effective technology are the main barriers associated with the future growth of e-services. In fact, *e-Health* nutrition apps store and share individuals` data with 3rd parties without their consent. Therefore, it increases risk perception and threat. In contrast, it reduces consumers` privacy, security and trust (Vest, J. R., & Gamm, L. D., 2010).

The unified theory of acceptance and use of technology proposed a model to enhance data privacy protection which contributes to better control the access to individuals' personal health data in digital platforms (Hsu, C. L., Lee, M. R., & Su, C. H., 2013).

A crucial factor which influences consumer behaviour to accept the usage of *e-Health* services is the psychological distance. Construal level theory found that higher psychological distance leads to different judgments and decisions than lower psychological distance (Trope, Y., Liberman, N., & Wakslak, C., 2007).

Traditional face-to-face healthcare services and new *e-Health* services differ in the distance between the user and the person who provides the service. For example, in the face-to-face nutrition consultation service, the nutritionist records users` eating habits closer to the patient of the service while in a nutrition consultation made through an app the same service is conceptually provided by professionals that are distant from the user. Additionally, this distance is even higher in apps services where professionals are represented by an abstract entity or not mentioned at all.

The technology acceptance model was extended to introduce new factors to assess and explain detailed consumers` acceptance and usage of new technology on *e-Health* nutrition services (Davis, Davis et al., 1980; Wu, J. H., & Wang, S. C., 2005). The present research also integrates the theory of planned behaviour to better predict and explain consumers` attitudes, perceptions, intentions and psychological behaviours (Holden, R. J., & Karsh, B. T., 2010; Wu, J. H., & Wang, S. C., 2005).

These theoretical frameworks were used to support and evaluate how *e-Health* services dedicated to assist eating habits will influence users' acceptance of information technology that stores and shares their personal health data.

This research will contribute to improve some of the factors that hinder the usage of nutrition *e-Health* services as well as to better understand the characteristics which make nutrition mobile apps services more effective in supporting behavioural changes and to increase educational knowledge about nutrition health.

### 1.2. Research Objectives and Questions

The purpose of this study is to understand in which conditions the usage of health IT (biometric and emotional states) database systems will help to boost trust and behavioural intention to use nutrition *e-Health* and well-being services in an online context in comparison with offline environments.

Specifically, it is argued that health IT can increase consumers' attitudes towards nutrition *e-Health* services by increasing individuals' expected satisfaction and efficacy of psychological well-being.

Additionally, it aims to better understand consumers` perceptions about their technology acceptance of nutrition services that use health IT in terms of security, trustfulness and privacy to stored and shared personal health data.

In summary, this study seeks to answer three main research questions related to the factors that may influence consumers' acceptance of using health IT on nutrition *e-Health* services:

**RQ1:** How does the presence and the type of health IT stored and shared influence the trust to use nutrition services in an online environment when compared to offline contexts?

**RQ2:** How does the presence and the type of health IT stored and shared influence consumers `perceptions and attitudes regarding the technology acceptance of using nutrition health services in an online environment when compared to offline contexts?

**RQ3:** How does the presence and the type of health IT stored and shared influence consumers' behavioural intention to use nutrition health services in an online environment when compared to offline contexts?

These research questions were answer based on an experimental design that aims to investigate the effect of perceived threat towards storing and sharing consumers` personal health data on nutrition *e-Health* services that use health IT system in comparison with offline services.

Similarly, on an individual level, it is assessed consumers` perceived utility, trust, expected efficacy of psychological well-being, technology acceptance of using health IT in nutrition services (perceived risk, data privacy, security and willingness to pay), expected satisfaction and behavioural intention to use those services.

This research examines literature related to the technology acceptance towards using health IT and consumer behaviour theory. Specifically, it studies the theory of construal level and the effects of psychological distance.

Additionally, it is assessed consumer behaviour and barriers associated with nutrition health and well-being services in an online versus offline context by evaluating the innovation and impact of personal choices on an individual level provided by the usage of information technology.

Furthermore, this chapter expands the role of the type of information towards users' judgments of perceived risk, data privacy and security associated with consumers data storing and sharing on health IT database systems.

Moreover, it is also discussed the factors that might influence consumers to change their perceptions and attitudes to use *e-Health* services as well as the effect of those factors towards increasing trust and behavioural intention to use these nutrition e-services.

To sum up, this research will contribute to gain new insights and to better understand how the technology acceptance of using health IT on nutrition health services can overcome some psychological and behavioural barriers associated to the usage of nutrition health and well-being apps.

# CHAPTER 2: LITERATURE REVIEW

## 2.1. Healthcare and Well-being Consumer Behaviour

### 2.1.1. Online versus Offline Context

In the last decades, the usage of e-services has been growing because of globalization and digitalization. The online experience is constantly improved by adapting to consumer behaviour changes in order to meet individuals needs and wants. Therefore, it enhances behaviour intention and motivation to use e-services (Kumar, D., & Dange, U., 2012; Wolfinbarger, M., & Gilly, M., 2000).

Studies have shown that online and offline consumer behaviour involve internal and external influences that contribute for different shopping experiences even when the same service is provided to consumers (Katawetawaraks, C., & Wang, C.,2011).

Online consumer behaviour is influenced by individuals' characteristics (personality traits) and how people process information (attitudes and perceptions). Additionally, it is also influenced by demographic factors such as socio-economics aspects, culture and the technology public policy associated with 3rd parties and legal frameworks (Kumar, D., & Dange, U., 2012).

Literature revealed that online usage of e-services is associated with higher levels of perceived risk (physical and psychological) and low levels of security associated with data privacy and trust (Holden, R. J., & Karsh, B. T., 2010).

The technology acceptance model and the innovative theory of planned behaviour contributes to understand online consumer behaviour since it is evolving the technology acceptance and use of health IT together with psychological behaviours (behavioural, normative and control beliefs) (Cao & Mokhtarian, 2007).

Attitude and normative beliefs depending on the context might influence consumer's behavioural intention to use e-services which will affect the actual consumer behaviour (Bae & Lee, 2011; Cao & Mokhtarian, 2007).

### 2.1.2. Psychology Distance

Individuals `mental construal can influence consumer behaviour, perceptions and predictions of quality, desirability and psychological characteristics about the use of health services. The construal level theory of psychological distance has shown that individuals' mental construal is affected by spatial psychological distance between consumers and nutrition health services.

As psychological distance increases the level of abstraction, nutrition services can be divided into low (face-to-face nutrition consultation services) and high (*e-Health* apps) levels of psychological distance (Trope, Y., Liberman, N., & Wakslak, C., 2007).

Over the time, *e-Health* nutrition services provide concerns of less reliability related to the information provided to consumers which make predictions about *e-Health* apps being influenced by general trends (Trope, Y., Liberman, N., & Wakslak, C., 2007).

For that reason, the construal level theory emphasizes the desirability-feasibility distinction information across consumers decision-making. In fact, desirability-related information strongly influences the behavioural intention to use *e-Health* services in comparison with face-to-face nutrition consultation services (Trope, Y., Liberman, N., & Wakslak, C., 2007).

As psychological distance increases, individuals` attitudes and perceptions towards the behaviour intention to use e-services and the perceived risk associated with those services make consumers rely more on *e-Health* nutrition apps (Trope, Y., Liberman, N., & Wakslak, C., 2007).

## 2.2. Health Information Technology

### 2.2.1. Technology Acceptance

The technology acceptance model and the unified theory of acceptance and use of technology help explain the factors that influence consumers acceptance or rejection to use information technology on nutrition health services (Davis, 1989; Adams, Nelson, and Todd, 1992; Jackson, Chow, and Leitch, 1997; Gefen et al., 2003; Venkatesh et al., 2003).

When a new information technology is introduced in healthcare and well-being services, the technology acceptance model is extended to study new factors that can influence the behavioural intention to accept and use IT, mainly, perceived usefulness and ease of use, trust, expected efficacy of psychological well-being, risk, data privacy, security, expected satisfaction, willingness to pay and behavioural intention to use the service.

As consumers are increasingly being more technology savvy, they require access to vital information related to the type of data stored and shared across the different types of nutrition health services (face-to-face consultations or *e-Health* apps) (Trope, Y., Liberman, N., & Wakslak, C., 2007).

Due to technological acceptance and progress, healthcare information sharing issues cannot be solved automatically which increases the concern related to data privacy and security when health information exchange collects personal health data.

However, health information exchange can cause some disruptive innovations since it contributes to improve the quality and efficiency of e-services as consumers behaviour profiles and trends are constantly changing (Vest, J. R., & Gamm, L. D., 2010).

The theory of planned behavior contributes to study the effects of health information technology towards consumers` psychological behavior changes (Cao & Mokhtarian, 2007; Holden, R. J., & Karsh, B. T. ,2010 & Wu, J. H., & Wang, S. C., 2005).

**2.2.1.1. Perceived Usefulness & Ease of Use**

Perceived usefulness is a factor that enhances the performance of nutrition services which uses health information technology to achieve more accurate consumer behaviour attitudes and perceptions about efficiency and efficacy of health services. (Holden, R. J., & Karsh, B. T., 2010; Papa, A., Mital, M., Pisano, P., & Del Giudice, M., 2020; Wu, J. H., & Wang, S. C., 2005).

To measure consumers ‘attitudes towards using nutrition health services, perceived usefulness is considered an independent effect that influences the behavioural intention to use those services (Papa, A., Mital, M., Pisano, P., & Del Giudice, M., 2020; Wu, J. H., & Wang, S. C., 2005).

The technology acceptance model emphasizes that perceived ease of use influences perceived usefulness because the perceived ease of use measures the ease and quick usage of the nutrition e-services to provide clear information to consumers (Wu, J. H., & Wang, S. C., 2005).

### 2.2.2. Health Information Technology Data

The adoption of electronic health information technology is used as a potential digital health IT infrastructure technique of information exchange not only to improve consumers quality of healthcare and well-being but also to promote a trade-off balance between individuals` data privacy, security and behavioural intention to use e-services (Vest, J. R., & Gamm, L. D., 2010; Wu, J. H., & Wang, S. C., 2005).

Literature defines IT as the applied information process of collecting, storing, managing, sharing and usage of health IT towards helping individuals to change their eating habits and well-being (Wu, J. H., & Wang, S. C., 2005).

Moreover, health IT is a crucial technique to determine the effects of efficacy, efficiency and expected satisfaction which influence the behavioural intention to use these nutrition *e-Health* services (Papa, A., Mital, M., Pisano, P., & Del Giudice, M., 2020).

However, there are some barriers associated with the fragmented information stored and shared that negatively influence the efficiency, usability and interoperability usage of *e-Health* nutrition services while individuals` personal data is processed (Vest, J. R., & Gamm, L. D., 2010).

#### 2.2.2.1. Psychology Health Data

In the online environment, data privacy can be collected, stored and shared by information technology database systems or 3rd parties that make consumers feel more anxious towards the diverse types of risk that may emerge when they use *e-Health* services, specially, when it is stored or shared their emotional states (De Castella, K., Platow, M. J., Tamir, M., & Gross, J. J., 2018; Wu, J. H., & Wang, S. C., 2005). Previous research revealed that low emotion regulation self-efficacy predicts high levels of anxiety and worry towards the usage of e-services (Tahmassian & Moghadam,2011).

