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A Predictive Model for the Acceptance of Wearable Ubiquitous Activity Monitoring Devices

DOCTORAL THESIS

Ricardo Nuno Araújo Sol

DOCTOR DEGREE IN INFORMATICS ENGINEERING
SPECIALIZATION: HUMAN-COMPUTER INTERACTION

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ORIENTATION
Karolina Baras

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University of Madeira

Exact Sciences and Engineering

Ricardo Nuno Araújo Sol de Jesus

This dissertation is submitted for the degree of

Doctor of Philosophy

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I would like to dedicate this thesis to my loving parents and grandmother.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University. This dissertation is the result of my own work and includes nothing that is the outcome of work done in collaboration, except where specifically indicated in the text. This dissertation contains less than 200 pages excluding the reference and the appendices.

Ricardo Nuno Araújo Sol de Jesus

2023

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Abstract

Acceptance of wearable ubiquitous activity monitoring devices that track activity has been a hot topic for the last decade. Several theories have been made, particularly how to think about the Technology Acceptance Model (TAM). These theories have been used in different situations to learn more about how people and organizations accept new technology. Even though the TAM is mature and works in different situations, there is not much published research that tries to expand its ability to predict how people will react to wearable ubiquitous activity monitoring devices. One reason for this gap could be that the TAM is based on the idea that people's acceptance behavior can only be predicted by two beliefs: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Literature shows that PU and PEOU beliefs are not enough. This means that they may not be able to explain why people accept new things, like Activity Trackers (AT). Because of this, it is important to include any other factors that can help predict how likely people are to use activity trackers.

As an extension of research on the TAM, this study created and tested two models of how people accept and use wearable ubiquitous activity monitoring devices, with two questionnaires with more than 200 respondents that shield light on the subject. The proposed models added key concepts from the research stream on how people accept information systems to the theoretical framework of the TAM and Health Information Technology Acceptance Model (HITAM). The resulting models were analyzed using a variety of statistical techniques including Structural Equation Analysis. The first model was reanalyzed via qualitative analysis with 20 interviews, and reanalyzed via another quantitative method of Artificial Neural Networks (ANN).

The most significant contributions of this dissertation are:

1. The construction of two models that predict activity tracking adoption and usage.
2. Guidelines for designing activity trackers.

These contributions can help promote activity trackers as an essential piece of equipment that helps monitor progress during workouts as well as other times, such as when the user is at rest or sleeping. We will see that by being continually reminded to walk about and avoid sitting for extended periods of time or doing nothing at all, this helps a person build healthy behaviors. Additionally, activity trackers should be designed to maintain a person's motivation to finish the daily activity routine, which is necessary for people to accomplish their health and fitness objectives. This thesis contributes with two quantitative models for the acceptance and use of activity trackers, and creates recommendations for different types of users.

Keywords: Physical Activity Tracking; User Acceptance; Ubiquitous Systems; Personal Informatics; Personal Data Tracking; Wearable Computers; Sports/Exercise; Survey; Extreme Users; User Centered Design (HCD); Human Computer Interaction (HCI); Technology Acceptance Model (TAM); Health Information Technology Acceptance Model (HITAM); Embodied Interaction; Artificial Neural Networks (ANN).

Resumo

A aceitação de dispositivos ubíquos vestíveis de monitorização de atividade que rastreiam a atividade tem sido um tema cálido na última década. Várias teorias foram concebidas, principalmente como pensar o Modelo de Aceitação de Tecnologia (TAM). Essas teorias têm sido usadas em diferentes situações para aprender mais sobre como as pessoas e as organizações aceitam novas tecnologias. Conquanto o TAM seja maturo e funcione em diferentes situações, não há muitas investigações publicadas que tentem expandir a sua capacidade de prever como as pessoas reagirão a dispositivos ubíquos vestíveis de monitoramento de atividade. Uma razão para essa lacuna pode ser porque o TAM é baseado na ideia de que o comportamento de aceitação das pessoas só pode ser previsto por duas asseverações: Facilidade de Uso Percebida (PEOU) e Utilidade Percebida (PU). A literatura mostra que as asseverações nas PU e PEOU não são suficientes. Isso significa que essas duas asseverações podem não ser capazes de explicar o porquê de as pessoas aceitarem coisas novas, como monitores de atividade (AT). Por isso, é importante incluir quaisquer outros fatores que possam ajudar a prever a probabilidade de as pessoas usarem monitorizadores de atividade.

Como extensão da pesquisa sobre o TAM, esta investigação criou e testou dois modelos de como as pessoas aceitam e usam dispositivos ubíquos vestíveis de monitorização de atividade, com dois questionários com mais de 200 repostas cada, que clarificam o assunto. Os modelos propostos agregaram conceitos-chave da pesquisa sobre como as pessoas aceitam os sistemas de informação ao referencial teórico do TAM e do Modelo de Aceitação de

Tecnologia da Informação em Saúde (HITAM). Os modelos resultantes foram analisados usando uma variedade de técnicas estatísticas, incluindo Modelação de Equações Estruturais. O primeiro modelo foi reanalisado por meio de uma análise qualitativa com 20 entrevistas, e de novo reanalisado por meio de outro método quantitativo com Redes Neurais Artificiais (RNA). A construção de dois modelos que predizem a adoção e uso do monitorização da atividade é a contribuição mais significativa que pode ser retirada deste trabalho, juntamente com as diretrizes para o design de monitorizadores de atividade.

Essas contribuições podem ajudar a promover os monitorizadores de atividade como um equipamento essencial que ajuda a monitorizar a evolução durante os treinos e em outros momentos, como quando o utilizador está em repouso ou dormindo. Ao ser continuamente lembrado para andar e evitar ficar sentado por longos períodos de tempo ou não fazer nada, isso ajuda o utilizador a construir comportamentos saudáveis. Além disso, os monitorizadores de atividade devem ser projetados para manter a motivação de uma pessoa em concluir a rotina diária de atividades, o que é necessário para que as pessoas atinjam seus objetivos de saúde e condição física. Esta tese contribui com modelos quantitativos para a aceitação e uso de monitorizadores de atividades e cria recomendações para diferentes tipos de utilizadores.

Palavras-Chave: Monitorização de Atividade Física; Aceitação pelo Utilizador; Sistemas Ubíquos; Informática Pessoal; Rastreio de Dados Pessoais; Computadores Vestíveis; Desporto/Exercício; Questionários; Utilizadores Extremos; Design Centrado no Humano (HCD); Interação Humano Computador (HCI); Modelo de Aceitação da Tecnologia (TAM); Modelo de Aceitação da Tecnologia de Informação em Saúde (HITAM); Interação Incorporada; Redes Neurais Artificiais (RNA).

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Abbreviations

AI – Artificial Intelligence

ANN – Artificial Neural Networks

ATTAM – Activity Trackers Technology Acceptance Model

AUTOS – Artifact, User, Task, Organization and Situation

CFA – Confirmatory Factor Analysis

DL – Deep Learning

DOI – Diffusion of Innovation Theory

EFA – Exploratory Factor Analysis

EU – Extreme Users

EUATTAM – Extreme Users of Activity Trackers Technology Acceptance Model

FNN – Feed Forward Neural Network

GFI – Goodness of Fit Index

GPS – Global Positioning System

HBM – Health Belief Model

HCD – Human Centered Design

HCI – Human Computer Interaction

HITAM – Health Information Technology Acceptance Model

MAE – Mean Absolute Error

ML – Machine Learning

ML – Maximum Likelihood

MLP – Multi-Layer Perceptron

MM – Motivational Model

MPCU – Model of Personal Computer Utilization

MSE – Mean Squared Errors

NAIR – Natural/Artificial versus Cognitive/Physical

PC – Personal Computer

PCA – Principal Component Analysis

PEoU – Perceived Ease of Use

PSevD – Perceived Severity to Disease

PSusD – Perceived Susceptibility to Disease

PU – Perceived Usefulness

ReLU – Rectified Linear Unit

RMSE – Root Mean of Squared Errors

SEM – Structural Equation Modeling

SFAC – Structure/Function - Abstract/Concrete

SCT – Social Cognitive Theory

SGD – Stochastic Gradient Descent

SSE – Sum of Squared Errors

TAM – Technology Acceptance Model

TPB – Theory of Planned Behavior

TRA – Theory of Reasoned Action

UTAUT – Unified Theory of Acceptance and Use of Technology

Chapter 1 Introduction

Wearable ubiquitous activity monitoring devices are becoming increasingly important in health behavior, socialization, and recreation, and thus an ever more important topic in Human Computer Interaction. Activity Trackers generate multi-million dollars revenues each year and come in the form of wearable or mobile technologies. The market value of consumer-based wearable physical activity trackers (or 'wearables') is projected to surpass $62,128 million by 2023, along with the growth of technologically savvy populations (Loomba & Khairnar, 2018).

Figure 1.1– Examples of Activity Trackers (Gemini, 2020)

Due to the success and attractiveness of Activity Trackers (see Figure 1.1), current important topics of study in Human Computer Interaction research are to understand what drives Activity Trackers use and acceptance, and how Activity Trackers influence human behavior. Previous research in Human Computer Interaction has generally followed a qualitative vision of Activity Trackers use (D. A. Epstein et al., 2015; Li et al., 2010). Whereas this thesis aims to provide an overall quantitative picture of Activity Tracker's core use, which may lead to their improvement by, for example, incrementing design iterations to identify weaknesses that need to be addressed.

This multidisciplinary research is edified upon existing work to establish novel extrapolative models that have their focus exclusively on Activity Trackers users that have not been found in the literature. This thesis will explore which share of Activity Trackers' use the models explains. These models try to provide an extensive view of these devices, by for example, not being exclusively based on users that search for Health Information. The proposed model can be used to broaden the iterative design process by showing shortcomings that need to be tackled in order to enhance user acceptance.

1.1 Thesis Statement

This thesis aims to address a research problem of identifying the factors that affect the use of activity monitoring devices, by developing and testing consolidated models of individual's belief towards activity monitoring devices acceptance and use.

The thesis statement of this work is:

"A quantitative model can explain behavioral intention to use activity trackers"

The proposed model integrates key constructs. Constructs are any complex psychological ideas into the theoretical frame of the model. The results of this work will contribute to literature on ubiquitous computing and technology acceptance. This work aims to achieve the following objectives:

- To abstract the constructs that constitute the user experience of the self-tracker for activity and rest;
- To describe those experiences using relevant constructs and a model;
- To develop a model of the constructs of self-trackers for activity and rest acceptance based on the technology acceptance model (TAM) as a foundation;
- To test the empirical validity of the proposed research model.

1.2 Contributions

The findings provide unique perspectives on various aspects of user view, purpose, and real usage behavior while accepting wearable ubiquitous activity monitoring devices. For health practitioners, this will mean better understanding of important factors that could assist them. For Information Technology designers and developers, understanding the critical factors related to activity monitoring devices use enables them to design more effective systems. The findings will also enhance the acceptance and use of activity monitoring devices among current and potential users. Additionally, this research will be useful for activity monitoring devices software consultants and vendors. It will provide them with a synopsis of crucial factors that can aid or undermine efforts of their provision of successful products and services to the clients and customers.

The models validated through the studies can also serve as a diagnostic tool to assist activity monitoring devices designers in understanding some reasons regarding why some systems are preferred to others for long-term use. The findings of this research will provide some very important essential aspects that will aid this understanding. Manipulating these important characteristics can then be used to influence the behavior of future activity trackers users. Designers may employ information technology resources effectively and efficiently in this manner.

This thesis’ most important theoretical contribution is two models that predict activity monitoring acceptance and use. In the first study, an expanded TAM model was utilized to examine how consumers accept and use activity trackers. Adding external components to the TAM (self-efficacy, image, hedonic motivation, etc.) proved effective. The findings suggest that the proposed model can explain and predict how individuals adopt and utilize activity monitors. Theoretically and empirically, merging external influences with the TAM makes sense, since the TAM is not fully explanatory model. The measurement and structural models were further assessed using structural equation modeling (SEM) and the AMOS statistical software, and one was retested with ANNs. The empirical investigations used e-mail and self-administered questionnaires to collect data. When combined, these approaches are versatile, quicker, and cheaper than the traditional approach. This second study drew on previous work to create prediction models showing how objective and subjective variables affect Extreme Users acceptability and usage. These models have two uses. First, they may be used to assess whether enough consumers will use a specific platform over time to warrant further development. Second, they may improve a design by identifying flaws to fix to promote user acceptability and usage.

1.3 Dissertation Roadmap

The remainder of this dissertation is organized as follows:

Chapter 2 covers background information including the history of technology acceptance, the state of the art of wearable activity monitoring devices and the challenges for accepting them. Additionally, it covers the theory behind the methods used in this research.

Chapters 3 to 6 present the four studies developed as the research in this dissertation. Each chapter provides a self-contained section on model validation.

Chapter 3, on a technology acceptance model for Activity Trackers, describes the design, evolution and evaluation of the Activity Trackers Acceptance Model. The research examined user adoption of Activity Trackers and the elements that influence users' intent to use Activity Trackers. The study methodology and hypotheses were evaluated using a cross-sectional convenience sample. Constructs and mediating factors from a dozen previous models were compiled into a suppositional model for Activity Trackers. Structural Equation analysis was used to examine the data.

Chapter 4, on extreme users, presents a different look, compared to previous research, at quantitative design research with a qualitative model. Extreme Users (EU) facilitates user-centered design in design groups. "Acceptance Models" is a theory in Information Systems that models how consumers accept and utilize technology. The research examined how Extreme Athletes adopt and utilize Activity Trackers (AT). A cross-sectional survey of 206 self-selected convenience samples yielded the results. The investigation examined variables influencing trail-runners. Structural Equation Modeling (SEM) was used to examine the data.

The goal was to see how well the Health Information Technology Acceptance Model (HITAM) predicts and describes how the EU uses AT.

Chapter 5, on comparing athlete versus health runners, describes the design and evaluation of a model using interviews. The research examines how Athletes and Health Runners utilize Activity Trackers for self-quantification. The research analyzes 20 semi-structured interviews, 10 with athletes. The Technology Acceptance Model (TAM) was applied to accomplish the interview aims.

Chapter 6, on models with artificial neural networks, presents the results of the attempts to use an artificial neural network to validate the technology acceptance model. This research aims to improve a Technology Acceptance Model (TAM) via an Artificial Neural Network (ANN) technique. This research looked at the Chapter 3 work that established a TAM for Activity Trackers (AT) using SEM and 247 individuals. This research employs the paper's constructions as input units in an ANN and the Root Mean Square of Errors to show good prediction accuracy.

Chapter 7 concludes with a summary of the contributions, a corresponding set of design guidelines for wearable ubiquitous activity monitoring devices, limitations of the research and ideas for future work.

Chapter 2 Background

This chapter presents the background material and related work relevant to this thesis. It specifically looks at the motivation behind this research, the history of technology acceptance, current state of the art in activity monitoring devices and the challenges for its design.

2.1 Overview

Physical inactivity is the fourth greatest cause of death worldwide and a serious public health concern (Batrakoulis & Fatouros, 2022), however it is manageable. Improving physical activity levels can lower the risk of mortality in people with chronic diseases like cardiovascular disease (Kris-Etherton et al., 2021) and diabetes (Shah et al., 2021), prevent the growth of secondary chronic conditions (Katzmarzyk et al., 2022), and manage and treat obesity, which can lead to these chronic diseases (Stone et al., 2021). Physical exercise is also very useful for healthy people who do not have chronic diseases. Observational studies have revealed that people who engage in more physical exercise had a lower chance of acquiring obesity (V. A. Taylor et al., 2021) and a variety of illnesses later in life (Carraça et al., 2021).

Despite the advantages of physical exercise in chronic illness management and prevention, 28% of individuals globally do not achieve the medical recommended physical activity levels, and the prevalence was more than two and a half times higher in nations with high incomes (36%) than in those with low incomes (16%) (Guthold et al., 2018).

Additional initiatives are required to address the worldwide issue of physical inactivity. To that purpose, there has been a lot of interest in using digital technology. The topic of digital health encompasses a diverse variety of technologies related to health and medicine (Lupton, 2014). However, the emphasis of this thesis is on technology that can offer behavior modification interventions. Those are consumer-based wearable physical activity trackers (or 'wearables') that have been a thriving sector, with a market value anticipated to exceed $62,128 million by 2023, parallel to the expansion of technologically competent populations (Loomba & Khairnar, 2018).

2.2 Wearable Activity Monitoring Devices

A non-research gadget or application that captures and analyses data on physical activity and other health-related indicators is known as a consumer-based activity tracker. The terms activity tracker, fitness tracker, activity monitor, and fitness monitor are often used interchangeably in this framework. These terms are defined as any wearable consumer-based smart device capable of recording physical activity or other health-related data via integrated sensors and algorithms, and capable of transmitting this data to a paired device (Aroganam et al., 2019).

Furthermore, activity tracker sensors are used in more complex wearables under a variety of different labels (Wright et al., 2017). Some terms are synonyms; some suggest a small variation in traits; while yet others imply significant distinctions. Other terms for activity-tracking wearables include smartwatch, sport watch, GPS (global positioning system) watch, smart band, smart bracelet, hybrid watch, smart ring, and smartphone.

In this dissertation, the word activity tracker or tracker will be used as an umbrella terms for any consumer-based wearables capable of collecting data on physical activity.

