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Adoption of mHealth: An empirical analysis regarding the acceptance of menstrual cycle apps by Portuguese women

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Abstract

Mobile Health (mHealth) solutions aim to facilitate access to healthcare services, provide information about the individual health status, and even promote a healthier lifestyle. One of the most disseminated mHealth products is mHealth apps, namely, smartphone apps, such as menstrual cycle tracking apps. Despite the enormous number of mHealth solutions, several projects fail to meet their goals and are incapable of being adopted by end users. Comprehending what motivates their intention to use such technologies is crucial to developing more precisely structured projects aligned with the customer's point of view. The present study aims to determine the factors influencing Portuguese women's acceptance of menstrual cycle tracking apps to provide valuable insights to managerial decision-making, especially to mHealth developers.

This dissertation applied the previously established second version of the Unified Theory of Acceptance and Use of Technology (UTAUT2) model to evaluate Portuguese women's perspective through the conduction of an online questionnaire. The respondents were classified into three different groups regarding their previous contact with menstrual cycle apps and the mentioned model was applied in each group with the necessary adaptions. Particularly, in the user group, actual usage was added to the model in order to disclose the influence of intention to use the apps in the effective use of those.

To test the theoretical hypotheses, the empirical study implemented the Partial Least Squares (PLS-SEM) approach, and the results show that the model moderately predicted the users' intention (R^2=0.556). Regarding users, facilitating conditions, habit, hedonic motivation, and performance expectancy were found to be relevant indicators of the behavioral intention to use menstrual cycle apps. In the former user group, habit and performance expectancy also expectancy predicted the intention to use menstrual cycle apps. The results indicate no significant difference between the factors that dictate the behavioral intention in users and former users, with emotional factors such as habit going hand in hand with practical factors such as performance expectancy.

Keywords: mHealth; mobile health; menstrual cycle tracking apps; UTAUT2; mHealth adoption; technology adoption; smartphone apps; marketing strategy.

Resumo

As soluções de Mobile Health (mHealth) pretendem facilitar o acesso aos serviços de saúde, fornecer informações sobre o estado de saúde individual e até promover um estilo de vida mais saudável. Um dos produtos mais disseminado são as aplicações de mHealth, nomeadamente as aplicações para smartphones, como as aplicações do ciclo menstrual. Apesar do enorme número de soluções de mHealth, vários projetos não atingem os seus objetivos e não conseguem ser adotados pelos utilizadores finais. Compreender o que motiva a sua intenção de utilizar estas tecnologias é crucial para desenvolver projetos estruturados de forma mais precisa e alinhados com o ponto de vista do cliente. O presente estudo tem como objetivo determinar os fatores que influenciam a aceitação de aplicações do ciclo menstrual por mulheres portuguesas, a fim de fornecer informações valiosas para a tomada de decisão, especialmente para os programadores de aplicações de mHealth.

Esta dissertação aplica a segunda versão do modelo previamente estabelecido da *Unified Theory of Acceptance and Use of Technology* (UTAUT2) para avaliar a perspetiva das mulheres portuguesas através da realização de um questionário online. As inquiridas foram classificadas em 3 grupos relativamente ao seu contacto prévio com aplicações do ciclo menstrual e o modelo mencionado foi aplicado a cada grupo com as necessárias adaptações. Em particular, no grupo das utilizadoras, a utilização efetiva foi adicionada ao modelo de forma a revelar o impacto da intenção de utilização das aplicações na utilização concreta das mesmas.

Os resultados, obtidos através do método *Partial Least Squares Structural Equation Modeling* (PLS-SEM), mostram que o modelo previu moderadamente a intenção das utilizadoras (R^2=0.556). Relativamente às utilizadoras, as condições facilitadoras, o hábito, a motivação hedónica e a expetativa de desempenho revelaram-se indicadores relevantes da intenção comportamental de utilização de aplicações do ciclo menstrual. No grupo das ex-utilizadoras, o hábito e a expetativa de desempenho previram a intenção de utilizar estas aplicações. Os resultados indicam que não existe uma diferença significativa entre os fatores que ditam a intenção comportamental em utilizadoras e ex-utilizadoras, sendo que fatores emocionais como o hábito andam de mãos dadas com fatores práticos como a expetativa de desempenho.

Palavras-chave: mHealth; mobile health; apps de monitorização do ciclo menstrual; UTAUT2; adoção de mHealth; adoção tecnológica; smartphone apps; estratégia de marketing.

List of abbreviations

AU – Actual Usage

AVE – Average Variance Extracted

BI – Behavioral Intention

EE – Effort Expectancy

eHealth – Electronic Health

FC – Facilitating Conditions

HM – Hedonic Motivation

HT – Habit

HTMT – Heterotrait-Monotrait Ratio

ICT – Information and Communication Technology

Infarmed – National Authority of Medicines and Health Products, I.P.

mHealth – Mobile Health

NHS – National Health Service (in Portuguese, *Serviço Nacional de Saúde*)

PE – Performance Expectancy

PLS – Partial Least Squares

PV – Price Value

PLS-SEM – Partial Least Squares Structural Equation Modeling

SEM – Structural Equation Modeling

SI – Social Influence

TAM – Technology Acceptance Model

TPB – Theory of Planned Behavior

TRA – Theory of Reasoned Action

UTAUT – Unified Theory of Acceptance and Use of Technology

VIF – Variance Inflation Factor

WHO – World Health Organization

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1. Introduction

In an increasingly digitalized world, it is necessary to know how to make the best use of the technological solutions that have been developed. The access to technology, and consequently the greater access to several sources of information, has made patients increasingly informed about their health status and demanding of the services that are provided to them. A more aware and informed patient also presents new opportunities for health systems, although they need to adapt and make the right decisions to better meet individual expectations and needs.

Since its introduction in 2007 by Robert Istepanian (Tucker, 2015), the term "mobile health" or "mHealth" has fascinated several academics, investigators, and healthcare professionals. In the past several years, mHealth solutions available to consumers have increased in an accelerating rhythm. Currently, millions of people are engaged with these solutions and are committed to improving their individual or their patients' health via mobile technologies. In healthcare, several technological solutions aim to facilitate access to healthcare services, provide information about the individual health status, and even promote a healthier lifestyle. Ultimately, these advantages, with the right integration within the healthcare sector, can greatly help in coping with several problems that the system is currently facing. mHealth harbors several technological solutions supported by mobile devices, such as smartphones. As will be further discussed, mHealth solutions have various benefits for both individuals and health organizations. Moreover, they have a significant role in the economic context, with a business global value of the mHealth market of around USD 46.048 million in 2019, and an estimated of USD 230.419 million by 2027 (Rajak & Shaw, 2021).

Achieving shared decision-making depends on patient-healthcare professional interactions. Innovations regarding mHealth can promote this relation. Therefore, it is important to analyze the motivations behind the patients' adoption of these solutions. This is an important step in promoting shared decision-making because it provides valuable guidelines for designing mobile interventions that actively promote patient participation in decision-making processes and, consequently, patient decision quality. Moreover, it can provide important initiatives toward a new decision support system (Nguyen & Poo, 2016).

Interest in mHealth technologies rose during the pandemic, with the lockdowns taking on great importance in the acceptance and use of mHealth, especially mHealth apps. Although the adoption of mHealth is a very complicated phenomenon since there is a lack of safety and quality validation of these technologies by medical regulatory bodies, despite an increasing effort, individuals have adopted them as self-management aids. Thus, assessing what makes these individuals use mHealth as a quotidian tool is crucial. It is of the utmost importance to provide a more structured direction to patients, health care providers, administrators, authorities, and mHealth developers to make sure that the medical systems can react through robust technological and organizational support and to prevent the potential improper use of mHealth apps by individuals (Bradway et al., 2017). As the role of mHealth in healthcare provision rises, it's crucial to understand the motivations behind the adoption of mHealth products by the patients for them to be safe and effective and add genuine value to the healthcare system. Moreover, it is important to highlight that mHealth is changing how healthcare services are provided, promoting a better self-aware customer and, therefore, rising as an opportunity to create more value for patients. As mentioned in the literature, healthcare organizations' customer is changing to a great extent due to the highly facilitated access to information. Consequently, the adaption of healthcare organizations is necessary since the traditional ideal looked to patients as sole recipients of care and know they are seen as partners of care so that they can participate actively in healthcare processes and decision-making (Wang et al., 2018). This perspective is crucial to the healthcare marketing actual paradigm.

Marketing academics are aware of the power that technological solutions, including smartphone apps, have in the empowerment of consumers, and, therefore, it is crucial to understand the position that these customers have towards these highly disseminated goods. Unfortunately, most of the research conducted in the mHealth field, especially regarding health-related smartphone apps had a focus on theoretical hypotheses and experts' perspectives about the efficiency of such apps, rather than the final consumer point of view (Chakraborty, 2020). It is also important to mention the social impact that health-related apps have because, more than ever, companies have to clearly define their contribution to society. These apps are particularly relevant for monitoring patients' health status and facilitating access to healthcare services, pharmaceutical products, and others by older individuals (Wang et al., 2018) or people who live in more excluded areas. These apps also allow marketers to establish new companies in rural and semi-urban markets, which can be of great importance for developing these areas' economic structure (Chakraborty, 2020).

With the expected benefits of mHealth, it is not a surprise that hundreds of companies have developed projects in this area. However, several of these projects fail to meet the expectations and are incapable of reaching and being adopted by users. This fact suggests that service providers are not sure how to introduce mHealth solutions into the market because they tend to focus mainly on technological issues, rather than adopt a user-oriented business model. Since digital advances are insufficient to ensure the success of a mHealth solution it is crucial to comprehend users' perceptions, attitudes, and behaviors, ultimately leading to a competitive advantage (E. Lee & Han, 2015). Marketers need to comprehend customers' motivations since it influences the acquisition behavior and experience during the service's usage. Knowing the expectations and intentions of their clients can help organizations define their marketing strategy as well as improve their service or product in order to meet those identified needs and preferences. It is key to identify the push effects that lead people to the adoption of these solutions as well as the pull effects. The push effects may be related to the several problems that the Portuguese healthcare system is currently facing, where access to health services might be difficult, and, as a consequence, people tend to adopt a self-monitoring mindset (Hsieh, 2021). The pull effects are the ones that this study aims to reveal, which are crucial to the business and marketing strategy of the mHealth app developers.

On that account, this study aims to also provide some practical implications and knowledge, especially, for mHealth manufacturers, to help them better understand and consequently address the necessities of end clients. Particularly, the results will be of great help to develop more precisely structured projects that are aligned with the customer's point-of-view and, therefore, expand the number of downloads. The design of apps that meet their client's needs and expectations can promote a good relationship between the enterprises and their customers, who eventually become loyal and long-lasting clients (Chakraborty, 2020).

As previously highlighted, mHealth is increasingly present in our day-to-day life, facilitating personalized health monitoring and management. Therefore, it is not surprising that mHealth developers have started designing mHealth solutions aimed at feminine and reproductive health. Continuous tracking and monitoring of the menstrual cycle is an essential aid in reproductive and general women's health management (Ko et al., 2022) and with that in mind, menstrual cycle-tracking apps were developed. These highly accessible (for most women) instruments aim to provide easy and accessible health information for women, and, simultaneously, deliver platforms allowing the record of all sorts of medical information, namely, menstrual symptoms and keeping track of the menstrual phases. These apps are becoming highly relevant for women nowadays. Since the most recent solutions are incorporating self-monitoring functions and providing related, they encourage users to check for signs and symptoms of health issues (Ko et al., 2022). Ultimately, this could promote users' health by promoting healthier lifestyles and individual awareness regarding their health status – one of the main objectives that mHealth commits to achieve.

As can be seen, in addition to the high prevalence of mHealth app users, menstrual cycle monitoring apps also have a significant use, coupled with their importance in the daily lives of the women who use them. On account of this evidence, the present study aims to find out what factors influence the willingness to adopt mHealth applications (apps), more specifically, menstrual cycle tracking apps by Portuguese women. Thus, the primary research question is: <u>What are the factors that affect the willingness to adopt mHealth menstrual cycle apps for Portuguese women?</u>

In the national context, there are very few studies developed around the intention of adopting mHealth solutions and studies are absent regarding this matter and related to menstrual cycle apps, despite these being widely used worldwide and recommended by gynecologists, general practice clinicians, and other physicians (Earle et al., 2021). Therefore, this study aims to contribute to the increasing literature about mHealth and the individual's motivation to use these solutions, especially in the Portuguese panorama.

To accomplish its main goal, this study's theoretical framework will be based on a previously validated model and widely used in business and social sciences – the UTAUT2 model. The UTAUT2, despite its short existence, has already garnered more than 6,000 citations with extensive usage in information systems, mHealth, and further (Tamilmani et al., 2021). The UTAUT2 model was originally aimed at users of the technology of interest (Venkatesh et al., 2012). However, in the present study, the respondents were divided into 3 distinct groups – users, former users, and non-users – to study the application of the UTAUT2 model in different contexts of usage. Moreover, an actual usage construct, based on Alam, Hu, et al., (2020), was added in the users' case to evaluate the impact of the behavioral intention to use menstrual cycle apps in the concrete usage of those apps. Additionally, 3 moderating constructs were considered – age, education, and digital literacy – to have an impact on the behavioral intention of the respondents. An online survey was conducted, upon a pilot survey that identified interpretation issues, through the LimeSurvey® platform. The questionnaire was filled by 672 Portuguese women, but only the women who had not been through menopause at the time of the questionnaire were considered in the data analysis, remaining 634 responses of women between the ages of 15 and 60 and mainly highly educated. The questionnaire was composed of questions regarding the 3 moderating variables, the usefulness, and functions of menstrual cycle apps, and finally the UTAUT2 model's questions with the necessary adaptions for each group.

As is common in UTAUT2-related literature, the data was analyzed through the PLS-SEM approach. This increasingly used method enables the estimation of complex models with many constructs designed to provide causal explanations (Hair et al., 2019). The results obtained demonstrated that Portuguese women found the menstrual cycle tracking apps to be useful for keeping track of menstrual status, such as the cycle's length, ovulation period, and recording of menstrual symptoms. In addition, the users also pointed out this function as the main reason why they use this type of app. In relation to the UTAUT2 model, it was not possible to proceed with the data analysis of the third group, the non-users, because most of the observations had a high percentage of missing values. On the other hand, the data from the users and former users was analyzed which allowed the author to conclude that facilitating conditions, habit, hedonic motivation, and performance expectancy were found to be relevant indicators of the behavioral intention in users, and only habit and performance expectancy were relevant to predict the use menstrual cycle apps by former users. However, in the former users' case, the model only weakly predicted (R^2=0.222) their intention to use menstrual cycle apps. The model moderately predicted the users' intention (R^2=0.556), but this intention only weakly predicted users' actual use of these apps (R^2=0.327). The results also indicated that none of the 3 moderating variables considered had a significant impact on the behavioral intention of both groups. Despite these results being in accordance with the review literature, this study points out the necessity to develop more robust and targeted models in order to evaluate mHealth adoption in particular.

The present dissertation is initiated with a literature review regarding fundamental aspects to support the theoretical basis of the work developed, such as actual insight into mHealth, where Portugal stands in terms of mHealth adoption, and the definition of some of the models currently available to determine the main reasons that promote de adherence to technological products, like mHealth solutions. The first section will end with a description of the importance of the solution in analysis – menstrual cycle tracking apps. Subsequently, there will be a section dedicated to the development of the hypotheses under investigation, as well as the proposed model. As the method of data collection chosen was the questionnaire, a part will be dedicated to its development and presentation, whose consultation should be completed with the attachments provided. Finally, the results of the data analysis through the SMART-PLS statistical method will be presented and the respective conclusions discussed at the end of the same section.

2. Literature Review

2.1. mHealth and mHealth apps

Mobile Health or mHealth is defined by the World Health Organization's (WHO) Global Observatory for eHealth as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices" (Bradway et al., 2017, p. 3). Following Duque et al. (2017), mHealth can be categorized into 13 categories:

i. Education and promotion of healthy behaviors;
ii. Sensors and diagnosis point-of-care;
iii. Health monitoring and surveillance;
iv. Electronic Health Records;
v. Training and education of healthcare providers;
vi. Human resources management;
vii. Stock management;
viii. Financial transactions and incentives;
ix. Communication and collaboration among healthcare providers;
x. Call centers;
xi. Public health;
xii. Electronic prescription;
xiii. Communication between providers and patients.

mHealth can also be defined as a narrower and more precise category of eHealth or electronic health. eHealth refers to healthcare services provided with the support of information and communication technology (ICT) such as personal and laptop computers, mobile phones, iPads, tablets, and satellite communications. It is very curious that, at the moment, an even broader term than eHealth is coming to life – "digital health" is a term encompassing eHealth as well as developing areas such as big data, genomics, and artificial intelligence. Both eHealth and mHealth are becoming prominent components of healthcare and together they encompass a vast spectrum of services, ranging from electronic prescribing and medical records to text messages to remind patients to take their medicines (Moss et al., 2019).