To reduce individuals` psychological risk associated with sharing issues of data privacy, the Federal Trade Commission prohibit *e-Health* services of storing and sharing consumers` personal health data if the usage of unfair and deceptive trade practices are violated (Earp and Baumer, 2001).

For that reason, the theory of planned behaviour contributes to measure psychological risks (anxiety, worry, increase of self-esteem and self-image) of individuals` sharing their emotional states as well as how it affects consumers` technology acceptance of using *e-Health* services that store and share their psychological information and emotional states (Holden, R. J., & Karsh, B. T.,2010).

### 2.2.3. Perceived Risk

The theory of perceived risk explains consumers behaviour intention to use *e-Health* nutrition services according to their perception of risk. Perceived risk is associated with physical, social and psychological risks when individuals use e-services (Wu, J. H., & Wang, S. C., 2005).

As risk is considered a major concern towards the usage of e-services, there are consumers who perceive potential risks of using immature health IT while other individuals do not feel trust to share their personal health data. Consequently, it leads to reduce privacy, security and efficiency of using *e-Health* services (Petrtyl,2012; Wu, J. H., & Wang, S. C.,2005).

Moreover, females perceive higher risk towards using online services compared to males, being females considered more worried, anxious and willing to search for more information and consumers` reviews before using a service in comparison to males (Bae & Lee, 2011; Ling, L. P., & Yazdanifard, R., 2014).

The construal level theory outlines that risk perception can be used as a distance-related factor to manipulate the concreteness risk associated with the communication of perceived threat throughout the level of psychological distance used in health services (online versus offline nutrition services). Thus, it will influence individuals` perceived threat associated with the storage and sharing of personal health data and the behavioural intention to use these services (Trope, Y., Liberman, N., & Wakslak, C., 2007).

Health insurance portability and accountability act established the necessity standards of using electronic data interchange and confidentiality towards individuals `personal health data with 3rd parties. In fact, security in cyberspace is associated by consumers` perception of risk affinity with the usage of *e-Health* services (Alreck, DiBartolo, Diriker & Settle, n.d.; Bae & Lee, 2011; Fan &

Miao, 2012; Garbarino & Strahilevitz, 2004; Sarkar, 2011; Veronika, 2013; Vest, J. R., & Gamm, L. D.,2010).

### 2.2.4. Perceived Security

Throughout the increased use of *e-Health* services, consumers `personal health data can be stored, shared and violated by 3rd parties easily. It contributes for privacy and security being considered a concern for e-consumers (Hsu, C. L., Lee, M. R., & Su, C. H., 2013).

Particularly, younger and wealthier consumers use *e-Health* services despite the concerns of perceived risk and security associated to the online context when similar services are offered in the offline context (Kumar, D., & Dange, U., 2012).

Information security is used to generate confidentiality, integrity and availability of consumers` personal health data, meaning that perceived security is associated to the degree of which an individual believes that using privacy-enhanced health information systems is secure and it generates an increase of trust to use *e-Health* nutrition services (Kumar, D., & Dange, U., 2012; Petrtyl, 2012; Suki, 2002).

Perceived security can be obtained by using third-party privacy and security protection such as encryption, passwords protection or *TRUSTe* to ensure security commitment for e-consumers. Thus, it contributes to increase consumers security and behavioural intention to use *e-Health* nutrition services more often (Hsu, C. L., Lee, M. R., & Su, C. H., 2013; Katawetawaraks, C., & Wang, C.,2011; Kumar, D., & Dange, U., 2012).

## 2.3. Behavioural intention to use services

The end-user satisfaction to technological acceptance of health information technology and social changes determines the behavioural intention to use *e-Health* services by measuring the reliability to predict actual individuals` usage of nutrition services (Holden, R.J., & Karsh, B. T., 2010; Papa, A., Mital, M., Pisano, P., & Del Giudice, M., 2020).

Perceived risk is an impactful determinant of consumers ‘attitudes and judgments towards the use of e-services which can have a direct negative effect on consumers` behavioral intention to use *e-*

*Health* services since the online context involves a certain degree of uncertainty (Wu, J. H., & Wang, S. C., 2005).

### 2.3.1. Perceived Trust

Online trust is the basis to build relationship with consumers. In fact, the use of e-services depends on consumers` level of perceived trust which negatively influence the behavioural intention to use *e-Health* services (Cheung and Lee, 2006).

Literature reveals that perceived online trust is lower than face-to-face nutrition consultation services interactions due to lower perceived security and lower data privacy sharing control over individuals` personal health data (Cassell and Bickmore, 2000; Kumar, D., & Dange, U., 2012).

For that reason, consumers` trust on e-services depends on how much data privacy security is given to individuals, meaning that *e-Health* services reliability is affected by external (reference groups, demographic characteristics, socioeconomics, technology and public policy) and internal (perceptions, motivations, self-image, attitudes and educational) factors that contributes for reducing consumers `trust (Kumar, D., & Dange, U., 2012).

### 2.3.2. Expected Satisfaction

Consumer satisfaction is an important key factor for the success of e-commerce services through the measurement of individuals` experiences and involvement with the use of *e-Health* nutrition services that it is positively influenced by consumers` expectations (Katawetawaraks, C., & Wang, C., 2011; Kumar, M., 2016).

Literature has outlined that higher levels of consumer satisfaction contribute to increase the level of consumer loyalty of using e-services which, consequently, increases the behavioral intention to use those nutrition services (Kumar, M., 2016).

In fact, satisfaction is measured according to consumers` rating and reviews towards their experience with *e-Health* services. Therefore, the use of e-services has been promoting more satisfaction to consumers who are looking for convenience and speed offered by the service in contrast with consumers who feel lack of trust to use e-services (Yu and Wu, 2007).

### 2.3.3. Willingness to Pay

Generically, consumers value more physical services in comparison with digital ones, meaning that individuals are willing to pay more for a face-to-face nutrition consultation service compared to the equivalent digital service. However, the convenience of *e-Health* services is considered a factor for consumers` willing to pay more (Kooti, F., Lerman, K., Aiello, L. M., Grbovic, M., Djuric, N., & Radosavljevic, V., 2016, February; Wang et al.,2005).

The difference of value between digital and physical services is mediated by the differences in psychological ownership of consumers individual perceptions related to the psychological distance between consumers and the service (face-to-face consultations or *e-Health* services). Specifically, offline services have higher capacity to associate the self (psychological and ownership) with the type of service provided to consumers in order to generate higher willingness to pay (Akalamkam, K., & Mitra, J. K., 2018).

Summing up, this research study adopted the technology acceptance model and extended it to study new factors that can positively or negatively affect the interaction between the type of service (online or offline) and the type of data stored and shared (control condition (no data stored), biometric data or emotional states). This method was adapted and extended to better understand consumer behaviour changes (attitudes and perceptions) across the environment that they are exposed to and the technology acceptance of using health IT database systems in nutrition services.

## CHAPTER 3: CONCEPTUAL MODEL AND FRAMEWORK

Throughout the literature review section, it was presented the factors that influence consumers` acceptance of using health IT on *e-Health* nutrition services as well as the degree of perceived threat associated with the type of data stored and shared provided by the services.

This chapter is focused on construing a conceptual model and underlying the hypotheses used to study the positive or negative effects as well as the barriers associated to consumer behaviour and perceived risk of using health IT on *e-Health* versus face-to-face nutrition consultation services.

It is proposed that the type of service and the type of data collected will influence perceived utility, trust, expected efficacy of psychological well-being (self-esteem, self-image, anxiety and worry), technology acceptance of using health IT database systems (data safety, willingness to pay and risk), expected satisfaction and behavioural intention to use *e-Health s*ervices.

Therefore, this research study suggests the following hypotheses:

**H1:** Nutrition apps lead to higher perceived utility than face-to-face nutrition consultation services.

**H2:** Nutrition apps lead to lower perceived data safety than face-to-face nutrition consultation services.

**H2.1.** Collecting data related emotional states leads to lower perceived data safety than collecting biometric data than no collection of any type of health data.

**H3:** Nutrition apps lead to lower perceived trust than face-to-face nutrition consultation services.

**H3.1.** Collecting data related to emotional states leads to lower perceived trust than collecting biometric data than no collection of any type of health data.

**H4:** Nutrition apps lead to lower willingness to pay than face-to-face nutrition consultation services.

**H5:** Nutrition apps lead to lower expected satisfaction than face-to-face nutrition consultation services.

**H6:** Nutrition apps lead to lower behavioral intention to use *e-Health* services than face-to-face nutrition consultation services.

**H7:** Nutrition apps lead to higher perceived risk towards consumers` sharing their personal biometric health data than face-to-face nutrition consultation services.

**H7.1.** Collecting data related to biometric data leads to higher perceived risk than no collection of any type of health data.

**H8:** Nutrition apps lead to higher perceived risk towards consumer's sharing their emotional states than face-to-face nutrition consultation services.

**H8.1.** Collecting data related to emotional states leads to higher perceived risk than collecting biometric data than no collection of any type of health data.

**H9:** Nutrition apps lead to lower consumers `expected efficacy of psychological well-being than face-to-face nutrition consultation services.

**H9.1.** Collecting data related to emotional states leads lower consumers` expected efficacy of psychological well-being than collecting biometric data than no collection of any type of health data.

# CHAPTER 4: METHODOLOGY

The survey developed allows to capture a wide variety of information through the possibility of asking a diversity of questions about participants 'decisions and actions after being exposed to different physical stimulus, general attitudes towards the use of nutrition health services and social-demographic information.

## 4.1. Initial methodological considerations *(Appendix 1)*

An online questionnaire was conducted with the purpose of collecting primary data. In fact, online survey is a convenient and flexible methodology that allows to interview many respondents and achieve a large number of observations in a short period of time. Additionally, it increases respondents` accessibility and availability to answer the survey as well as it increases participants` response rate.

The online survey was developed in *Qualtrics,* a platform that provides several options related to question structure and it also contains tools that facilitate the process of randomization between different stimulus conditions.

### 4.1.1. Participants *(Appendix 2)*

The sample size was defined a *priori* assuming 30 participants as the minimum statistically number of respondents per experimental condition to assess the research hypotheses. It was collected around 30 - 40 volunteer responses per condition from different age groups and genders, meaning it was collected around 180 - 240 answers in the total of the six experimental conditions presented in the online questionnaire.

Foreign participants were not considered for this research study due the existence of cultural difference attitudes towards the use of nutrition healthcare and well-being services that can result in less accurate and in data bias analysis of the main findings of this topic. For instance, participants were screened through the nationality question being the Portuguese market the focus of this study.

Participants were randomly assigned to one of the six experimental design conditions where three designs were considered to assess individuals` consumer behavior and psychology in a low level of psychology distance (Face-to-face nutrition consultation services) with the presence of three different types of health data stored and shared in health IT database systems (Control condition: no store or share of data; Biometric data: store and share; Emotional States: store and share).