The consumer market for activity trackers has evolved over time. The first mechanical hip-worn pedometers for step counting were popular in the 1990s and were progressively phased out in the early 2000s by more precise accelerometer-based devices. Eventually, new technology enabled these devices to link wirelessly to smartphones through Bluetooth. This enabled the calculation of more complicated measures, and the relatively basic hip-mounted pedometer developed into today's more powerful multi sensor systems (i.e. activity trackers), which are now more typically worn on the wrist.

According to Deborah Lupton, self-tracking is an activity that involves frequently monitoring, documenting, and typically measuring aspects of an individual's behavior or physical processes (Lupton, 2016). Activity trackers may be used to facilitate self-tracking. Depending on the gadget, these activity trackers monitor various health and fitness parameters such as steps, heart rate, sleep quality and duration, distance, burnt calories, and much more. Researchers attempted to understand why individuals use activity trackers to self-quantify their behavior and how well such systems can help users (Epstein et al., 2015). The primary function of these systems is to inform individuals about themselves. They also emphasize the need to be effective and easy to use in addressing those users' demands to self-quantify their activity (Li et al., 2010).

Others discovered that information from the *Fitbit* device grew less meaningful or relevant for many participants over time, as its representations became conventional and lacked sufficient novelty to keep their attention (Jarrahi et al., 2018). This is analogous to the finding that users disconnect with the tracker as they become more likely to accomplish their daily walking targets (Gouveia et al., 2015).

A comprehensive literature review of 78 publications covered the issues of acceptance, adoption, and abandonment. The authors emphasized the need to appropriately address acceptability and adoption. Their research demonstrated that the studies do not focus on cultural differences or similarities. Furthermore, the studies were based on limited samples between eight to one hundred participants (Shin et al., 2019). This is a gap in the literature/research that this thesis will address by making surveys to more than two hundred participants, and by doing so, increasing the probability of detecting the statistical size/magnitude of the effect being investigated.

The integration of Artificial Intelligence (AI) into the field of healthcare is becoming more prevalent. This emergence of a data-driven approach to using artificial intelligence (AI) in healthcare has been facilitated by the substantial amount of data created by health systems from, for example, Activity Trackers. This raises ethical concerns.

There are further apprehensions over the potential influence derived from possessing such data. There are concerns over the potential concentration of power among Healthcare businesses in the absence of unidentified information.

Due to the prevailing skepticism towards private enterprises, there exists a significant focus on the implementation of laws and regulations to provide effective oversight of these organizations.

While it may be impractical to entirely disregard rules, private technology businesses should recognize the need of adhering to ethical standards in the healthcare sector in order to be seen as ethical actors and pursue profitability. It is crucial for these organizations to foster ethical cultures and implement ethical practices.

2.3 Ubiquitous / Pervasive Computing

Mark Weiser's seminal paper on ubiquitous computing was written in 1991, at the start of what is now a different way of thinking about how computers can be used in society (Weiser, 1991). He had realized that as the number of computers in society grew, it would get harder and harder to use them in a useful way.

Weiser thought it was important to move away from the traditional idea of the personal computer and toward a way of thinking in which physical spaces would be made up of computing devices that would be built into everyday objects and connected to technology. In this world, people would constantly use hundreds of devices that are all connected to each other. These devices would blend into the background and become almost invisible to the people who use them. In this paper Weiser wrote that:

“The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it“ (Weiser, 1991).

The sentence shows that Weiser thinks that for technologies to really be a part of daily life, they need to be so ingrained in the users minds that one does not have to think about using them. This would let people who use computers focus on their goals instead of the tools they use. Ubiquitous computing is a term used to describe technology that does not need the users constant attention but is also ready to use at a moment's notice. Weiser's idea of "*ubiquitous computing*" was based on the fact that most of the millions of personal computers in society were not connected to each other and were mostly getting in the way of people. He knew that computers were not going away, but that they were getting more and more attention from their users.

The idea of ubiquitous computing has been the focus of a lot of research for the past three decades, turning it from a dream into a reality bit by bit (Bell & Dourish, 2007; Caceres & Friday, 2011). Even though it is not possible to say that the idea is fully realized, many of today's innovations, such as wireless and mobile services, products and devices with sensors, smart pads and phones, and many others, have helped computers become less limited in time and space.

At the beginning of the 21st century, two articles were published, one by IBM corporation and the other by Satyanarayanan from Carnegie Mellon University. Both articles talked about what they thought would be needed for the infrastructure of future networks of computers and devices that can do computation. The first one came up with the term "*autonomic computing*" (Manifesto, 2001) and the second one, ironically, pushed for "*pervasive computing*" which

IBM had been promoting (Satyanarayanan, 2001). Seven years after Weiser's vision was introduced, IBM's Lohr and Markhoff used the phrase ubiquitous computing for the first time, imagining a post-PC future in which computers would leave their desktops and be accessible everywhere (Lohr & Markoff, 1998). Later, in IBM, Germany, the term pervasive computing was coined in accordance with the idea of ubiquitous computing, emphasizing the feature of "*everywhere at anytime*" (Hansmann et al., 2003).

Ark and Selker looked at the term "*pervasive computing*" as a continuation of the work done by the Human Computer Interaction (HCI) community on how people interact with pervasive computers. They did this in an editorial (Ark & Selker, 1999). The terms "*pervasive computing*" and "*ubiquitous computing*" were used interchangeably in this issue of the journal. Both articles talked about both low-level and high-level aspects of the new computing era. For example, they talked about the technical structure and deployment of technologies, as well as the design and creation of software architectures that support environments where users can get the services they need without being interrupted.

IBM's manifesto said that the growing complexity of the IT industry has made it harder for it to serve people, which is its main goal. They said that their proposed architecture for autonomic computing would handle the complexity of existing computer infrastructure systems without relying on human intervention or management.

Both IBM (2001) and Satyanarayanan (2001) were in favor of building complexity into the software and hardware system infrastructure and automating its administration. However, Weiser was trying to get the HCI community to agree that users should be able to focus on what they want to do instead of how they want to do it.

When one looks at the eight features that IBM put forward for their vision, however, it was not found much about how the "*autonomic computing*" system will deal with what users want from it. From the same point of view, Satyanarayanan shows care for the user by writing that a pervasive computer environments system includes all the known features of distributed and mobile computing. He also shows that it must be scalable while allowing environments with different physical and computational capabilities to communicate. He summed up these systems by saying that they are proactive systems that let one link knowledge from different parts to infer knowledge and predict with as little user distraction as possible (Satyanarayanan, 2001, 2011).

In truth, there is no obvious distinction between a ubiquitous system and a non-ubiquitous system; rather, there exists a degree to which a system incorporates a set of ubiquitous computing features or none.

2.4 Technology Acceptance and Use in Applied Psychology

Research in the Management of Information Systems (MIS) field has identified three major pillars in an Information Systems (IS) environment, namely Personnel, Process, and Technology (Kling & Lamb, 1999). These authors advocate for a "*social-technical*" strategy to managing information technology in the digital economy. With a few examples, it was demonstrated why Information Technologies (IT) is a social-technical system and outlines essential socio-technical viewpoints that distinguish it from conventional IT conceptualizations. Literature has found significant support for an individual's intention as a key predictor of new IT system acceptance and usage (Fishbein & Ajzen, 1977; Venkatesh & Morris, 2000) and proposed models with a theoretical foundation in social psychology. These intention-based models predict information system adoption and utilization based on behavioral intention.

Technology acceptance research has yielded a variety of models and hypotheses, with components mostly drawn from psychology, sociology, management, and the information technology area. The Technology Acceptance Model (TAM) is the prominent model in this domain and its major representation (Davis, 1989). It is hardly an exaggeration to state that TAM was the beginning point for this research stream, affecting much of the writing that followed. Based on the Theory of Reasoned Action (TRA), Davis introduced TAM to explain the user's behavioral intention to utilize an Information System (IS). Because the Theory of Reasoned Action has formed the foundation of TAM and the technology adoption stream is heavily impacted by TAM, it is crucial to dedicate the following sections to discussing how this theory works, with references to Theory of Planned Behavior, which is a development of TRA.

2.4.1 Theory of Reasoned Action

The Theory of Reasoned Action (TRA) is a popular social psychology concept that investigates the factors that influence consciously planned behavior. According to the Theory of Reasoned Action, a person's action is determined by the person’s intention to execute the activity, which is defined by the person’s attitude toward the behavior and subjective norm (Azjen, 1980).

The behavioral purpose to perform determines a person's conduct. This purpose is established by the individual's views and subjective norms about the activity. Fishbein and Ajzen define subjective norms as "*the person’s perception that most people who are important to him think he should or should not perform the behavior in question*" (Fishbein & Ajzen, 1977).

The TRA hypothesis states that an individual's Behavioral Intention (BI) to conduct an actual activity is jointly driven by the person's Attitude toward completing the Behavior (ATB) and Subjective Norm (SN), which is the general view of what relevant people believe the individual should or should not do. A schematic of the relationships among constructs in TRA is represented in Figure 2.1.

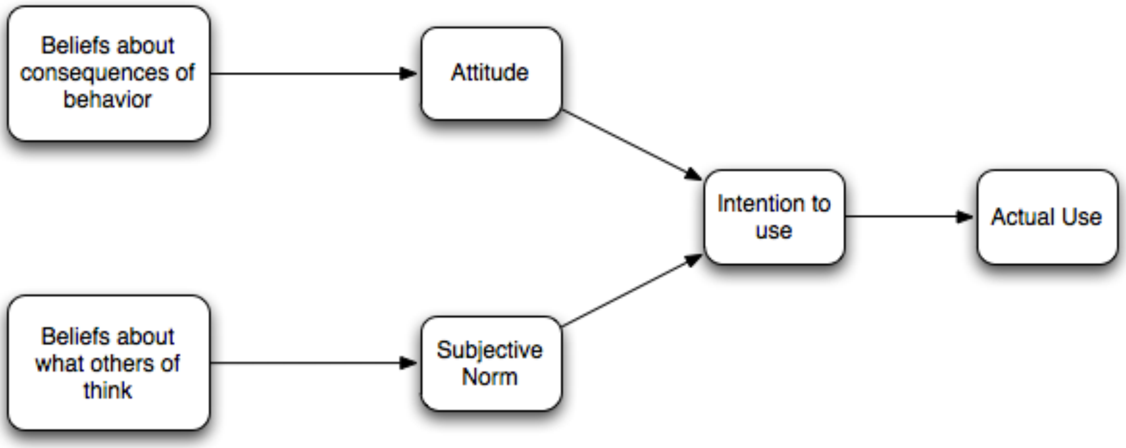

Figure 2.1– Theory of Reasoned Action (Fishbein, 1979)

To summarize, TRA predicts behavior through behavioral intention, assuming that there is a substantial influence between these two components. Behavioral Intention, in turn, is determined by both the person's attitude toward the activity and the societal standards imposed on them. Lastly, in this bound relationship, the individual forms behavioral attitudes through an accumulation of ideas about the conduct and their advantageousness to the person.

A meta-analysis of the application of the TRA revealed that the model might yield accurate predictions of an individual's decisions when faced with several options (Sheppard et al., 1988).

The TRA has been widely utilized and evaluated in several studies to predict and explain both intended and actual behavior performance (Rossmann, 2021). Nevertheless, as this theory was implemented in many academic areas, researchers realized that it was insufficient and had several drawbacks when used in specific contexts (Ajzen, 1991). According to Davis, TRA is a generic behavioral theory that does not specify which beliefs are suitable in which contexts (Davis et al., 1989).

Moreover, the TRA hypothesis has been criticized for being inappropriate for predicting circumstances in which individuals have little volitional control (Ajzen, 1985). To overcome these shortcomings, Ajzen expanded the TRA and created a new theory called Theory of Planned Behavior (TPB), which is addressed in the next section (Ajzen, 1991).

2.4.2 Theory of Planned Behavior

Even if the findings of TRA-based research indicated a good prediction of behavior intention, the applicability of TRA drops significantly when the participants under observation have little self-control over actions.

The TRA was expanded by introducing a new concept called perceived behavioral control to predict actions when people have limited volitional control (Ajzen, 1985). The expanded model is known as the Theory of Planned Behavior (TPB).

The main distinction between TRA and TPB is the inclusion of a third predictor of behavioral intention; perceived behavioral control. Perceived behavioral control is governed by two factors: control beliefs and perceived power. Thought behavioral control implies that a person's motivation is determined by how difficult the actions are perceived to be, together with how well the individual can, or cannot, accomplish the activity. If users have strong control beliefs regarding the presence of elements that will enable behavior, the user will have high perceived control over the behavior. In contrast, if the user has strong control beliefs that restrict the behavior, they will have a poor feeling of control. A schematic of the relationships among constructs in the TRA is represented in Figure 2.2.

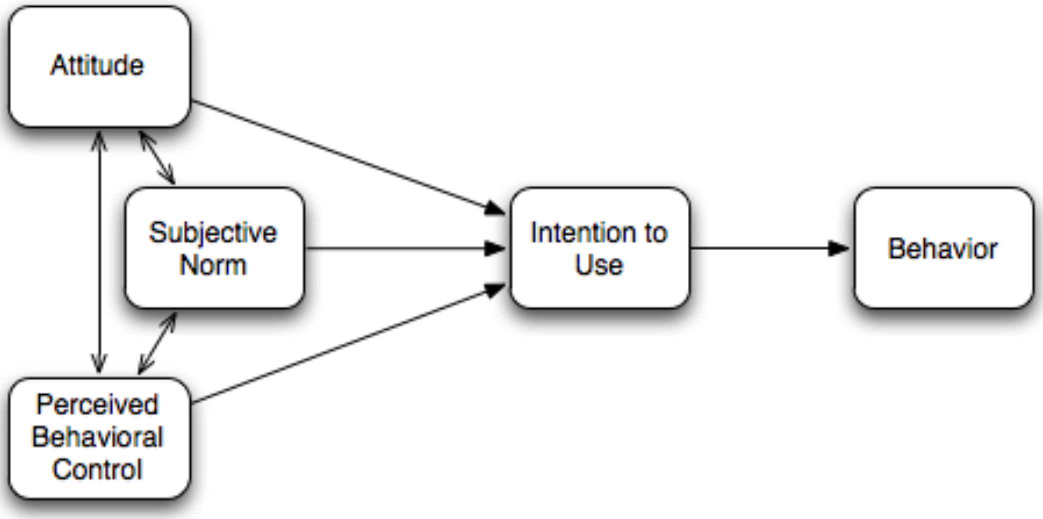

Figure 2.2– Theory of Planned Behavior (Ajzen, 1985)

Perceived behavioral control relates to easily accessible resources, abilities, and opportunities, as well as the individual's judgment of the significance of accomplishing the desired objectives. The idea of Perceived Behavioral Control is similar to Bandura's concept of Self-Efficacy (Bandura, 1982). The latter describes how an individual's ideas about their self-efficacy might impact their choice of activities, preparation for the activity, and, lastly, the effort they will perform during the activity in question.

Though prior information system research studies revealed that perceived behavioral control was an important predictor of both intent to use and actual use (Mathieson et al., 2001; S. Taylor & Todd, 1995) empirical data reveals that with the behavioral control construct, the function of self-efficacy is not only an essential addition to the theory, but it often emerges as the most significant component impacting both behavioral intention and actual usage (Armitage & Conner, 2001).

The TPB has been used effectively in a number of settings to foresee the outcomes of behavior and intention (Hagger et al., 2022). Nonetheless, the theory of planned behavior ignores emotion variables such as threat, fear, pleasure, and enjoyment since it does not distinguish between affective and evaluative reactions to an activity. The next section discusses Davis's Technologies of Acceptance Model (TAM), which he developed to solve the limitations found in the other models.

2.4.3 Technology Acceptance Model

Davis developed the Technology Acceptance Model (TAM) to model user acceptance of information technologies (Davis, 1985). On the basis of user perceptions, TAM describes user acceptance of an information system. TAM utilizes the causal links between two essential assumptions described in TRA (Fishbein, 1979) and the attitudes, intentions, and actual system adoption behavior of users. The major objective of the TAM is to forecast information systems or information technology acceptance and detect design flaws even prior to actual user adoption of new systems. Therefore, the TAM has been extensively used for forecasting, explaining, and enhancing the knowledge of user acceptability of information systems in a variety of sectors. The TAM is likely the most generally acknowledged and utilized technology acceptance and dissemination model among information system researchers. The TAM's appeal may be owing to its parsimony, information system-specific character, and empirical backing from various research studies (Gefen & Straub, 1997; Mathieson, 1991).

Two theoretical notions, perceived usefulness and perceived ease of use, are crucial predictors of user adoption of an information system, according to the TAM. The definition of Perceived Usefulness (PU) is: "*The extent to which a person believes that using a particular system would improve his or her job performance*" (Davis, 1989). Perceived Ease of Use (PEoU) refers to: "*The extent to which a person believes that employing a specific system would be effortless*" (Davis, 1989).

The TAM says that users' beliefs about Perceived Usefulness and Perceived Ease of Use affect how they feel about using information systems. Their attitude has a direct effect on their Behavioral Intention (BI) to use, which in turn will affect how they use the system. Both PU and PEoU affect Behavioral Intention. Perceived Ease of Use also changes Perceived Usefulness. PU and PEoU are two outside factors that have an indirect effect on BI.

The TAM proposed that user acceptance of a new technology is driven by their behavioral intention to use the systems, which can be described jointly by the user's view of the utility of the technology and attitude toward technology usage (Beaudry et al., 2020). A schematic of the relationships among constructs in TAM is represented in Figure 2.3.