Digital technologies are becoming an important resource for health services delivery and public health, with mobile wireless technologies, such as smartphone apps being particularly relevant, due to their ease of use, broad reach, and wide acceptance. Undoubtedly, the most disseminated technology worldwide is the smartphone, with the most recent numbers pointing to 6,648 billion users in December 2022, which corresponds to approximately 83% of the world's population owning a smartphone (Turner, 2022). Smartphones are crucial for self-monitoring purposes. The majority of healthcare providers lack the time to provide patients with continuous care and keep close track of fluctuations regarding their health status, especially, chronic patients. Despite the bias associated with self-monitoring, these solutions can improve the delivery care process, by reducing costs and saving time, improving accessibility, and mitigating geographical coverage gaps (Reychav et al., 2019).

The growth in health-related applications has accompanied the trends mentioned above. During the last trimester of 2022, 54 546 healthcare and medical apps were available on the Google Play Store (Ceci, 2022b) and there were 41 517 available on the Apple App Store (Ceci, 2022a). Birkmeyer et al. (2021) define "mHealth services as services that improve personal healthcare through the use of mobile technologies". WHO also concluded that mHealth has the potential to transform how healthcare services are delivered, but also can be a tool of great importance for public health monitoring worldwide (Birkmeyer et al., 2021). Smartphones allow identifying consumer features such as spatial and temporal trajectories and social contacts. Moreover, they have a huge role in detecting, monitoring, and controlling infectious diseases and enhancing the health system's performance jointly with internet-connected medical equipment (El-Sherif & Abouzid, 2022).

2.2. Potential Benefits and Perils of mHealth

The main benefit of mHealth is the fact that these solutions are designed to improve healthcare processes and delivery by supporting consumers and healthcare providers, through education promotion, diagnosis support, patient management, or target communication between healthcare services and patients. For example, mobile apps can help reduce medication low adherence, allowing healthcare professionals to track medication adherence as well as send reminders to patients to take their medication on a specific schedule (Alzahrani et al., 2022). mHealth is the central concept of pervasive healthcare where information and resources services can reach anyone, anytime, and anywhere, by removing temporal, geographical, and other barriers (Gagnon et al., 2016). These solutions allow individuals to be more informed and empowered, promoting "patient 2.0", a more conscious and capable patient. Patients' decisions are supported by these technological solutions eliminating the need to travel to a healthcare center. When combined with the correct analysis, mHealth and the data generated from it provide a plethora of interesting potential for all stakeholders, including patients, providers, and mHealth solutions manufacturers (El-

Sherif & Abouzid, 2022; Rahimi et al., 2017). mHealth carries several advantages to meeting unmet medical necessities, generating more patient-centric endpoints, and enhancing existing trial endpoints. It has been proven that mHealth apps have a positive impact on the level of self-management among patients with chronic conditions, by collecting several health data to help the disease management (Alzahrani et al., 2022). This is especially true when talking about chronic diseases, allowing more efficient management of these health issues through the introduction of remote monitoring and consultation (Birkmeyer et al., 2021). On the other hand, mHealth is also an affordable option to increase health promotion, health literacy, disease, and risk behaviors prevention, provision of care, and adoption of healthy quotidian activities (El-Sherif & Abouzid, 2022). Despite being a low-cost alternative, mHealth solutions offer real-time access to dynamic information (Birkmeyer et al., 2021) on several disorders, risk behaviors, social interactions, environmental toxins, and metabolites, and measure other physical and physiological variables (Bajwa, 2014). Moreover, mHealth also contributes to mitigating differences between different patients, regarding social and economic status, but also demographic challenges can be overcome. These solutions promote access to healthcare services, especially in remote areas or areas with human resources deficits (Birkmeyer et al., 2021). In a context, such as the Portuguese one, where there are clear differences in resource access between different country regions (e.g., interior populations vs. coastline populations), these solutions may be fundamental to promote a more evenly coverage of the health response. A more customized and effective way of taking care of the patients could be achieved by implementing mHealth initiatives since the mHealth prospects include drug development facilitation and acceleration, patient-reported data collecting, and diagnostic algorithm advancement. Furthermore, data collected through mHealth will give real-world safety information, enhance predictive modeling, and facilitate comparative effectiveness studies (El-Sherif & Abouzid, 2022). Studies also pointed out that mHealth technologies can greatly help the shared decision-making process and stimulate and facilitate this process between clinicians and healthcare providers (Rahimi et al., 2017). Another benefit will be promoting collaboration and communications between healthcare providers, but also between them and academic institutions, and the pharmaceutical sector. This is probably the next challenge faced by mHealth companies since this collaboration will require the extension of mHealth use and the influence that data may have on healthcare policies (El-Sherif & Abouzid, 2022).

However, the usage of mHealth devices is not free from disadvantages and risks. The major setbacks these solutions face include resistance to innovation, which can also be associated with technology anxiety, lack of infrastructural support, and the cost (monetary cost but also in terms of time, if additional training is necessary) of acquiring the technology (Bajwa, 2014; Rahimi et al., 2017). Mobile applications that send alerts or reminders can increase anxiety in patients (Rahimi et al., 2017). Moreover, more detailed apps can require patient and healthcare professionals' education, which consumes human and financial resources. Consequently, they can create more health disparities between those who fully take advantage of these solutions and those who lack the literacy to make the most of the information they offer or simply cannot use them (Rahimi et al., 2017). Another crucial barrier to mHealth resides in security threats. With the increased connectivity, also comes a higher possibility of accessing data stored in the devices or recorded by them. The most common threats related to the use of mobile devices include loss and theft of the mobile devices; off-site data storage since the increasing storage capabilities lead to the storage of corporate sensitive data on these devices; and network access out of the users' control since these devices can connect to any wireless interface, which exposes them to possible attack vectors (Bajwa, 2014). Since mHealth uses wireless atmospheric media to transmit the information as radio signals, the devices became extremely exposed to eavesdropping, modification, theft, distortion, and even loss of the collected data (Bajwa, 2014). Moreover, the fact that mobile apps contain sensible and personal information about its user, such as email, telephone numbers, etc., can create some reluctance to use the app (Alzahrani et al., 2022) because of possible wrongful access to that data. An additional issue related to these solutions is the lack of a universal regulatory system and few regulations around mHealth apps. The fact that there is no regulatory frame adequate for these applications, makes it possible to have available apps that provide false, incorrect, or inaccurate information to the users (Alzahrani et al., 2022; Rahimi et al., 2017). An effective tool requires manpower and a well-functioning regulatory system in order to provide patients and professional information of high quality as well as provide the best decision support they can (Rahimi et al., 2017). Finally, other barriers pointed out at mHealth apps are related to difficulties in using some apps, even by experienced users, and also the lack of clinicians' recommendations and evidence about the effectiveness of medical health apps (Alzahrani et al., 2022).

2.3. Acceptance of mHealth

Several studies have used technology acceptance models to find the influential factors behind the intention and actual use of mHealth and eHealth by patients or certain groups of patients (Table 1).

After the entering of technology into our everyday life, it was necessary to discern the reasons why technology was being rejected or accepted. In this context, there was the need to have models that can explain how users embrace different technological solutions, and that is also the case for mHealth applications. To answer those needs, over the past two decades, many models relating to technology acceptance were developed and tested, mostly regarding the acceptance of a broad spectrum of ICT systems like electronic medical records and personal assistants (Rajak & Shaw, 2021).

Table 1: Summary of the research on mHealth adoption in different countries (Adapted from Alam et al., 2020).

Reference	Country	Theoretical Framework	Key Findings
Mohamed et al. (2011)	UK	Extended TAM	Social, cultural, and technological constructs, perceived usefulness, and perceived ease of use
Wu et al. (2011)	Taiwan	TAM and TPB	Perceived usefulness, subjective norms, perceived behavioral control, and attitudes
Phichitchaisopa & Naenna (2013)	Thailand	UTAUT	Performance expectancy, facilitating conditions, effort expectancy
Yang (2013)	USA	TPB, TAM and Gratification Theory	Perceived usefulness, perceived enjoyment, ease of use, subjective norms, and perceived behavioral control
Cho et al. (2014)	USA	Extended TAM	Subjective norm, health consciousness, health information orientation, and Internet health information use efficacy
Kang (2014)	USA	Extended TAM	Performance expectancy, effort expectancy, social influence, entertainment, and communication
Yuan et al. (2015a)	USA	UTAUT2	Performance expectancy, hedonic motivations, price value, and habit
Chang et al. (2016)	China	TAM and TPB	Perceived usefulness, perceived ease of use, social influence, attitudes, self-efficacy, involvement, and perceived behavioral control
Hoque (2016)	Bangladesh	Extended TAM	Perceived usefulness, trust, subjective norms, and perceived ease of use

Cho (2016)	Korea	PAM and TAM	Perceived usefulness, perceived ease of use, confirmation, and satisfaction
Hoque & Sorwar (2017)	Bangladesh	Extended UTAUT	Performance expectancy, social influence, effort expectancy, technology anxiety, and resistance to change
Okumus et al. (2018)	USA	Extended UTAUT	Performance expectancy, social influence and effort expectancy, innovativeness
Alam et al. (2019)	Bangladesh and China	Extended UTAUT (cross-country analysis)	Bangladesh: Performance expectancy, social influence, facilitating conditions, and perceive reliability China: Performance expectancy, effort expectancy, social influence, and price value
Alam et al. (2020)	Bangladesh	Extended UTAUT	Performance expectancy, social influence, facilitating conditions, perceive reliability
Rajak & Shaw (2021)	India	Extended TAM	Technology anxiety, social influence, perceived risk, trust, resistance to change, and perceived physical condition
Schomakers et al. (2022)	Germany	Extended UTAUT2	Lifestyle apps: Hedonic motivation, and habit Therapy apps: Social influence, and trust

One model was presented in 1985 by Fred Davis and would become the dominant model in investigating factors affecting users' acceptance of technology – the Technology Acceptance Model (TAM). This model was based on the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), an extension of the first one (Marangunić & Granić, 2015). The initial TAM has five dimensions: (i) perceived usefulness; (ii) perceived ease of use; (iii) attitude; (iv) behavioral intention; and (v) actual use (Davis, 1985). The TAM is a well establish and robust model, with its constructs being validated several times in different contexts, not only in the health sector but also in the education and industrial sector as well. However, the explanatory power of this model stays roughly around 40% (Rajak & Shaw, 2021). In 2000, Venkatesh and Davis suggested an extension to the traditional TAM, proposing TAM2, which included new factors that would affect compliance with technological solutions: (i) subjective norm, that would capture the influence of social compliance on perceived usefulness through internationalization; (ii) image, that reflects individual confidence that using technology will increase performance and, therefore, enhancing perceived usefulness; (iii) job relevance; (iv) output quality; (v) result demonstrability (Venkatesh & Davis, 2000; Zhang et al., 2010). As said before, the TAM was applied in various areas other than health, where the authors added external factors related to those areas. For example, Rajak & Shaw (2021) applied the same thought and added four other factors that could affect the behavioral intention of accepting mHealth solutions: (i) technology anxiety; (ii) social influence; (iii) perceived risk; (iv) trust; (v) resistance to change; and (vi) perceived physical condition. Likewise, Mohamed et al. (2011) extended the traditional TAM model by adding subjective norms, tangibility, and Hofstede's cultural dimensions.

However, the low explanatory power and the absence of moderator variables in TAM are pointed out as important limitations by various authors. This criticism might justify the emergence of another model – the Unified Theory of Acceptance and Use of Technology (UTAUT). This framework was developed based on eight technology acceptance theories and models: TRA, TPB, TAM, the motivation model, the augmented TAM, the model of personal computer utilization, the innovation diffusion theory, and social cognitive theory (Binyamin & Zafar, 2021). The UTAUT postulates that user intention and actual behavior are determined by four independent factors – (i) performance expectancy; (ii) effort expectancy; (iii) social influence; and (iv) facilitating conditions – and four moderating variables – (i) gender; (ii) age; (iii) experience; and (iv) voluntariness of use (Binyamin & Zafar, 2021). In 2012, the UTAUT was extended, creating the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which aimed to explain consumer behavior by adding three additional key constructs from prior marketing research – (i) hedonic motivation; (ii) price value; and (iii) habit – and three moderating variables – (i) age; (ii) gender; and (iii) experience (Venkatesh et al., 2012), altering some of the formerly existing relationships in the original UTAUT (Al-Nuaimi & Al-Emran, 2021).

The UTAUT and UTAUT2 models produce more papers in the Business area in comparison with other areas such as Computer Science Information Systems and the number of citations is much higher in UTAUT and UTAUT2 models than in TAM. In conclusion, from a bibliometric approach, UTAUT and UTAUT2 models are the most relevant theory in terms of publications, citations, and emerging themes, although both sets of theories are currently in use (Sebastián et al., 2022). On the other hand, UTAUT2 focuses on accepting commercially available technologies (Schomakers et al., 2022). The UTAUT2 model has been proven to be an effective model and it is being used by recent studies due to its simplicity, parsimony, and robustness (El-Masri & Tarhini, 2017). Also, this model has been developed in marketing settings, contrary to the original UTAUT which has been developed in organizational settings (Al-Nuaimi & Al-Emran, 2021). Therefore, this model is used for investigation purposes regarding the impacts on consumers' acceptance and adoption of a given application (Al-Nuaimi & Al-Emran, 2021). For example, Macedo (2017) used the UTAUT2 model to predict the acceptance and use of information and communication technological tools by Portuguese adults over the age of 55. Yuan et al. (2015) used the same model to evaluate the adoption of health and fitness apps by American college-aged smartphone users. In turn, Schomakers et al. (2022) added trust and privacy concerns to the UTAUT model in a study that aimed to reveal the factors that influenced behavioral intention to use lifestyle and therapy apps by German individuals.

As previously highlighted in the introductory section, the healthcare sector is increasingly getting closer to its end customers, which predicts a change in current business models towards more customized approaches and targeted strategies for the management of chronic diseases. With consumers increasingly informed, it is essential to have ways to empower them, something that can be achieved through the use of mHealth products (Wang et al., 2018). The increase in the number of patients and costs associated with healthcare also stimulates the search for solutions to mitigate these impacts. Thus, and as with all technological products, mHealth solutions are being developed at an extraordinary pace. However, despite the immense diversity of products available, many developers do not take the end user's point of view into account, meaning that many solutions are not adopted. Hence the importance of these technology acceptance models. These models make it possible to assess what is behind the acceptance of a certain technological product. This proves to be crucial for the delineation of marketing strategies, as it provides insights into the end customer's expectations, opinions, and attitudes (Chakraborty, 2020). These models also contribute to identifying the push effects that lead consumers to the adoption of mHealth solutions as well as the pull effects (Hsieh, 2021). Therefore, mHealth products can be designed to meet the expectations and desires of their potential users, as well as being continuously improved to fulfill them. This will be indispensable for establishing and maintaining lasting relationships with users and attracting new customers.

In similarity to what happens with the large majority of the literature mentioned and studies that applied the UTAUT2 model, the statistical method elected by the author of this study was the PLS-SEM, which "estimates partial model structures by combining principal components analysis with ordinary least squares regressions" (Hair et al., 2019, p. 4).

2.4. mHealth in Portugal

According to Duque et al. (2017), before the dissemination of smartphones throughout the Portuguese population, the eHealth study was mainly focused on telemedicine. Telemedicine consists of delivering healthcare services at a distance, where healthcare professionals use ICT to exchange valid information for diagnosis, treatment, and disease prevention, in the best interest of the patient and community (*Consolidated Telemedicine Implementation Guide*, 2022). A study conducted by the Calouste Gulbenkian Foundation in 2007 revealed that the most common telemedicine practices in the Portuguese context were telediagnosis, by the imaging and neuroradiology departments, and teleconsultation, by the cardiology and dermatology departments. Seven years later, in 2014, a survey conducted by Statistics Portugal concluded that teleradiology and teleconsultation remain the most relevant telemedicine domains in the 33% of Portuguese hospitals that had telemedicine initiatives implemented (*WP5-Policy and Innovation: Overview of MHealth Policies in Portugal*, 2020).