The other three designs were considered experimental conditions which also assess individuals` consumer behavior and psychology in a high level of psychology distance (Nutrition calories counter app) with the presence of three different types of health data stored and shared in health IT database systems (Control condition: no store or share of data; Biometric data: store and share; Emotional States: store and share).

### 4.2. Materials

An online fictional nutrition calories counter app and offline face-to-face consultation service were created as stimuli for this study. To better understand if stimuli were properly developed, a qualitative pre-test with 6 participants was performed. Based on those outputs, it was possible to improve the final surveys stimuli (*Appendix 1*).

Respondents were randomly exposed to one of the six different stimuli. In the high level of psychology distance, it was shown different pictures of calories counter app that provide the same type of service to consumers. In the low level of psychology distance, it was shown different pictures of face-to-face nutrition consultation services that provide the same type of service.

The six stimuli contain the same text description template that includes a brief explanation about the functionalities of the service as well as how health IT database systems will store and share consumers data adapted to each condition.

Control (face-to-face nutrition consultations) and experimental (*e-Health* nutrition apps) conditions were exposed to different scenarios of perceived threat where participants were informed about how their biometric health data will be stored and shared, how the calculations of their eating habits are made and how recommendations are based on individuals` emotional states.

Nutrition calories counter apps and face-to-face consultation services were considered stimuli since they are simple, easy and adaptable nutrition health services to assess the innovation and impact of consumers 'personal choices about their technology acceptance, trust and behavioural intention to use health services.

Throughout the six experimental conditions, participants were asked to imagine themselves in a fictional scenario where they were invited for a party during the weekend where they ate and drunk a lot of caloric food and drinks (sugars and carbohydrates). Respondents were asked to use an app or a face-to-face nutrition consultation service to help them regulate their behavioural eating habits, health and to access the service by considering the variables mention in the section below.

### 4.2.1. Independent Variables (*Appendix 3)*

Type of service: Psychology Distance

This variable is divided into two conditions whereas participants were exposed to a stimulus displaying a nutrition calories counter app in an online context (high psychology distance) or exposed to a stimulus displaying a face-to-face nutrition consultation service in an offline context (low psychology distance).

Type of health data stored and shared: Perceived Threat

This variable is composed by three conditions whereas respondents were exposed to stimuli with no store and shared of data (control condition), biometric data that is stored and shared (non-threatening data) or emotional states that are stored and shared by health IT systems or 3rd parties (threatening data).

### 4.2.2. Dependent Variables

After participants being exposed to different stimuli, they were asked to evaluate the service by using an adapted 9-point Likert scale to increase the strength of the variance effect of the following factors. According to the Cronbach `Alpha test, the dependent variables assessed present good internal consistency reliability (*Appendix 4*).

In the results section, judgments of perceived usefulness and perceived ease of use were aggregated together in one single variable named as perceived utility.

Perceived Usefulness: Participants were asked to rate their level of perceived usefulness towards using nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not useful at all to 9- Extremely useful) (Papa, A., Mital, M., Pisano, P., & Del Giudice, M, 2020).

<u>Perceived Ease of Use:</u> Participants were asked to rate their level of perceived ease of use towards using nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not easy to use at all to 9- Extremely easy to use) (Papa, A., Mital, M., Pisano, P., & Del Giudice, M, 2020).

<u>Perceived Risk (Biometric data & Emotional States):</u> Respondents were asked to rate their level of perceived risk towards sharing their biometric health data such as weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass, fats eaten, carbs eaten, protein eaten, daily eating habits, number of meals per day, number of soft non-alcoholic drink (e.g., Coke), number of soft alcoholic drinks (e.g., Beer), number of hard alcoholic drink (e.g., Vodka), number of sugars / candies / desserts eaten, daily practice of sports, number of steps, number of sleeping hours, daily energy expenditure and emotional states such as self-esteem, self-image, anxiety, avoidance of problems and sadness (1- Not comfortable at all to 9- Extremely comfortable) (Galak, J., Redden, J. P., Yang, Y., & Kyung, E. J. , (2014) and Papa, A., Mital, M., Pisano, P., & Del Giudice, M, 2020).

Related to the technology acceptance variables towards consumers being technology savvy of health IT in nutrition services, it was considered the following factors:

<u>Perceived Security:</u> Participants were asked to rate their level of security towards sharing their personal data and using nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not secure at all to 9- Extremely secure) (Hsu, C. L., Lee, M. R., & Su, C. H., 2013).

<u>Data Privacy:</u> Participants were asked to rate their level of data privacy towards sharing their personal data and using nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not secure at all to 9- Extremely secure) (Hsu, C. L., Lee, M. R., & Su, C. H., 2013).

In the results section, judgments of perceived security and data privacy were aggregated together in one single variable named perceived data safety.

Perceived Trust: Participants were asked to rate their level of trust towards using nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not trustful at all to 9- Extremely trustful) (Kumar, D., & Dange, U., 2012).

WTP: Participants were asked to rate their level of willingness to pay for using nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not WTP at all to 9- Extremely WTP) (Akalamkam, K., & Mitra, J. K., 2018).

Expected Satisfaction: Participants were asked to rate their level of expected satisfaction to use nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1-Not expected satisfied at all to 9-Extremely expected satisfied) (Kumar, M., 2016).

Behavioural Intention to use: Participants were asked to rate their level of behavioural intention to use nutrition calories counter *e-Health* apps or face-to-face consultation services after seeing the stimulus (1- Not behavioural intended to use at all to 9- Extremely intended to use) (Holden, R. J., & Karsh, B. T., 2010 and Papa, A., Mital, M., Pisano, P., & Del Giudice, M., 2020).

Regarding the expected efficacy of psychological well-being variables, it was considered the following variables of emotional states:

Anxiety to share personal health data: Participants were asked to rate their level of anxiety related to the reliability of nutrition and educational health data given by nutrition *e-Health* apps and face-to-face consultation services after seeing the stimulus (1- Not anxious at all to 9- Extremely anxious) (DiFilippo, K. N., Huang, W. H., Andrade, J. E., & Chapman-Novakofski, K. M., 2015).

Worry with changes in health and well-being: Participants were asked to rate their level of worry related to the reliability of nutrition and educational health data given by nutrition *e-Health* apps and face-to-face consultation services after seeing the stimulus (1- Not worried at all to 9- Extremely worried) (DiFilippo, K. N., Huang, W. H., Andrade, J. E., & Chapman-Novakofski, K. M., 2015).

Expected Self-Esteem Comfort: Participants were asked to rate their level of self-esteem about how they feel with personalized nutrition and educational health data given by nutrition *e-Health* apps and face-to-face consultation services after seeing the stimulus (1- No self-esteem at all to 9 –

Extremely self-esteem) (DiFilippo, K. N., Huang, W. H., Andrade, J. E., & Chapman-Novakofski, K. M., 2015).

Expected increase of Self-Image: Participants were asked to rate their level of self-image about how they feel after receiving nutritional and educational health data given by *e-Health* apps and face-to-face consultation services after seeing the stimulus (1- No self-image at all to 9- Extreme self-image) (DiFilippo, K. N., Huang, W. H., Andrade, J. E., & Chapman-Novakofski, K. M., 2015).

### 4.3. Procedure

This paper aims to study Portuguese consumer behaviours towards the use of nutrition health and well-being services in an online versus offline context by conducting an English and Portuguese questionnaire version. Firstly, a brief explanation about the context and main objectives of the survey was presented without revealing the main purpose of the study to participants. Then, respondents provided a consent form where they agreed to participate in the research study. After that, participants were randomly assigned to one of the six experimental conditions.

Respondents were randomly exposed to a control or experimental condition with three different levels of manipulated stimuli of perceived threat towards storing and sharing personal health data. The type of data stored and shared is used to measure perceived risk associated with the technology acceptance of using health IT database systems.

After being exposed to the stimulus, participants were firstly asked to answer a sequence of manipulation questions regarding the condition they were exposed. Respondents were asked about their perception to assess the comfort towards sharing their personal health data, perceived utility, anxiety, worry, expected efficacy of psychological well-being (self-esteem and self-image) and technology savvy (data privacy safety, willingness to pay, trust, expected satisfaction and behavioural intention to use the service).

Additionally, respondents were asked to assess their general attitudes and perceptions about *e-Health* nutrition calories counter apps and face-to-face consultations. Moreover, participants were asked to rate their level of efficiency about those services towards increasing health and well-being on a 9-point Likert scale. Lastly, some demographic questions and a small debrief about the study was presented at the end.

### 4.4. Research Design

The survey follows a between subject design 2*3 with two types of service (Online / App versus Offline / Face-to-face consultations) and three levels of data stored and shared (Control data, Biometric Data and Emotional States), manipulated between subjects, which results in a design with six different experimental conditions:

1. Offline nutrition healthcare and well-being: Face-to-Face nutrition consultation service in the presence of no store of data (Control Condition)

2. Offline nutrition healthcare and well-being: Face-to-Face nutrition consultation service in the presence of biometric store and share of data (Non-threatening Data)

3. Offline nutrition healthcare and well-being: Face-to-Face nutrition consultation service in the presence of store and share of emotional states (Threatening Data)

4. Nutrition *e-Health* and well-being service: Nutrition calories counter app in the presence of no store and share of data (Control Condition)

5. Nutrition *e-Health* and well-being service: Nutrition calories counter app in the presence of biometric store and share of data (Non-threatening Data)

6. Nutrition *e-Health* and well-being service: Nutrition calories counter app in the presence of store and share of emotional states (Threatening Data)

## CHAPTER 5: RESULTS AND DISCUSSION

### 5.1. Sample Characterization *(Appendix 5)*

Throughout one week, 437 people started filling out the survey. However, 244 responses were incomplete, being only considered 193 responses for analysis. Additionally, the demographic question related to nationality was used as a screening filter to eliminate respondents from the sample that are not Portuguese. Thus, a total of 185 answers represents a sample of the Portuguese population considered the main target of this study.

In terms of gender, the sample was composed by 68.6% females, 30.8% males, 0.05% rather not disclose their identity and .00% third gender. Regarding age, 63.2% of the respondents belong to the age interval between 18 – 24 years old, 11.9% between 45-54 years old, 9.2% belongs to 25 – 34 years old, 7.6% between 35 – 44 years old, 3.8% between 55 – 64 years old, 2.7% have an age higher than 65 years old and 1.6% have an age lower than 18 years old.

The monthly gross income indicates that 36.2% of the respondents have an income lower than 635 euros, followed by 15.7% of the participants who have an income higher than 2000 euros, 14.1% between 635 – 1000 euros or between 1001 – 1500 euros, 10.7% prefer not to say and 9.7% between 1501 – 2000 euros.

Related to participants` occupation, 44.3% of the sample is composed by students, 31.9% employed, 20.0% student-workers, 2.7% retired, 1.1% unemployed and .0% self-employed. In terms of completed education, 56.8% have a bachelor’s degree, 35.1% a master`s degree, 7.0% high school or lower and 1.1% PhD.