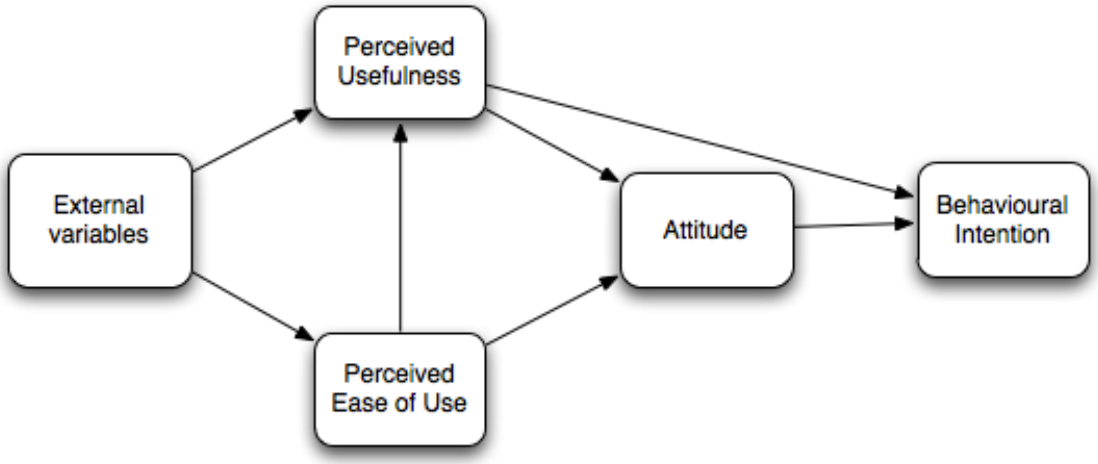

Figure 2.3– Technology Acceptance Model (Davis, 1985)

External elements among other tasks, user characteristics, political pressures, and organizational issues are predicted to have an indirect impact on technology adoption behavior by influencing perceived usefulness and perceived ease of use (Szajna, 1996). Furthermore, perceived simplicity of usage influences perceived usefulness.

Nonetheless, the most common problem with TAM is that it relies on self-reporting from respondents and assumes that self-reported usage is the same as actual usage (Legris et al., 2003). Others advised re-evaluation of measurement instruments after each application, arguing:

"*No absolute measures for those constructs exist across varying technological and organizational context.... Measurement models must be rigorously assessed and, if necessary, respecified*" (Segars & Grover, 1993).

So, Venkatesh and Davis developed a revised TAM that includes new categories about subjective norm and cognitive instrument process (Venkatesh & Davis, 2000), which is addressed in the next section.

2.4.4 Extensions and Integrations of TAM

The Technology Acceptance Model has done a good job of explaining how users accept different Information Technologies / Information Systems applications. Because of this, a number of additions have been made to the TAM model. In the original TAM, Perceived Usefulness (PU) and Perceived Ease of Use (PEoU) were seen as important predictors of intention to use. After that, the TAM model was changed to include a number of other factors that were thought to affect how people used the technology. At least three ways have been tried to make the TAM longer. These methods include adding new factors like subjective norm, trust, or perceived resources, adding extra or different beliefs, and looking at the mediators and causes of PU and PEoU (Kurniawan et al., 2022).

Davis and Venkatesh added to the original TAM model to explain how social influence processes and cognitive instrumental processes explain how useful something is seen to be and how likely someone is to use it. They called the model with more parts TAM2 (Venkatesh & Davis, 2000). In TAM2, the social influence process shows how three interconnected factors affect users' decisions about whether to use a newly developed information system. There are three factors: subjective norms, voluntariness, and image. In the cognitive instrumental process, the TAM2 shows how relevant and high-quality a person's work is to PU and PEoU. Also, the ability to show results and how easy it is to use are key factors in user acceptance. Venkatesh and Davis did a long-term study that included two voluntary settings and two forced settings. The results of their study showed that being able to be shown, image, subjective norms, job relevance, and results were all important factors in figuring out how useful a technology was. Additionally, a study by Venkatesh showed that computer anxiety, computer self-efficacy, perceptions of external control, and objective usability were important factors for the ease of use construct (Venkatesh, 2000). A schematic of the relationships among constructs in TAM2 is represented in Figure 2.4.

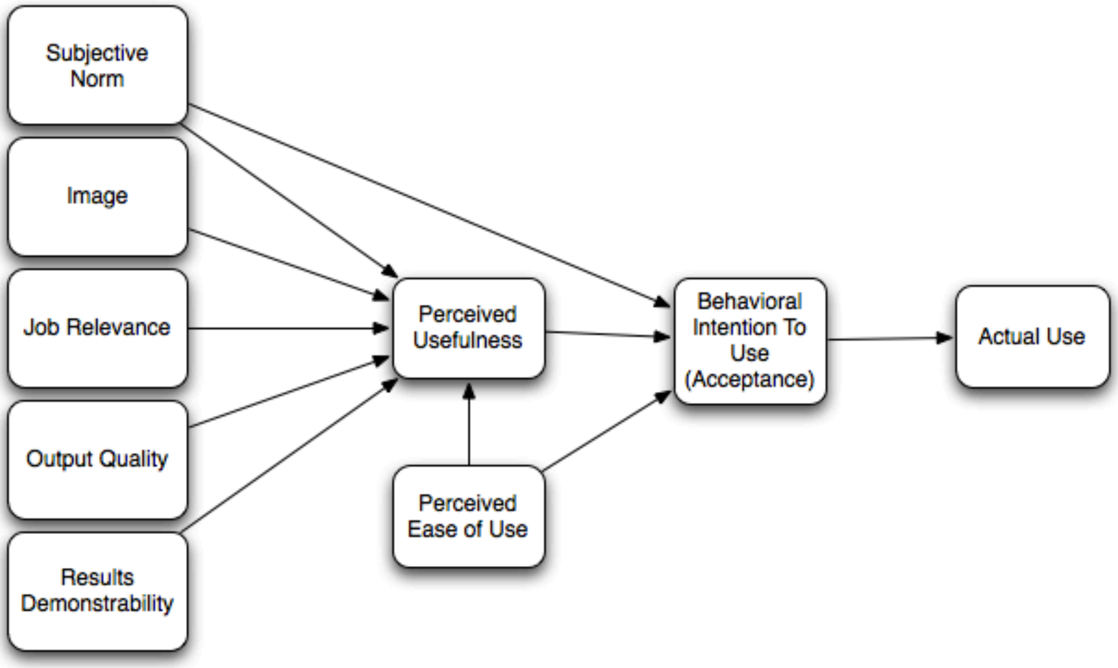

Figure 2.4– Technology Acceptance Model 2 (Venkatesh & Davis, 2000)

TAM2 brought together what had been done before and took into account the previous request for the model to be made more detailed. It defined the external variables of perceived usefulness and ease of use and gave a concrete way to move the multi-level model forward. The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the following models that builds on TAM (Venkatesh et al., 2003). It considers most of the popular models that try to predict how people will accept technology, and it will be discussed in the next sub-section.

2.4.5 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most popular frameworks in the field of general technology acceptance models. UTAUT is a combination of the Technology Acceptance Model (TAM), models that added to TAM, other adoption theories, and theories about how people act, to cover a total of eight models. These models are the Social Cognitive Theory (SCT), Diffusion of Innovation Theory (DOI), the Model of PC Utilization (MPCU), the Motivational Model (MM), TAM2, TAM, TPB, and TRA. Based on the conceptual and empirical similarities between these eight models, a single model has been made. So, the goal of UTAUT was to combine the different models that were already out there and give the research community a reference model to study how people accept new technologies (Venkatesh et al., 2003).

These models gave strong empirical support to UTAUT, which states that there are three direct predictors of intention to use (performance expectancy, effort expectancy, and social influence) and two direct predictors of usage behavior (intention and facilitating conditions).

Like other acceptance models, it tries to explain why users want to use an Information System (IS) and how they do so. This synthesized model shows a more complete picture of the acceptance process than was possible with the individual models that came before it. An integrated model was made by putting together eight models that had been used in the IS field before. All these models came from psychology, sociology, and communications.

The UTAUT looks at four things to predict a person's intention to do something or use something: performance expectations, effort expectations, social influence, and facilitating conditions. It is thought that gender, age, experience, and whether the use is voluntary moderate the effects of the four key constructs on usage intention and behavior as shown in Figure 2.5.

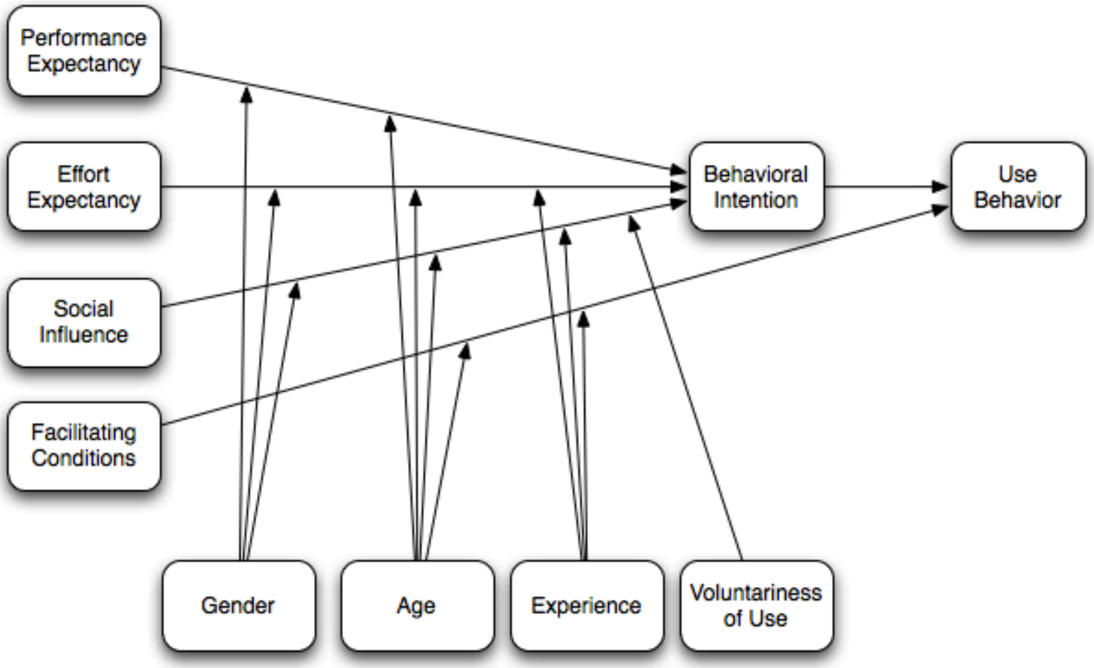

Figure 2.5– UATUT (Venkatesh et al., 2003)

Also, the UTAUT model tries to explain how differences between people affect how they use technology. More specifically, age, gender, and experience can change the link between perceived usefulness, ease of use, and intention to use. For example, the strength of the link between perceived usefulness and intention to use changes based on age and gender. For men and younger workers, this link is more important. The effect of perceived ease of use on intention is also moderated by gender and age, so that it is more important for older and female workers and less important for those with more experience (Venkatesh et al., 2003).

2.4.6 Health Information Technology Acceptance Model

Kim and Park built the Health Information Technology Acceptance Model (HITAM) as an extension of TAM that also used ideas from the Theory of Planned Behavior (TPB) and the Health Belief Model (HBM), because as digital innovation spread to healthcare, user acceptance theories also changed, and new models came out to reflect this (J. Kim & Park, 2012).

The Health Information Technology Acceptance Model (HITAM) adds three more areas to the Technology Acceptance Model. The first domain is the health zone, which has two causes and one process that connects them. The first antecedent is health status, which describes the user's age, gender, and health condition. The second antecedent is the user's health beliefs and concerns. These are the user's personal beliefs that affect their health behaviors depending on how much they care about their health and how important it is to them. The two antecedents affect the process of perceived threat mediating, which means that when users think their health might get worse, they may use HIT to better manage their health.

The second domain is the information zone, which consists of one antecedent process and one mediating process. Subjective norm is based on how important people to the patient think the patient should not use a technology. This factor affects the process of perceived usefulness, which is the user's belief that using HIT will help them find health information.

The third area is technology, which has to do with HIT itself. This zone is made up of two causes, three intermediaries that happen in the middle, and two results. The first one is HIT reliability, which is the quality of the technology's output and the result of using the technology. This can be found out either through direct experience with the technology or through the experience of others who have used the technology. The information zone overlaps with the HIT reliability zone. The second antecedent is the user's confidence in using technology, which is measured by HIT self-efficacy.

The three mediating processes in the technology zone are affected by these two causes. The first is perceived usefulness, which was covered in the information zone. The second factor is how easy the users think it will be to use HIT, which affects how useful they think it will be. The third process that can act as a mediator is attitude, which is how someone feels about HIT and how happy or unhappy they are with it. Perceived usefulness and perceived ease of use affect how people feel about something. The two outcomes in the technology zone are behavioral intention and behavior, which is affected by attitude. The user's behavioral intention is their plan and willingness to use HIT. Behavior is anything the user does to improve, protect, or keep their health (J. Kim & Park, 2012). A schematic of the relationships among constructs in HITAM is represented in Figure 2.6.

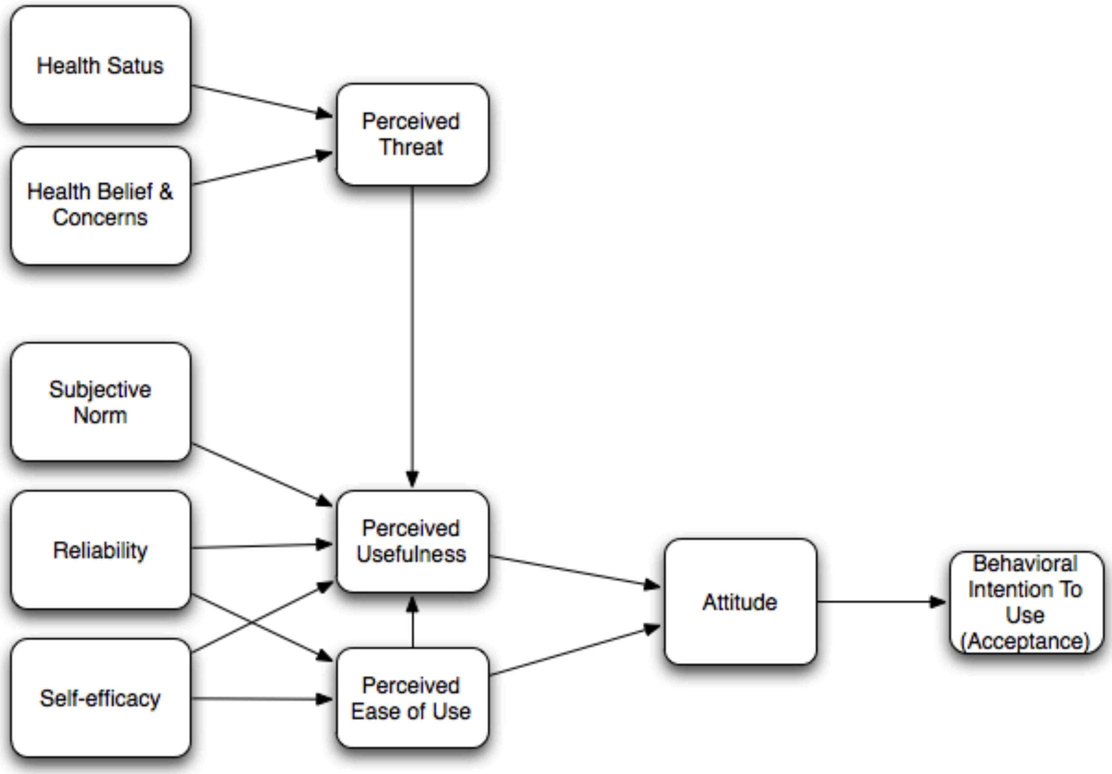

Figure 2.6– HITAM (J. Kim & Park, 2012)

A systematic review of the technology acceptance model in health informatics discussed the theoretical frameworks that were used by various studies and systematically summarizes previous studies in the field (Rahimi et al., 2018). The methodology used in past research and how the data was analyzed and was talked about, was detailed in systematic review (AlQudah et al., 2021). The TAM and HITAM are major factors in this thesis.

2.5 Design Methods

There are various sorts of design approaches, and one way to differentiate them is by the objective they aim to fulfill. For example, research procedures are designed to assist scientists in developing world hypotheses that are backed by empirical data and place a focus on the dependability and validity of their findings. Artists use artistic approaches to assist them to produce aesthetic pleasance, with a particular focus on the expressive and aesthetic characteristics of their results. Designing is a human activity that aims to transform undesirable conditions into desirable ones (Rylander Eklund et al., 2022). One of the goals of this thesis is to give design recommendations for activity trackers. Thinking like a designer may change how products, services, processes, and strategies are created. This approach, known as design thinking, combines what is desired from a human standpoint with what is technologically practical and economically viable. It also enables individuals who are not designers to utilize creative techniques to solve a wide variety of problems (Cross, 2021). One of these techniques is described in the following section.

2.5.1 Extreme Users

IDEO is a design firm noted for its trans-disciplinary, human-centered approach that generates good impact via design. As early pioneers in the profession of design thinking, they used their creative mindsets and talents to train others to do the same. IDEO, as a design firm, and as a problem solver, drives change, launches new businesses, and creates digital and physical experiences (IDEO, 2017).