As consumers demand digital health services that respond to their needs where and when needed, Portugal started to develop mobile health interactions, with the redesign of some processes with emphasis on the patients as well as introducing mobile solutions to respond to the growing tendency for healthcare collaboration (*WP5-Policy and Innovation: Overview of MHealth Policies in Portugal*, 2020). In October 2016, the National Strategy for the Health Information Ecosystem 2020 (ENESIS 2020) was approved, which aimed to promote acceptance of the generic understanding of "Health in all policies", namely in adopting the concept of mHealth. At the time Duque et al. (2017) developed their work, they concluded that mobile applications or apps used in smartphones with internet connection were the most common technological solution in Portugal, especially those whose aim was health monitoring and surveillance as well as those who promote communications between healthcare professionals and between them and their patients.

The ENESIS 2020 ended in December 2019, being replaced by the National Strategy for the Health Information Ecosystem (ENESIS 2022), designed for the three-year period from 2020 to 2022, whose aim was to continue the progress by the first one, promoting digital transformation of the Portuguese health sector as well as creating indispensable conditions for the evolution of the Health Information Ecosystem (eSIS) (*WP5-Policy and Innovation: Overview of MHealth Policies in Portugal*, 2020). ENESIS 2022 main goal is to promote greater availability, convenience, accessibility, speed, and humanization of healthcare services, but also expand and improve the care delivery network, improve resource management and quality of care as well as promote a better articulation between the different NHS's stakeholders and strength individuals' powers (*WP5-Policy and Innovation: Overview of MHealth Policies in Portugal*, 2020).

With the recent pandemic covid-19, the context has shifted, which obliged the National Health Service (NHS) but also the private health sector to adapt and use telemedicine, particularly teleconsultation, as a solution to facilitate patient appointments. As a sequel of the pandemic, the vast majority of Portuguese hospitals and primary healthcare centers have adopted telemedicine in certain cases (O'Neill et al., 2022), even with the current policies of no restrictions. The larger Portuguese private health companies have developed apps to facilitate patient's access to medical exams, consultation booking, and emergency room waiting time, among others. Moreover, the Portuguese NHS has been developing some other initiatives in the mHealth area, including the apps STAY AWAY COVID, which was intended to establish a network of covid-19 contacts to control possible outbreaks, MySNS, MySNS Tempos, SNS 24, eMed.pt (powered by Infarmed), and Dador.pt.

2.5. Menstrual cycle tracking apps

In order to perform this study, a specific type of mHealth app was elected – menstrual cycle tracking apps. This allowed a more focused approach to the questionnaire, easier concretization, and a more precise definition of a target population.

Certainly, apps have changed the way we conducted certain operations during our quotidian, making them easier to perform, more accessible, and less time-consuming, among others. Therefore, it is not surprising that app developers started to apply all of these advantages to health-related realities. Given their high number and current annual growth rate, health apps represent one of the most dynamic and growing technological solutions in the areas of biomedicine and health care (Levy & Romo-Avilés, 2019). There are immensely varied mHealth apps, from lifestyle apps to sleep monitoring apps. Regarding women's health, in particular, technological companies saw an opportunity to develop such apps as frequently women turn to web search engines, apps, and social media during pregnancy and fertile life in order to obtain information on whether their experience is normal (Epstein et al., 2017). So, the development of more accessible and personalized platforms that would help women achieve their individual fertility goals and be more aware of their reproductive health seemed a natural market for these firms.

FemTech app is a recent term used to describe women-oriented technologies whose aim is to aid women's health and harbors a vast range of technological solutions such as fertility-based apps for pregnancy planning and menstrual cycle apps for the tracking of periods and symptoms (also known as period tracker apps). The first menstrual cycle-tracking app came out in 2013 ("Glow") and since then the industry has continuously expanded, with the FemTech market estimated to be worth 50 billion dollars by 2025 (Broad et al., 2022). As mentioned before, menstrual cycle tracking apps are a subgroup of mHealth apps. Menstrual cycle apps are among the most widespread health apps, a booming market with millions of users where start-ups are attracting investor capital of tens of thousands of dollars (Frank-Herrmann et al., 2021). Today, around 7% of the 90.088 health apps in the Apple Store are focused on women's health and pregnancy (Broad et al., 2022).

Epstein et al. (2017) found out that 47% of the women surveyed used an app on their phone to track their menstrual cycle and this was the first menstrual cycle-tracking method they thought of – as one of the participants said: "[it is] common sense, there had to be an app for it. There's an app for everything.". The same study identified five principal reasons for women to track their menstrual cycle, as follows: (1) be aware of how their body state, (2) understand their body's reactions to different phases of the menstrual cycle, (3) be prepared, (4) become pregnant, and (5) establish informed discussions with healthcare professionals (Epstein et al., 2017). In turn, Broad et al. (2022) 91.2% of the users interviewed had downloaded these apps because they wanted to understand more about their body and menstrual cycle, especially because they wanted to plan and prepare for their period, but also leave hormonal contraception or try to get pregnant.

These apps allow the observation and analysis of the menstrual cycle and also various related factors. There are three types of fertility awareness-based apps: (a) calendar apps that look at the length of the menstrual cycle and assume average phase lengths; (b) basal body temperature-based apps that detect the rise of the lowest resting body temperature; and (c) symptothermal apps that measure other parameters, such as cervical mucus changes (Bull et al., 2019). Most menstrual cycle-tracking apps have three basic functions (Levy & Romo-Avilés, 2019):

1) Tracking of menstrual cycle-related factors, such as mood swings, pain, sleeping patterns, medication and oral contraceptives intake, sex-life, vaginal discharge, food cravings, and physical activity;
2) A menstrual calendar indicating period and ovulation dates and duration;
3) A statistical analysis is displayed as graphs, tables, or numerical depictions, with information regarding average cycle lengths, changes in body weight, mood, body temperature, and others.

A few apps also offer access to online forums and provide clinical information through links or pop-ups. Several facilitate user interaction with healthcare professionals or other users.

One of the first contributions of these apps was the prediction of the "fertile window", which helped women trying to conceive by timing sexual intercourse (Freis et al., 2018). More recently, with the rise of data-powered health, it is now possible to identify menstrual patterns at scale and explore their relationships with several symptoms. Observational health data sources, such as these apps, have shed light on individual clinical paths, and increased self-awareness about individual health (Freis et al., 2018). This and other advantages made menstrual cycle-tracking apps the second most popular app for adolescent girls and the fourth most popular for adult women (Li et al., 2020).

It is also noteworthy the fact that these apps were also proven useful in terms of research regarding reproductive health. For example, Grieger & Norman (2020) and Bull et al. (2019) analyzed and described differences in menstrual cycle length, variability, and menstrual phase across women of different ages and body mass index (BMI) among a global cohort of Flo app users and the database from a non-identified app, respectively. The information collected from these studies and others is of the utmost importance to support updates of current clinical guidelines around menstrual cycle duration and patterns for clinical application in fertility programs.

However, it is important to stress that smartphone apps are not regulated like medical devices, and therefore some concerns around reliability, effectiveness, privacy, and accountability rise. Regulations regarding mHealth are in their initial state, even though they are increasingly needed due to the high variety of mHealth apps in the market. Despite their popularity among users, a low number of these apps have been rigorously evaluated, and their methods to predict events such as ovulation days or fertile windows are often not disclosed by app companies (Zwingerman et al., 2020). Therefore, even apps with very positive user reviews and highly ranked are often inaccurate, since several attempts to regulate mHealth apps have failed (J. Lee & Kim, 2019). Some of the apps are only intended for use for cycle monitoring, but practice shows that as soon as apps display a fertile window, they are often also used for contraception, regardless of what the disclaimer says regarding their suitability for correctly displaying the fertile window or safety for contraception (Frank-Herrmann et al., 2021). Also, safety and privacy concerns regarding personal data are risen, which leads to necessary control and regulation by the competent authorities regarding these aspects.

Concluding, these apps must be more transparent with the extent of their ability to accurately predict menstrual cycle dates, and improve their data protection policies, because users trust these apps, and, therefore, inaccurate, or imprecise predictions can have a big impact on other aspects of users' health, especially their mental health (Broad et al., 2022).

2.6. Measurement of mHealth Acceptance

Because of its higher explanatory power and the inclusion of moderator variables, as well as due to its widespread use in literature, this study will be conducted through the application of the UTAUT2 model. Therefore, and as shown in Figure 1, seven factors will be considered relevant to the behavioral intention of using the menstrual cycle apps. Moreover, three variables regarding respodents' individual characteristics will be considered, namely, age, education (Macedo, 2017; Venkatesh et al., 2012), and digital literacy. Regarding the later, the questions were based on van der Vaart & Drossaert (2017). In the literature it is possible to find other possible moderating variables, for example, app familiarity, health-app familiarity, privacy disposition, and propensity to trust apps (Schomakers et al., 2022).

1. Performance Expectancy (PE)

PE is described as the extent to which a user perceives utilizing the new mHealth solution will allow her to obtain gains or benefits and, thus, is tied to the perception of usefulness (Schomakers et al., 2022; Venkatesh et al., 2003). Generally, individuals seem to be more motivated to use and accept new technology if they perceive that this technology is advantageous and useful in their quotidian (Alam, Hu, et al., 2020).

H1: PE positively influences the behavioral intention to use mHealth apps.

2. Effort Expectancy (EE)

EE is identified as the degree of simplicity or ease of usage associated with the mHealth application (Venkatesh et al., 2003). In general, individuals tend to consider the efforts required by the technology before using it (Alam, Hoque, et al., 2020; Hoque & Sorwar, 2017).

H2: EE positively influences the behavioral intention to use mHealth apps.

3. Social Influence (SI)

SI is defined as the degree to which an individual perceives that influential people to her believe that she should use the mHealth solution (Hoque & Sorwar, 2017; Venkatesh et al., 2003). Several studies found that the use of technology is influenced by the common beliefs of an individual's surrounding environment (Alam, Hu, et al., 2020; Schomakers et al., 2022).

H3: SI positively influences the behavioral intention to use mHealth apps.

4. Facilitating Conditions (FC)

FC are defined as the degree to which an individual thinks that objective factors in the environment, namely the organizational and technical infrastructure, offer support to the adoption of mHealth solution (Venkatesh et al., 2003). It is hypothesized that if individuals feel that they have a sufficient level of organizational, technical, infrastructural, and human support, they will more easily accept the use of mHealth apps (Alam, Hoque, et al., 2020; Hoque & Sorwar, 2017).

H4: FC positively influences the behavioral intention to use mHealth apps.

5. Hedonic Motivation (HM)

HM is defined as the perceived pleasure or enjoyment that the individuals experience while using the mHealth solution. (Schomakers et al., 2022; Venkatesh et al., 2012)It is hypothesized that individuals may also use mHealth apps for task performances and personal entertainment (Alam, Hu, et al., 2020).

H5: HM positively influences the behavioral intention to use mHealth apps.

6. Price Value (PV)

PV is calculated by the difference between the total perceived benefits of the mHealth solutions and the total monetary or non-monetary cost of usage. Therefore, the PV is positive when the solution's benefits are perceived as greater than the monetary and non-monetary costs (Venkatesh et al., 2012). It is hypothesized that individuals will expect higher quality if they pay an increased monetary amount (Alam, Hu, et al., 2020).

H6: PV positively influences the behavioral intention to use mHealth apps.

In order to maintain the accuracy and rigor of further results and conclusions, the variable Price Value was not included in the data analysis, as explained in more detail in that particular section. Therefore, the sixth hypothesis was not considered.

7. Habit (HT)

Habit is defined in two different ways: (i) prior behavior; and (ii) measured as the extent to which the individual believes the behavior to be automatic (Venkatesh et al., 2012). For that reason, HT is established as the point at which individuals intend to perform their behaviors automatically as a reflection of past learning experiences. It is hypothesized that individuals' familiarization with mHealth apps will drive to continuous usage (Alam, Hu, et al., 2020).

H7: HT positively influences the behavioral intention to use mHealth apps.

8. Behavioral Intention (BI)

BI is defined as the extent to which an individual deliberately intends to carry out a concrete action (Hoque & Sorwar, 2017). Therefore, it is hypothesized that it is positively associated with actual usage behavior (Alam, Hu, et al., 2020).

H8: BI positively influences the actual usage (AU) of mHealth apps.

9. Age, Digital Literacy and Education

This study, as opposed to what Venkatesh et al. (2012) proposed with the original paper regarding UTAUT2, does not include age, gender, and experience as moderators of the relationships of the predictor variables with behavioral intention. Instead, it is proposed that age, digital literacy, and education have a significant effect on behavioral intention as demonstrated by Schomakers et al. (2022) regarding the acceptance of mHealth apps.

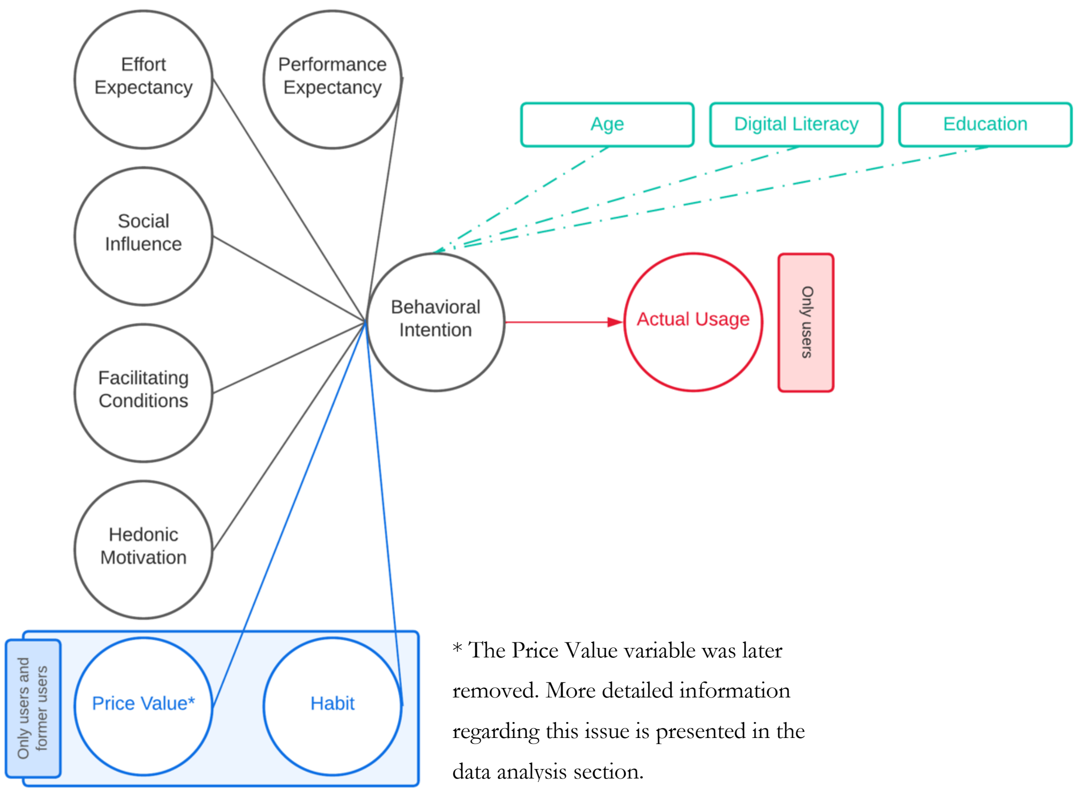

Figure 1: Conceptual framework based on the UTAUT2 model (Adapted from Alam et al. (2019); Schomakers et al. (2022); Venkatesh et al. (2012)).

3. Methodology

3.1. Data Collection

In business and management research, there are several methods of collecting data, including surveys, archival research, and case studies. A survey is normally associated with deductive research and is the recommended method to find out how the target population feels about a particular issue. This strategy allows the collection of quantitative data which can be analyzed quantitatively using descriptive and inferential statistics (Saunders et al., 2012). The data collected using a survey can be then used to suggest possible reasons for relationships between variables and subsequently produce models. Other advantages are the higher control over the research process, in comparison with other methods, and the capability to obtain a representative sample at a lower cost. Finally, when choosing a survey strategy, the dependence on other sources to supply the data is eliminated.

Thus, this study will be conducted through a questionnaire, the main method used in a survey strategy. The data will be collected through an electronic survey, implemented in the online platform LimeSurvey®.

3.2. Survey Design

The questionnaire's target population is the Portuguese feminine population in fertile years, with access to a smartphone.