A descriptive statistics and chi-square test was used to measure some control judgments about consumers` general attitudes towards the use of nutrition health services.

Starting with the familiarity about e-services, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and the familiarity with e-services *($X$ (1) = 0.436, $p$ = 0.509)*. It means that participants exposed to online nutrition services are equally familiar with e-services (51.1%) as well as respondents exposed to face-to-face consultation services (46.2%).

Identically, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and the familiarity with offline consultations (*X (1) = 1.966, p = 0.161)*. It indicates that participants exposed to online nutrition services are equally familiar with offline services (57.6%) as respondents exposed to face-to-face consultation services (47.3%).

In terms of the use of *e-Health* services, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and the currently use of e-services (*X (1) = .032, p = 0.889)*. It means that participants exposed to online nutrition services are used to e-services (14.1%) as respondents exposed to face-to-face consultation services (15.1%).

Similarly, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and the currently use of face-to-face nutrition consultation services (*X (1) = 1.112, p = 0.292)*. It indicates that respondents exposed to online nutrition services are used to offline consultations (17.4%) as participants exposed to face-to-face consultation services (23.7%).

To control for respondents who incurred in a diet in the past, are currently on a diet or intend to start a diet next month, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and individuals` intention to do a diet (*X diet in the past (1) = 2.839, p = 0.092 ; X currently on a diet (1) = .049, p =.825 ; X start diet next month (1) = .001 , p = .971)*. It means that participants exposed to online nutrition services have already incurred on a diet in the past (73.9% online vs 62.4% offline), are currently on a diet (20.7% online vs 19.4% offline) and intend to start a diet next month (19.6% online vs 19.4% offline).

To control the efficiency of using *e-Health* services to increase health and well-being, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and the efficiency of e-services (*X (8) = 7.779, p = .455)*. It indicates that respondents exposed to online nutrition services classify the efficiency of e-services identically as participants exposed to face-to-face consultation services (6 out of a 9-point Likert scale).

Identically, to control the efficiency of using offline services to increase health and well-being, it was found that neither participants exposed to an online nor respondents exposed to an offline nutrition service, revealed statistically significant associations between the type of service and the efficiency of offline services (*X (8) = 7.047, p = .532)*. It means that participants exposed to online nutrition services classify the efficiency of offline nutrition services identically as individuals exposed to face-to-face consultation services (7 or 8 out of a 9-point Likert scale).

### 5.2. Main Results

Two-way ANOVA at 95% confidence level was the method used to test the hypotheses under study. All the hypotheses considered throughout this research study fulfill the assumptions necessary to use ANOVA tests: Dependent variables are metric (9-Point Likert-scale used), independent variables are categorical, independence of observations, normality, homogeneity of variance and no outliers to reduce accuracy (*Appendix 2, 3 and 5* to consult the materials used).

#### 5.2.1. Hypothesis Testing *(Table 1)*

**H1:** Nutrition apps lead to higher perceived utility than face-to-face nutrition consultation services.

An ANOVA 2 Types of service x 3 Types of data on judgments of perceived utility revealed no significant main effect on the type of service *(F (1, 184) = 3.257, p = .073) (M online = 6.55*, *SD online = 1.62; M offline = 6.96, SD offline = 1.44*), suggesting that perceived utility is not affected by psychological distance of the health service. Additionally, it was not found any significant main effect on the type of data stored and shared (*F (2, 183) = 1.006, p = .368) (M no data = 6.98*, *SD no data = 1.63; M bio = 6.63, SD bio = 1.59*; *M psych = 6.66, SD psych =1.41)*, meaning that perceived utility is not affected by perceived threat associated with the type of data.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .916, p = .402)*. Hence, **H1** is **rejected**.

**H2:** Nutrition apps lead to lower perceived data safety than face-to-face nutrition consultation services.

**H2.1.** Collecting data related emotional states leads to lower perceived data safety than collecting biometric data than no collection of any type of health data.

An ANOVA 2 Types of service x 3 Types of data on judgments of perceived data safety revealed a significant main effect on the type of service *(F (1, 184) = 8.991, p = .003) (M online = 5.80, SD online = 2.07; M offline = 6.61, SD offline = 1.64*), suggesting that perceived data safety is affected by psychological distance of the health service, in which offline context leads to higher data safety than online context. Additionally, it was found a significant main effect on the type of data stored and shared (*F (2, 183) = 4.098, p = .018) (M no data = 6.71*, *SD no data = 1.65; M bio = 6.15, SD bio = 1.79*; *M psych = 5.77, SD psych =2.16),* meaning that perceived data safety is affected by perceived threat associated with the type of data.

An independent sample T-test found that data safety does not statistically change between different types of data *(t no data and bio data (122) =1.823, p= .935; t no data and psych (121) = 2.714, p = .059; t bio and psych (121) = 1.049, p = .094) (M no data = 6.71 , SD no data = 1.65 ; M bio = 6.15, SD bio = 1.79; M psych = 5.77, SD psych = 2.16)*. However, the results highlight a tendency to perceive higher data safety for the no data condition than for the psychology data condition.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .100, p = .905)*. Thus, **H2** and **H2.1.** is **accepted.**

**H3:** Nutrition apps lead to lower perceived trust than face-to-face nutrition consultation services.

**H3.1.** Collecting data related to emotional states leads to lower perceived trust than collecting biometric data than no collection of any type of health data.

An ANOVA 2 Types of service x 3 Types of data on judgments of consumers` perceived trust revealed a significant main effect on the type of service *(F (1, 184) = 32.676, p = .000) (M online = 5.80*, *SD online = 1.54; M offline = 6.92, SD offline = 1.12*), suggesting that perceived trust is affected by psychological distance of the health service, in which offline context leads to higher perceived trust than online context. However, it was not found a significant main effect on the type of data stored and shared (*F (2, 183) = 2.908, p = .057) (M no data = 6.69*, *SD no data = 1.34; M bio = 6.15, SD bio = 1.43*; *M psych = 6.25, SD psych =1.55),* meaning that perceived trust is not affected by perceived threat associated with the type of data.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .243, p = .785)*. Hence, **H3** is **accepted** while **H3.1.** is **rejected.**

**H4:** Nutrition apps lead to lower willingness to pay than face-to-face nutrition consultation services.

An ANOVA 2 Types of service x 3 Types of data on judgments of willingness to pay revealed a significant main effect on the type of service *(F (1, 184) = 57.252, p = .000) (M online = 3.45*, *SD online = 2.02; M offline = 5.59, SD offline = 1.81*), suggesting that willingness to pay is affected by psychological distance of the health service, in which offline context leads to higher willingness to pay than online context. However, it was not found any significant main effect on the type of data stored and shared (*F (2, 183) = .736, p = .480) (M no data = 4.68*, *SD no data = 2.29; M bio = 4.60, SD bio = 2.00*; *M psych = 4.30, SD psych = 2.30),* meaning that willingness to pay is not affected by perceived threat associated with the type of data.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .053, p = .948)*. Thus, **H4** is **accepted.**

**H5:** Nutrition apps lead to lower expected satisfaction than face-to-face nutrition consultation services.

An ANOVA 2 Types of service x 3 Types of data on judgments of consumers` expected satisfaction revealed a significant main effect on the type of service *(F (1, 184) = 17.912, p = .000) (M online* = 5.79, *SD online = 1.49; M offline = 6.69, SD offline = 1.35*), suggesting that expected satisfaction is affected by psychological distance of the health service, in which offline context leads to higher expected satisfaction than online context. However, it was not found any significant main effect on the type of data stored and shared (*F (2, 183) = .376, p = .687) (M no data = 6.29*, *SD no data = 1.42; M bio = 6.11, SD bio = 1.43*; *M psych = 6.33, SD psych = 1.63),* meaning that expected satisfaction is not affected by perceived threat associated with the type of data.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .050, p = .951)*. Hence, **H5** is **accepted.**

**H6:** Nutrition apps lead to lower behavioral intention to use *e-Health* services than face-to-face nutrition consultation services.

An ANOVA 2 Types of service x 3 Types of data on judgments of consumers` behavioural intention to use health services revealed a significant main effect on the type of service *(F (1, 184) = 4.443, p = .036) (M online* = 5.89, *SD online = 1.73; M offline = 6.42, SD offline = 1.64*), suggesting that consumers` behavioural intention to use is affected by psychological distance of the health service, in which offline context leads to higher behaviour intention to use the service than online context. However, it was not found any significant main effect on the type of data stored and shared (*F (2, 183) = .258, p = .773) (M no data = 6.24*, *SD no data = 1.74; M bio = 6.03, SD bio = 1.72*; *M psych = 6.20, SD psych = 1.66),* meaning that behavioural intention to use health services is not affected by perceived threat associated with the type of data.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .035, p = .966)*. Thus, **H6** is **accepted.**

**H7:** Nutrition apps lead to higher perceived risk towards consumers` sharing their personal biometric health data than face-to-face nutrition consultation services.

**H7.1.** Collecting data related to biometric data leads to higher perceived risk than no collection of any type of health data.

An ANOVA 2 Types of service x 3 Types of data of judgments about consumers` perceived risk towards sharing biometric health data revealed no significant main effect on the type of service *(F (1, 184) = 1.726, p = .191) (M online* = 7.54, *SD online = 1.70; M offline = 7.86, SD offline = 1.70*), suggesting that perceived risk is not affected by psychological distance of the health service. Additionally, it was not found any significant main effect on the type of data stored and shared (*F (2, 183) = .850, p = .429) (M no data = 7.93*, *SD no data = 1.43; M bio = 7.58, SD bio = 1.95*; *M psych = 7.59, SD psych = 1.69),* meaning that perceived risk is not affected by perceived threat associated with the type of data.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .251, p = .778)*. Hence, **H7** and **H7.1.** is rejected.

**H8:** Nutrition apps lead to higher perceived risk towards consumer's sharing their emotional states than face-to-face nutrition consultation services.

**H8.1.** Collecting data related to emotional states leads to higher perceived risk than collecting biometric data than no collection of any type of health data.

An ANOVA 2 Types of service x 3 Types of data of judgments about consumers` perceived risk towards sharing emotional states revealed no significant main effect on the type of service *(F (1, 184) = 1.565, p = .213) (M online* = 5.92, *SD online = 2.62; M offline = 6.35, SD offline = 2.17*), suggesting that perceived risk is not affected by psychological distance of the health service. However, it was found a significant main effect on the type of data stored and shared (*F (2, 183) = 3.590, p = .030) (M no data* = 6.70, *SD no data =2.02; M bio = 6.16, SD bio = 2.47*; *M psych = 5.55, SD psych = 2.41),* meaning that perceived risk is affected by perceived threat associated with the type of data.