Design thinking was not invented by IDEO, however, IDEO has developed several techniques, and one is Extreme Users. Extreme users are those who fall at either extremity of the use range for a product or service. Designing a solution that works for everyone entails speaking with both extreme users and those who fall somewhere in the center of the designer's target audience. When looking for interview users, designers should consider both the broad mainstream and individuals on either end of the spectrum. An approach that works for one extreme user will probably work for the vast majority of others. And without knowing what those on the periphery of the solution need, it is impossible to arrive at solutions that will work for everyone. More significantly, conversing with extreme users may inspire innovation by introducing designers to use cases, hacks, and design options they had not previously considered (IDEO, 2003).

First, designers should consider all of the potential users of their solution. Extreme users may fall on a range of spectrums therefore diversity is required. Designers can converse with people who live alone as well as those who live with a huge extended family. Designers can communicate with both the elderly and youngsters. Each will provide a unique perspective on the topic, which may spark new ideas.

Second, while talking to an extreme user, designers should inquire how that extreme user would utilize a solution. They should inquire if they are currently using anything comparable and how it meets or does not meet their requirements.

Third, identify acceptable community connections to assist in the organization of meetings and individual interviews. Designers must ensure that they are speaking to a broad audience.

Designers may come to encounter an extreme user in another situation and wish to speak with them there.

Finally, while interviewing candidates, designers should be aware of certain extremes, that are often left out of talks, so designers should make them feel welcome and emphasize the importance of their contributions to the study (Fuge & Agogino, 2014). Extreme users will be preponderant in the development of this thesis.

2.5.2 Surveys: Questionnaires and Interviews

In Human-Computer Interaction (HCI) research, surveys are a very important tool. They offer feedback from the users' point of view. They give information about what users like and what they think about the design at many different stages of interface development. The way people use an interface can have a big effect on how it is designed and built. But not every survey is helpful. The information from a survey can be wrong. This means that the answers to some kinds of questions, like those about measuring time or the number of times something happens, may not be accurate (Zhang et al., 2017).

Setting the goals is the most important part of designing a survey. The questions and people who will be asked depend on what the survey's goals are. If the goals are not clear, it will be hard to know what the survey will show. It is important to figure out the target population correctly, it should include the people who will be using the interface, and any bias should be taken out.

The following paragraphs are about questionnaires and interviews, which are two types of surveys that are often used for evaluating users acceptance and use.

Interviews need people who are sensitive and able to change, as well as people who can stick to the rules of the interview. Interviews are a common way to do HCI research because they are flexible and allow people to take part. Interviews are flexible because the person asking the questions can change some of the questions or the order in which they are asked based on how the users respond. Lastly, interviews are participatory because both the interviewer and the person being interviewed have to talk back and forth with each other.

Compared to the isolated effect of the questionnaires, this is a big plus because the users share the experience. As such, interviews are more suited, to the research in this thesis, to get information from users than questionnaires because they are more personal (Adams & Cox, 2008).

During the early stages of usability evaluation, unstructured interviewing is used. At this stage, the goal of the interviewer is to find out as much as possible about the user's experience and what they expect from the system. Semi-structured interviews are used when the person doing the interview knows more about what the system needs. A more focused interview design can be used to focus on the things that are important. However, there can still be a little bit of room for the user to add more to an answer. Lastly, structured interviewing has a specific, planned agenda with specific questions to guide and direct the interview. In this design, the interviewer has a fully developed product and comes up with questions to find out how the user feels about it. One could say that interviews are like ethnographic methods. Both are ways to collect information from users, and both can be changed to fit different needs (Phellas et al., 2011).

Questionnaires are forms that people fill out. They are used to find out about a person's background, views, and interests. It is a way to find out information, write it down, and collect it. Researchers in HCI use questionnaires as tools to find out what users are thinking. Data from a group of users is saved on a permanent medium so that it can be analyzed and referred to in the future (Codó, 2008).

There are two main ways in which self-administered questionnaires and structured interviews are different from each other. The first is whether the interviewer is there or not and what that means for implementation, non-response, and the quality of the data. During data collection, interviewers may be able to persuade people who do not want to answer, get people to answer, or give more instruction or explanation. At the same time, just being in the same room as the interviewer can change how people answer and cause unintended interviewer effects, especially when talking about sensitive topics. The second biggest difference is that questionnaires are self-administrated. In a psychological test, a mail survey, or a web questionnaire, the users taking the test see the questions. In a structured interview, on the other hand, users usually do not see the questions, but they may see things like flash cards with response categories. Because of this, the way questions look and how the questionnaire is laid out are much more important in self-administered questionnaires and different from those used in interviews (Cummings et al., 2013). A significant distinction lies in the potential for obtaining a large n (sample size) through questionnaires, given proper recruitment. Conversely, interviews are constrained by time limitations. Additionally, questionnaires facilitate quantitative analysis, making it a considerably simpler process compared to interviews. Questionnaires and interviews will have a major role in this thesis.

2.6 Structural Equation Models

The term structural equation modeling (SEM) refers to a group of multivariate approaches that examine correlations between constructs (conceptual or latent variables), which can only be assessed inadequately by observable variables. SEM makes it feasible to explore complicated patterns of relationships among the constructs of a theory and evaluates, both in a general sense and in terms of particular relationships among constructs, how well the hypothesized model characterizes the data (Hair, 2009).

Structural equation models are made up of two parts. The first part covers the relationships amongst theoretic notions that are apprehended in the structural model. In the second part, the theoretic notions are modeled, thus portraying the relationships amongst constructs and their associated observed variables.

An important part of structural equation modeling is factor analysis. Factor analysis pursues the finding of common factors. The procedural aim of extracting factors is to endeavor to take out as much common variance as possible in the first factor. The next factors are considered to account for the maximum amount of the remaining common variance until, if things go perfectly, no common variance remains (Kline, 2014).

2.6.1 Principal Component Analysis

The main notion behind Principal Component Analysis (PCA) is to lower the dimensionality of data comprised of a large quantity of interrelated variables, yet maintaining as much as variation existent in the data as possible. This is done by converting into a new set of variables (the principal components) those variables which are uncorrelated, and which are ordered so that the first few hold most of the variation existent in all of the initial variables (Spearman, 1904).

The data is represented in a matrix, and the mean of each column (ā) is calculated. An important statistical metric is covariance, which measures the direction of the relationship between two variables. If the value of covariance is positive, when one variable is big the other is also big. If the value of covariance is negative, when one variable is small the other is also small. To calculate the covariance of two variables A and B, the equation (2.1) is used.

$$cov(A,B) = \frac{1}{n-1} * \sum_{i=1}^{n} (Ai - \bar{a}) + (Bi - \bar{b}) \tag{2.1}$$

The result will be the covariance matrix, a square matrix of dimension equal to the number of columns of the original matrix. As mentioned, the goal of PCA is to lower the dimensionality of data comprised of a large quantity of interrelated variables. So, geometrically speaking, the eigenvectors will form the axes of this new variables subspace. An eigenvector is a vector whose direction rests unaffected after a linear transformation is applied to it. Nevertheless, the eigenvectors only explain the directions of the new axis, because they all have an identical unit length (Gorsuch, 2014).

Consequently, in order to choose which eigenvector(s) is dropped, it is necessary to calculate the matching eigenvalues of the eigenvectors. The eigenvectors with the smallest eigenvalues assume the smallest information about the distribution of the data, so they should be dropped.

So, let **A** be a square matrix, if a nonzero vector **v** and a scalar **λ** that fulfills Av = λv, then **λ** is an eigenvalue linked with eigenvector **v** of **A**.

$$Av = \lambda v \Leftrightarrow Av - \lambda v = 0 \Leftrightarrow (\mathrm{A} - \lambda \mathrm{I})v = 0 \tag{2.2}$$

Where I is the identity matrix. The null space of (A – λI) is called the eigenspace of A linked with eigenvalue **λ**. The eigenvalues of **A** are obtained through the roots of the polynomial:

$$\det(\mathrm{A} - \lambda \mathrm{I}) = 0 \tag{2.3}$$

Where ***det*** is the determinant, which is a scalar property of square matrices that is applied to determine whether the matrix can be inverted. The matching eigenvectors are the nonzero solutions of the linear system, which is solved for **λ**, to obtain the eigenvalue of a matrix (Hair, 2009).

Figure 2.7 displays a reflective measurement model that represents the relationship between one block of observed variables and the common factor that connects them.

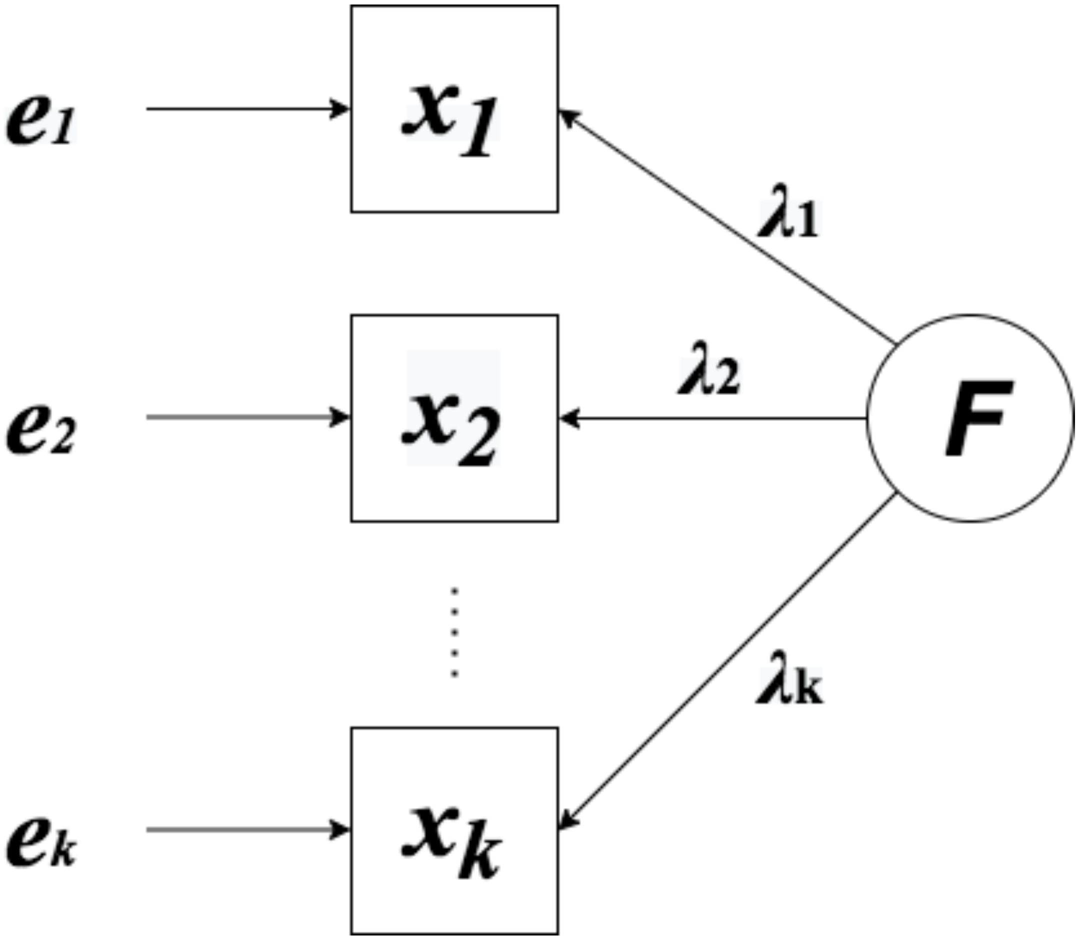

Figure 2.7– An example of a common factor model

2.6.2 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) can be defined as organized simplification of interrelated measures. EFA, is usually applied to study the likely underlying factor structure of a set of observed variables deprived of forcing a predetermined structure on the result (Mulaik, 2009).

Factor Analysis is an extension of Principal Component Analysis (PCA). PCA summarizes the data; it does not involve probabilistic assumptions nor does it support statistical inferences. It does give information about the population or stochastic process that created the data.

Both Factor Analysis and PCA attempt to approximate the covariance matrix, but Factor Analysis requests whether the data is coherent with a particular prearranged configuration. In PCA when dropping the smallest principal components an error is introduced, represented by **E**. Where an unrotated factor model is generally represented as in equation (2.4).

$$\mathrm{X}_p = a_{p1} * F_1 + a_{p2} * F_2 + \cdots + a_{pm} * F_m + e_p \tag{2.4}$$

In EFA the model for one factor can be expressed in matrix form by equation (2.5).

$$X = F * A + \epsilon \tag{2.5}$$

Where **X** stores the matrix of measured variables and is followed by the independent unobservable variables: **F** that stores the matrix of common factors, **A** that stores the matrix of factor loadings (weights), and $\boldsymbol{\epsilon}$ that stores a matrix of errors. This is what differentiates the factor model from the multivariate regression model, in a factor model the independent variables cannot be observed.

The matrix of weights **A** can be described as in equation (2.6).

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{1p} & \cdots & a_{pm} \end{bmatrix} \tag{2.6}$$

Where the various $\mathbf{a}_{\mathrm{pm}}$ are the factor loadings for the *ith* test.

As the variables are unobservable it is not possible to directly verify the factor model, so it is assumed that the mean and covariance for **F** and **ϵ** are:

$$\mathrm{E[F]} = 0;\ Cov(F) = E[FF^T] = I \tag{2.7}$$

Where E[F] is the expected value of **F**, sometimes also called the mean of **F**.

$$\mathrm{E[X]} = 0;\ Cov(X) = I \tag{2.8}$$

Also **F** and **ϵ** are independent, so:

$$Cov(\epsilon, F) = 0 \tag{2.9}$$

The uniqueness for each variable, that is the amount of variance that cannot be explained by any factor, is **Ψ**:

$$\mathrm{E}[\epsilon] = 0;\ Cov(\epsilon) = \Psi = \begin{bmatrix} \Psi_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Psi_p \end{bmatrix} \tag{2.10}$$

The communality of a variable specifies what proportion of the variable's variance is a consequence of either the principal components or the correlations between each variable and individual factor:

$$h_i^2 = \sum_{j=1}^{m} i_j^2 \tag{2.11}$$

Where the i_{th} communality is then the sum of squares of loadings for that variable (Hair, 2009).

2.6.3 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is a method that is applied when one has several variables and wants to verify whether these variables can be explained by a lesser number of factors. CFA is applied when one does not have a priori hypotheses about which variables are arranged together as indicators of a core construct and wish to test how well one's data matches the model. In a confirmatory factor analysis, one stipulates where the variables ought to load, and the software discloses just whether the model fits the data. If the model does not fit the data, there are limited pointers on how to rearrange the variables around to make the model fit the data in a better way (Hair, 2009).

The factor model representation is as in exploratory factor analysis. In confirmatory factor analysis the mean and covariance for **F** and **ϵ** are:

$$\mathrm{E[F]} = 0;\ Cov(F) = \ \Phi \tag{2.12}$$

Where **E[F]** is the expected value of **F**, sometimes also called the mean of **F**, and **Φ** is a square matrix of the covariances and variances of the latent construct.

$$\mathrm{E[X]} = 0;\ Cov(X) = \Sigma \tag{2.13}$$

Where ∑ is a square matrix of covariances and variances indicators.

$$E(\epsilon) = 0; Cov(e) = W \tag{2.14}$$

Where **W** is a square matrix of the covariances and variances of the error terms, so:

$$Cov(X) = \Sigma = A\Phi A^{|} + W \tag{2.15}$$

In detail this will be shown as:

$$\Sigma = \begin{bmatrix} \lambda_{11} & \cdots & 0 & 0 \\ \cdots & \cdots & 0 & 0 \\ \lambda_{\frac{p}{2}1} & \cdots & 0 & 0 \\ 0 & 0 & \cdots & \cdots \\ 0 & 0 & \cdots & \cdots \\ 0 & 0 & \cdots & \lambda_{pm} \end{bmatrix} \left[\begin{bmatrix} \sigma_{F1}^2 & \cdots & \sigma_{F1,Fm} \\ \vdots & \ddots & \vdots \\ \sigma_{Fm,F1} & \cdots & \sigma_{Fm}^2 \end{bmatrix}\right] \begin{bmatrix} \lambda_{11} & \cdots & \lambda_{\frac{p}{2}1} & 0 & 0 & 0 \\ \cdots & \cdots & \cdots & 0 & 0 & 0 \\ 0 & 0 & 0 & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & \cdots & \lambda_{pm} \end{bmatrix}$$

$$+ \begin{bmatrix} \sigma_{e1}^2 & 0 & 0 & & 0 & 0 & 0 \\ 0 & \sigma_{e2}^2 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & \sigma_{e3}^2 & & 0 & 0 & 0 \\ & \vdots & & \ddots & & \vdots & \\ 0 & 0 & 0 & & \sigma_{ep-2}^2 & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & \sigma_{ep-1}^2 & 0 \\ 0 & 0 & 0 & & 0 & 0 & \sigma_{ep}^2 \end{bmatrix} \tag{2.16}$$

There are various fit indices to measure the degree of general fit of a model to data. One independence model based is the Goodness of Fit Index (GFI) is a squared multiple correlation in multiple regression and is given by equation (2.17).

$$GFI = 1 - \frac{tr[(\Sigma\mathrm{C} - \mathrm{I})^2]}{tr[(\Sigma\mathrm{C})^2]} \tag{2.17}$$

Where the trace (tr) of a matrix is defined as the sum of its diagonal elements, and C is the sample covariance matrix (Joseph Jr, 2010).