The first part of the questionnaire will be aimed at collecting demographic data, such as age and educational level. Regarding the latter, the different levels present will be primary education graduate, secondary education graduate, tertiary education graduate, high school graduate, or university graduate – bachelor or equivalent, master's or doctorate graduate. Then, a couple of questions will evaluate different levels of smartphone app literacy, based on van der Vaart & Drossaert (2017). After questions will be conducted in order to evaluate if the woman inquired is in her fertile years (if not, the answers will not be considered). The following question aims to identify this type of app's current users, previous users, and non-users. Before posing the questions related to the study model, the respondents were asked if they consider these apps useful in terms of conception and recording of menstrual symptoms and helpful for women who are trying to conceive.

The next answers are related to the seven dimensions of the UTAUT2 with the necessary adaptations regarding the scales presented by Venkatesh et al. (2012). The scales developed by Alam et al. (2019) and Schomakers et al. (2022) will be also used as a base to construct the present study's scale. The constructs of the UTAUT2 were previously operationalized using previously validated multi-item scales. In this study, the answers will be given through a Likert-type response offering a range of options between 1 (strongly disagree) and 5 (strongly agree). Likert-type responses can be interpreted as ordered, but since the distance between each response choice is not necessarily constant, this type of response reflects ordinal rather than interval data (Batterton & Hale, 2017).

Previously to the dissemination of the questionnaire, a pilot study was conducted in March 2023 conducted by 6 women between the ages of 23 and 42 (designated by 1 to 6 from now on). The aim of this pilot study was to identify weaknesses and obtain suggestions regarding the explicitness of the questions presented. Suggestions were made regarding the phrasing and the overall structure of the questionnaire. These suggestions were discussed, and changes were performed in order to improve the survey, as summarized in the following schematic table (Table 2).

Table 2: Summarized feedback obtained from the pilot study and alterations made.

Question or Group	Subject	Feedback	New Version
Indicate whether monitoring your menstrual cycle is still relevant at this point in your life	**2**	Right now, it makes no sense for me to monitor my menstrual cycle, because I take the birth contraceptive pill.	The questionnaire was open to these women as well. These respondents will be considered users for the purposes of the questionnaire (**former users**).
	6	Right now, it makes no sense for me to monitor my menstrual cycle, because I have an intrauterine contraceptive device. I think it could be interesting to obtain the opinion of women that like me previously used these apps but do not anymore.	
EE group	**4**	The questions are similar, so it requires more attention when reading to understand each one well.	No alteration was made.
PE2. Using menstrual cycle tracking apps helps me accomplish things more quickly	**1**	Improve the clarity of the questions.	No alteration was made.
PE3. Using menstrual cycle tracking apps increases my productivity	**1**		**PE3.** Using a menstrual cycle monitoring app helps me take care of my health[1]
SI1. People who are important to me think	**5**	The questions are confusing.	There were no changes made.

that I should use menstrual cycle tracking apps			
SI2. People who influence my behavior think that I should use menstrual cycle tracking apps	**1**	These are questions that can only be discussed with people close to you.	There were no changes made.
	3	In my case it is indifferent, but I put 1 (strongly disagree).	
	5	The questions are confusing.	
SI3. People whose opinions I value prefer that I use menstrual cycle tracking apps	**1**	These are questions that can only be discussed with people close to you.	**SI3.** I use menstrual cycle monitoring apps because many people do[2]
	3	In my case it is indifferent, but I put 1 (strongly disagree).	
	5	The questions are confusing.	
FC3. Menstrual cycle tracking apps are compatible with other technologies I use	**3**	It was not clear what kind of technologies.	**FC3.** Menstrual cycle tracking apps are compatible with other technologies I use (e.g., smartwatch, tablet)
FC5. Guidance will be available to me in the use of menstrual cycle tracking apps	**3**	It was not clear whether the guidance was provided by the application itself.	**FC5.** It's easy to obtain guidance when using menstrual cycle monitoring apps (e.g., in the app itself, in user guides, on the internet, from other users)[2]
PV group	**5**	I believe most apps are free so it would be nice to include this fact.	A question to distinguish users of paid and free versions of apps was introduced (PV4).

[1] Adapted from Schomakers et al. (2022)
[2] Adapted from Tak & Panwar (2017)

Following the conclusions drawn from the pilot study, the questionnaire was also open (with the necessary adaptions) to women who had already used this kind of mHealth app, establishing a third group to be further analyzed – the former users (Table 3). Regarding these previous users, two additional questions were asked, namely, how long ago the woman stopped using the app and whether her menstrual cycle monitoring was still relevant. The latter is intended to distinguish women who have stopped using the app for reasons related to their menstrual health (e.g., adopting hormonal contraceptive methods or becoming pregnant) from those who have stopped using the app for reasons that can be attributed to the app itself.

Moreover, after the questions raised during the pilot study, the questionnaire included one additional question related to the price variable. Since most of these apps offer both a free and a paid version, the respondents were asked which version they used, in the case of previous users, or use, in the case of current users. Only the women who answered the paid version will answer the three questions of the price value variable. The others will only answer question PV4 (see Table 3). Later on, this comparative analysis between the two groups is expected to be relevant, since women with access to the paid version will have access to more resources, which should influence their answers.

Table 3: Questions regarding the UTAUT2 constructs.

	Reference
Effort Expectancy (EE)	
EE1. Learning how to use menstrual cycle tracking apps is easy for me	Venkatesh et al. (2012)
EE2. My interaction with menstrual cycle tracking apps is clear and understandable	
EE3. I find menstrual cycle tracking apps easy to use	
EE4. It is easy for me to become skillful at using menstrual cycle tracking apps	
Performance Expectancy (PE)	
PE1. I find menstrual cycle tracking apps useful in my daily life	Venkatesh et al. (2012)
PE2. Using menstrual cycle tracking apps helps me accomplish things more quickly	
PE3. Using a menstrual cycle monitoring app helps me take care of my health	Schomakers et al. (2022)
Social Influence (SI)	
SI1. People who are important to me think that I should use menstrual cycle tracking apps	Venkatesh et al. (2012)
SI2. People who influence my behavior think that I should use menstrual cycle tracking apps	
SI3. I use menstrual cycle monitoring apps because many people do	Tak & Panwar (2017)
Facilitating Conditions (FC)	
FC1. I have the resources necessary to use menstrual cycle tracking apps	Venkatesh et al. (2012)
FC2. I have the knowledge necessary to use menstrual cycle tracking apps	
FC3. Menstrual cycle tracking apps are compatible with other technologies I use (e.g., smartwatch, tablet)	
FC4. I can get help from others when I have difficulties using menstrual cycle tracking apps	Alam et al. (2019)
FC5. It's easy to obtain guidance when using menstrual cycle monitoring apps (e.g., in the app itself, in user guides, on the internet, from other users)	Tak & Panwar (2017)
Hedonic Motivation (HM)	
HM1. Menstrual cycle tracking apps are fun	

HM2. Using menstrual cycle tracking apps is enjoyable	Venkatesh et al. (2012)
HM3. Using menstrual cycle tracking apps is very entertaining	
Price Value (PV)	
USERS AND FORMER USERS ONLY – PAY VERSION	
PV1. Menstrual cycle tracking apps are reasonably priced	Venkatesh et al. (2012)
PV2. Menstrual cycle tracking apps are a good value for the money	
PV3. At the current price, menstrual cycle tracking apps provides a good value	
USERS AND FORMER USERS ONLY – FREE VERSION	
PV4. Menstrual cycle tracking apps are a good value	NA
Habit (HT)	
USERS AND FORMER USERS ONLY	
HT1. The use of menstrual cycle tracking apps has become a habit for me	Schomakers et al. (2022)
HT2. I cannot do without menstrual cycle tracking apps anymore	
HT3. I must use menstrual cycle tracking apps	
Behavior Intention (BI)	
USERS	
BIU1. I intend to continue using menstrual cycle tracking apps in the future	Venkatesh et al. (2012)
BIU2. I will always try to use menstrual cycle tracking apps in my daily life	
BIU3. I plan to continue to use menstrual cycle tracking apps frequently	
NON-USERS	
BINU1. I intend to try out menstrual cycle tracking apps	Schomakers et al. (2022)
BINU2. I want to use menstrual cycle tracking apps in my daily life	
BINU3. In the future I will use menstrual cycle tracking apps frequently	
FORMER USERS	
BIEXU1. I intend to use menstrual cycle tracking apps again.	NA
BIEXU2. I want to use menstrual tracking apps in my daily life again.	
BIEXU3. In the future, I will use menstrual cycle tracking apps frequently	
Actual Usage (AU)	
USERS ONLY	
AU1. Using menstrual cycle tracking apps is a pleasant experience	Alam et al. (2019)
AU2. I spend a lot of time on menstrual cycle tracking apps	
AU3. I use menstrual cycle tracking apps on regular basis	

NA: Not applicable.

Afterwards, the questions regarding the UTAUT2 model were translated into Portuguese (see Appendix I).

3.3. Survey Dissemination

There were 672 complete answers to the questionnaire, which were obtained between the 7th and 31st of May of 2023. The primary channels used to distribute the questionnaire were institutional channels related to the University of Porto and channels from a couple of their investigation institutes, such as INESC TEC. The questionnaire was also disseminated among professionals working in two health units (one public and one private). After contacting several institutions related to women's studies and feminine health, two of them also shared the questionnaire with their followers, one through social media channels – *Associação Portuguesa para o Planeamento da Família* (APF) – and the other through their private contact network – *Associação MulherEndo: Associação Portuguesa de Apoio a Mulheres com Endometriose*. Finally, the study was spread to personal contacts of the investigators, especially through social media platforms. These methods allow the collection of data from women in different age groups but also with distinct economic, social, and educational backgrounds.

3.4. Data analysis

3.4.1. Primary data treatment with SPSS Statistics

SPSS Statistics software was used in the primary data analysis. With this tool, it was possible to screen respondents and eliminate observations from those outside the study population target, namely women who had already been through menopause. The descriptive statistics were also performed through this software.

3.4.2. Data analysis using the PLS-SEM method with SmartPLS 4

In order to perform the statistical analysis, the chosen method was Structural Equation Modeling (SEM). SEM is a second-generation multivariate method, which overcomes the weaknesses of first-generation methods such as multiple regression or cluster analysis (Hair Jr. et al., 2017). This method, created in the early 1900s, provides a flexible framework for developing and analyzing complex relationships among multiple variables, combining a factor analysis and multiple regression analysis (Beran & Violato, 2010). The SEM methods allow the incorporation of unobservable variables measured indirectly by indicator variables and facilitate the identification of measurement errors in observed variables (Hair Jr. et al., 2017). SEM has other several functions as pointed out by Putri et al. (2021) such as providing flexible assumptions, and good graphic models which facilitate users' analyses. Therefore, this method is one of the most widely used methods of multivariate data analysis in the areas of business and social sciences and, most importantly, the number of papers using this method is constantly increasing and those have been published in top-ranked journals with high impact factors (Memon et al., 2021). To do so, in the present study SmartPLS 4 – a world-renowned software for data analysis using the SEM method – was used.

There are two types of SEM: the covariance-based SEM or CB-SEM, a confirmatory method, and the partial least squares SEM or PLS-SEM, an exploratory method (Hair Jr. et al., 2017). In the present study, PLS-SEM was used. This method is useful for developing theories in exploratory research since it focuses "on explaining the variance in the dependent variables when examining the model" (Hair Jr. et al., 2017, p. 4). PLS-SEM is analyzed by conducting the measurement model or outer model and the structural model or inner model (Putri et al., 2021). The structural model presented before is an outer model of exogenous latent variables or constructs, that is those constructs explain other constructs in the model (Hair Jr. et al., 2017). Regarding the measurement theory, which stipulates how the latent variables are measured, it is possible to distinguish between a formative measurement model and a reflective measurement model. In this case, all the constructs are reflective constructs. The reflective measurement model is directly based on classical test theory, according to which the measures represent the effects of an underlying construct. Therefore, when a reflective measure is presented, it means that all indicator items are "caused" by the same construct, and consequently the indicators associated with a particular construct should show a high correlation between them (Hair Jr. et al., 2022). Regarding the reflective measurement model, the causal priority between the indicator and the construct is presented from the construct to the indicators, and the construct is a trait explaining the indicators. The indicators represent the consequences of the construct, and the items are mutually interchangeable. It is also necessarily true that all the items will change in a similar manner if the trait changes, assuming that they are equally coded (Hair Jr. et al., 2022).

4. Results

4.1. Descriptive Statistics

The questionnaire obtained 672 complete answers. However, to meet the criteria previously defined regarding the target population of this study, it was asked if the respondents had already been through menopause. With that being said, the respondents whose answer was "yes" were excluded from answering the following questions. Only 38 (5.7%) respondents were excluded concerning this criterion.

Of those 634 respondents, most respondents were between 20 to 24 years old (mean: 26.64, standard deviation: 8.54), being the youngest respondent a female at 15 years, and the oldest was 60 years. More detailed information is gathered in Appendix II.

Concerning the respondents' level of education, it was possible to determine that most respondents were highly educated since most of them were college graduates (n=496, 78.2%), as displayed in Figure 2. These results might be a result of the survey's dissemination channels used, with the highly qualified being more likely to respond to online surveys and participate in online research. However, it is also more likely that the users of such apps are highly educated women and, thus, these results don't come as a surprise.

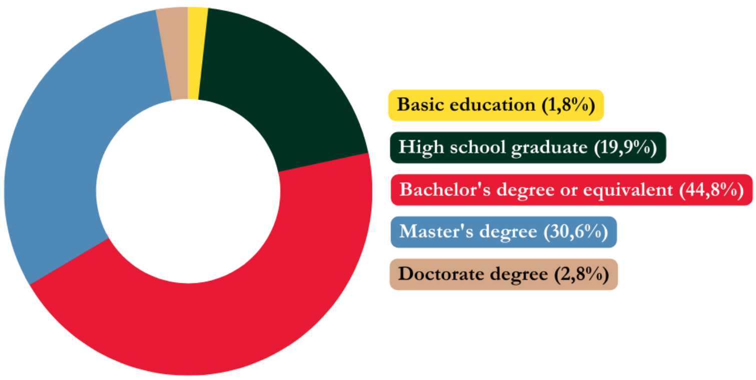

Figure 2: Summary regarding the respondents' level of education.

Moreover, a group of two questions regarding digital literacy was presented to the respondents. These questions were based on van der Vaart & Drossaert (2017) and provided insights on smartphone app literacy (Figure 3). Unsurprisingly, the vast majority of respondents use smartphone apps daily and rate their ability to perform with such apps as excellent or good.

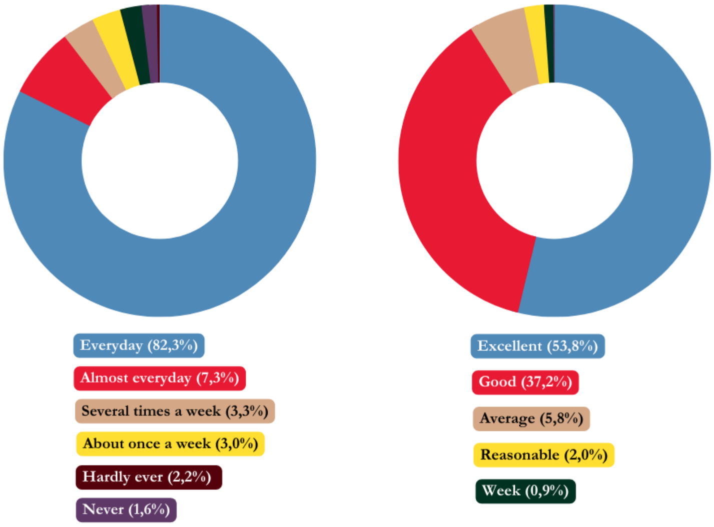

Figure 3: Percentage of answers obtained in the group related to digital literacy. Data regarding both questions of the group, namely "How often do you use smartphone apps?" (Left diagram) and "How would you rate your ability to use smartphone apps?" (Right diagram).

Before going through with the model's questions, and to classify the respondents into three distinct groups it was asked if the respondent was a (i) **current user** or **user**, (ii) **former user**, or (iii) **non-user** of menstrual cycle tracking apps (Figure 4). As mentioned earlier in this paper, the three different groups had distinct questions due to their different levels of experience with these apps. A current user, as the denomination indicates, is someone who is currently using the app daily. A former user is a woman who used these apps in the past but is not currently using them. And, finally, a non-user is someone who never had contact with or used these apps.