An independent sample T-test found that perceived risk has statistically change effects between different types of data *(t no data and bio (122) =1.330, p= .147; t no data and psych (121) = 2.727, p = .014; t bio and psych (121) = 1.328, p = .368)* (*M no data = 6.70 , SD no data = 2.02 ; M bio = 6.16, SD bio = 2.47 ; M psych = 5.56, SD psych = 2.61)*. Results show tendency to perceive higher perceived risk for the no data condition than for the psychology data condition.

Moreover, it was found no interaction effect between type of service and data (*F (2, 183) = .186, p = .830)*. Thus, **H8** while **H8.1.** is **rejected**.

**H9:** Nutrition apps lead to lower consumers `expected efficacy of psychological well-being than face-to-face nutrition consultation services.

**H9.1.** Collecting data related to emotional states leads lower consumers` expected efficacy of psychological well-being than collecting biometric data than no collection of any type of health data.

An ANOVA 2 Types of service x 3 Types of data of judgments about consumer `expected efficacy of psychological well-being revealed a significant main effect on the type of service *(F (1, 184) = 5.121, p = .025) (M online* = 4.97, *SD online = 1.02; M offline = 5.32, SD offline = 1.12*), suggesting that expected efficacy of psychological well-being is affected by psychological distance of the health service, in which offline context leads to higher expected efficacy of psychological well-being than online context. Additionally, it was found a significant main effect on the type of data stored and shared ($F (2, 183) = 7.824, p = .001$) (*M no data* = 4.96, *SD no data* = 1.18; *M bio* = 4.91, *SD bio* = 1.01; *M psych* = 5.57, *SD psych* = 0.93), meaning that expected efficacy of psychological well-being is affected by perceived threat associated with the type of data.

An independent sample T-test found that expected efficacy of psychological well-being does not statistically change between different types of data (*t no data and bio data* (122) = .246, *p*= .464; *t no data and psych* (121) = -3.213, *p* = .163; *t bio and psych* (121) = -3.792, *p* = .460) (*M no data* = 4.96 , *SD no data* = 1.18 ; *M bio* = 4.91, *SD bio* = 1.01 ; *M psych* = 5.57, *SD psych* = .93).

Moreover, it was found no interaction effect between type of service and data ($F (2, 183) = .753, p = .472$). Hence, **H9** is **accepted** while **H9.1.** is **rejected.**

| | Type of service | | Type of Data | | | F-Test (p-value) | | F-Test Interaction |
|---|---|---|---|---|---|---|---|---|
| | Online | Offline | No data | Biometric Data | Emotional States | | | |
| | M (SD) | M (SD) | M (SD) | M (SD) | M (SD) | Type of service (Ts) | Type of data (Td) | Ts*Td |
| **Utility** | 6.55 (1.62) | 6.96 (1.44) | 6.98 (1.63) | 6.63 (1.59) | 6.66 (1.41) | F (1,184) = 3.257 p = .073 | F (2,183) = 1.006 p = .368 | F (2,183) = .916 p = .402 |
| **Trust** | 5.80 (1.54) | 6.92 (1.12) | 6.69 (1.34) | 6.15 (1.43) | 6.25 (1.55) | F (1, 184) = 32.676 p = .000 | F (2, 183) = 2.908 p = .057 | F (2, 183) = .243 p = .785 |
| **Perceived Risk (Biometric Data)** | 7.54 (1.70) | 7.86 (1.70) | 7.93 (1.43) | 7.58 (1.95) | 7.59 (1.69) | F (1, 184) = 1.726 p = .191 | F (2, 183) = .850 p = .429 | F (2, 183) = .251 p = .778 |
| **Perceived Risk (Emotional States)** | 5.92 (2.62) | 6.35 (2.17) | 6.70 (2.02) | 6.16 (2.47) | 5.55 (2.41) | F (1, 184) = 1.565 p = .213 | F (2, 183) = 3.590 p = .030 | F (2, 183) = .186 p = .830 |
| **Data Safety** | 5.80 (2.07) | 6.61 (1.64) | 6.71 (1.65) | 6.15 (1.79) | 5.77 (2.16) | F (1, 184) = 8.991 p = .003 | F (2,183) = 4.098 p = .018 | F (2,183) = .100 p = .905 |
| **WTP** | 3.45 (2.02) | 5.59 (1.81) | 4.68 (2.29) | 4.60 (2.00) | 4.30 (2.30) | F (1, 184) = 57.252 p = .000) | F (2, 183) = .736 p = .480 | F (2, 183) = .053 p = .948 |
| **Satisfaction** | 5.79 (1.49) | 6.69 (1.35) | 6.29 (1.42) | 6.11 (1.43) | 6.33 (1.63) | F (1, 184) = 17.912 p = .000 | F (2, 183) = .376 p = .887 | F (2, 183) = .050 p = .951 |
| **Behavioural Intention to Use** | 5.89 (1.73) | 6.42 (1.64) | 6.24 (1.74) | 6.03 (1.72) | 6.20 (1.66) | F (1, 184) = 4.443 p = .036 | F (2, 183) = .258 p = .773 | F (2, 183) = .035 p = .966 |
| **Efficacy of Psychological Well-being** | 4.97 (1.02) | 5.32 (1.12) | 4.96 (1.18) | 4.91 (1.01) | 5.57 (0.93) | F (1, 184) = 5.121 p = .025 | F (2, 183) = .7.824 p = .001 | F (2, 183) = .753 p = .472 |

**Table 1:** Means (standard deviation in parentheses) for each dependent variable for each independent variable (type of service and data). F-Test and p-value for the type of service and type of data stored and shared for each dependent variable

**5.3. Discussion**

**5.3.1. Summary of main findings**

This research aims to study consumers` technology acceptance of using health IT to store and share health data (biometric and emotional states) while they are using health services to change nutrition eating habits in an online versus offline context.

The results obtained from the data analysis revealed that *e-Health* calories counter app leads to lower perceived data safety, trust, willingness to pay, expected satisfaction, behavioral intention to use *e-Health* services, expected efficacy of psychological well-being and perceived risk towards emotional states than offline services (face-to-face consultations).

Additionally, the results highlight that the type of data has statistically significant negative main effects towards data safety when emotional states are stored and shared and negative expected efficacy of psychological well-being in comparison with the other types of data. However, the independent sample T-test revealed that there is no statistically significant effect between the three types of data for perceived data safety and expected efficacy of psychological well-being.

Moreover, the type of data has statistically significant negative main effects towards perceived risk when emotional states are stored and shared compared with the other types of data. The independent sample T-test revealed that perceived risk is higher when emotional states are collected than when no data is collected.

In contrast, *e-Health* app does not have any statistically significant effect towards perceived utility and perceived risk of sharing biometric data than face-to-face nutrition consultation services.

Related to the type of data, there is no statistically significant main effect towards perceived utility, trust, willingness to pay, expected satisfaction, behavioral intention to use nutrition services and perceived risk towards sharing biometric data compared with other types of data.

There was no interaction effect between type of service and data on any of the hypotheses formulated.

Lastly, the participants of this study reflect a non-representativeness of the Portuguese population due to the existence of some demographic discrepancies between gender, age and occupation. Most of the respondents` opinion about nutrition health services in an online versus offline context were given by female consumers who belong to the age interval between 18 – 24 years old and who are identically familiar with the use of both *e-Health* and face-to-face nutrition consultation services.

# CHAPTER 6: IMPLICATIONS, FUTURE RESEARCH, LIMITATIONS AND CONCLUSION

## 6.1. Main Theoretical & Managerial Implications

### 6.1.1. Main Theoretical Implications

In healthcare industry, the constant advances to offer new personalized services solutions by using health information technology, provides interesting and managerial findings related to the main factors that can influence consumers` acceptance and perceptions about the use of nutrition *e-Health* apps compared to face-to-face consultations.

Contrary as it was stated in the literature review section, this study revealed that *e-Health* nutrition apps lead to lower levels of perceived utility. Another insight from the analysis of the results is the fact that perceived risk of using *e-Health* nutrition services depends on the type of data collected by the service (biometric or emotional states). As suggested by literature, consumers are concern about data safety and trust when they use e-services where they share personal information.

If e-services clarify the privacy policy used to ensure consumers` data privacy with an integrated mechanism to safeguard consumers` health information, it will reduce individuals' perceived risk and it contribute to increase trust and consumer satisfaction on *e-Health* nutrition services (Katawetawaraks, C., & Wang, C., 2011).

In fact, consumer satisfaction is considered a key factor for the success of online services as it is a way to build and sustain relationship with consumers based on reliability, confidence and security (Kumar, M.,2016).

Research showed that there was no interaction effect between the type of service and data due to consumers being technology savvy users and their technology perception is constantly changing over time (Wu, J. H., & Wang, S. C., 2005).

The barriers and challenges associated with technology acceptance about health IT on *e-Health* services can be overcomed with information search about information technology and through consumers` review rates which contribute to increase the behavioral intention to use online services (Akalamkam, K., & Mitra, J. K., 2018; Kumar, M.,2016).

### 6.1.2. Managerial Implications

The evolution of telemedicine technology and the significant growth of e-commerce driven by information technology, transformed the healthcare industry and consumer behavior since health IT is gaining popularity (Wu, J. H., & Wang, S. C., 2005).

Regarding academic applicability, the present paper covers the theories of technology acceptance model and the unified theory of acceptance and use of technology which contribute to gain new insights and knowledge about the acceptance of new health IT in nutrition services and perceived threat associated with the type of data.

By studying a new path to combine the technology acceptance and use of health IT with the construal level of psychology distance, the technology acceptance model has been extended by introducing new factors such as perceived risk, security, data privacy, trust willingness to pay, expected satisfaction, behavioral intention to use the service and expected efficacy of psychological well-being which contribute to make the model more complex.

This dissertation contributes to study consumer behavior changes towards using nutrition apps in contrast with previous studies where behavioral theories revealed that targeting behavior changes to study the use of apps did not provide relevant outcomes (DiFilippo, K. N., Huang, W. H., Andrade, J. E., & Chapman-Novakofski, K. M., 2015).

Related to managerial applicability, the present paper allows researchers to think about how healthcare industry and consumers can take advantage and benefit from considering the speed of health information technology as a strategy to provide knowledge and useful insights about consumers` perception changes related to the use of *e-Health* services.

Starting with healthcare industry, the speed control of mobile information technology used to store and share personal data should include data privacy and cybersecurity policies as a mechanism to safeguard health data. For example, if *e-Health* nutrition apps, implement consumers` face – ID recognition for nutritionists and 3rd parties to have access to individuals' health data, it will increase the use of e-services and reduce risk perception.

As risk perception is considered the main barrier for the growth of e-services, increasing awareness about *e-Health* apps by especially focusing on educating consumers about the benefits of using nutrition mobile apps will contribute to reduce risk perception. Additionally, satisfied consumers should share their opinion and experience with the use of nutrition *e-Health* apps which allows potential consumers of having a second source of information about the service (Katawetawaraks, C., & Wang, C., 2011).

Covid-19 pandemic catalyzed changes in healthcare sector by increasing the potential use of new health technology data-driven nutrition services that combine a personalized people - driven, preventive, digital, human, convenient and integrated into daily life health experience to consumers.