2.6.4 Structural Equation Modeling

Instead of being restricted to outline paths among the measured variables, in Structural Equation Modeling (SEM) one can outline paths among the latent variables. Every one of the latent variables has to have ideally at least three related measured variables, so that every latent variable turns out to be a small independent unit of Confirmatory Factor Analysis (CFA) on its own (Kline, 2014).

SEM provides two significant benefits over other, similar methods (e.g., exploratory factor analysis, regression analysis).

First, and perhaps most crucially, SEM allows for a detailed investigation of the quality of measurement of theoretical ideas of interest using observable metrics. One would often establish an explicit measurement model in which each observed variable is connected to a theoretical idea of interest (thought of as a latent variable of substantive interest) and the measurement error when employing SEM for measurement analysis. More complicated measurement models that include causes of systematic covariation between observed measurements other than a shared underlying concept can also be developed. This is significant since the majority of conceptual variables of interest can only be measured with error (both random and systematic) and disregarding the measurement error has negative consequences for model estimation and testing.

Second, SEM allows one to analyze complicated patterns of interactions across components in one's theory and assess how well the hypothesized model captures the data, both overall and in terms of particular correlations among constructs. The latent variable (or structural) model is the model that describes the links between the components in one's theory. One can, for example, test whether several perceived benefits of self-monitoring technologies influence actual use of such technologies directly or indirectly via attitudes toward such technologies (e.g., whether attitudes mediate the effects of beliefs on behavior), and one can also investigate whether the relationships of interest are gender or other potential invariant moderators (Hair, 2009).

The estimation process entails determining model parameter values that minimize the difference between the sample variance/covariance matrix of the observed variables and the variance/covariance matrix suggested by the estimated model parameters. Although numerous estimate approaches (e.g., unweighted least squares, weighted least squares) are available, Maximum Likelihood (ML) estimation based on the assumption of multivariate normality of the observed variables is frequently the method of choice. The assumption for ML estimation is that the data is independently and identically multivariate-normally distributed, and that the sample size is big (Hair, 2009). One must make certain that these assumptions are not substantially broken (e.g., that the skewness and kurtosis of the observed variables, both individually and jointly, is not excessive).

An algebraic or visual structural equation model can be provided. Graphical models when done correctly, provide a thorough statement of the underlying model and frequently express the intended definition more naturally. An example is represented in Figure 2.8.

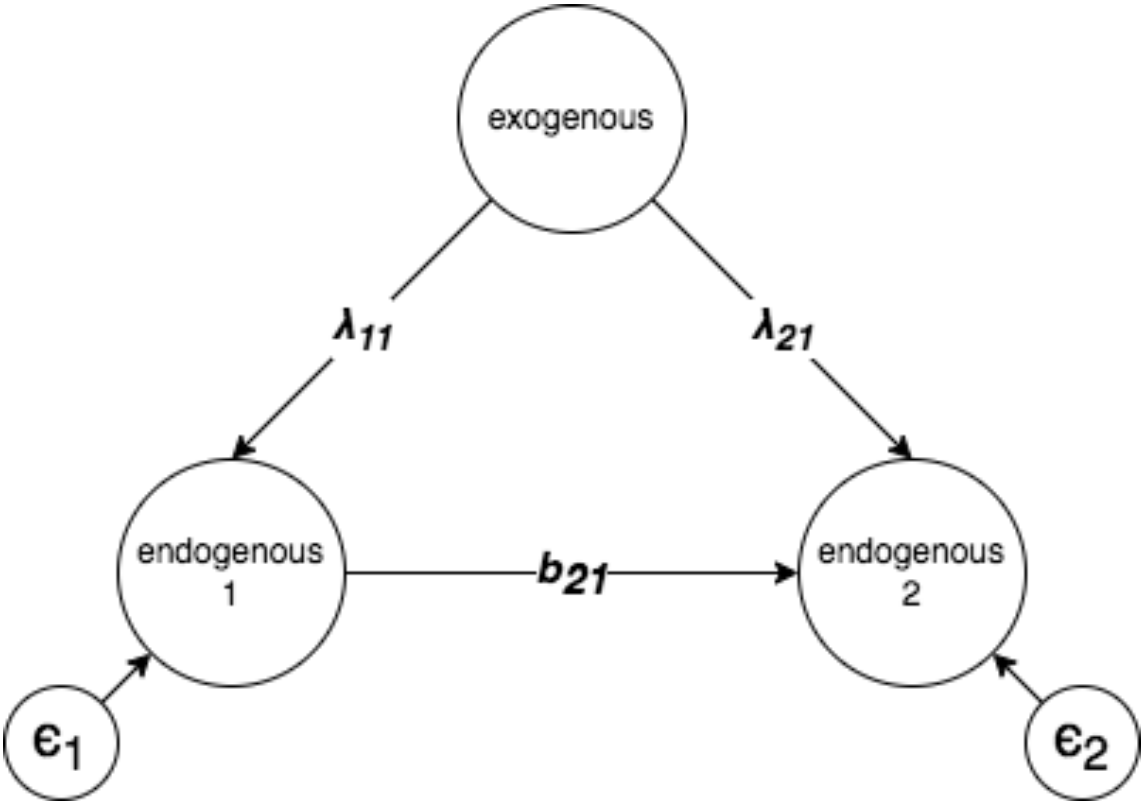

Figure 2.8– An example of a structural model

2.7 Artificial Neural Networks (ANNs)

The purpose of this section is to explain the basic ideas and terminology found in ANN literature in order to improve the comprehension of the work described in the rest of this thesis.

John McCarthy, an American cognitive and computer scientist, offered the following definition of Artificial Intelligence (AI) in 1955:

"*The science and engineering of making intelligent machines, especially intelligent computer programs*" (McCarthy, 1955).

In this context, the word intelligence is quite vague. Opportunely, Alan Turing, an English cryptanalyst, computer scientist, mathematician, and theoretical biologist, created a helpful test to determine if a machine is intelligent. Earlier known as the Imitation Game, the Turing Test is played by two people and one machine, with an interrogator (as a human) separated from the other two participants. The interrogator's task is to attempt to find out which of the other two is human and which is a machine by asking both of them written questions (Turing & Haugeland, 1950).

Machine Learning (ML), is viewed as a generic method to creating AI and, eventually, relishing its associated advantages. Arthur Samuel described it in 1959 as:

"*The field of study that gives computers the ability to learn without being explicitly programed*" (Samuel, 1959).

Deep Learning (DL) is a collection of approaches that seek to overcome the constraints of traditional machine learning by composing dispersed characteristics derived from various layers of sequential and parallel processing.

While deep learning is a broad term that encompasses a variety of methodologies in machine learning, Artificial Neural Networks (ANNs) are one of the most efficient ML strategies for handling a wide range of AI-related issues (Goodfellow et al., 2016). ANNs may be seen as computer models that mimic the brain's neuronal architecture and information processing capacity in order to perform experience-based learning (Russell, 2010). Moreover, according to Fausett's definition, an artificial neural network is:

"*A system for information processing that has some performance characteristics as biological neural networks*" (Fausett, 1994).

When the physiologists Waren McCulloch and Walter Pitts created a model of artificial neurons with two input neurons and one output neuron, with each neuron exhibiting the qualities of being either on or off depending on stimuli (McCulloch & Pitts, 1943), the field of artificial neural networks was founded. However, two decades later, according to a book by Marvin Minsky and Seymour Papert, this kind of neuronal network could only tackle linearly separable issues (Minsky & Papert, 1969). This resulted in a decade-long exodus from the ANN field, until the discovery of the Back-propagation learning process. Still, today ANNs can infer complicated (linear or non-linear) correlations that are fundamental to the data attributes when given a data collection.

2.7.1 Perceptron

Artificial neural networks that translate the input directly to the output (no hidden layers) are sometimes referred to as single-layer neural networks and can only learn linearly distinct patterns. A perceptron is a supervised single-layer neural network and a mathematical representation of a biological neuron (Russell, 2010). Similar to a real neuron, a perceptron regulates the degree to which one neuron influences another. This is achieved effectively by using learnable weights $\mathbf{w_k}$. Adding the weighted values of the inputs generates the final signal. If the resultant signal exceeds a certain threshold, the neuron emits (or "fires") its signal. A perceptron is represented in Figure 2.9.

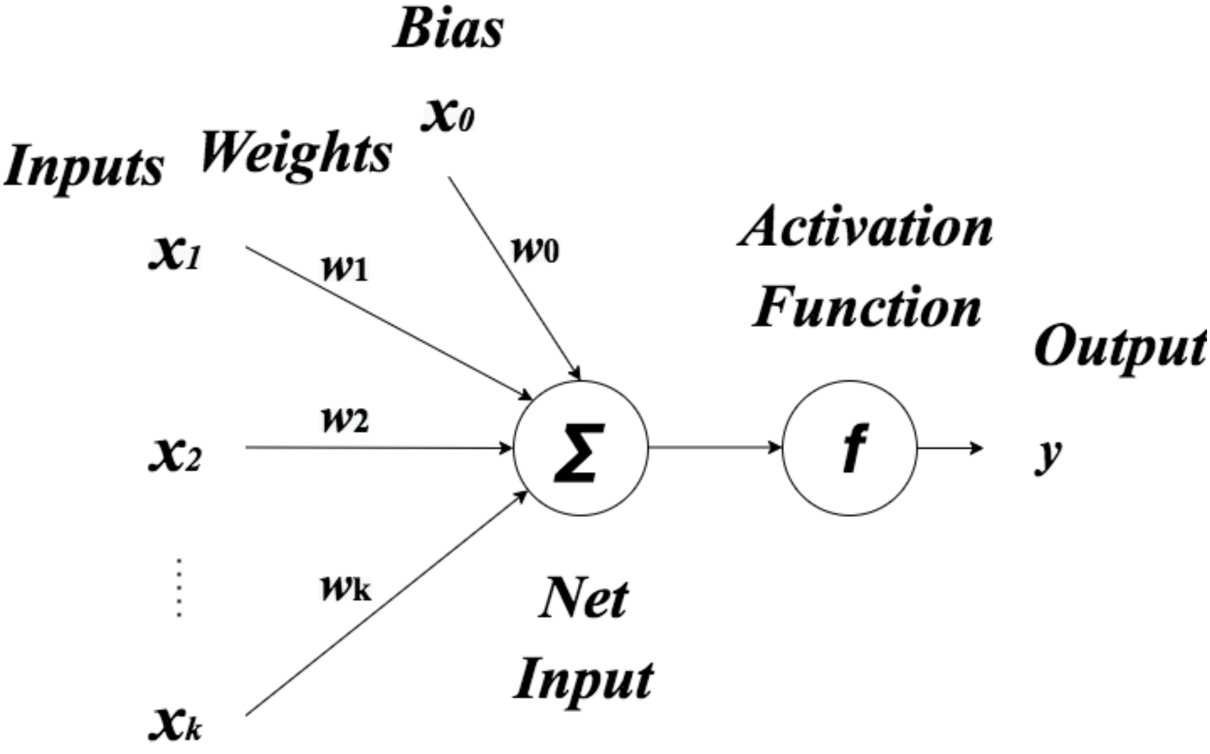

Figure 2.9– Perceptron (Rosenblatt, 1958)

Neurons in an ANN are linked together by directed communication links that let input signals $\mathbf{x}_k$ move through the network and, as a result, send information. The i_{th} communication link has a weight $\mathbf{w}_k$, which is used to scale the input. Weights can be thought of as adjustable network parameters that control how the input signal affects the network. Depending on the rules, relationships, and patterns in the data, the input signal can be either excitatory or inhibiting, depending on whether the weight value is positive or negative. During a process called "training," the ANN can learn these weights and figure out how the data are really represented mathematically (Haykin, 2010). Formally, the weighted sum of the input values of the node is calculated with equation (2.18).

$$z = w_0 + \sum_{i=1}^{n} x_i w_i \tag{2.18}$$

For the neuron's output value, y, to be obtained, the aggregated input, which is the weighted sum of the input values and is denoted by $\mathbf{z}$, must be first calculated. However, the signal's value might be anywhere amid $-\infty$ and ∞. Consequently, it is essential to establish the limits of the neuron's signal. Using an activation function, the firing rate is represented effectively. Each neuron is also linked to a bias value $\mathbf{x_0}$. By adding this bias value, one can move the activation function to the left or right, which changes the neuron's natural threshold. Activation functions will be tackled in the following section.

2.7.2 Activation Functions

An activation function decides whether a neuron should be turned on (fired) based on how important it is to the model's final prediction. ANNs have the capability of using either linear or non-linear activation functions. However, a nonlinear activation function adds nonlinearity to the model, which lets it adapt to more complicated tasks. Formally, the output of the node is calculated with equation (2.19).

$$y = f\left(w_0 + \sum_{i=1}^{n} x_i w_i\right) \tag{2.19}$$

The goal of the activation function **f** is to mathematically represent the firing process of the neuron. However, nonlinear functions entail a higher computing load. Typically, the activation function is a function that increases as the total input to the neuron increases (Saraph et al., 2004). In what follows, the most common nonlinear activation functions for neural networks are explained, along with their benefits and inconveniences.

The first noteworthy activation function is the sigmoid function. This function is given by:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2.20}$$

The sigmoid function compacts a value between 0 and 1, which is a neuron's firing rate when it has reached its maximum. Because the value of a saturated neuron is 0, it can cause the network to get stuck, which means that the weights do not change. This is called the vanishing gradient problem. Also, since the sigmoid function is not zero-centered, if the input is always positive, all the gradients of the weights are either all negative or all positive.

Another activation function commonly employed is the hyperbolic tangent function. This function is given by:

$$f(x) = \tanh x \tag{2.21}$$

The output of hyperbolic tangent function is compacted between [1, 1], it is zero-centered, and it is often used for tasks that require only two possible answers. On the plus side, hyperbolic tangent function maps inputs that are strongly negative to outputs that are close to zero. But even with hyperbolic tangent function as the activation function, neurons that are full have a gradient that is close to 0. This makes the network vulnerable to the vanishing gradient problem.

The Rectified Linear Unit (ReLU) function is another popular activation function. This function is given by:

$$f(x) = max(0, x) \tag{2.22}$$

With ReLU as the activation function, all negative values are assigned to zero, enabling the network to quickly develop a sparse representation for enhanced predictive ability. Also, the network does not have the vanishing gradient problem because the positive inputs never reach their limits. Another benefit is that ReLU is easy to compute, which reduces the amount of work that needs to be done and speeds up convergence. Unfortunately, ReLU leads to "dead neurons," which means that if neurons are not turned on at the start, they will never be turned on again during learning.

Another activation function commonly employed is the softmax function. This function is given by:

$$f(x)_j = \frac{e^{x_j}}{\sum_{k=1}^{k} e^{x_k}} \tag{2.23}$$

Most of the time, the softmax function is used after the last layer of a neural network that is being used as a classifier. Softmax compacts the unit output scores between 0 and 1, and the sum of all **k** units is 1. This means that the input can be described as a discrete probability distribution.

Independently of the activation function, a perceptron can perform all basic logical operations, such as AND, OR, and NOT. However, more sophisticated functions, such as XOR, do not produce a linear separable pattern and hence cannot be represented by a single perceptron (Minsky & Papert, 1969). In this scenario, a multi-layer perceptron (MLP) with a nonlinear activation function is necessary. Multi-Layer Perceptron will be tackled in the following section.

2.7.3 Multi-Layer Perceptron (MLP)

One of the first forms of ANNs is a feedforward fully connected network known as a Multilayer Perceptron (MLP). An MLP is a multilayer ANN in which every node in each layer is linked to every node in the preceding layer. The MLP was one of the earliest architectures utilized in the area of deep learning. MLPs are utilized for many different sorts of data and as a component sub-network/module of practically every ANN to serve various goals such as creating classification output, routing input in routed ANNs (Rosenbaum et al., 2019), and attentional processes (Yang et al., 2016). A multi-layer perceptron is represented in Figure 2.10.