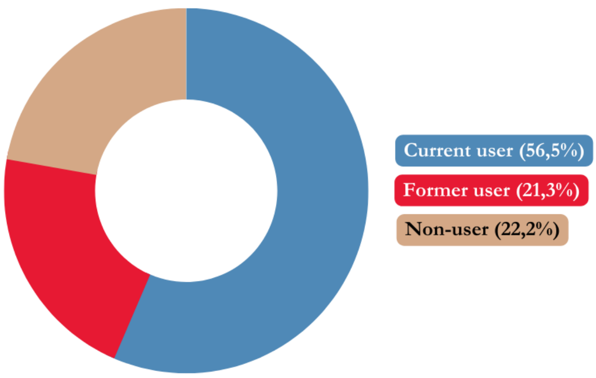

Figure 4: Data regarding the distribution of the three distinct groups of respondents on account of their response to the question "Are you a menstrual cycle monitoring app user?".

When a respondent was a previous user of menstrual cycle apps, a couple of questions were introduced in order to obtain more information about the reason behind leaving the app. The aim of the first question was to understand if the respondent had ceased using this kind of app due to a health-related issue, namely, if the tracking of her menstrual cycle was no longer important (for example, because the respondent had become pregnant). The study found that of the 135 former users that had responded to the questionnaire 74 (57.4%) women considered the monitoring of their menstrual cycle still relevant and 55 (42.6%) said the contrary. Therefore, it can be possible to theorize that the first group of women ceased the usage of the app due to reasons related to the app itself (for example, they did not find the app useful enough to continue using it in their daily life). The second question asked the respondents how long ago they stopped using the app. The results revealed that 42 (31.3%) of women had discontinued their app use in the previous year, 62 (46.3 %) in the last three years, 20 (14.9%) in the last 5 years, and only 10 (7.5%) have not used such apps in more than 5 years.

Afterward, it was questioned what purpose of this type of app women found more relevant. As presented in the table below (Table 4), in general, most respondents agree with the utility of menstrual cycle-tracking apps regarding birth control, pregnancy, and menstrual cycle status. 63.4% of the women agreed or strongly agree with the apps' usability in relation to birth control techniques. However, this is the topic where there was a larger percentage of respondents who did not agree or strongly disagree with the utility of these apps (16.4%) – in comparison with the usefulness to those who want to get pregnant (3.8%) and keep track of the menstrual status (0.5%).

Table 4: Data obtained from the question regarding what purpose of the menstrual cycle tracking apps women found more relevant.

These apps are useful for contraception/birth control			
Answers	**Frequency**	**Percentage**	**Valid percentage**
Strongly disagree	44	6.9%	7.4%
Disagree	60	9.5%	10.1%
Neither agree nor disagree	87	13.7%	14.7%
Agree	228	36.0%	38.4%
Strongly agree	174	27.4%	29.3%
[Missing]	41	6.5%	-
These apps are useful to those who want to get pregnant			
Answers	**Frequency**	**Percentage**	**Valid percentage**
Strongly disagree	8	1.3%	1.4%
Disagree	16	2.5%	2.8%
Neither agree nor disagree	66	10.4%	11.6%
Agree	274	43.2%	48.2%
Strongly agree	204	32.2%	35.9%

[Missing]	66	10.4%	-
These apps are useful to keep track of menstrual status (e.g., length of cycle, ovulation period, recording of menstrual symptoms)			
Answers	**Frequency**	**Percentage**	**Valid percentage**
Strongly disagree	2	0.3%	0.3%
Disagree	1	0.2%	0.2%
Neither agree nor disagree	18	2.8%	3.0%
Agree	145	22.9%	23.8%
Strongly agree	444	70.0%	72.8%
[Missing]	24	3.8%	-

It seems that there is almost a consensus that the use of these apps is mostly associated with monitoring menstrual status, namely menstrual symptoms, and duration of ovulation. This may be a strong indicator that the use of these apps may be related to this goal. To assess the veracity of this statement, the same three questions were asked at the end of the questionnaire only to female users to collect their individual perspectives. The data obtained with this question are presented in Table 5. As previously hypothesized, the data indicates that most respondents use this kind of app in order to keep track of their menstrual status, since 95.2% agreed or strongly agree with the citation. These results are consistent with the literature findings displayed in the first chapter of this dissertation. This is so because most women stated that used menstrual cycle tracing apps to be more informed about their body state and comprehend their body's response to different menstrual phases (Broad et al., 2022; Epstein et al., 2017).

Table 5: Data obtained from the question regarding what purpose of the menstrual cycle tracking apps women found more relevant in their individual context.

These apps are useful for contraception/birth control			
Answers	**Frequency**	**Percentage**	**Valid percentage**
Strongly disagree	28	7.8%	9.2%
Disagree	43	12.0%	14.1%
Neither agree nor disagree	34	9.4%	11.1%
Agree	117	32.7%	38.2%
Strongly agree	84	23.5%	27.5%
Non-applicable*	31	8.7%	-
[Missing]	21	5.9%	-
These apps are useful to those who want to get pregnant			
Answers	**Frequency**	**Percentage**	**Valid percentage**
Strongly disagree	23	6.4%	8.9%
Disagree	18	5.0%	7.0%

Neither agree nor disagree	40	11.2%	15.5%
Agree	111	31.0%	43.0%
Strongly agree	66	18.4%	25.6%
Non-applicable*	74	20.7%	-
[Missing]	26	7.3%	-
These apps are useful to keep track of menstrual status (e.g., length of cycle, ovulation period, recording of menstrual symptoms)			
Answers	**Frequency**	**Percentage**	**Valid percentage**
Strongly disagree	0	0.0%	0.0%
Disagree	1	0.3%	0.3%
Neither agree nor disagree	4	1.1%	1.2%
Agree	75	21.0%	21.7%
Strongly agree	266	74.3%	76.9%
Non-applicable*	4	1.1%	-
[Missing]	8	2.2%	-

*Non-applicable to the respondent's personal context.

In the subsequent PLS-SEM analysis, as recommended by Hair Jr. et al. (2017), the observations with more than 15% missing values were removed and not included in the subsequent analysis. This calculation considered the number of questions that each group of respondents (users, former users, and non-users) was presented. Thus, 97 observations were removed from the total of 634 respondents who have never been through menopause, remaining 537 observations to be included in the subsequent analysis.

As previously demonstrated, it was the author's intention to study the factors that could lead to a behavioral intention of future use by women who never had contact with this type of app (non-users) through the application of the UTAUT2 model. However, after the removal of the observations following the above criteria, only 62 observations of non-users remained. Moreover, 10 indicators exceed the 5% of missing values (Hair Jr. et al., 2022) and, for the sake of the rigor of the present investigation, were removed from the model. The subsequent PLS-SEM analysis revealed very few significant relations between the latent variables, and of the few significant ones, the relations were weak. This can be a strong indicator that the UTAUT2 original model is not the most adequate to analyze the factors that can influence the non-users' behavioral intention to use mHealth apps. Therefore, it is important to develop new strategies to achieve this goal – this idea is further developed in the Future Research section.

Before going into further details regarding the data analysis of the two remaining groups – users and former users – it is important to clarify that the variable Price Value was not included in the subsequent analysis. As can be inferred from the questionnaire design, it was the author's intention to differentiate those users or former users who use(d) the paid version of the menstrual cycle app from those who use(d) the free version. Therefore, as previously shown, two sets of questions were made – PV1, PV2, and PV3 to the paid version's respondents and PV4 to the free version's respondents. However, despite the quite large number of responses obtained, only 18 (5.2%) respondents were users of the paid version, and only 1 (0.8%) former user had used this version. Due to this low number of respondents, it is impossible to draw any plausible and statistically significant conclusion. Further analysis revealed that the PV4 indicator had also a higher percentage of missing values than desired (higher than 5%). Consequently, it was not possible to use this indicator in the model analysis. Considering that it was the only indicator for the variable Price Value regarding the free version users and former users, and the previously indicated facts regarding the other indicators, the decision to remove the variable Price Value from the model was made. This consists of one of the study's limitations and is further detailed in the Future Research section.

The majority of menstrual cycle apps choose a freemium design, an increasingly common design in other mHealth apps and general apps, that combines different settings of free and paid (premium) features (Eagle et al., 2022). Allowing users to have basic app functions for free stimulates the adhesion of new users, but it can also dissuade them from purchasing the premium version. Thus, this approach reveals to be feasible merely when the benefits of the free version, such as increasing the number of users, can outweigh the potential loss in sales (Boudreau et al., 2022). As can be expected, users tend to be more likely to download and use a free version of the app compared to paid additional features. For example, Purohit et al. (2023) found out that for detox associated apps the paid model is perceived to be significantly less valuable than free and freemium models. Moreover, Gray et al. (2021) concluded that consumers may even perceive a particular digital product in a negative way as well as feel manipulated if payment is mandatory for the digital product or if in-app purchases (i.e., users can buy premium features from the app itself later on (Purohit et al., 2023)) are permitted. All the facts presented are indicators that the population of Portuguese users and former users of the paid version of menstrual cycle apps is smaller than that for the free version. This would explain the difference between the number of respondents obtained for both versions.

4.2. Measurement Model Evaluation

In order to assess a reflective measurement model like the one presented it is necessary to evaluate the measures' reliability, both on an indicator and construct level, through indicator reliability and internal consistency reliability, respectively.

As recommended by Hair Jr. et al. (2022), the indicators with a percentage of missing values superior to 5% were removed from the model in favor of the study's accuracy. Therefore, in regard to the users' group, the SI1 (32.9%), SI2 (30.6%), FC3 (22.5%), and FC4 (13.3%) indicators were not included in the following analysis. On the other hand, concerning the former users' group, the SI1 (21.3%), SI2 (19.7%), FC3 (17.3%), FC4 (11.8%), FC5 (7.9%), and BIEXU3 (7.9%) indicators were not included in the following analysis.

The structural model results of the **users' group** enable the determination that Habit has the strongest effect on BI (0.483), followed by PE (0.239), FC (0.179), and HM (0.089). Moreover, the six constructs explain 55.6% of the variance of the endogenous construct BI (R2 = 0.556), as indicated by the value in the circle (see Appendixes IV). Based on the sizes of the path coefficients, it would appear that the relationships HT → BI, PE → BI, and FC → BI are significant. However, it seems very unlikely that the hypothesized paths relationships HM → BI, SI → BI, and PE → BI are significant since low values close to 0 are usually not statistically significant (Hair Jr. et al., 2022). Therefore, it seems that HT and PE are moderately strong predictors of BI regarding the users' data. It is also important to highlight that BI is a moderately strong predictor of AU (0.572), and this one construct explains 32.7% of the variance of the endogenous construct AU ($R^2 = 0.327$).

In a similar way, the structural model results of the **former users' group** enable the determination that Habit has the strongest effect on BI (0.326), followed by PE (0.192), FC (0.141), and HM (0.136). The six constructs explain 22.2% of the variance of the endogenous construct BI ($R^2 = 0.222$) (see Appendix IV). Based on the sizes of the path coefficients, it would appear that only the relationship HT → BI is significant. But it seems very unlikely that the hypothesized paths relationships HM → BI, FC → BI, and PE → BI are significant since they presented low values close to 0. So, it seems that, regarding the former users' data, HT is a moderately strong predictor of BI.

a) Indicator Reliability

Primary, when evaluating the reflective measurement model is necessary to examine the **outer loadings** of the indicators (Hair et al., 2019). As an established rule of thumb, a latent variable should explain a substantial portion of each indicator's variance, i.e., at least 50%. Explaining at least 50% of an indicator's variance implies that the variance shared between the construct and its indicator exceeds the measurement error (Hair Jr. et al., 2022). Hence, an indicator's standardized outer loading, as provided by the PLS-SEM results, should be 0.708 (0.708^2=0.50). A value of 0.70 is considered close enough to 0.708 to be acceptable.

Table 6: Outer loading regarding the users' structural model.

	AU	BI	EE	FC	HM	HT	PE	SI
AU1	0.778							
AU2	0.421							
AU3	0.807							
BIU1		0.849						
BIU2		0.823						
BIU3		0.912						
EE1			0.856					
EE2			0.919					
EE3			0.904					
EE4			0.883					
FC1				0.819				
FC2				0.876				
FC5				0.631				
HM1					0.894			
HM2					0.717			
HM3					0.887			
HT1						0.804		
HT2						0.876		
HT3						0.812		
PE1							0.820	
PE2							0.719	
PE3							0.810	
SI								1.000

As presented in Table 6, the indicator HM2 (outer loading: 0.717) has the smallest indicator reliability with a value of 0.514 (0.717^2), and the indicator EE2 (outer loading: 0.919) has the highest indicator reliability, with a value of 0.845 (0.919^2). While the latent variable explains less than 50% of the variance of the indicators AU2 and FC5, which, as said before, implies that the variance shared between the construct FC and its indicator FC5, and between AU and its indicator AU2 is greater than the measurement error. As it was suggested by Hair Jr.

et al. (2022), the indicator AU2 was removed (as it has a loading between 0.40 and 0.60). Nevertheless, this remotion did not increase its internal consistency reliability.

Table 7: Outer loading regarding the former users' structural model.

	BI	EE	FC	HM	HT	PE	SI
BIEXU1	0.941						
BIEXU2	0.958						
EE1		0.912					
EE2		0.881					
EE3		0.950					
EE4		0.900					
FC1			0.957				
FC2			0.506				
HM1				0.863			
HM2				0.890			
HM3				0.906			
HT1					0.645		
HT2					0.892		
HT3					0.920		
PE1						0.869	
PE2						0.839	
PE3						0.690	
SI							1.000

On the other hand, after analyzing the former users' data, it was possible to see the indicator PE2 (outer loading: 0.839) has the smallest indicator reliability with a value of 0.704 (0.839^2), and the indicator EE2 (outer loading: 0.958) has the highest indicator reliability, with a value of 0.918 (0.958^2). While the latent variable explains less than 50% of the variance of the indicators FC2, HT1, and PE3, which, as said before, implies that the variance between the constructs and its indicators is greater than the measurement error. The indicator FC2 was removed to understand if this remotion would increase its internal consistency reliability, but this was not possible since it would make the FC construct a single item construct.

b) Internal Consistency Reliability

The traditional criterion for measuring internal consistency reliability is **Cronbach's alpha**, which provides an estimate of the reliability based on the inter-correlations of the observed indicator (Hair et al., 2019). Since PLS-SEM prioritizes the indicators according to their different individual reliabilities, it is also technically appropriate to apply a different measure of internal consistency reliability, referred to as **composite reliability** (ρ_C). Both measures vary between 0 and 1, with higher values indicating higher levels of reliability. In this study, values of 0.60 to 0.90 were considered satisfactory, as pointed out by Hair Jr. et al. (2022). Research later conducted pointed out the **reliability coefficient** (ρ_A) as a good reliability metric to be used since it usually lies between Cronbach's alpha and the composite reliability and is therefore considered a good compromise between the two (Hair et al., 2019).

Table 8: Internal consistency reliability evaluating metrics and AVE regarding users' data.

	Cronbach's alpha	Reliability coefficient (ρ_A)	Composite reliability (ρ_C)	Average variance extracted (AVE)
AU	0.499	0.527	0.720	0.478
BI	0.826	0.833	0.897	0.743
EE	0.913	0.917	0.939	0.794
FC	0.670	0.688	0.823	0.612
HT	0.778	0.789	0.870	0.691
HM	0.779	0.777	0.874	0.700
PE	0.691	0.709	0.827	0.615

The majority of values from Cronbach's alpha and reliability coefficient (ρ_A), and all composite reliability (ρ_C) values for the seven constructs are above the 0.60 threshold (see Table 8). Therefore, with ρ_A values of 0.917 (EE), 0.688 (FC), 0.789 (HT), 0.777 (HM), 0.709 (PE), and 0.833 (BI), the reflective constructs have high levels of internal consistency reliability.

Table 9: Internal consistency reliability evaluating metrics and AVE regarding former users' data.