Smart health system is considered a technology – driven improvement of efficiency and quality of care which integrates physical and virtual interaction by promoting sustainable health experience focus on environmental, economic and social impacts.

For that reason, the adoption of digital health technology services benefits both nutritionists and consumers. It allows nutritionists to easy access patients portals in a secure and permissioned way to make diagnosis and recommendations based on users' history and real-time data, do phone and video consultations, remote monitoring and to manage chronic disease via cloud. For consumers, it allows to make online appointment scheduling, do phone and video consultations, text messaging with nutritionists and linking telehealth with 24 hours over 7 days coaching.

Through the adoption of smart mirrors integrated into *e-Health* nutrition apps, trials will be simplified to integrate real world data for both consumers and nutritionists. Smart mirrors will work as a self - healthcare system to monitor consumers health and make personalized daily status through the incorporation of sensors to measure biometric data (weight, total body water, fat mass, muscle mass, sports practice and total daily expenditure) and emotional states (stress, anxiety, self-image, self-esteem and sadness).

The lifecare provides a customer - oriented personalized data monitoring, diagnosis and analysis of lifestyle as well as a predictive prevention. It will be centered on individuals needs by providing a personalized nutrition service that promotes healthcare solutions integrated into daily life (e.g. supplements to exercise, living, mobility and nutrition) through digital health apps.

Lastly, the disease care system promotes an early detection of a disease through digital routine checks and diagnostics. It provides personalized treatments of adverse health conditions with consumers having a more active role on defining the treatment which is most suitable for their situation. Therefore, the decision-making in disease care is not only based on individuals` healthcare data but it also incorporates lifestyle information.

### 6.2. Future Research

As online consumer behavior is explained by a variety of factors, it would be interesting to study in more detail how consumers` technology acceptance of using health IT in nutrition health services is influenced by demographic factors (e.g.: age) in an online versus offline context.

The generational gap contributes to the existence of differences in exposure to technology. In fact, elderly generations have low levels of digital and health literacy while younger generations are considered more technology savvy and willingness to use online health services (Cummins, N., & Schuller, B.W., 2020).

Future research will reveal potential main effects and interesting outcomes of demographic factors and related interaction effects with the type of service and data. For example, future research should focus on the interactions between type of service and type of data; and between age, type of service and type of data.

In fact, from the online survey it was possible to conclude that individuals did not distinguish the type of data that was stored and shared by the nutrition health service they were asked to assess. Specifically, future studies can change and improve the images used to illustrate the online and offline nutrition services. It should also be included control variables and manipulation check to make sure participants clearly understand the type of data that is stored and shared by the service as well as the type of service they are evaluating.

An associative mindset priming introductory question can be added to the online survey to expose participants to a first stimulus (e.g.: Question about which biometric data and emotional states they are more comfortable to share in a nutrition service). Then, they will be exposed to a second stimulus related to the first one (e.g.: Image and text associated with the nutrition service for each of the six experimental conditions). In fact, the first stimulus will affect the response to the second stimulus, meaning that it "primes" the second response. Based on mindset priming, participants will answer the following questions of the survey in a "biased" way to obtain more valuable and reliable insights.

Future studies can verify if the existence of other factors such as social influence of references groups or public policy will generate interaction effects between the type of service and data related to the use of health IT.

### 6.3. Limitations

The online questionnaire used to gather primary data presents some disadvantages: Low response rate which contributes for a non – representativeness of the Portuguese population between different gender and age groups and the lack of control over the participants` identity.

Throughout the development of the online survey, it was not included a manipulation check control to make sure that respondents were correctly making judgments and evaluate the type of service and data of the nutrition health service. Consequently, participants did not analyze and assess in a correct way the diverse types of data when they were exposed to one out of the six experimental conditions. Therefore, it reveals that the materials used for the development of the online questionnaire were not strong enough to culminate this factor as well as the nonexistence of any interaction effect between type of service and data.

In addition, future research can improve and better manipulate the materials used to collect data throughout the online questionnaire by making them more objective and clearer. It should also be acknowledged that the six stimuli created for this study were developed for this research. To overcome potential confounds throughout this research, a pre-test of the materials would help to ensure that participants perceived the proposed health services and type of data collected as it was intended. Further studies should consider a development of a pre-test stimuli.

The literature review used for the development of this dissertation is not specifically for the Portuguese market which was the target considered on the quantitative analysis. This might be a reason that explains some of the unexpected and contrary results obtained throughout the analysis of the hypotheses. Some of the results obtained revealed that it was not included other variables such as culture variables or the effects of social influence. Especially, the reduced number of available studies related to nutrition mobile apps associated with the technology acceptance of using health IT in online versus offline consumer behavior limited the literature review of this study. The use of nutrition *e-Health* apps is considered a relatively new trend and topic where research is needed to gain more knowledge and insights related to healthcare education and behavior change.

### 6.4. Conclusion

Over the next decade, the transformation of healthcare will have rapid changes that will generate an ongoing health data explosion with data being generated “everywhere” at any time and it shapes the success of nutrition *e-Health* services in an unprecedented way.

New technologies such as health IT are rapidly overcoming “technological barriers” about data sharing. Nevertheless, healthcare industry is still behind the curve related to information sharing compared to other industries. However, literature suggests that accessibility to individuals ` health data is the path to improve the quality of e-services and to provide solutions which ensure that health information exchange relies on the safest technology (legislation and regulation) to both benefit nutritionists and consumers (Vest, J. R., & Gamm, L. D., 2010).

The results should prove that the rapid transformation of healthcare will promote the conversion to virtual customized and preventive health services models which require the integration of lifecare system that merge well care and disease systems and enables consumers` acceptance of using smart devices.

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## APPENDICES

### Appendix 1 – Survey

**Section 1: Experimental Design – Interaction between Online service and Perceived Threat**

**Instructions to complete the task:**

You will be asked to make judgments about a nutrition calories counter food app.

In this study, you will be presented with a food app that help you regulate your healthy eating habits. Please, imagine that you want to have healthier eating habits and you are considering using an *e-Health* app to help you regulate what you eat.

We would like to ask you to evaluate this app. To help you relate the app with your own needs, we will present you an eating scenario. Please, imagine yourself in this scenario and try to picture yourself using this app.

For the app, you will be asked to make several judgments. Please, pay careful attention to the information provided about the following app.

**Please go to the next page when you feel ready to start the study.**

**Scenario 1 to 3:** High Abstraction Level of Psychology Distance (Online *e-Health* service / App)

**Scenario 1:** No stored and shared of data (Control Data)

**MyPlate Calories Counter App**

MyPlate Calories Counter is a user-friendly app that has a health IT system integrated designed to help you lose weight and improve your health. The calories counter app offers an easy-to-use nutritional fact, personalized daily calories goals, healthy meal plans, a barcode scanner to quickly scan items and to create your own custom food as well as it has an extensive food database. Additionally, it gives detailed statistics about your nutrition: daily nutrition charts, daily caloric breakdown fat, protein, carbs and net calories by day and week.

This app will make tailored calculations based on the information you provide at each moment. **It will ask you biometric information**: weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass and total daily energy expenditure. It will make calculations based on your eating habits according to the type of food you eat or drink, the amount of food you eat or drink and the time of your meals.

Finally, it will adjust the calculations and recommendations after you provide **your emotional state during the eating moments**, including your emotions and how you were feeling about yourself. **After computing all the calculations, this app does not store any of the information you provided. This app does not share your information with 3rd parties that can be relevant and helpful for your health.**


Imagine that you were invited for a party last weekend where you ate and drunk a lot of caloric food and drinks (sugar and carbohydrates). After that weekend, you felt it would be important for you to regulate your eating behaviors. To achieve your goal, you decide to download and start using MyPlate Calories Counter app.

**Q1** How comfortable would you be with sharing the following data with MyPlate Calories Counter app? For each type of data, please select the option that best indicate your opinion.

| | **Not comfortable at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely Comfortable**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| Weight | | | | | | | | | |
| Total Body Water | | | | | | | | | |
| Fat-Free Mass | | | | | | | | | |
| Fat Mass | | | | | | | | | |
| Body Cell Mass | | | | | | | | | |
| Muscle Mass | | | | | | | | | |
| Fast eaten / day | | | | | | | | | |
| Carbs eaten / day | | | | | | | | | |
| Protein eaten / day | | | | | | | | | |
| Daily Eating / Drinking Habits (Breakfast, Snacks, Lunch, Dinner) | | | | | | | | | |
| Number of meals per day | | | | | | | | | |
| First food you eat in the day | | | | | | | | | |
| Number of soft alcoholic drinks (e.g. Beer) | | | | | | | | | |
| Number of hard alcoholic drinks (e.g. Vodka) | | | | | | | | | |
| Number of soft non-alcoholic | | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| drinks (e.g. Coke) | | | | | | | | | |
| Number of sugars / candies / cakes / desserts | | | | | | | | | |
| Daily Practice of Sports Habits | | | | | | | | | |
| Daily Number of steps / walks | | | | | | | | | |
| Daily number of sleeping hours | | | | | | | | | |
| Total daily energy expenditure (Calories Counter consumed, burned, left) | | | | | | | | | |
| Your level of self-esteem (Gain / Maintain / Lose weight) | | | | | | | | | |
| Your comfort with your self-image (Feel happy, healthier, beautiful with yourself) | | | | | | | | | |
| Your level of avoidance problems | | | | | | | | | |
| Your level of anxiety | | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| (Display changing in eating habits) | | | | | | | | | |
| Your level of sadness | | | | | | | | | |

**Q2** How useful is MyPlate Calories Counter app for you? Please select the option that best indicate your opinion.

| | **Not useful at all** <br> **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely useful** <br> **9** |
|---|---|---|---|---|---|---|---|---|---|
| **Usefulness** | | | | | | | | | |

**Q3** How easy is it for you to use MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | **Not easy to use at all** <br> **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely** <br> **Easy to use** <br> **9** |
|---|---|---|---|---|---|---|---|---|---|
| **Easiness to Use** | | | | | | | | | |

**Q4** How reliable and trustworthy is for you the feedback given by MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | **Not reliable / trustful at all** <br> **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely reliable / trustful** <br> **9** |
|---|---|---|---|---|---|---|---|---|---|
| **Reliability / Trustiness** | | | | | | | | | |

**Q5** How anxious would you feel about sharing your personal data in MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | Not anxious at all<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Extremely anxious<br>9 |
|---|---|---|---|---|---|---|---|---|---|
| **Anxiety** | | | | | | | | | |

**Q6** How worry would you feel with changes in nutrition eating habits and health given by MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | Not worried at all<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Extremely worried<br>9 |
|---|---|---|---|---|---|---|---|---|---|
| **Worry** | | | | | | | | | |

**Q7** How is your expected self-esteem comfort after receiving the feedback given by MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | No self-esteem at all<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Extreme self-esteem<br>9 |
|---|---|---|---|---|---|---|---|---|---|
| **Expected Self-Esteem** | | | | | | | | | |