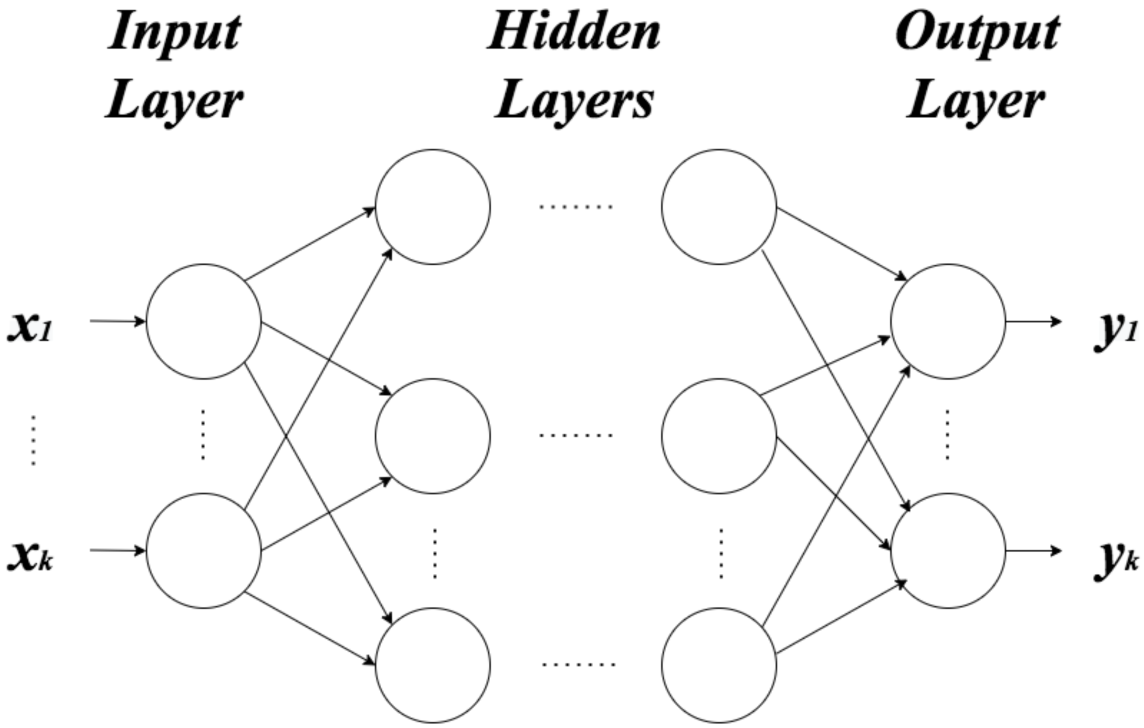

Figure 2.10– Multi-Layer Perceptron

The weights between the input layer and the hidden layer, denoted by **w**, and the input activations denoted by **a**, including bias, may be used to calculate the hidden layer's activations denoted by **b**. The activation functions used in this layer, denoted by **f**, are then implemented. This mathematical procedure may be expressed as:

$$\begin{bmatrix} b_1 \\ \vdots \\ b_j \\ \vdots \\ b_m \end{bmatrix} = f^{(1)} \left(\begin{bmatrix} w_{10}^0 & w_{11}^0 & \cdots & w_{1i}^0 & \cdots & w_{1n}^0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{j0}^0 & w_{j1}^0 & \cdots & w_{ji}^0 & \cdots & w_{jn}^0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{m0}^0 & w_{m1}^0 & \cdots & w_{mi}^0 & \cdots & w_{wm}^0 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_i \\ \vdots \\ a_m \end{bmatrix} \right) \tag{2.24}$$

In the hidden layer activations, the output layer activations are expressed similarly.

2.7.4 Learning Types

It could be said that the most important part of an ANN is learning, which is how the network is trained. Simon Haykin says that learning is:

"*A process by which the free parameters of an ANN are adapted through a process of stimulation by the environment in which the network is embedded*" (Haykin, 2010).

These free parameters are mostly made up of the weights and biases, but they may also comprise other hyper-parameters like the number of hidden neurons or layers. The way the training algorithm is chosen and used depends on how the ANN learns. There are four main ways to learn: supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning (Russell, 2010). In supervised learning, the model is given inputs and the outputs that correspond to it (labeled data), and the model must implicitly estimate the conditional probability distribution so that the ANN can accurately categorize related patterns at the time of inference. In semi-supervised learning, the process is the same, however, only a small number of the given inputs has a correspondent output (Zhu, 2005). In unsupervised learning the model is given inputs without any correspondent outputs. In reinforcement learning, an agent perceives and acts on its surroundings (Bishop & Nasrabadi, 2006). At each interaction phase, the agent takes information about the current state of the environment and selects an output action. The agent receives a scalar reinforcement signal when the action modifies the environment's state. The agent's activities should improve the reinforcement signal's long-term total, and systematic trial and error can teach it (Silver et al., 2017).

2.7.5 ANNs performance

A loss function or cost function that examines the performance of an algorithm on the provided dataset is one method for measuring the performance of an artificial neural network. It gauges the difference between an algorithm's prediction and the genuine label. The overall loss is the average of all individual losses determined for each sample in a dataset. Following are the expressions of the most prevalent loss functions.

The Mean Absolute Error (MAE) is mathematically represented by:

$$\frac{1}{Q}\sum_{q=1}^{Q}\sum_{k=1}^{o}\left|y_k^q - c_k^q\right| \tag{2.25}$$

The Sum of Squared Errors (SSE) is expressed by:

$$\sum_{q=1}^{Q}\sum_{k=1}^{o}\left(y_k^q - c_k^q\right)^2 \tag{2.26}$$

The Mean Squared Errors (MSE) is expressed by:

$$\frac{1}{Q}\sum_{q=1}^{Q}\sum_{k=1}^{o}\left(y_k^q - c_k^q\right)^2 \tag{2.27}$$

The Root Mean of Squared Errors (RMSE) is expressed by:

$$\sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\sum_{k=1}^{o}\left(y_k^q - c_k^q\right)^2} \tag{2.28}$$

Each of these measures gives an idea of how far off the estimates or approximations made by the model are. This error could be seen as the price someone is willing to pay for guessing the values c instead of y. In each case, the error for the whole set of data is calculated, which is why the summation in each case is done across all Q input-output observations (Pfanzagl, 2011).

2.7.6 Learning Procedures

Even though the ultimate goal of neural network training is to identify global optima, researchers have shown that achieving a local optimum with a tolerable low error is adequate. Usually, iterative gradient-based optimizers are used to train neural networks. The gradient is used to decrease the loss function, and back-propagation is used to find the gradient. Most of the commonly used methods for optimizing ANNs today are usually improvements or tweaks of Stochastic Gradient Descent (SGD) (Goodfellow et al., 2016). Back-propagation and stochastic gradient descent are described in the sections that follow.

2.7.6.1 Backpropagation

To calculate the gradient, the back-propagation technique allows the error generated by the ANN to travel backward through the network. Back-propagation has a particularly effective sequence of operations for computing the calculus chain-rule. The chain-rule says that the derivative of f(g(x)) is given as f'(g(x).g(x), that is:

$$\frac{dy}{dx} = \frac{dg}{dz}\frac{dz}{dx} \tag{2.29}$$

With **x** as a scalar and **f** and also **g** as real value functions, the same is true for vector valued inputs:

$$\frac{\delta y}{\delta x_i} = \sum_j \frac{\delta y}{\delta z_j}\frac{\delta z_j}{\delta x_j} \tag{2.30}$$

Consequently, the value for every hidden neuron may be determined by propagating the values backward from neurons in subsequent layers. In the next subsection, an optimization approach for updating the weights, i.e. performing learning, in an ANN is explained.

2.7.6.2 Stochastic Gradient Descent

Gradient Descent is an iterative process that descends a function's slope in stages from a random point until it reaches the function's lowest point. However, Stochastic Gradient Descend (SGD) randomly selects only one data point from the whole data set at each iteration in order to drastically minimize the number of calculations. This mathematical procedure may be expressed as:

$$\theta = \theta - \alpha * \nabla_\theta L(\theta; x, y) \tag{2.31}$$

Where **L** is the loss function, **α** is the learning rate and only one sample from the dataset is used to update the weights, with (**x,y**) being an input-output pair from the dataset **θ**.

2.8 Conclusion

The purpose of this chapter was to explain the basic ideas and terminology found in the remaining of this thesis. The reader has now an improved comprehension of the work described in the rest of this thesis and is ready to better understand the following chapters.

Chapter 3 Activity Trackers TAM (ATTAM) – Paper I

Parts of the content of this chapter were published at:

Sol, R., & Baras, K. (2016, September). Assessment of activity trackers: toward an acceptance model. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct (pp. 570-575). https://doi.org/10.1145/2968219.2968323

The conducted study explored the relationships of the factors influencing users' acceptance of Activity Trackers. The proposed research model and hypotheses were validated and tested with data collected from a cross-sectional survey conducted using a self-selected convenience sample. Constructs and mediating variables from a dozen of established models were gathered into a suppositional model, based on their hypothetical applicable relevance towards Activity Trackers use. The results were analyzed using a variety of statistical techniques including Structural Equation Analysis. The research was a broad exploration and examination of the factors that affect users' intention to use Activity Trackers. The final result can be a first step for researchers aiming to complement their own studies by taking into account factors affecting Activity Trackers' users, for example, in usability evaluations.

3.1 Introduction

Activity Trackers are becoming increasingly important for health behavior, socialization, and recreation, and thus an ever more important topic in Human Computer Interaction. Activity Trackers generate millions of dollar in revenue each year and come in wearable or mobile form factors. In the United States, revenue from the Activity Trackers market increased from $344 millions to $755 millions in the first eight months of 2015 (NPD, 2015). Activity Trackers attract an enormous number of users and are increasing in popularity. For example, one popular Activity Tracker, *Fitbit* (Fitbit, 2016), reached 82 percent market share in the United States. Furthermore, consumers doubled their spending on wearable devices from 2014 to 2015 (NPD, 2015). In 2015, it was predicted that during the next several years a double-digit growth in the number of United States' consumers using wearable devices is expected to happen (eMarketer, 2015). Actually, the global Fitness Trackers market size reached the valued of $27,907 millions in 2021 (FMR, 2022).

The success and attractiveness of Activity Trackers, an important topic of study in Human Computer Interaction research is understand what drives Activity Trackers use and acceptance, and how they influence human behavior. This research aims to understand what drives Activity Trackers use, Activity Trackers acceptance, and how Activity Trackers influence human behavior. Additional research can build on previous research of Activity Tracker's core structure to improve them, can increment design iterations by identifying weaknesses that need to be addressed, and also can integrate that core structure into other technologies.

An influential paradigm to follow in this research path is the Technology Acceptance Model (TAM) by Fred Davis (Davis, 1989), which postulates that user acceptance can be described by two ideas: Perceived Usefulness (PU), and Perceived Ease of Use (PEoU). TAM was originally developed on extrinsic motivation only. Nevertheless, intrinsic motivation was included later (Davis et al., 1992) with the construct Perceived Enjoyment (PE). However, this addition attached little importance, since the majority of TAM research centers exclusively on utilitarian systems (Heijden, 2004). Another paradigm is Everett Rogers' Diffusion of Innovations (Rogers, 2003) that tackles the proliferation of abstract concepts and ideas, technological information, and factual practices in a social structure. There is also Health Belief Model (HBM) that predicts general health behavior. This model has been evolving over the years, and, according to Irwin Rosenstock (Rosenstock, 1974), it was Godfrey Hochbaum who initially developed this model (G. M. Hochbaum, 1958).

Leaning on these paradigms, Jeongeun Kim and Hyeoun-Ae Park built a model that characterizes the mechanism of acceptance and use, by users of Health Information Technology (HIT), for health management called the Health Information Technology Acceptance Model (HITAM) (J. Kim & Park, 2012). Their study involved 728 participants, recruited from three Internet health portals in Korea. Later, Kim complemented that study by abstracting the constructs that make up the user experiences of self-trackers for activity, sleep, and diet (J. Kim, 2014).

In another study, Stuart Moran and his colleagues (Moran et al., 2013) used the Moran's Perception of System Attributes –Behavioral Intention Model (Moran, 2011) to understand the users' significant perceptions, attitudes, and intentions concerning the use of wearable devices. They claim that improving users views of these technologies might influence the long-term intention to use them.

Despite the commercial success stated above, a recent survey (Ledger & McCaffrey, 2014) exposed that 34% of users of commercially accessible Activity Trackers stopped using them over six to twelve months after acquisition. Ruben Gouveia et al. tackled this problem and proposed three directions for design: "*designing for different levels of 'readiness', designing for multilayered and playful goal setting, and designing for sustained engagement*" (Gouveia et al., 2015). However, this work foresees the need for additional research that can understand the long-term use of Activity Trackers.

In the first stage, it was planned to build upon current research to develop an initial extrapolative model that focuses primarily on 250 Activity Tracker users. This model tries to provide an extensive view of these devices, by not being exclusively based on Health Information users, for example. The proposed model can be used to broaden the design iterative process by showing shortcomings that need to be tackled in order to enhance user acceptance. Further ahead, it can be used to determine if activity trackers can gain enough acceptance from users over the long-term.

The following section summarizes the models that inspired the model in this work. Then comes the proposition of the hypotheses, the description the methodology, and the validation process for the model. Finally the results are discussed the conclusion is made, and possible options for the future work are envisioned.

3.2 Particular Literature Review

The rationale of the hypotheses considered in the work are loosely coupled to the context of several theories: Technology Acceptance Model (TAM) and its successor TAM2, Innovation Diffusion Theory, Social Cognitive Theory, Unified Theory of Acceptance and Use of Technology (UTAUT) and its successor UTAUT2, Pervasive Technology Acceptance Model, Pervasive Information System Acceptance Model, Perception of System Attributes – Behavioral Intention Model, Health Belief Model, and Health Information Technology Acceptance Model.

The TAM is based on Martin Fishbein and Icek Ajzen's Theory of Reasoned Action, a theory from social psychology that illustrates the behavior of a human being based on their intentions (Fishbein & Ajzen, 1977). The TAM in particular focuses on computer control by introducing two constructs: Perceived Usefulness (PU) and Perceived Ease-of-Use (PEoU) that determines Intention to Use (IU) via Attitude (Venkatesh & Davis, 2000). Perceived usefulness is defined as: "*The degree to which a person believes that using a particular system would enhance his or her job performance*." Perceived ease of use is defined as: "*The degree to which a person believes that using a particular system would be free of effort*" (Davis, 1989).

The TAM was expanded to TAM2 to add Subjective Norm as a third determinant of intent, and also brought Experience, Voluntariness, Image, Job Relevance, Output Quality and Result Demonstrability in determining acceptance. Output Quality is defined as: "*How well a system does what it does*" (Venkatesh & Davis, 2000). Gary Moore and Izak Benbasat defined Result Demonstrability as: "*The tangibility of the results of using the innovation*" (Moore & Benbasat, 1991).

Moore and Benbasat interpreted Innovation Diffusion Theory from sociology of a technology point of view. Even though they defined a few constructs similar to PU and PEU, they also looked at Image, which was defined as: "*The degree to which use of an innovation is perceived to enhance one's image or status in one's social system*" (Moore & Benbasat, 1991).

Albert Bandura created one of the most prevailing theories of human behavior, the Social Cognitive Theory (Bandura, 1986), where beyond Outcome Expectations (Performance, and Personal), Affect and Anxiety, he added Self-Efficacy (SE) defined as: "*The judgment of one's ability to use a technology (e.g., computer) to accomplish a particular job or task*" (Compeau & Higgins, 1995).

As seen above researchers have come out with several theoretical models, rooted in psychology, sociology, and information systems. Faced with a choice amongst a plethora of models, Venkatesh and his colleagues saw the need to formulate the Unified Theory of Acceptance and Use of Technology (UTAUT) a unified view of user acceptance, from a review and integration of eight models (Venkatesh et al., 2003). They posit that four constructs take substantial part as direct determinants of user acceptance and behavior, being those constructs: Expectancy (Performance, and Effort), Social Influence, and Facilitating Conditions. Social Influence is defined as: "*The degree to which an individual perceives that important others believe he or she should use the new system*" (Venkatesh et al., 2003). Facilitating Conditions are defined as: "*The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system*" (Venkatesh et al., 2003).

Recently the Unified Theory of Acceptance and Use of Technology was expanded by Venkatesh et al. to UTAUT2 bringing Hedonic Motivation, Habit, and Price Value in determining acceptance (Venkatesh et al., 2012). Hedonic Motivation is defined as: "*The fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use*" (Brown & Venkatesh, 2005). Habit is defined as: "*The extent to which people tend to perform behaviors automatically because of learning*" (Limayem et al., 2007).

With technologies, such as Activity Trackers, becoming pervasive in daily lives, in both utilitarian and hedonic respects, there was a need to extend technology acceptance models to explain the use for this field with ample sphere of influence, and group of users. Kay Connelly looked at this, and proposed the Pervasive Technology Acceptance Model that brought the constructs Integration, and Trust (Connelly, 2007). Trust is defined as: "*The degree to which a person believes they can trust the application*" (Connelly, 2007).

Pervasiveness was also studied by Dimitris Karaiskos, but from an Information Systems point of view (Karaiskos, 2009). He created the Pervasive Information System Acceptance Model, which had one of its constructs as Personal Innovativeness defined as: "*The willingness of an individual to try out any new information technology*" (Agarwal & Karahanna, 2000).

The specificity of activity trackers as wearable devices encouraged the look into Stuart Moran's Perception of System Attributes – Behavioral Intention Model from which are acknowledge the constructs Perceived Privacy Invasion, and Perceived Data Control (Moran, 2011). Perceived Privacy Invasion is defined as: "*The degree to which a person feels that the monitoring is invasive of their privacy*" (Dryer et al., 1999). Perceived Data Control is defined as: "*The degree to which a person feels they have control over the use of, and access to, the data collected*" (Theofanos & Scholtz, 2005).

The evolution of the Health Belief Model (HBM) over time focuses on: Perceived Susceptibility of Disease, Perceived Severity of Disease, and Health Threat. Perceived Susceptibility of Disease is defined as: "*The perception of the likelihood of experiencing a condition that would adversely affect one's health*" (G. Hochbaum et al., 1952).

Perceived Severity of Disease is defined as: "*The beliefs a person holds concerning the effects a given disease or condition would have on one's state of affairs*". And Health Threat is defined as: "*Abstract assessing the susceptibility and the severity, of disease-specificity*" (G. Hochbaum et al., 1952).

Finally, the Health Information Technology Acceptance Model (J. Kim & Park, 2012) has a construct similar to one in HBM, that is Health Consciousness, defined as: "*The degree to which health concerns are integrated into a person's daily activities*" (Jayanti & Burns, 1998).

3.3 Theorized Model

Established hypotheses have been discussed in the above models, models where the hypotheses of this initial model were based. Those hypotheses are as follows:

Hypothesis 1a. Self-Efficacy will have a direct effect on Perceived Ease of Use.