	Cronbach's alpha	Reliability coefficient (ρ_A)	Composite reliability (ρ_C)	Average variance extracted (AVE)
BI	0.891	0.908	0.948	0.902
EE	0.934	0.986	0.951	0.830
FC	0.847	-4.368	0.721	0.586
HT	0.774	0.919	0.865	0.686
HM	0.868	0.909	0.917	0.786
PE	0.733	0.796	0.844	0.645

In the former users' situation, all values from Cronbach's alpha and reliability coefficient (ρ_A), and all composite reliability (ρ_C) values for the seven constructs are above the 0.60 threshold (see Table 9). Therefore, with ρ_A values of 0.986 (EE), 0.919 (HT), 0.909 (HM), 0.796 (PE), and 0.908 (BI), the reflective constructs have high levels of internal consistency reliability. Values above 0.90 (and definitely above 0.95), are not desirable because they typically result from semantically redundant items, i.e., rephrasing the same question (Hair et al., 2019).

c) Convergent Validity

Convergent validity is the extent to which a measure correlates positively with alternative measures of the same construct, being usually assessed using **average variance extracted** (AVE), on the construct level (Hair et al., 2019). An AVE value of 0.50 or higher indicates that, on average, the construct explicates more than half of the variance of its indicators (Hair Jr. et al., 2022). As displayed in Table 8, the values from AVE values for all users' constructs, except AU, are above the minimum 0.50 threshold, which means that the measures of the six reflective constructs have high levels of convergent validity. Similarly, the values from AVE values for all former users' constructs are above the referred 0.50 threshold (Table 9).

d) Discriminant Validity

Establishing discriminant validity implies that a construct is unique and captures phenomena not represented by other constructs in the model. In this study, in order to evaluate the discriminant validity of the measurement model, the **heterotrait-monotrait ratio** (HTMT) was elected. HTMT is the ratio of the between-trait correlations to the within-trait correlations (Hair Jr. et al., 2022). In other words, HTMT calculates the mean of all correlations of indicators across constructs measuring different constructs in relation to the mean of the average correlations of indicators measuring the same construct. As pointed out by (Henseler et al., 2015) an HTMT value above 0.90 suggests a lack of discriminant validity.

Table 10: Heterotrait-monotrait ratio (HTMT) results regarding users' data.

	AU	**BI**	**EE**	**FC**	**HT**	**HM**	**PE**
AU							
BI	0.773						
EE	0.471	0.437					
FC	0.664	0.538	0.796				
HT	0.809	0.807	0.353	0.305			
HM	0.858	0.502	0.324	0.325	0.535		
PE	0.805	0.772	0.532	0.569	0.620	0.495	
SI	0.224	0.103	0.070	0.139	0.147	0.163	0.108

Table 11: Heterotrait-monotrait ratio (HTMT) results regarding former users' data.

	BI	**EE**	**FC**	**HT**	**HM**	**PE**

BI						
EE	0.073					
FC	0.049	0.683				
HT	0.412	0.137	0.303			
HM	0.166	0.394	0.142	0.215		
PE	0.340	0.397	0.412	0.552	0.336	
SI	0.058	0.035	0.082	0.185	0.173	0.088

As shown, all HTMT values are lower than the threshold value of 0.90. The **bootstrap** confidence intervals were also analyzed in order to assess whether the HTMT values differ from the 0.90 thresholds for all combinations of constructs. To obtain these confidence intervals a number of 10 000 subsamples was selected as well as a one-tailed test type at a 0.05 significance level. This statistical test focuses on the right tail of the bootstrap interval to demonstrate that an HTMT value is significantly lower than the corresponding threshold value of 0.90 with a 5% probability of error. In the users' case, the upper limit displayed in the 95% column is lower than 0.90, except for the relationships BI → AU, HT → AU, HM → AU, and PE → AU. The bootstrap confidence interval results of the HTMT measure showed the discriminant validity of the other constructs. In the former user's context, the bootstrap confidence interval results of the HTMT measure show the discriminant validity of all constructs.

4.3. Structural Model Evaluation

a) Assess the Structural Model for Collinearity

To assess collinearity **tolerance** and **variance inflation factor** (VIF) values should be applied. The VIF values in the predictor constructs should be below 5 and preferably below 3 to guarantee that collinearity has no substantial effect on the structural model estimates (Hair et al., 2019). Regarding both users' and former users' structural models, all VIF values are below the threshold of 5. The majority of the indicators are also below 3. Therefore, it is possible to conclude that collinearity among the predictor constructs is not a critical concern in the structural model (see Appendix IV).

b) Evaluate the Structural Model Relationships' Significance and Relevance

The significance of a coefficient ultimately depends on its standard error obtained through bootstrapping. The bootstrap standard error allows the computation of the empirical **t values** and **p values** for all structural path coefficients (Hair et al., 2019). Moreover, the bootstrapping confidence interval enables the researcher to test whether a path coefficient significantly differs from zero.

As stated before, regarding users' data, Habit (HT) has the strongest effect (0.483) on Behavioral Intention (BI) to use menstrual cycle-tracking apps. By taking the construct's indicator **outer weights** into consideration, it was possible to identify which specific element of quality needs to be addressed (see Appendix IV). In this case, the indicator HT1 has the highest outer weight (0.450). This item refers to the question "The use of menstrual cycle tracking apps has become a habit for me". Therefore, it seems important to marketing managers to try to enhance, through marketing campaigns and activities, certain app functions and advantages that can lead it to be a frequent tool in the daily life of the users. Moreover, BI was revealed to be a strong predictor of Actual Usage (AU), with the most relevant indicator being BIU3 (0.418). This refers to "I plan to continue to use menstrual cycle tracking apps frequently" which supports the previous advice. On the other hand, former users' data analysis also revealed that HT had the strongest effect (0.326) on BI to use menstrual cycle-tracking apps. Although, in this case, the indicator HT3 has the highest outer weight (0.563). This item refers to the question, "I must use menstrual cycle tracking apps". Therefore, it seems important to marketing managers to try to enhance, through marketing strategies and activities, certain app functions that can create a sense of necessity in the users to use this tool in their daily life.

Posteriorly, the bootstrapping method was performed with a number of 10 000 subsamples as well as a two-tailed test type at a 0.05 significance level. The results are presented in Table 12 and Table 13.

Table 12: Evaluation results of the study hypothesis regarding the users' group.

	Path coefficients	**t values**	**p values**	**95% Confidence Intervals**	**Significance**
BI → AU	0.572	15.637	0.000	[0.501;0.642]	Significant*
EE → BI	-0.013	0.234	0.815	[-0.120;0.094]	Not significant
FC → BI	0.179	4.002	0.000	[0.093;0.269]	Significant*
HT → BI	0.483	10.261	0.000	[0.390;0.574]	Significant*
HM → BI	0.089	2.048	0.041	[0.001;0.173]	Significant*
PE → BI	0.239	4.254	0.000	[0.132;0.351]	Significant*
SI → BI	-0.067	1.684	0.092	[-0.145;0.011]	Significant**

Significance level: *p<0.05 and **p<0.10

Based on these results, and assuming a 5% significance level, it was possible to find that the majority of the relationships in the users' structural model are significant. These results are in concordance with the literature because the significant path coefficients should be positive (Daryanto et al., 2019). Thus, the present study found the facilitating conditions, habit, hedonic motivation, and performance expectancy to be relevant indicators of the behavioral intention to use menstrual cycle apps. Moreover, behavioral intention was found a significant predictor of actual usage of these apps, in concordance with the results found by Alam et al. (2019). If considered a 10% significance level, the social influence was also a relevant indicator of the behavioral intention to use menstrual cycle apps.

Table 13: Evaluation results of the study hypothesis regarding the former users' group.

	Path coefficients	**t values**	**p values**	**95% Confidence Intervals**	**Significance ($p < 5\%$)**
EE → BI	-0.270	2.074	0.038	[-0.489;0.036]	Significant
FC → BI	0.141	1.049	0.294	[-0.169;0.356]	Not significant
HT → BI	0.326	4.144	0.000	[0.162;0.471]	Significant
HM → BI	0.136	1.499	0.134	[-0.068;0.306]	Not significant
PE → BI	0.192	2.052	0.040	[0.007;0.375]	Significant
SI → BI	-0.039	0.143	0.680	[-0.205;0.155]	Not significant

Regarding former users, because the path coefficients should be positive the EE → BI should not be considered (Daryanto et al., 2019). As in Schomakers et al. (2022), this study tried to analyze the previous users' perception by applying the UTAUT2 model, but differently from the mentioned author, the questionnaire design was adapted to these respondents. Even though the approach was distinct, both studies found habit one relevant indicator of behavioral intention. Similarly, to what was concluded from the user group, performance expectancy (Yuan et al, 2015, Alam et al, 2019, Schretzlmaier et al, 2022, Pancar et al, 2021) was found to be relevant.

c) <u>Measure the Model's Explanatory Power</u>

The explanatory power of a structural model relates to its ability to fit the data by measuring the strength of the association indicated by the PLS path model (Hair Jr. et al., 2022).. The most regularly used measure to evaluate the explanatory power is the **coefficient of determination** (R^2) value, which is calculated as the squared correlation between a specific endogenous construct's actual and predicted values – the R^2 value symbolizes the combined effects of the exogenous latent variables on the endogenous latent variable, i.e., its explained variance. The R^2 value ranges from 0 to 1, with higher levels indicating higher levels of explanatory power, but there is no recommended threshold since acceptable values are based on context (Hair Jr. et al., 2022).

The users' coefficient of the endogenous latent variable BI is moderately strong (following the rule of thumb), with a value of 0.556. This means that the structural model presented was a rather reasonable explanatory power. On the other hand, the R^2 value for AU is lower (0.327) which indicates a lower explanatory power, but this can be due to the fact that this particular construct was not in the original UTAUT2 model and was adapted from Alam et al. (2019).

Additionally, the R^2 value of the endogenous latent variable BI in the former users' group is rather weak (following the rule of thumb), with a value of 0.222. This means that the structural model presented was a rather weak explanatory power, which can be due to the fact that the original UTAUT2 model was more aimed at current users.

d) Measure the Model's Predictive Power

For a PLS model to be useful for management decision-making, the model needs to produce generalizable findings, and it is fundamental to assess the model's out-of-sample predictive power. The main approach for assessing the predictive power of a PLS path model is the $PLS_{predict}$ procedure, designed by Shmueli et al. (2016). To initiate the analysis, the $PLS_{predict}$ was run with 10 folds and 10 repetitions.

Table 14: PLSpredict results for the users' group.

	Q^2 predict	RMSE (PLS)	MAE (PLS)	RMSE (LM)	MAE (LM)
AU1	0.235	0.594	0.464	0.529	0.412
AU2	0.036	0.885	0.629	0.849	0.622
AU3	0.222	0.861	0.672	0.809	0.638
BIU1	0.363	0.472	0.358	0.472	0.354
BIU2	0.360	0.703	0.515	0.713	0.525
BIU3	0.452	0.479	0.363	0.487	0.364

Table 15: PLSpredict results for the former users' group.

	Q^2 predict	RMSE (PLS)	MAE (PLS)	RMSE (LM)	MAE (LM)
BIEXU1	0.042	0.981	0.795	1.007	0.810
BIEXU2	0.105	0.989	0.816	1.008	0.807

Primarily, if the Q^2 statistic values are analyzed, it is possible to conclude that these values are larger than zero (positive Q^2 values), suggesting that the PLS path model outperforms the most naïve benchmark. Moreover, by comparing the **root mean square error (RMSE)** values produced by the PLS-SEM analysis with those produced by the naïve **linear regression model (LM) benchmark model**, it is possible to check that the PLS-SEM analysis produces smaller prediction errors than those produced by LM for all three BI indicators (e.g., for BIU2 indicator the PLS RMSE value is 0.703 and the LM RMSE value is 0.713 and for the BIEXU1 the values are 0.981 and 1.007, respectively). Therefore, these results support the conclusion that the model has high predictive power because the PLS-SEM analysis outperforms the naïve LM benchmark model for all three BI indicators.

4.4. Impact of Age, Education, and Digital Literacy on Behavioral Intention

As previously mentioned, this study focused on the direct effects of the original UTAUT2's moderating variables (age, education, and digital literacy) on behavioral intention. This differs from the original UTAUT2 model since it postulates that age, gender, and experience moderate the relationships of the predictor variables with behavioral intention (Venkatesh et al., 2012).

Table 16: Moderating variables relationships results regarding users' data.

	Path coefficients	t values	p values	95% Confidence Intervals	Significance (p < 5%)
Age → BI	-0.062	1.546	0.122	[-0.138;0.019]	Not significant
Education → BI	-0.015	0.935	0.350	[-0.098;0.065]	Not significant
Digital Literacy → BI	-0.040	0.368	0.713	[-0.125;0.043]	Not significant

Table 17: Moderating variables relationships results regarding former users' data.

	Path coefficients	t values	p values	95% Confidence Intervals	Significance (p < 5%)
Age → BI	-0.072	0.765	0.445	[-0.244;0.129]	Not significant
Education → BI	0.025	0.282	0.778	[-0.158;0.190]	Not significant
Digital Literacy → BI	0.099	1.148	0.251	[-0.089;0.260]	Not significant

Regarding the elected moderating variables, none of the hypothesized relationships was found statistically relevant (Table 16 and Table 17). None of the p-values (obtained through bootstrapping) for these moderating relationships were significant, which means that the three variables (age, education level, and digital literacy) had no statistically significant effects on the relationships between the constructs and users' and former users' behavioral intention, as previously hypothesized. This result follows the same line as the one found in

Schomakers et al. (2022), as the cited authors only found a weak correlation with the behavioral intention to use mHealth apps. Thus, the obtained results do not come as a surprise.

4.5. Main Findings

This study concluded that the UTAUT2 model can only explain a small amount of variance in the intention of former users to use mHealth apps (22.2%) but can explain more than half of the variance in the users' behavioral intention (55.6%) and almost a third of the variance verified in actual usage (32.7%).

Despite the limitations already highlighted of the UTAUT2 model itself and also the skepticism of some authors regarding its application in such a particular context as it is the health sector and health-related technologies (Vassli & Farshchian, 2018), this study's results have come to similar conclusions as previous research (Alam et al., 2019; Pancar & Ozkan Yildirim, 2023; Schomakers et al., 2022; Schretzlmaier et al., 2022; P. Wu et al., 2022; Yuan et al., 2015).

These results suggest that menstrual cycle tracking app developers should concentrate their marketing efforts on the development of app functions that contribute to the continuous use of the app on a daily basis and also contribute to a pleasant experience for the user. Moreover, the marketing strategy should enhance the usefulness of the apps on a daily life basis, as well as promote the potential of these apps to meet their user's goals, especially, in terms of productivity and efficacy. This does not come as a surprise since mobile app consumers, despite the absurd number of options, tend to use only apps that are perceived as useful in their routine.

Concerning the moderate variables' direct impact on behavioral intention, the results obtained are contradictory to what was concluded by Schomakers et al. (2022) since these authors found the direct influence of these variables and gender to be statically significant. However, the results of this study can differ from those because of the particularities of the sample and target population. In other words, the target audience of the questionnaire were women in fertile age and, therefore, relatively young. The median age of respondents is a considerably young age which is also associated, in Portuguese panorama, with superior levels of education and a high digital literacy. Consequently, it is possible that this direct relation could not be as significant because the users of these apps are a rather homogenous group regarding these aspects (age, education, and digital literacy).

The study's results pointed out that, on one hand, not all factors proposed by the UTAUT2 had a significant influence, and that, and, on the other hand, this model needs to be extended by the addiction of additional influencing factors, such as data privacy concerns (Guo et al., 2016). The empirical evidence obtained also allows tends to support the conclusion that the applicability of the UTAUT2 is not entirely applicable to the mHealth context, or at least might not be the more accurate model to draw solid (and helpful for managerial decision-making) conclusions from.

5. Conclusion

With technological development, access to apps has become a constant in everyone's life. This development has also reached the health area, which has benefited not only from the fabrication of information management software but also from products that have shortened the distance between the patient and the provision of health care. Among these solutions are mHealth products, more specifically mHealth apps. These apps encompass a variety of health and medical services, such as support for diagnosis, health status remote monitoring, and medicine intake reminders (Schomakers et al., 2022). Therefore, mHealth is becoming an important help in chronic disease prevention and monitoring, but also in the promotion of healthier lifestyles and informing patients and informal caregivers.

Period tracker apps are a subgroup of mHealth apps and are among the most widespread health apps. These apps allow the observation and sometimes analyses of the menstrual cycle and also various related factors, such as the start date of the next period or ovulation. Menstrual cycle-tracking apps are very popular among users, especially adolescent girls, but they are also incredibly important in terms of collecting information regarding reproductive health that can help health systems and providers to obtain great amounts of data that allows the improvement of feminine and reproductive healthcare guidelines and approaches.

User’s acceptance of mHealth apps is crucial to anticipate their adoption and widespread across the target population of the app in question. Although, if the various requirements of potential users are not fulfilled by the app, they can turn out to be major barriers to app adoption. As mentioned before, in this study, the technology acceptance model elected was the UTAUT2 technology acceptance model. This model was used to predict behavioral intention to use mHealth apps in non-user women and also to predict actual usage in user and former user women. The model was also applied to women that never used such apps (non-users), in order to find possible patterns that could lead to information regarding what makes them not use menstrual cycle apps or what they expect to achieve by using the app. This information is of utmost importance for marketers in order to channel marketing strategies to attract new users and could be also essential if the app developers are opting for a market development strategy.