**Q8** How is your expected increase of self-image after receiving the feedback given by MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | No self-image at all<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Extreme self-image<br>9 |
|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Expected Self-Image** | | | | | | | | | |

**Q9** In general, how technology savvy is you to feel secure / safe while sharing your personal health data in MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | **Not secure / safe at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely secure / safe**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| **Security / Safety** | | | | | | | | | |

**Q10** In general, how technology savvy is you to feel MyPlate Calories Counter app trustful? Please select the option that best indicate your opinion.

| | **Not trustful at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely trustful**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| **Trustiness** | | | | | | | | | |

**Q11** In general, how technology savvy is you to be willing to pay (WTP) for using MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | **Not WTP at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely WTP**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| **WTP** | | | | | | | | | |

**Q12** How is your expected satisfaction to use MyPlate Calories Counter app? Please select the option that best indicate your opinion.

| | **Not expected** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely expected satisfied** |
|---|---|---|---|---|---|---|---|---|---|

| | satisfied at all<br><br>1 | | | | | | | | 9 |
|---|---|---|---|---|---|---|---|---|---|
| **Expected Satisfaction** | | | | | | | | | |

**Q13** In what extent would you like to use MyPlate Calories Counter app to help you regulate your eating habits and health? Please select the option that best indicate your opinion.

| | **Not intended to use at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely intended to use**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| **Behavioral Intention to Use** | | | | | | | | | |

**Scenario 2:** Stored and shared of biometric data

**HEALTHY OUT App**

Healthy Out Calories Counter is a user-friendly app that has a health IT system integrated designed to help you lose weight and improve your health. The calories counter app offers an easy-to-use nutritional fact, personalized daily calories goals, healthy meal plans, a barcode scanner to quickly scan items and to create your own custom food as well as it has an extensive food database. Additionally, it gives detailed statistics about your nutrition: daily nutrition charts, daily caloric breakdown fat, protein, carbs and net calories by day and week.

This app will make tailored calculations based on the information you provide at each moment. **This app will ask you biometric information**: weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass and total daily energy expenditure. It will make calculations based on your eating habits according to the type of food you eat or drink, the amount of food you eat or drink and the time of your meals.

Finally, it will adjust the calculations and recommendations after you provide **your emotional state** during the eating moments, including your emotions and how you were feeling about yourself. **After computing all the calculations, this app only stores the biometric information that you provide about yourself. This app only shares the biometric information with 3rd parties that can be relevant and helpful for your health.**



Imagine that you were invited for a party last weekend where you ate and drunk a lot of caloric food and drinks (sugar and carbohydrates). After that weekend, you felt it would be really important for you to regulate your eating behaviors. To achieve your goal, you decide to download and start using Healthy Out app.

- Respondents were asked to answer the same questions from **Q1** to **Q13** of **scenario 1** adapted to the information given in **scenario 2**

<u>**Scenario 3:**</u> Stored and shared of emotional states data

**My Net Diary App**

My Net Diary Calories Counter is a user-friendly app that has a health IT system integrated designed to help you lose weight and improve your health. The calories counter app offers an easy-to-use nutritional fact, personalized daily calories goals, healthy meal plans, a barcode scanner to quickly scan items and to create your own custom food as well as it has an extensive food database. Additionally, it gives detailed statistics about your nutrition: daily nutrition charts, daily caloric breakdown fat, protein, carbs and net calories by day and week.

This app will make tailored calculations based on the information you provide at each moment. **This app will ask you biometric information**: weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass and total daily energy expenditure. It will make calculations based on your eating habits according to the type of food you eat or drink, the amount of food you eat or drink and the time of your meals.

Finally, it will adjust the calculations and recommendations after you provide **your emotional state** during the eating moments, including your emotions and how you were feeling about yourself. **After computing all the calculations, this app only stores the emotional states that you provide about yourself. This app only shares your emotional states with 3rd parties that can be relevant and helpful for your health.**


Imagine that you were invited for a party last weekend where you ate and drunk a lot of caloric food and drinks (sugar and carbohydrates). After that weekend, you felt it would be really important for you to regulate your eating behaviors. To achieve your goal, you decide to download and start using My Net Diary app.

- Respondents were asked to answer the same questions from **Q1** to **Q13** of **scenario 1** adapted to the information given in **scenario 3**

**Scenarios 4 to 6:** Low Abstraction Level of Psychology Distance (Offline / Face-to-Face nutrition consultation service)

**Instructions to complete the task:**

You will be asked to make judgments related to a face-to-face nutrition consultation service. In this study, you will be presented with a face-to-face nutrition consultation service that help you to regulate your healthy eating habits. Please, imagine that you want to have healthier eating habits and you are considering a nutrition consultation service to help you regulate what you eat.

We would like to ask you to evaluate this service. To help you relate this nutrition service with your own needs, we will present you an eating scenario. Please, imagine yourself in this scenario and try to picture yourself on a nutrition consultation scenario. For the service, you will be asked to make several judgments. Please, pay careful attention to the information provided about the following scenario.

**Please go to the next page when you feel ready to start the study.**

**Scenario 4:** No stored and shared of data (Control Data)

**Nutricionista.com Face-to-Face Consultation Service**

Nutricionista.com is a user-friendly face-to-face consultation service that has a health IT system designed to help you lose weight and improve your health. The service offers an easy-to-use nutritional fact, personalized daily calories goals, healthy meal plans, a barcode scanner to quickly scan items and to create your own custom food as well as it has an extensive food database. Additionally, it gives detailed statistics about your nutrition: daily nutrition charts, daily caloric breakdown fat, protein, carbs and net calories by day and week.

The nutritionist will make tailored calculations based on the information you provide at each moment. **The nutritionist will ask you biometric information**: weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass and total daily energy expenditure. The nutritionist will make calculations based on your eating habits according to the type of food you eat or drink, the amount of food you eat or drink and the time of your meals.

Finally, the nutritionist will adjust the calculations and recommendations after you provide **your emotional state during the eating moments**, including your emotions and how you were feeling about yourself. **After computing all the calculations, the nutritionist does not store any of the information you provided. The nutritionist does not share any of your information with 3rd parties that can be relevant and helpful for your health.**

Imagine that you were invited for a party last weekend where you ate and drunk a lot of caloric food and drinks (sugar and carbohydrates). After that weekend, you felt it would be really important for you to regulate your eating behaviors. To achieve your goal, you decide to have a face-to-face nutrition consultation service with Nutricionista.com

- Respondents were asked to answer the same questions from **Q1** to **Q13** of **scenario 1** adapted to the information given in **scenario 4**

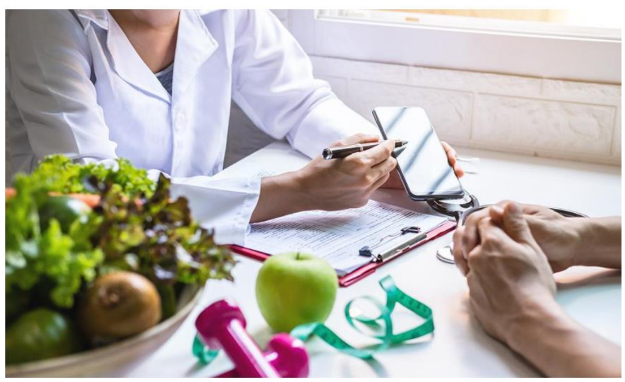
**Scenario 5:** Stored and shared of biometric data

**HEALTHY OUT Face-to-Face Nutrition Consultation Service**

Healthy Out is a user-friendly face-to-face nutrition consultation service that has a health IT system integrated designed to help you lose weight and improve your health. The calories counter service offers an easy-to-use nutritional fact, personalized daily calories goals, healthy meal plans, a barcode scanner to quickly scan items and to create your own custom food as well as it has an extensive food database. Additionally, it gives detailed statistics about your nutrition: daily nutrition charts, daily caloric breakdown fat, protein, carbs and net calories by day and week.

The nutritionist will make tailored calculations based on the information you provide at each moment. **The nutritionist will ask you biometric information**: weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass and total daily energy expenditure. The nutritionist will make calculations based on your eating habits according to the type of food you eat or drink, the amount of food you eat or drink and the time of your meals.

Finally, the nutritionist will adjust the calculations and recommendations after you provide **your emotional state** during the eating moments, including your emotions and how you were feeling about yourself. **After computing all the calculations, the nutritionist only stores the biometric information that you provide about yourself. The nutritionist only shares your biometric information with 3rd parties that can be relevant and helpful for your health.**



Imagine that you were invited for a party last weekend where you ate and drunk a lot of caloric food and drinks (sugar and carbohydrates). After that weekend, you felt it would be really important for you to regulate your eating behaviors. To achieve your goal, you decide to have a face-to-face nutrition consultation with Healthy Out.

- Respondents were asked to answer the same questions from **Q1** to **Q13** of **scenario 2** adapted to the information given in **scenario 5**

<u>**Scenario 6:**</u> Stored and shared of emotional states data

**My Net Diary Face-to-Face Nutrition Consultation service**

My Net Diary is a user-friendly face-to-face nutrition consultations services that has a health IT system integrated designed to help you lose weight and improve your health. The service offers an easy-to-use nutritional fact, personalized daily calories goals, healthy meal plans, a barcode scanner to quickly scan items and to create your own custom food as well as it has an extensive food database. Additionally, it gives detailed statistics about your nutrition: daily nutrition charts, daily caloric breakdown fat, protein, carbs and net calories by day and week.

The nutritionist will make tailored calculations based on the information you provide at each moment. **The nutritionist will ask you biometric information**: weight, total body water, fat-free mass, fat mass, body cell mass, muscle mass and total daily energy expenditure. The nutritionist will make calculations based on your eating habits according to the type of food you eat or drink, the amount of food you eat or drink and the time of your meals.

Finally, the nutritionist will adjust the calculations and recommendations after you provide **your emotional states** during the eating moments, including your emotions and how you were feeling about yourself. **After computing all the calculations, the nutritionist only stores the emotional states that you provide about yourself. The nutritionist only shares your emotional states with 3rd parties that can be relevant and helpful for your health.**

Imagine that you were invited for a party last weekend where you ate and drunk a lot of caloric food and drinks (sugar and carbohydrates). After that weekend, you felt it would be really important for you to regulate your eating behaviors. To achieve your goal, you decide to have a face-to-face nutrition consultation with My Net Diary.

- Respondents were asked to answer the same questions from **Q1** to **Q13** of **scenario 3** adapted to the information given in **scenario 6**

**<u>Section 2:</u> General attitudes towards nutrition healthcare and well-being services**

Now, we would like to ask you some questions regarding your general thoughts / attitudes towards nutrition healthcare and well-being services.

**Please go to the next page when you feel ready to start answering these questions.**

**Q1** Have you already used or are familiar with nutrition calories counter healthcare and well-being **e-services / apps**?

- Yes / No

**Q2** Have you already used or are familiar with nutrition calories counter healthcare and well-being **Face-to-Face nutrition consultation** services?