Hypothesis 1b. Self-Efficacy will have a direct effect on Perceived Usefulness.

Hypothesis 2. Hedonic Motivation will have a direct effect on Perceived Usefulness.

Hypothesis 3. Image will have a direct effect on Perceived Usefulness.

Hypothesis 4a. Perceived Susceptibility will have a direct effect on Health Consciousness.

Hypothesis 4b. Perceived Severity will have a direct effect on Health Consciousness.

Hypothesis 5. Health Consciousness will have a direct effect on Perceived Usefulness.

Hypothesis 6. Habit will have a direct effect on Attitude.

Hypothesis 7a. Perceived Privacy Invasion will have a direct effect on Attitude.

Hypothesis 7b. Perceived Privacy Invasion will have a direct effect on Perceived Usefulness.

Hypothesis 8a. Perceived Data Control will have a direct effect on Attitude.

Hypothesis 8b. Perceived Data Control will have a direct effect on Perceived Ease of Use.

Hypothesis 9a. Perceived Usefulness will have a direct effect on Attitude.

Hypothesis 9b. Perceived Ease of Use will have a direct effect on Attitude.

Hypothesis 10. Attitude will have a direct effect on Behavioral Intention.

These hypotheses are represented in Figure 3.1.

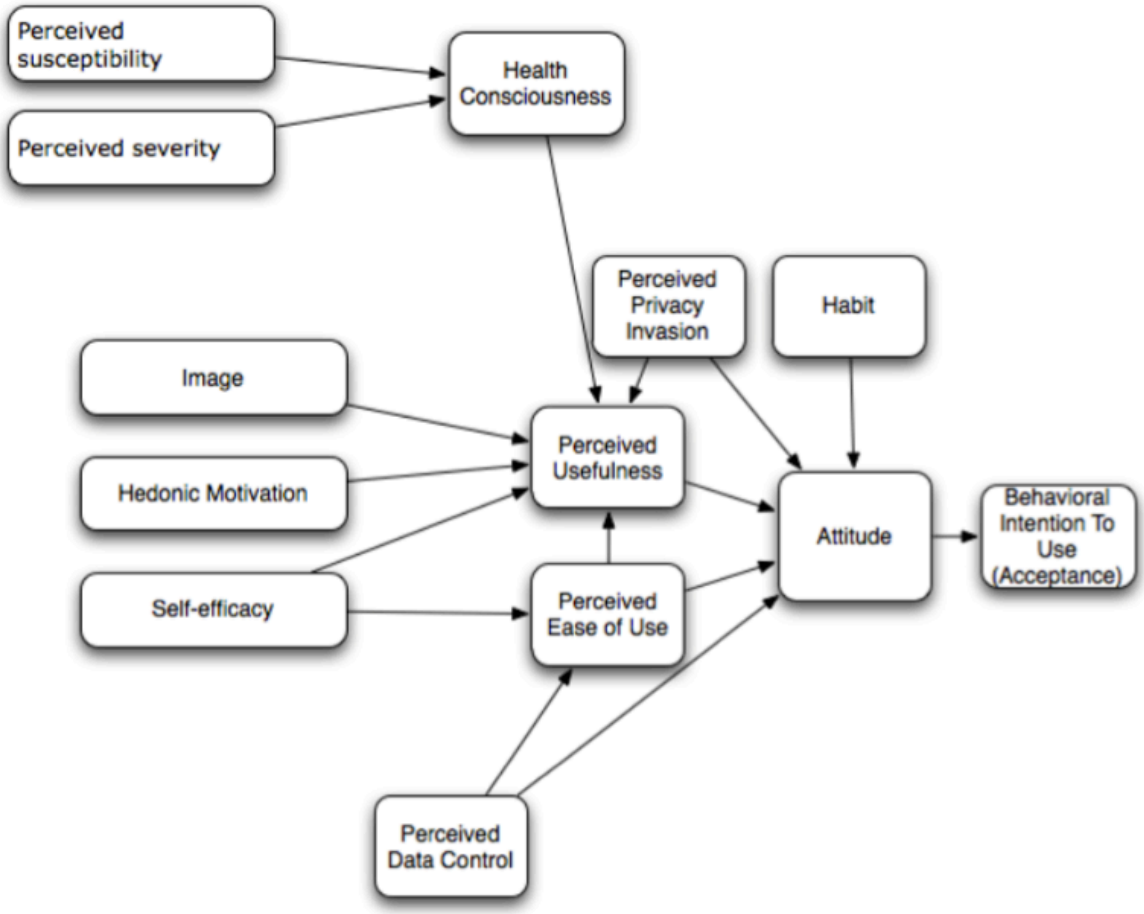

Figure 3.1– Proposed Model

3.4 Methodology

The target population were the current users of Activity Trackers. They were recruited on social media, and on Prolific a micro work site (Damer & Bradley, 2014). The questionnaire included 80 questions adapted from prior research (see Appendix A). The micro workers received a compensation of approximately 1.5 US Dollars.

All of the scales were adapted from prior research. The scales for the Technology Acceptance Model (TAM) constructs (i.e., Perceived Usefulness and Perceived Ease-of-Use, Intention to Use, and Attitude) were adapted from Venkatesh and Davis (Venkatesh & Davis, 2000). The scales for the TAM2 constructs (i.e., Intention to Use, Output Quality and Result Demonstrability) were adapted from Venkatesh and Davis (Venkatesh & Davis, 2000). The scales for the Unified Theory of Acceptance and Use of Technology (UTAUT) constructs (i.e., Social Influence, and Facilitating Conditions) were adapted from Venkatesh (Venkatesh et al., 2003). The scales for the UTAUT2 constructs (i.e., Hedonic Motivation, and Habit) were adapted from Venkatesh et al. (Venkatesh et al., 2012). The scales for the Pervasive Technology Acceptance Model constructs (i.e., Trust) were adapted from Watzdorf (von Watzdorf et al., 2010). The scales for the Pervasive Information System Acceptance Model constructs (i.e., Personal Innovativeness) were adapted from Karaiskos (Karaiskos, 2009). The scales for the Perception of System Attributes – Behavioral Intention Model constructs (i.e., Perceived Privacy Invasion, and Perceived Data Control) were adapted from Moran (Moran, 2011). The scales for the Health Belief Model constructs (i.e., Perceived Susceptibility, Perceived Severity, and Health Threat) were adapted from Angela Bryan et al. (Bryan et al., 1997) and Mei-Fang Chen (Chen, 2011). The scales for the Health Information

Technology Acceptance Model constructs (i.e., Health Consciousness) were adapted from Kim and Park (J. Kim & Park, 2012).

The items were scored using a seven-point Likert scale, from “Strongly Disagree” to “Strongly Agree.” Age was considered in years. Gender was coded using 0 and 1, where 0 stood for women.

There was a total of 360 returned responses, 112 from social media, and 248 from the micro work site. From the total number of participants, there were 113 invalid responses that were eliminated before the data analysis, 25 from social media, and 88 from the micro work site. There was an overall response acceptance rate of 68.8 percent. Consequently, 247 users completed the survey, of which 144 were male (58.3 percent) and 103 were female (41.7 percent). The average age was 33 (standard deviation: 10.6). The most represented countries were the United States with 118 respondents (47.8 percent), the United Kingdom with 69 respondents (27.9 percent) and Portugal with 22 respondents (8.9 percent).

3.5 Analysis

The proposed model was analyzed using maximum likelihood parameter estimation. Descriptive statistics, and Exploratory Factor Analysis were conducted using IBM SPSS version 23. The structural equation model was built-in with maximum likelihood estimation routines in the software IBM SPSS Amos 23.

Cronbach alphas for each measure indicated that construct reliability was higher than 0.7, except for the constructs Health Threat (0.495) and Facilitating Conditions (0.487), which were dropped, leaving the model with 19 of the initial 21 constructs. The Kurtosis analysis found normality issues, with values higher that 2, in the following items, item 2 of the construct Perceived Usefulness, item 2 of the construct Perceived Ease of Use, items 1, 2, and 4 of the construct Attitude, item 1 of the construct Intention to Use, item 3 of the construct Results Demonstrability, and in all items of the construct Behavioral Intention. However, with the exception of Results Demonstrability these constructs passed on the Exploratory Factor Analysis, which followed.

The Exploratory Factor Analysis trimmed the initial model in 7 of the 19 constructs. In the Appendix A, the Table presents the Factor Loadings for the solution using Maximum Likelihood analysis with Promax Rotation. Perceived Usefulness, and Attitude loaded as one factor. Item 1 of the construct Heath Conscious was not loading in any factor and was discarded. Item 1 of the construct Habit, and item 1 of the construct Perceived Severity to Chronicle Diseases had factor loadings around 0.46. This last item was also cross loading on Perceived Susceptibility to Chronicle Diseases. Nevertheless it was decided to maintain them for the sake of the model. The total variance explained was 71.9 percent.

The correlations coefficients for the measured variables vary from 0.005 to 0.620, and can be observed in Table 3.1.

Table 3.1 – Correlation coefficients between measured variables

Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Perceived Usefulness	1										
Health Consciousness	.423	1									
Perceived Data Control	-.314	-.095	1								
Behavioural Intention	.550	.200	-.297	1							
Self-Efficacy	-.381	-.239	.175	-298	1						
Perceived severity to chronic diseases	.125	.127	.134	.073	-.186	1					
Perceived Ease of Use	.513	.416	-.325	.431	-.406	-.111	1				
Perceived susceptibility to chronic diseases	.009	-.084	.187	-.039	-.033	.255	-.170	1			

Image	.005	.120	.087	-.070	-.039	-.092	.023	.122	1		
Habit	.553	.356	-.186	.230	-.180	-.018	.407	.092	.241	1	
Hedonic motivation	.620	.416	-.150	.356	-.234	-.009	.424	-.087	.067	.508	1

The data was collected through a unique online survey. Common Methods Bias was tested during the Confirmatory Factor Analysis, and it was concluded that it was not a serious concern. The convergent and discriminant validity of the scales, with the Average Variance Extracted (AVE) that is the average quantity of variance in variables that a construct is able to explain, always exceeded 0.50, and Critical Ratios exceeded 0.80. In Table 3.2 one can observe these tests and the Maximum Shared Variance (MSV), and the Averaged Shared Variance (ASV) are also reported:

Table 3.2 – Results for the convergent and discriminant validity of the scales

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
CR	.870	.940	.879	.940	.878	.977	.888	.886	.884	.819	.899
AVE	.633	.663	.551	.799	.645	.934	.670	.663	.719	.612	.751
MSV	.500	.578	.203	.086	.151	.326	.071	.297	.071	.035	.578
ASV	.180	.208	.093	.043	.065	.107	.019	.142	.020	.013	.170

Habit	.796	.707	.425	-.245	-.310	.453	.008	.545	.035	.188	.654
Perceived Usefulness		.814	.418	-.294	-.355	.571	.138	.518	-.029	.067	.760
Health Consciousness			.742	-.090	-.246	.241	.151	.450	-.108	.157	.432
Perceived Data Control				.894	.163	-.280	.142	-.282	.208	.018	-.171
Self-Efficacy					.803	-.253	-.172	-.388	-.039	-.133	-.271
Behavioral Intention						.966	.104	.380	-.098	.042	.414
Perceived severity to chronic diseases							.819	-.091	.267	-.056	.056
Perceived Ease of Use								.814	-.195	.152	.458
Perceived susceptibility to chronic diseases									.848	.105	-.111
Image										.078	.075

Hedonic motivation											.867

The finalized model exhibited the fit to the data with a Chi-square of 67.573, 23 degrees of freedom, P < .001, goodness of fit index of 0.957, root mean square error of approximation of 0.089.

The model accounts for 36 percent of the variance in behavioral intention, 28 percent of the variance in Health Consciousness, 43 percent of the variance in perceived ease of use, and 63 percent of the variance in perceived usefulness. The final model obtained is represented in Figure 3.2.

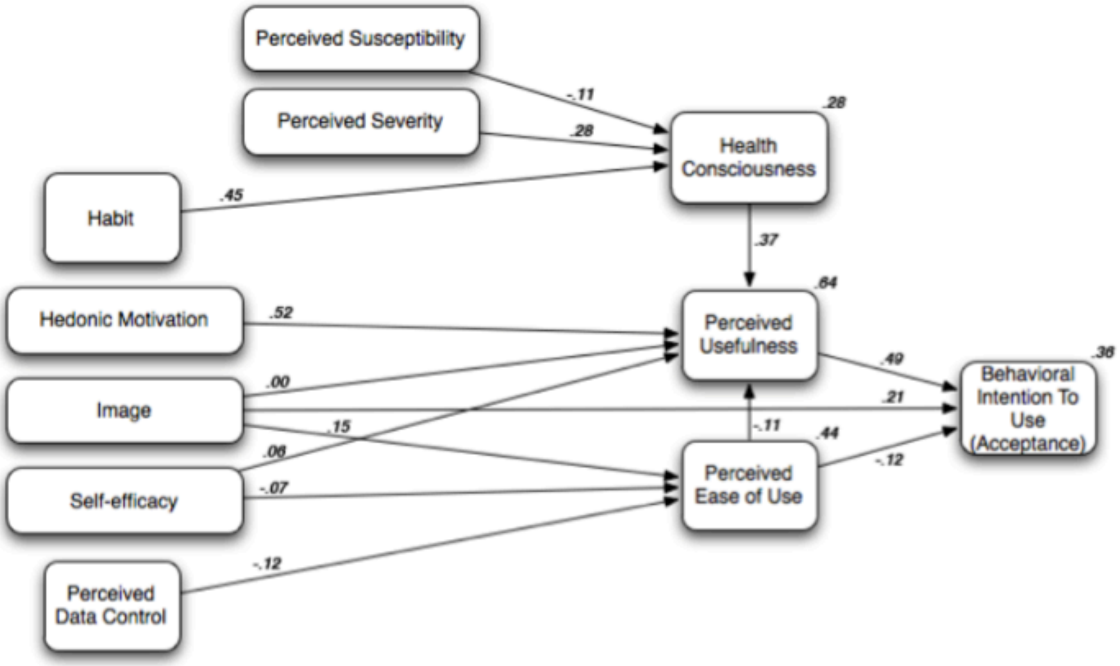

Figure 3.2– Finalized ATTAM

The summary of items and factor loadings with Promax Rotation can been observed in the Appendix B.

3.6 Discussion

Through an online survey it was accessed the use of Activity Trackers. It was proposed an exploratory model that could explain this use. The constructs of this model were submitted to statistical analysis and obtained the resulting final model was obtained.

As expected from an exploratory assessment the majority of the hypothesis did not prevail. The final model that was derived from the analyses results has the same level of prevision as the original TAM (Davis, 1989). The described study supports the hypotheses that Perceived Usefulness and Perceived Ease of Use are stronger determinants of Behavioral Intention to use Activity Trackers than Health Consciousness. The conclusion is that the Health Information nature of an Activity Tracker is not a strong condition to the validity of its use and acceptance. Specifically, Health Consciousness loses its prevailing value in favor of Perceived Ease of Use and Perceived Usefulness.

The deeper repercussion for further research is that Health Consciousness is exhausted by the important role of system usefulness. This finding advocates that development in Health acceptance should be made by focusing on the nature of system use in addition to the inclusion of additional determinants.

This study supports that Hedonic Motivation aids Perceived Usefulness in giving utilitarian value. More significantly, Perceived Usefulness straightforwardly contributes to potential intentions to use the Activity Tracker by either enhancing or inhibiting the hedonic use. One repercussion of this conclusion, in parallel with the fact that Perceived Usefulness load with Attitude, is that while Perceived Usefulness is a serious system development variable in general, it is remarkably important for Activity Trackers.

Another conclusion from the study is the straightforward link between Image and the direct intention to use an Activity Tracker. This finding need to be further studied. Also, further study needs to be done to disclose how much superficiality is hidden in this connection.

One key limitation of this study is that the sample is biased concerning users. Those non-users who perhaps perceive Activity Trackers as difficult to use and/or less useful were rejected in the response selection. It is plausible that a user's motivation for using an Activity Tracker has a distinctive model from a user's motivation not to use an Activity Tracker.

Another key limitation of this study is the sample size. Also, there were statistical limitations in the loadings of some factors, represented by some covariance between the factors.

This research, however, suggests that Image can play a pivotal role to increase acceptance of Activity Trackers. Consequently, if users reject Activity Trackers, designers may need to add Image related features to achieve user acceptance.

3.7 Conclusion

Research and design opportunities abound in the Activity Trackers sphere, and the goal was to obtain a preliminary understanding of Activity Trackers use. In this study, a TAM like model has been created and examined to explain and predict factors affecting Activity Trackers use. Health consciousness, Hedonic Motivation, Self-Efficacy, Perceived Data Control, Habit, and Image included as antecedents in this model were found to influence user's beliefs and indirectly influence Activity Trackers use. The model improves on existing models, due to its specialization in predicting Activity Tracker use. Like other studies, the model supports Perceived Usefulness as a strong predictor of Behavior Intention to use. Therefore, this study will help specifically Activity Trackers' designers by unveiling what makes users use these devices. Such knowledge will contribute to the improvement of Activity Trackers, through enhanced ability to assess users beliefs.