As previously mentioned, the aim of applying the UTATU2 model was to identify the factors that had an influence on the users’ and former users’ behavioral intention to use menstrual cycle tracking apps, and how this intention might be related to the users’ actual use of these apps. The results obtained indicate that few hypothesized predictors – facilitating conditions, habit, hedonic motivation, and performance expectancy – were significant regarding the users and only a couple of predictors – habit and performance expectancy – were found relevant when talking about former users. Both stated predictors were considered significant in both groups which can indicate a stronger influence in comparison with the other indicators and that there is not a significant difference between the behavioral intention's predictors of both groups. Is also interesting to note that the model only had the capability of weakly explained the variance observed in the former users' group (about 20%), but its capability increased to about 50% when using users' data. This is most likely due to the fact that the UTAUT2 model was originally designed to be applied to users of the technology in study. Has it can be deduced by the previously presented results, emotional predictors, such as habit or hedonic motivation, might be considered to be as important as practical, utilitarian, and usefulness factors, such as performance expectancy and facilitating conditions.

5.1. Future Research

In May of the present year, some news arose regarding the illegal sharing and selling of users' personal data of the Flo menstrual cycling monitoring app to publicity and data processing enterprises (Dantas, 2023). These accusations started in the United States, but in Portugal, the Association for the Defense of Consumer Rights also issued a position by suing the company responsible for the app. Taking into consideration this situation, it would be of big interest to conduct projects that include the consumers' point of view of data protection regarding these apps (and other mHealth apps) and how mistrust can affect the adoption of such. Multiple authors, such as Schomakers et al. (2022), have already incorporated privacy concerns and trust as additional constructs to the UTAUT2. It would be noteworthy to apply an extended UTAUT2 model considering privacy concerns, as mentioned before, in the Portuguese context since cultural aspects can lead to different effects of these constructs than those found in other countries. However, there are no new models that integrate these concepts in order to evaluate their influence on consumers' behavior and their will to adopt mHealth. Therefore, it would be of major importance to develop a new model that would respond to this necessity.

Nowadays, there is a lack of literature regarding specific models designed to evaluate mHealth technologies adherence. Authors like Yuan et al. (2015) and Alam, Hoque, et al. (2020) used the UTAUT models to identify determinants of mHealth adoption, but there is still no model that combines different perspectives and findings of several studies that adapt the UTAUT model to meet their goals in order to provide a single model that can be used when analyzing these specific technologies – similar to what Mohamed et al. (2011) did with the TAM model.

This study aimed to provide insights regarding the intention to use such apps in possible users that have never been in contact with menstrual cycle-tracking apps before, in order to find evidence to support a more focused marketing approach to recruit new customers. However, since the UTAUT2 model was designed to be performed by users of said technological product, it is important to develop new strategies similar to this model with the aim to identify what is missing for people to adhere to a certain app or similar. It is important to the marketing strategy, not only to adopt retention strategies but also to develop strategies to increase the client portfolio.

As previously mentioned, the variable Price Value was not included in the PLS-SEM analysis due to the lack of an adequate amount of data in order to produce statistically significant results and conclusions. Due to the huge number of apps and also mHealth apps that have become available in the previous years, different pricing models and options are now additionally available (freemium, free, and paid models). Traditionally, price was perceived by consumers as an indicator of quality, with expensive products being perceived as products with higher quality. However, researchers are now finding that the behavior that consumers have in the online context is very different from their offline tendencies, and there is insufficient research conducted in order to find out how pricing models affect the perceived value of digital products (Purohit et al., 2023). Perceived value is a key concept to attain better insight into consumer behavior in digital products such as apps, making Price Value an essential construct that should be studied regarding its influence on behavioral intention, as it was the authors' intention. Therefore, since the perceived value is an important factor in promoting the usage of the app (Purohit et al., 2023), it is important to conduct research that highlights the different consumers' perspectives towards different pricing models.

Another limitation was the fact that some of the answers to the questionnaire were obtained by convenience sampling method, a type of non-probabilistic sampling where the subjects are selected based on the fact that they meet certain practical criteria (Etikan, 2016). According to the literature review conducted, the vast majority of the studies that follow the same line of thought and with similar objectives opt for convenience sampling. In this case, some of the subjects were selected from the author's social contacts and through divulgation via institutional channels of the University of Porto. The application of this sampling method aimed to obtain a heterogeneous sample, regarding age, education, and use of menstrual cycle tracking apps, but also to obtain responses from people with different economic backgrounds. A central challenge for population-based survey experiments is their cost, so the convenience method offers a much cheaper and easy-to-perform alternative (Etikan, 2016; Mullinix et al., 2015). However, convenience sampling can lead to a sample that is not representative of the population and, therefore, is likely to be biased. Consequently, the problems associated with this non-probability sampling can be considered limitations of the present study.

Finally, another limitation is linked to the fact that there is no validated translation of the UTAUT2 items to Portuguese, and also no validated adaption to the mHealth context is currently available. This means that an unvalidated translation was made, and even though a pilot study was conducted in order to identify possible miscomprehension of the questions, the adaptions might have decreased the validity of the results.

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7. Appendixes

Appendix I. Translation of the UTAUT2 model questions to Portuguese language

Table 1: Translation of the UTAUT2 questions to Portuguese language.

ENGLISH	PORTUGUESE
Effort Expectancy (EE)	
EE1. Learning how to use menstrual cycle tracking apps is easy for me	**EE1.** Aprender como utilizar aplicações de monitorização do ciclo menstrual é fácil
EE2. My interaction with menstrual cycle tracking apps is clear and understandable	**EE2.** A interação com estas aplicações é clara e compreensível
EE3. I find menstrual cycle tracking apps easy to use	**EE3.** Eu acho que a utilização das aplicações de monitorização do ciclo menstrual é fácil
EE4. It is easy for me to become skillful at using menstrual cycle tracking apps	**EE4.** É fácil tornar-me hábil na utilização de aplicações de monitorização do ciclo menstrual
Performance Expectancy (PE)	
PE1. I find menstrual cycle tracking apps useful in my daily life	**PE1.** Estas aplicações são úteis no quotidiano
PE2. Using menstrual cycle tracking apps helps me accomplish things more quickly	**PE2.** A utilização de aplicações de monitorização do ciclo menstrual ajuda a realizar as coisas mais rapidamente
PE3. Using a menstrual cycle monitoring app helps me take care of my health	**PE3.** A utilização de uma aplicação de monitorização de ciclo menstrual ajuda-me a cuidar da minha saúde
Social Influence (SI)	
SI1. People who are important to me think that I should use menstrual cycle tracking apps	**SI1.** As pessoas que me são importantes pensam que eu deveria usar aplicações de monitorização do ciclo menstrual
SI2. People who influence my behavior think that I should use menstrual cycle tracking apps	**SI2.** As pessoas que influenciam o meu comportamento pensam que eu deveria usar aplicações de monitorização do ciclo menstrual
SI3. I use menstrual cycle monitoring apps because many people do	**SI3.** Eu uso as aplicações de monitorização do ciclo menstrual, porque muitas pessoas o fazem
Facilitating Conditions (FC)	
FC1. I have the resources necessary to use menstrual cycle tracking apps	**FC1.** Tenho os recursos necessários para utilizar aplicações de monitorização do ciclo menstrual
FC2. I have the knowledge necessary to use menstrual cycle tracking apps	**FC2.** Tenho os conhecimentos necessários para utilizar aplicações de monitorização do ciclo menstrual

FC3. Menstrual cycle tracking apps are compatible with other technologies I use (e.g., smartwatch, tablet)	**FC3.** As aplicações de monitorização do ciclo menstrual são compatíveis com outras apps/tecnologias que utilizo (por exemplo, smartwatch, tablet)
FC4. I can get help from others when I have difficulties using menstrual cycle tracking apps	**FC4.** Posso obter ajuda de outros quando tenho dificuldades na utilização de aplicações de monitorização do ciclo menstrual
FC5. It's easy to obtain guidance when using menstrual cycle monitoring apps (e.g., in the app itself, in user guides, on the internet, from other users)	**FC5.** É fácil obter orientação durante a utilização das aplicações de monitorização do ciclo menstrual (por exemplo, na própria app, em guias de utilizadores, na internet, através de outros utilizadores)
Hedonic Motivation (HM)	
HM1. Menstrual cycle tracking apps are fun	**HM1.** As aplicações de monitorização do ciclo menstrual são divertidas
HM2. Using menstrual cycle tracking apps is enjoyable	**HM2.** A utilização de aplicações de monitorização do ciclo menstrual é agradável
HM3. Using menstrual cycle tracking apps is very entertaining	**HM3.** A utilização de aplicações de monitorização do ciclo menstrual é divertida
Price Value (PV)	
USERS AND FORMER USERS ONLY – PAY VERSION	
PV1. Menstrual cycle tracking apps are reasonably priced	**PV1.** As aplicações de monitorização do ciclo menstrual têm um preço razoável
PV2. Menstrual cycle tracking apps are a good value for the money	**PV2.** As aplicações de monitorização do ciclo menstrual têm uma boa relação custo-benefício
PV3. At the current price, menstrual cycle tracking apps provides a good value	**PV3.** Ao preço atual, as aplicações de monitorização do ciclo menstrual fornecem um bom valor
USERS AND FORMER USERS ONLY – FREE VERSION	
PV4. Menstrual cycle tracking apps provides a good value	**PV4.** As aplicações de monitorização do ciclo menstrual fornecem um bom valor
Habit (HT)	
USERS AND FORMER USERS ONLY	
HT1. The use of menstrual cycle tracking apps has become a habit for me	**HT1.** O uso de aplicações de monitorização do ciclo menstrual tornou-se um hábito para mim
HT2. I cannot do without menstrual cycle tracking apps anymore	**HT2.** Já não posso prescindir de aplicações de monitorização do ciclo menstrual
HT3. I must use menstrual cycle tracking apps	**HT3.** Tenho de usar aplicações de monitorização do ciclo menstrual
Behavior Intention (BI)	

USERS	
BIU1. I intend to continue using menstrual cycle tracking apps in the future	**BIU1.** Pretendo continuar a utilizar aplicações de monitorização do ciclo menstrual no futuro
BIU2. I will always try to use menstrual cycle tracking apps in my daily life	**BIU2.** Tentarei sempre usar aplicações de monitorização do ciclo menstrual na minha vida diária
BIU3. I plan to continue to use menstrual cycle tracking apps frequently	**BIU3.** Pretendo continuar a utilizar frequentemente aplicações de monitorização do ciclo menstrual
NON-USERS	
BINU1. I intend to try out menstrual cycle tracking apps	**BINU1.** Pretendo experimentar aplicações de monitorização do ciclo menstrual
BINU2. I want to use menstrual cycle tracking apps in my daily life	**BINU2.** Quero usar aplicações de monitorização do ciclo menstrual na minha vida diária
BINU3. In the future I will use menstrual cycle tracking apps frequently	**BINU3.** No futuro, irei usar frequentemente aplicações de monitorização do ciclo menstrual
FORMER USERS	
BIEXU1. I intend to use menstrual cycle tracking apps again	**BIEXU1.** Pretendo voltar a experimentar aplicações de monitorização do ciclo menstrual.
BIEXU2. I want to use menstrual tracking apps in my daily life again	**BIEXU2.** Quero voltar a usar aplicações de monitorização do ciclo menstrual na minha vida diária
BIEXU3. In the future, I will use menstrual cycle tracking apps frequently	**BIEXU3.** No futuro, voltarei a usar frequentemente aplicações de monitorização do ciclo menstrual
Actual Usage (AU)	
USERS ONLY	
AU1. Using menstrual cycle tracking apps is a pleasant experience	**AU1.** A utilização de aplicações de monitorização do ciclo menstrual é uma experiência agradável
AU2. I spend a lot of time on menstrual cycle tracking apps	**AU2.** Passo muito tempo em aplicações de monitorização do ciclo menstrual
AU3. I use menstrual cycle tracking apps on regular basis	**AU3.** Utilizo regularmente aplicações de monitorização do ciclo menstrual

Appendix II. Respondents' age group distribution

Table 1: Data regarding the respondent's age group. The age groups displayed are the same ones used by Statistics Portugal (INE).

Age Group	Frequency	Percentage of respondents
15 – 19 years old	82	12,9%
20 – 24 years old	300	47,3%
25 – 29 years old	85	13,4%
30 – 34 years old	53	8,4%
35 – 39 years old	42	6,6%
40 – 44 years old	24	3,8%
45 – 49 years old	25	3,9%
50 – 54 years old	14	2,2%
55 or more	2	0,3%
[Missing]	7	1,1%
Total	**634**	**100%**

Appendix III: Detailed statistics and frequencies of the UTAUT2 model questions

Table 1: Frequencies of each EE group response, in total percentage and valid percentage.

	Effort Expectancy (EE)							
	EE1	**Valid %**	**EE2**	**Valid %**	**EE3**	**Valid %**	**EE4**	**Valid %**
Discordo totalmente	0,3%	0,3%	0,2%	0,2%	0,3%	0,3%	0,3%	0,3%
Discordo	2,7%	3,0%	3,5%	3,9%	2,8%	3,1%	2,7%	2,9%
Nem concordo nem discordo	9,6%	10,5%	12,8%	14,3%	8,4%	9,3%	8,0%	8,7%
Concordo	39,6%	43,5%	39,5%	44,2%	38,8%	43,0%	41,6%	45,4%
Concordo totalmente	38,8%	42,6%	33,4%	37,4%	39,9%	44,2%	39,1%	42,6%
NS/NR	9,0%	-	10,6%	-	9,8%	-	8,2%	-
Total	100%	100%	100%	100%	100%	100%	100%	100%

Table 2: Frequencies of each PE group response, in total percentage and valid percentage.

	Performance Expectancy (PE)					
	PE1	**Valid %**	**PE2**	**Valid %**	**PE3**	**Valid %**
Discordo totalmente	0,5%	0,5%	1,1%	1,2%	0,6%	0,6%
Discordo	2,1%	2,2%	8,4%	9,3%	2,8%	3,0%
Nem concordo nem discordo	8,7%	9,0%	34,5%	38,4%	17,7%	18,7%
Concordo	50,2%	51,7%	28,9%	32,1%	42,6%	45,0%
Concordo totalmente	35,6%	36,7%	17,0%	18,9%	30,9%	32,7%
NS/NR	3,0%	-	10,1%	-	5,4%	-
Total	100%	100%	100%	100%	100%	100%

Table 3: Frequencies of each SI group response, in total percentage and valid percentage.

	Social Influence (SI)					
	SI1	**Valid %**	**SI2**	**Valid %**	**SI3**	**Valid %**
Discordo totalmente	15,9%	23,6%	18,0%	26,2%	42,7%	47,1%
Discordo	11,4%	16,9%	13,1%	19,0%	30,0%	33,1%
Nem concordo nem discordo	32,0%	47,5%	31,1%	45,2%	12,3%	13,6%
Concordo	6,2%	9,2%	4,7%	6,8%	4,7%	5,2%
Concordo totalmente	1,9%	2,8%	1,9%	2,8%	0,9%	1,0%
NS/NR	32,6%	-	31,2%	-	9,3%	-
Total	100%	100%	100%	100%	100%	100%

Table 4: Frequencies of each FC group response, in total percentage and valid percentage.

	Facilitating Conditions (FC)									
	FC1	**Valid %**	**FC2**	**Valid %**	**FC3**	**Valid %**	**FC4**	**Valid %**	**FC5**	**Valid %**
Discordo totalmente	0,8%	0,8%	0,5%	0,5%	1,4%	1,9%	2,1%	2,5%	0,8%	1,0%
Discordo	0,9%	0,9%	1,6%	1,7%	4,3%	5,9%	8,7%	10,4%	5,2%	6,2%
Nem concordo nem discordo	3,6%	3,7%	4,6%	4,8%	11,8%	16,1%	21,8%	26,1%	13,7%	16,3%
Concordo	30,8%	31,7%	35,2%	36,6%	24,6%	33,5%	32,2%	38,6%	38,0%	45,2%
Concordo totalmente	61,0%	62,8%	54,4%	56,5%	31,4%	42,7%	18,6%	22,3%	26,3%	31,3%
NS/NR	2,8%	-	3,8%	-	26,5%	-	16,7%	-	15,9%	-
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 5: Frequencies of each HM group response, in total percentage and valid percentage.