- Yes / No

**Q3** Do you currently use any nutrition calories counter healthcare and well-being **e-service / app**?

- Yes / No

**Q4** Do you currently use any **Face-to-Face nutrition consultation** service?

- Yes / No

**Q5** Have you ever gone on a diet in the past?

- Yes / No

**Q6** Are you currently on a diet?

- Yes / No

**Q7** Do you intend to start a diet next month?

- Yes / No

**Q8** In general, how efficient are nutrition *e-Health* services / apps towards increasing health and well-being? Please select the option that best indicate your opinion.

| | **Not efficiency at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely efficiency**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| **Efficiency** | | | | | | | | | |

**Q9** In general, how efficient are Face-to-Face nutrition health services towards increasing health and well-being? Please select the option that best indicate your opinion.

| | **Not efficiency at all**<br><br>**1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **Extremely efficiency**<br><br>**9** |
|---|---|---|---|---|---|---|---|---|---|
| **Efficiency** | | | | | | | | | |

## <u>Section 3:</u> Demographic

**Q1** Gender

- Male
- Female
- Non-binary / Third gender
- Prefer not to say

**Q2** Age

- < 18 years old
- 18 - 24 years old
- 25 - 34 years old
- 35 - 44 years old
- 45 - 54 years old
- 55 - 64 years old
- > 65 years old

**Q3** Nationality

Please write your nationality: ______________________

**Q4** Monthly Gross Income

- Less than 635 euros
- 635 euros - 1000 euros
- 1001 euros - 1500 euros
- 1501 euros - 2000 euros
- More than 2000 euros
- Prefer not to say

**Q5** Occupation

- Student
- Student -Worker
- Employed
- Unemployed
- Self-Employed
- Retired

**Q6** Completed Education

- High School or Lower
- Undergraduate / Bachelor
- Master
- PhD

Thank you for your time, attention, sincerity, honesty and effort to complete this survey. Your answers are extremely important and valuable to gain new insights in this field to support my thesis. The result will allow us to better understand in which conditions *e-Health* services can be perceived as useful or risky in comparison with face-to-face consultations.

**End of Survey**

We thank you for your time spent taking this survey

## Appendix 2 - Frequencies per Experimental Condition

Respondents were randomly assigned to a specific experimental condition. As shown in the frequency table 2, experimental conditions 1, 2, 4, 5 and 6 were exposed to 31 individuals while the experimental condition 3 was only exposed to 30 individuals.

| Frequencies per experimental condition | | |
|---|---|---|
| **Experimental Condition (EC)** | **Frequency** | **Percentage** |
| **EC 1** – Nutrition calories counter app where there is no store or share of data by health IT (Control Condition) | 31 | 16. 8% |
| **EC 2** - Nutrition calories counter app where there is store and share of biometric data by health IT (Non-threatening data) | 31 | 16.8% |
| **EC 3** - Nutrition calories counter app where there is store and share of emotional states by health IT (Threatening data) | 30 | 16.0% |
| **EC 4** – Face-to-Face nutrition consultation service where there is no store or share of data by health IT (Control Condition) | 31 | 16.8% |
| **EC 5** - Face-to-Face nutrition consultation service where there is store and share of biometric data by health IT (Non-threatening data) | 31 | 16.8% |

| | | |
|---|---|---|
| **EC 6** - Face-to-Face nutrition consultation service where there is store and share of emotional states by health IT (Threatening data) | 31 | 16.8% |
| **Total** | 185 | 100 |

**Table 2:** Frequencies per Experimental Condition

**Appendix 3 – Variables Added & Created**

New variables were created and added to the existing ones assessed throughout the questionnaire. The first variable created was a dummy variable called "**Type of service**" that assumes two different values: "**1**" if the respondent was exposed to an online *e-health* nutrition app or "**2**" if the participant was exposed to a face-to-face nutrition consultation service.

A second dummy variable called "**Type of data**" was created and it assumes two different values: "**1**" if the participant was exposed to a nutrition service without storing and sharing any type of personal health data, "**2**" if the respondent was exposed to a nutrition service where biometric data is stored and shared by health IT database systems and "**3**" if the participant was exposed to a nutrition service where emotional states are stored and shared by health IT database systems.

The constructs assessed throughout the online survey were subject to manipulation. Specifically, five new variables were created and added to the study as a technique to make an average between the measurement items between the six experimental design conditions.

In detail, perceived usefulness (including one measurement item), perceived ease of use (including one measurement item), reliability (including one measurement item), perceived trust (including one measurement item), biometric perceived risk (including nineteen measurement items), emotional states perceived risk (including five measurement items) and expected efficacy of psychological health and well-being (including four measurement items) were the ones subject to manipulation.

New variables created were called: Perceived Utility, Perceived Data Safety, Average Biometric Perceived Risk, Average Emotional States Perceived Risk and Average Expected Efficacy of Psychological Health & Well-Being.

| Variables Created | Values | Meaning |
|---|---|---|
| "Type of service" | "1" | *E-health* nutrition app |
| | "2" | Face-to-face nutrition consultation service |
| "Type of data" | "1" | Any type of personal health data is not stored or shared in the health IT database system |
| | "2" | Personal biometric health data is stored and shared in the health IT database system |
| | "3" | Personal emotional states health data is stored and shared in the health IT database system |

**Table 3:** Variables Added & Created

## Appendix 4 - Measurement Reliability & Validity

The Cronbach alpha test was used to measure reliability and internal consistency of the Likert scale items used to construct the online survey. The table below shows good internal consistency since all the dependent variables considered for this research study have alphas above 0.845. It means there was no need to raise any item from the Likert scale.

| **Reliability Analysis** | | |
|---|---|---|
| **Scale** | **Number of Items** | **Cronbach's Alpha** |
| **Perceived Usefulness** | 1 | 0.853 |
| **Perceived Ease of Use** | 1 | 0.857 |
| **Reliability** | 1 | 0.846 |
| **Perceived Trust** | 1 | 0.847 |
| **Perceived Risk (Biometric data)** | 19 | 0.857 |
| **Perceived Risk (Emotional States data)** | 5 | 0.866 |
| **Expected Efficacy of psychological health & well-being (Anxiety, Worry, Self-Esteem, Self-Image)** | 4 | 0.884 |
| **Data Privacy & Security** | 1 | 0.849 |
| **Willingness to Pay** | 1 | 0.864 |
| **Expected Satisfaction** | 1 | 0.847 |
| **Behavioral Intention to Use** | 1 | 0.852 |

**Table 4:** Reliability Analysis – Cronbach `Alpha Test

## Appendix 5 – Survey Statistics: Demographic Characteristics & General Attitudes

### Demographic Characteristics

<table>
<tr><th></th><th colspan="7">Percent</th></tr>
<tr><td>Gender</td><td>Male<br>30.8%</td><td>Female<br>68.6%</td><td>Non-binary<br>.00%</td><td colspan="4">Prefer not to say<br>.05%</td></tr>
<tr><td>Age</td><td><18 years old:<br>1.6%</td><td>18 – 24 years old:<br>63.2%</td><td>25 – 34 years old:<br>9.2%</td><td>35 – 44 years old:<br>7.6%</td><td>45 – 54 years old:<br>11.9%</td><td>55 - 64 years old:<br>3.8%</td><td>>65 years old:<br>2.7%</td></tr>
<tr><td>Monthly Gross Income</td><td>< 635 euros<br>(36.2%)</td><td>635 euros - 1000 euros<br>(14.1%)</td><td>1001 euros - 1500 euros<br>(14.1%)</td><td>1501 euros - 2000 euros<br>(9.7%)</td><td>> 2000 euros<br>(15.7%)</td><td colspan="2">Prefer not to say (10.3%)</td></tr>
<tr><td>Occupation</td><td>Student<br>(44.3%)</td><td>Student - Workers<br>(20.0%)</td><td>Employed<br>(31.9%)</td><td>Unemployed<br>(1.1%)</td><td>Self-Employed<br>(0.0%)</td><td colspan="2">Retired (2.7%)</td></tr>
<tr><td>Completed Education</td><td>High School or Lower<br>(7.0%)</td><td>Bachelor<br>(56.8%)</td><td>Master<br>(35.1%)</td><td colspan="4">PhD<br>(1.1%)</td></tr>
<tr><td>Nationality</td><td colspan="7">Portuguese<br>100%</td></tr>
</table>

**Table 5:** Survey Statistics – Demographic Characteristic

### General Attitudes towards the use of nutrition healthcare and well-being services

| Chi-Square Test | Familiarity with e-services | Familiarity with offline consultations | Currently use of e-services | Currently use of offline consultations | Diet in the past | Currently in diet | Start diet next month |
|---|---|---|---|---|---|---|---|
| **Pearson Chi-Square** | *X (1) = .436* | *X (1) = 1.966* | *X (1) = .032* | *X (1) = 1.112* | *X (1) = 2.839* | *X (1) = .049* | *X (1) = .001* |
| **p-value** | *.509* | *.161* | *.859* | *.292* | *.092* | *.825* | *.971* |

| | Online | Offline |
|---|---|---|
| **Familiarity with e-services** | **Yes:** 51.1% | **Yes:** 46.2% |
| **Familiarity with offline consultations** | **Yes:** 57.6% | **Yes:** 47.3% |
| **Currently use of e-services** | **Yes:** 14.1% | **Yes:** 15.1% |
| **Currently use of offline consultations** | **Yes:** 17.4% | **Yes:** 23.7% |
| **Diet in the past** | **Yes:** 73.9% | **Yes:** 62.4% |
| **Currently in diet** | **Yes:** 20.7% | **Yes:** 19.4% |
| **Start diet next month** | **Yes:** 19.6% | **Yes:** 19.4% |
| **Efficiency about e-services** | **1-** .00%<br>**2-** 4.3%<br>**3-** .00%<br>**4-** 8.7%<br>**5-** 25.0%<br>**6-** 25.0%<br>**7-** 13.0%<br>**8-** 7.6%<br>**9-** 5.4% | **1-** 1.1%<br>**2-** 3.2%<br>**3-** 3.2%<br>**4-** 9.7%<br>**5-** 23.7%<br>**6-** 24.7%<br>**7-** 23.7%<br>**8-** 8.6%<br>**9-** 2.2% |
| **Efficiency about offline health services** | **1-** .00%<br>**2-** .00%<br>**3-** 1.1%<br>**4-** 1.1%<br>**5-** 13.0%<br>**6-** 18.5%<br>**7-** 31.5%<br>**8-** 22.8%<br>**9-** 12.0% | **1-** 1.1%<br>**2-** 1.1%<br>**3-** 1.1%<br>**4-** 4.3%<br>**5-** 12.9%<br>**6-** 12.9%<br>**7-** 22.6%<br>**8-** 29.0% |

| | | |
|---|---|---|
| | | **9-** 15.1% |

**Table 6:** Survey Statistics – General Attitudes towards the use of nutrition healthcare and well-being services (Chi-Square Test)

**Legend:**

- Efficiency is rated on a 9-point Likert Scale (1- Not efficient at all to 9- Extremely efficient)