	Hedonic Motivation (HM)					
	HM1	**Valid %**	**HM2**	**Valid %**	**HM3**	**Valid %**
Discordo totalmente	3,0%	3,5%	0,9%	1,0%	2,5%	2,9%
Discordo	15,6%	18,1%	3,9%	4,5%	15,1%	17,6%
Nem concordo nem discordo	42,1%	48,8%	25,4%	29,4%	46,7%	54,6%
Concordo	21,3%	24,7%	43,7%	50,6%	16,9%	19,7%
Concordo totalmente	4,3%	5,0%	12,5%	14,5%	4,4%	5,1%
NS/NR	13,7%	-	13,6%	-	14,4%	-
Total	100%	100%	100%	100%	100%	100%

Table 6: Frequencies of each version of the app (paid or free) in percentage.

	Price Value	
	Frequency	**Correspondent %**
Paid version	19	3,9%
Free version	474	96,1%

Table 7: Frequencies of each PV group response for the paid version, in total percentage and valid percentage.

	Paid version					
	PV1	**Valid %**	**PV2**	**Valid %**	**PV3**	**Valid %**
Discordo totalmente	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Discordo	5,3%	5,9%	5,3%	5,6%	5,3%	5,6%
Nem concordo nem discordo	31,6%	35,3%	21,1%	22,2%	36,8%	38,9%
Concordo	36,8%	41,2%	52,6%	55,6%	31,6%	33,3%
Concordo totalmente	15,8%	17,6%	15,8%	16,7%	21,1%	22,2%

NS/NR	10,5%	-	5,3%	-	5,3%	-
Total	100%	100%	100%	100%	100%	100%

Table 8: Frequencies of each PV group response for the free version, in total percentage and valid percentage.

	Versão Gratuita	
	PV4	**Valid %**
Discordo totalmente	3,0%	3,6%
Discordo	13,5%	16,5%
Nem concordo nem discordo	22,4%	27,4%
Concordo	34,0%	41,6%
Concordo totalmente	8,9%	10,9%
NS/NR	18,4%	-
Total	100%	100%

Table 9: Frequencies of each HT group response, in total percentage and valid percentage.

	Habit					
	HT1	**Valid %**	**HT2**	**Valid %**	**HT3**	**Valid %**
Discordo totalmente	4,1%	4,1%	14,2%	14,4%	14,6%	14,8%
Discordo	17,2%	17,4%	28,0%	28,5%	29,0%	29,4%
Nem concordo nem discordo	8,9%	9,0%	18,7%	19,0%	17,0%	17,2%
Concordo	36,5%	36,8%	21,1%	21,4%	22,9%	23,2%
Concordo totalmente	32,5%	32,7%	16,4%	16,7%	15,2%	15,4%
NS/NR	0,8%	-	1,6%	-	1,2%	-
Total	100%	100%	100%	100%	100%	100%

Table 10: Frequencies of each BI group non-users' response, in total percentage and valid percentage.

	Behavior Intention (BI): Non-users					
	BINU1	**Valid %**	**BINU2**	**Valid %**	**BINU3**	**Valid %**
Discordo totalmente	16,3%	17,6%	19,1%	20,9%	12,1%	14,7%
Discordo	17,0%	18,3%	22,7%	24,8%	17,0%	20,7%
Nem concordo nem discordo	20,6%	22,1%	22,0%	24,0%	27,0%	32,8%
Concordo	32,6%	35,1%	21,3%	23,3%	20,6%	25,0%
Concordo totalmente	6,4%	6,9%	6,4%	7,0%	5,7%	6,9%
NS/NR	7,1%	-	8,5%	-	17,7%	-
Total	100%	100%	100%	100%	100%	100%

Table 11: Frequencies of each BI group users' response, in total percentage and valid percentage.

	Behavior Intention (BI): Users					
	BIU1	**Valid %**	**BIU2**	**Valid %**	**BIU3**	**Valid %**

Discordo totalmente	0,3%	0,3%	0,0%	0,0%	0,0%	0,0%
Discordo	0,6%	0,6%	7,0%	7,0%	1,4%	1,4%
Nem concordo nem discordo	1,4%	1,4%	14,0%	14,0%	5,3%	5,3%
Concordo	41,3%	41,6%	42,5%	42,7%	48,6%	48,7%
Concordo totalmente	55,9%	56,2%	36,0%	36,2%	44,4%	44,5%
NS/NR	0,6%	-	0,6%	-	0,3%	-
Total	100%	100%	100%	100%	100%	100%

Table 12: Frequencies of each BI group former users' response, in total percentage and valid percentage.

	Behavior Intention (BI): Former users					
	BIEXU1	**Valid %**	**BIEXU2**	**Valid %**	**BIEXU3**	**Valid %**
Discordo totalmente	6,7%	7,1%	8,1%	8,5%	4,4%	5,0%
Discordo	10,4%	11,0%	20,7%	21,5%	11,1%	12,4%
Nem concordo nem discordo	32,6%	34,6%	30,4%	31,5%	34,1%	38,0%
Concordo	34,8%	37,0%	31,1%	32,3%	32,6%	36,4%
Concordo totalmente	9,6%	10,2%	5,9%	6,2%	7,4%	8,3%
NS/NR	5,9%	-	3,7%	-	10,4%	-
Total	100%	100%	100%	100%	100%	100%

Table 13: Frequencies of each AU group response, in total percentage and valid percentage.

	Actual Usage (AU)					
	AU1	**Valid %**	**AU2**	**Valid %**	**AU3**	**Valid %**
Discordo totalmente	0,0%	0,0%	37,2%	37,3%	2,2%	2,2%
Discordo	0,8%	0,8%	48,0%	48,2%	12,6%	12,6%
Nem concordo nem discordo	24,6%	24,9%	8,7%	8,7%	15,1%	15,1%
Concordo	54,5%	55,1%	3,4%	3,4%	52,5%	52,7%
Concordo totalmente	19,0%	19,2%	2,5%	2,5%	17,3%	17,4%
NS/NR	1,1%	-	0,3%	-	0,3%	-
Total	100%	100%	100%	100%	100%	100%

Table 14: Minimum and maximum, mean, and standard deviation of each groups' questions.

	Question	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Effort Expectancy	**EE1**	1	5	4.26	0.788
	EE2	1	5	4.16	0.817
	EE3	1	5	4.28	0.787
	EE4	1	5	4.28	0.779
Performance Expectancy	**PE1**	1	5	4.26	0.714
	PE2	1	5	3.60	0.922
	PE3	1	5	4.07	0.821
Social Influence	**SI1**	1	5	2.58	1.006
	SI2	1	5	2.50	1.013
	SI3	1	5	1.84	0.938
Facilitating Conditions	**FC1**	1	5	4.54	0.713
	FC2	1	5	4.47	0.721
	FC3	1	5	4.06	1.013

	FC4	1	5	3.64	1.026
	FC5	1	5	3.98	0.911
Hedonic Motivation	**HM1**	1	5	3.11	0.859
	HM2	1	5	3.74	0.784
	HM3	1	5	3.07	0.828
Price Value	**PV1**	2	5	3.71	0.849
	PV2	2	5	3.83	0.786
	PV3	2	5	3.72	0.895
	PV4	1	5	3.39	1.002
Habit	**HT1**	1	5	3.77	1.188
	HT2	1	5	2.98	1.319
	HT3	1	5	2.96	1.312
Behavioral Intention	**BINU1**	1	5	3.22	1.170
	BINU2	1	5	2.90	1.241
	BINU3	1	5	3.09	1.159
	BIU1	1	5	4.52	0.591
	BIU2	2	5	4.09	0.878
	BIU3	2	5	4.37	0.647
	BIEXU1	1	5	3.34	1.019
	BIEXU2	1	5	3.07	1.049
	BIEXU3	1	5	3.33	0.928
Actual Usage	**AU1**	2	5	3.94	0.681
	AU2	1	5	1.88	0.900
	AU3	1	5	3.71	0.975

* These results refer to the 537 observations remaining after the removal of the observations with more than 15% of missing values.

** 1 (Discordo totalmente); 2 (Discordo); 5 (Concordo totalmente)

Appendix IV: Structural models outputs from SmartPLS 4

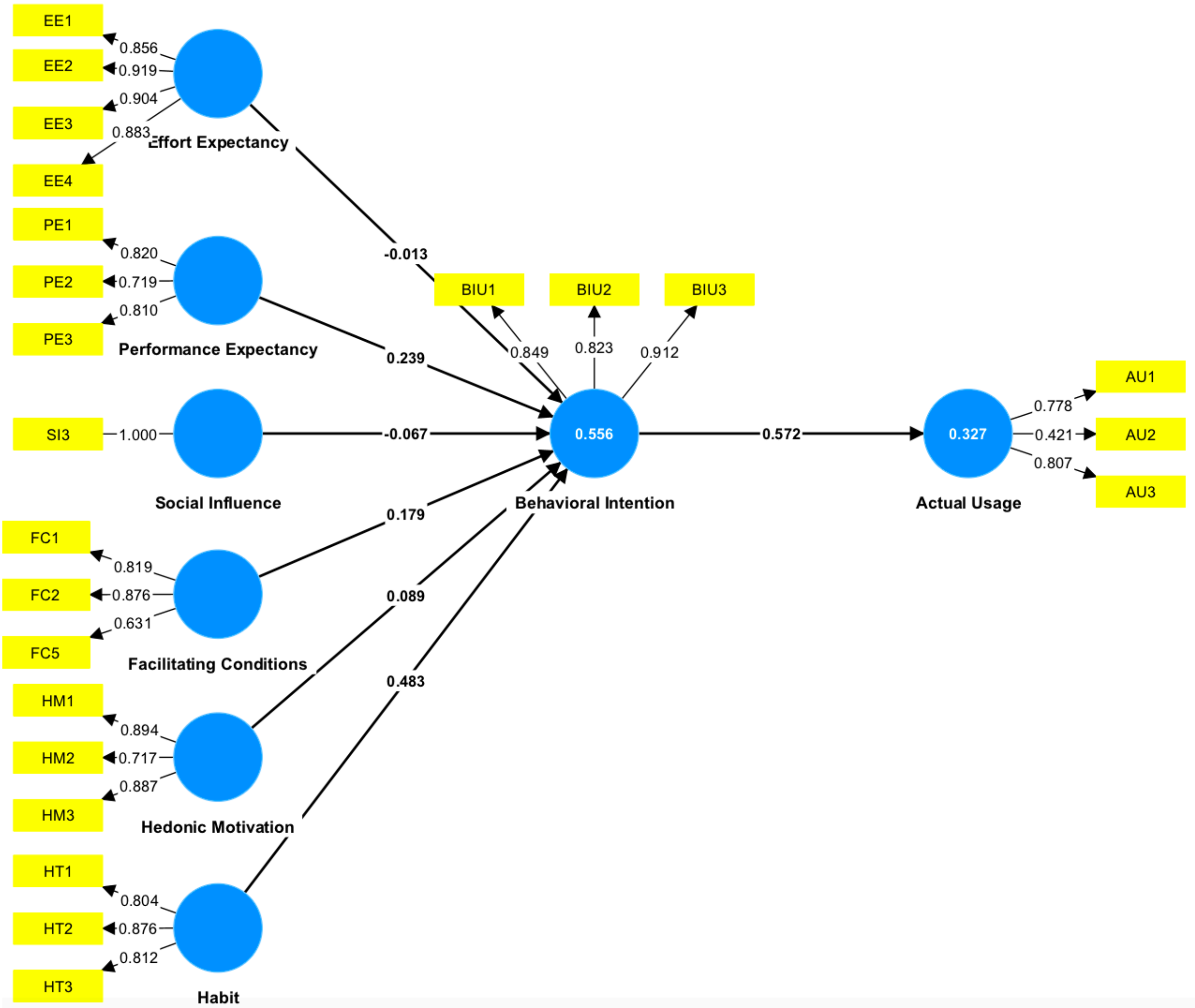

Figure 1: Structural model results of the users' group obtained with SmartPLS4 through PLS-SEM algorithm.

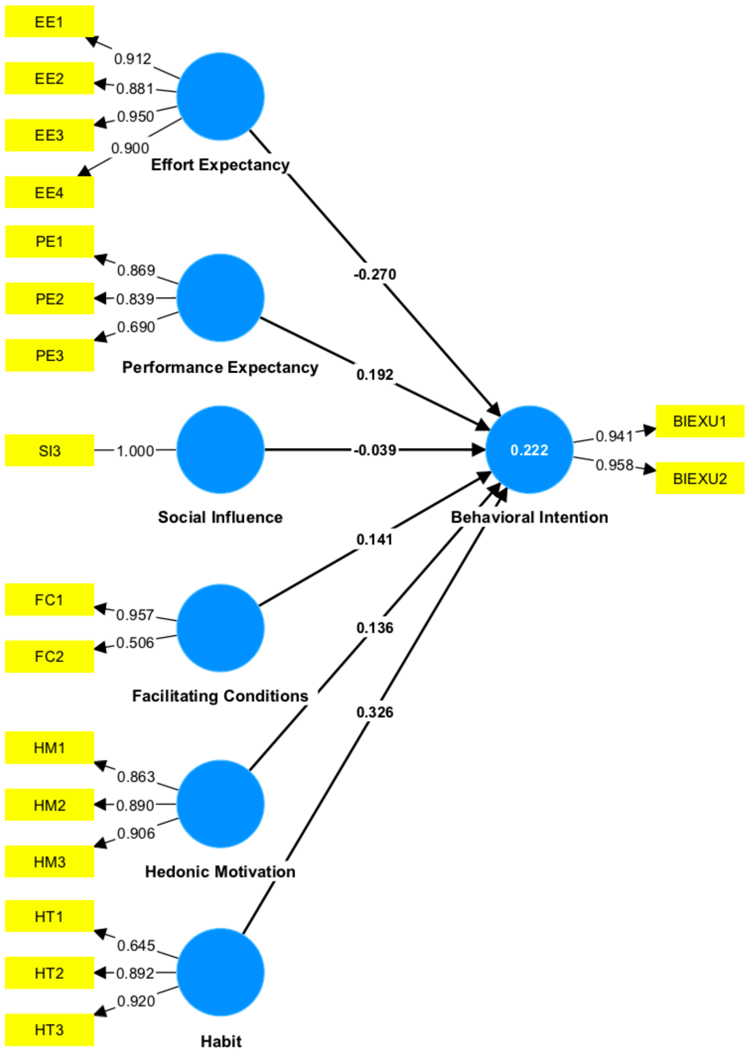

Figure 2: Structural model results of the former users' group obtained with SmartPLS4 through PLS-SEM algorithm.

Table 1: VIF values regarding users' structural model.

	VIF
AU1	1.102
AU2	1.099
AU3	1.153
BIU1	1.966
BIU2	1.707
BIU3	2.463
EE1	2.455
EE2	3.648
EE3	3.320
EE4	2.637
FC1	1.730
FC2	1.893
FC5	1.145

HM1	3.635
HM2	1.193
HM3	3.605
HT1	1.363
HT2	2.113
HT3	1.927
PE1	1.329
PE2	1.312
PE3	1.410
SI	1.000

Table 2: VIF values regarding former users' structural model.

	VIF
BIU1	2.830
BIU2	2.830
EE1	3.526
EE2	3.635
EE3	6.024
EE4	3.154
FC1	2.169
FC2	2.169
HM1	2.650
HM2	1.880
HM3	2.903
HT1	1.318
HT2	2.416
HT3	2.145
PE1	1.478
PE2	1.649
PE3	1.352
SI	1.000

Table 3: Indicators' outer weights for users.

	AU	**BI**	**EE**	**FC**	**HM**	**HT**	**PE**	**SI**
AU1	0.581							
AU2	0.145							
AU3	0.603							
BIU1		0.372						
BIU2		0.368						
BIU3		0.418						

EE1		0.256					
EE2		0.294					
EE3		0.275					
EE4		0.296					
FC1			0.447				
FC2			0.451				
FC5			0.378				
HM1				0.404			
HM2				0.411			
HM3				0.388			
HT1					0.450		
HT2					0.424		
HT3					0.328		
PE1						0.492	
PE2						0.337	
PE3						0.437	
SI							1.000

Table 4: Indicators' outer weights for former users.

	BI	**EE**	**FC**	**HM**	**HT**	**PE**	**SI**
BIEXU1	0.485						
BIEXU2	0.568						
EE1		0.360					
EE2		0.130					
EE3		0.258					
EE4		0.347					
FC1			1.270				
FC2			-0.426				
HM1				0.277			
HM2				0.464			
HM3				0.384			
HT1					0.256		
HT2					0.356		
HT3					0.563		
PE1						0.536	
PE2						0.404	
PE3						0.283	
SI							1.000