Chapter 4 Extreme Users via HITAM – Paper II

Parts of the content of this chapter were published at:

Ricardo Sol and Karolina Baras, "Acceptance Model in Designing for Extreme Users: Extreme Athletes Using Activity Trackers," Journal of Image and Graphics, Vol. 9, No. 2, pp. 31-38, June 2021. doi: 10.18178/joig.9.2.31-38

Extreme Users (EU) is a design method in Human Computer Interaction, which allows user-centered design in design groups. ‘Acceptance Models’ is a theory in Information Systems, which models how users accept and use technology. A study was conducted to explore the relationships of the factors influencing Extreme Athletes in the acceptance and use of Activity Trackers (AT). The data was collected from a cross-sectional survey conducted using a self-selected convenience sample of 206. The research rendered an exploration and an examination of the factors affecting trail-running athletes. The results were analyzed using several statistical techniques including Structural Equation Analysis. The goal was to observe to what extent the Health Information Technology Acceptance Model patterns and outlines EU use of AT. This contribution, to the best of current knowledge, is new given that the obtained model can be an initial quantitative working primary tool for designers using the EU design method.

4.1 Introduction

Models may be very helpful in the design and evaluation of interactive applications, even though some researchers who think of them as too theoretical criticize these types of approaches. Indeed, researchers working with interfaces of applications who had frequently been skeptical began to admit that such approaches could be helpful (Myers et al., 2000).

This is unsurprising, if one considers that people actually make models to comprehend reality and understand interactions with reality. In the design of interactive systems, the variety of imaginable design alternatives is extensive and numerous aspects need to be contemplated. Model-based approaches can help to cope with this level of complexity. The objective of model-based design is to find high-level models that allow designers to analyze and detail interactive applications with additional semantic-oriented levels instead of immediately beginning to tackle these at the implementation level.

Models have tried to influence their way into three major socio-technical communities: Human Factors and Ergonomics, initially developed to correct engineering production problems (Dul et al., 2012), Human Computer Interaction (HCI) that contributed to the shift from corrective ergonomics to interaction design, and Human Systems Integration that combined Systems Engineering and Human Centered Design (G. A. Boy & Narkevicius, 2014).

For this research an influential paradigm was followed which was the Health Information Technology Acceptance Model (HITAM) by Jeongeun Kim and Hyeoun-Ae Park. They built a model characterizing the mechanism of acceptance and use for health management by users of Health Information Technology (HIT) (J. Kim & Park, 2012).

HITAM leaned on the Technology Acceptance Model (TAM) developed in a Ph.D. thesis by Fred Davis in 1985 (Davis, 1989). HITAM also leaned on the Health Belief Model (HBM) that predicts general health behavior. This model has been evolving since Godfrey Hochbaum initially developed it in 1958 (G. M. Hochbaum, 1958). TAM is a broadly adopted technology acceptance theory used to elucidate why people are more or less prone to adopting and using a particular technology (Venkatesh et al., 2003).

Wearable devices, such as Activity Trackers are becoming increasingly important in monitoring health behavior, socialization, and recreation, and thus constitute a viable and significant research topic. Activity Trackers generate multi-million dollar returns each year and materialize in the form of mobile or wearable technologies. Estimates show that wearable personal-tracking technologies will reach $70 billion by 2024 (IDTechEx, 2014).

Knowing the success and attractiveness of Activity Trackers, researchers are yet to fully understand what drives Activity Trackers use, Activity Trackers acceptance, and how Activity Trackers can influence human actions. Additional research can increment Activity Tracker’s design iterations by reinforcing previous or identifying new strengths and weaknesses that need to be addressed.

However, despite the commercial success stated earlier, a survey (Ledger & McCaffrey, 2014) exposed that 34% of users of commercially accessible Activity Trackers stopped using them over one to two semesters after acquisition. Ruben Gouveia et al. tackled this issue and came up with three design directions: "*designing for different levels of 'readiness', designing for multilayered and playful goal setting, and designing for sustained engagement*" (Gouveia et al., 2015).

A global design and consultancy company, IDEO, based in Palo Alto, California, with more than 700 employees (IDEO, 2017), has a design tool 'Method Cards' with 51 methods to inspire User Centered Design. The Method Card named Extreme Users explores the frequent selection and observation of users at the extreme ends of a distribution, instead of the average or typical user (IDEO, 2003).

The first stage of this work is based on HITAM, to establish an initial extrapolative model that has its focus exclusively on 206 Activity Trackers' extreme users. Extreme users, in this case, are users who use the devices in extreme conditions like ultra-trail running. This model tries to provide a view of these devices based on physical Health Information search. The proposed model can be used to broaden the designing for the extreme users iterative method by showing shortcomings that need to be tackled in order to enhance user acceptance. To the best of our knowledge, this is the first study to employ a TAM like model based on a design method.

In the following sections, HITAM and the designing for Extreme Users method are discussed. The methodology and the validation process for the model are described. Lastly, the results are discussed, along with a conclusion, and possible options for future work.

4.2 Particular Literature Review

Among models present in Human Centered Design (HCD), three are highlighted that offer suitable concepts and relationships between systems and humans. The SFAC model (Structure/Function - Abstract/Concrete) offers articulation among declarative knowledge, procedural knowledge, static objects, and dynamic processes. The NAIR model (Natural/Artificial versus Cognitive/Physical) rationalizes natural or artificial systems with their cognitive or physical features (G. A. Boy, 2017). Finally, the AUTOS model (Artifact, User, Task, Organization and Situation) is a framework that supports structuring HCD and engineering (G. Boy, 2011). Modeling and simulation in HCD make observation and analysis feasible, allowing the development of complex, design systems.

The use of models captures semantically significant properties, and so designers can further cope with the rising intricacy of interactive applications and analyze these throughout the whole process. Numerous notations for a model-based design of interactive systems have been proposed. Model-based approaches in HCI promote the illustration of interaction solutions that allow designers to reflect on and take adequate design decisions. Several models can help in the design process, including Interaction, Interface, User, Presentation, Application, Context, and Dialog among other models (A. Puerta, 1996; A. R. Puerta, 1997). Most widely used are: Domain Models that represent the information and nature of the work performed, Application Models that represent the utility, advantages, activities, and options (Thevenin, 2001) and Task Models that represent utility, reasoning, and hierarchies (Paterno, 1999).

Models led to model-based user interface development like Mobi-D which is a model-based integrated development environment that connects numerous models, helps the user interface designers with the conception of these models, and also aids with the decisions that have to be made during the design of the user interface (A. R. Puerta, 1997). Another is ArtStudio, which is a model-based design tool that helps the visual specification of task, abstract presentation, and domain models (Thevenin, 2001).

The rationale considered in this work is closely tied up with the context of the Health Information Technology Acceptance Model (HITAM). HITAM constructs and the constructs' questions asked in the survey come from many models and are described below. In Information Systems HITAM is an important model that is based on the Technology Acceptance Model (TAM), Theory of Planned Behavior, and Health Belief Model. TAM in turn is based on Martin Fishbein and Icek Ajzen's Theory of Reasoned Action, a theory from social psychology that illustrates the behavior of a human being based on their intentions (Fishbein, 1979). In their work, Subjective Norm is defined as "*person's perception that most people who are important to the user think he should or should not perform the behavior in question*." TAM specifically focuses on computer control by featuring two constructs: Perceived Ease of Use (PEoU) and Perceived Usefulness (PU) that determine Intention to Use (IU) via Attitude (Venkatesh & Davis, 2000). Perceived Ease of Use is the construct that in the model looks at the aspects of usability.

Theory of Reasoned Action was improved by the Theory of Planned Behavior which is a psychology theory regarding the relationship connecting attitude and behavior (Ajzen, 1991). So, there are several theoretical models, rooted in psychology, sociology, and information systems. Faced with a choice amongst a plethora of models, Venkatesh and his colleagues saw the need to formulate the Unified Theory of Acceptance and Use of Technology (UTAUT) a unified view of user acceptance, from a review and integration of eight models (Venkatesh et al., 2003). They posit four constructs: Expectancy (Performance, and Effort), Social Influence, and Facilitating Conditions. These take substantial part as direct determinants of the constructs representing Behavior Intention and User Behavior.

Albert Bandura shaped one of the most predominant theories of human behavior, the Social Cognitive Theory (Bandura, 1986), where ahead of Outcome Expectations (Performance, and Personal), Affect and Anxiety, he created Self-Efficacy (SE).

The evolution of the Health Belief Model (HBM) over time brought the following constructs: Perceived Severity of Disease, Perceived Susceptibility of Disease, and Health Threat. Perceived Severity of Disease is defined as “*the beliefs a person holds concerning the effects a given disease or condition would have on one's state of affairs*.” Perceived Susceptibility of Disease is defined as “*the perception of the likelihood of experiencing a condition that would adversely affect one's health*.” Health Threat is defined as “*abstract assessing the susceptibility and the severity of disease-specificity*” (G. Hochbaum et al., 1952).

HITAM (J. Kim & Park, 2012) has a construct equivalent to one in HBM, that is Health Consciousness, defined as “*the degree to which health concerns are integrated into a person’s daily activities*” (Jayanti & Burns, 1998). The mentioned models are too general and are not specific enough for a particular application.

In the HITAM study with 728 users, Kim and Park categorized the leading factors that have an impact on the behavioral intention to quantify, save, and handle health data into three domains namely technology zone, information zone, and the health zone. They suggest that users enjoying the use of Health Information Technology (HIT) and gaining confidence in their skill to use HIT increase their likelihood of continuing to use HIT. Particularly, if Self-Efficacy improves then the PEoU also improves.

HITAM is a concise and robust model, that had its internal consistency and understandability of the items tested. HITAM rearranges and revises prior results in the field, by pinpointing the central factors that have the biggest influence. The predicting factors identified in the three zones are: HIT Reliability, and Subjective Norm in the information zone, Health Beliefs, and Health Status and concerns in the Health Zone, and HIT Self-efficacy in the technology zone.

Kim and Park's study showed that, even though the TAM has broadened and extended its usefulness in numerous areas and has been effectively applied, its application in the HIT field has been minimal and limited. In light of this, with the rapid development of information technology and its consequent influence on health management, a model that foresees and seizes a variety of nuances of the users' acceptance was missing.

Later, Kim complemented their study by interviewing 18 female college students to qualitatively abstract the constructs that sustain the user experience of self-trackers for activity, diet, and sleep (J. Kim, 2014). This complemented the initial work in developing HITAM, as well as enhancing it with more thorough analysis of user experience. Kim used a hybrid approach called methodological triangulation that provides detail and abductive inspiration. Interviews with users can adjust the research to the suitable elements. Moreover, qualitative research can also put in order quantitative data that has been previously collected or insinuate new possibilities with regards to the observable facts. It also brings clarification to seemingly incoherent findings established by the quantitative results. Hence, the impact of her qualitative study is in performing a relatively innovative research methodology that backs up a research question by finding an undisclosed event in an earlier investigation.

Sol and Baras took steps towards the establishment of an Activity Trackers acceptance model (Sol & Baras, 2016). From their hypothesized model with 21 constructs they obtained a final model with only 11 constructs. Interestingly, it should be noticed that 7 of those final constructs are also included in HITAM.

When it comes to design, in literature one can find a plethora of design methods and practices. IDEO's design practice is an iterative loop that follows from understanding, to observing, visualizing, evaluating, refining and implementing. The Extreme Users method represents the far end of the usability requirements range, not its average reaches. This method supports the line of thought that starting the design process with relatively limited type of users is advantageous (Bontoft & Pullin, 2003). The experience of the extreme users acts like a provocation that tends to enrich the process of the designer who engages with these users. This gives the designer a keener understanding of a design breakdown and gives them the skill to articulate both the extreme users' peculiar response to it, and also the problem (Cassim & Dong, 2003). Research based on extreme users is more likely to offer memorable insights that keep all stakeholders focused on the user (Gilmore & Velázquez, 2000). Also Pullin and Newell also suggested the concept of designing for "*extra-ordinary*" users and enumerated the benefits not only for extra-ordinary users but also for "*ordinary*" users in "*extra-ordinary environments*" (Pullin & Newell, 2007).

Designers, computer and social scientists have the responsibility to look critically at the integration of such methods and models. Of particular interest is the work of Consolvo et al., who suggest that designers should design in order that the AT gives credit to the user, creates awareness, foments social interaction, and is aware of lifestyle constraints (Consolvo et al., 2006). Shih et al., suggest the use of reminders, looking into gender differences, fomenting social interaction, and insists on the devices accuracy (Shih et al., 2015). Lazar et al. suggest appealing to the user's identity and motivation, to have proactive feedback, and that the AT should provide motivation to the user (Lazar et al., 2015). Klasnja et al. suggest the use of more behavior change strategies. Rooksby et al. noticed that the users do not use only one technology, that there is a need to attend to the physicality, and to look into the user's emotionality (Rooksby et al., 2014). However, none of these researchers look into the user's health beliefs.

In this chapter a specific perspective in a novel application of these models within methods of design is considered. It is considered the method not simply instinctively, but also calculably. Going beyond technology related constructs this model also gives importance to the user's health beliefs by having related constructs. This is because there is lack of research in modeling quantitatively the patterns of acceptance and usage of extreme users of Activity Trackers.

4.3 Methodology

The target population was ultra-trail runners using Activity Trackers. They were recruited via the mailing list of the participants of a competition that is part of the Ultra Trail World Tour (Clube de Montanha, 2017). Analogously to Pullin and Newell (Pullin & Newell, 2007) these users are defined as Extreme Users because of their use of the devices in extreme competitions. The data was collected through an online questionnaire sent by email (see Appendix C). The questions of the Health Information Technology Acceptance Model were adapted to focus specifically on physical condition. For example, one item of Perceived Ease of Use was "*It takes less effort to use Activity Trackers than other means for physical condition information and management*." One item of HIT Reliability was "*Activity Tracker findings for provision of physical condition information and management are of acceptable quality*."

All the scales were adapted from the Health Information Technology Acceptance Model constructs by Kim and Park (J. Kim & Park, 2012). The constructs were measured with five items for Health Belief & Concerns, five items for Subjective Norm, three items for Perceived Susceptibility, four items for Perceived Seriousness, six items for HIT Self-Efficacy, five items for HIT Reliability, five items for Perceived Ease of Use, five items for Perceived Usefulness, three items for Attitude, and three items for Behavioral Intention. In the diagram of a TAM like model as HITAM there are arrows pointing between constructs. Each of these arrows represents a hypothesis in the model. HITAM has 12 different hypotheses. For example, for Self-Efficacy, Hypothesis 1a is: Self-Efficacy will have a direct effect on Perceived Ease of Use. Hypothesis 1b is: Self-Efficacy will have a direct effect on

Perceived Usefulness. For Attitude, Hypothesis 9a is: Perceived Usefulness will have a direct effect on Attitude. Hypothesis 9b is: Perceived Ease of Use will have a direct effect on Attitude.

The items were considered using a seven-point Likert scale, between “Strongly Disagree” and “Strongly Agree.” Age was considered in years. Gender was coded using 1 and 2, where 1 stood for women.

It was attempted to reach 2050 athletes via email from 40 countries mainly from Western Europe, which participate in international competitions. It was obtained an overall response acceptance rate of 10.2 percent. Of a total of 209 returned responses, three were invalid and were eliminated before the data analysis. Consequently, 206 users successfully completed the survey, of which 168 were male (81.6 percent) and 38 were female (18.4 percent), and the average age was 38.5 years (standard deviation: 7.7). Regarding education levels, three users had Mid School or lower (1.5 percent), 40 had high school (19.4 percent), 42 had bachelor degree (20.4 percent), 88 had master degree (42.7 percent), and 19 had PhD degree (9.2 percent).

4.4 Analysis

It was analyzed the proposed model using maximum likelihood parameter estimation. Descriptive statistics and Exploratory Factor Analysis were conducted using IBM SPSS version 22. The structural equation model was built-in with maximum likelihood estimation routines in IBM SPSS Amos 24.

Cronbach alphas were higher than 0.7, except for Perceived Susceptibility (0.644). This indicates that there was construct reliability, meaning that the questions of the construct were related to each other. The Kurtosis analysis did not find normality issues.

The Exploratory Factor Analysis trimmed the initial model using Maximum Likelihood analysis with Promax Rotation. All loadings were above 0.420, except for HIT Self-Efficacy's items 3 and 4 with 0.370 and 0.380 respectively, which is bearable for the sample size (Joseph Jr, 2010). Item 2 of the construct Health Belief, item 1 of Subjective Norm, item 1 of Perceived Seriousness, items 5 and 6 of HIT Self-Efficacy, items 1 and 3 of HIT Reliability, items 4 and 5 of Perceived Usefulness, item 3 of Intention to Use, and all items of Attitude had to be discarded for the integrity of the model. Item 3 of HIT Self-Efficacy loaded prominently with the HIT Reliability construct. The remaining 3 items of Perceived Usefulness loaded with the 5 items of Perceived Ease of Use, creating a more UTAUT like dependent variable construct that was named as Perceived Ease of Use & Perceived Usefulness. The total variance explained was 56.1 percent.

In Table 4.1, one can observe the correlation coefficients for the measured variables, which vary from 0.000093 to 0.669, all are below the 0.7 threshold. For example, the coefficient -0.05 between HIT Reliability and Health Belief signifies that the questions of one construct are not needed to explain the other.

Table 4.1 – Correlation coefficients between measured variable

	1	**2**	**3**	**4**	**5**	**6**	**7**
Health Belief & Concerns	1						
Subjective Norm	.322	1					
Perceived Seriousness	.537	.497	1				
HIT Self-Efficacy	.407	.201	.285	1			
HIT Reliability	-.005	.115	.134	.073	1		
Perceived Ease of Use & Perceived Usefulness	.597	.325	.443	.251	.000	1	
Intention to use	.597	.432	.599	.379	-.011	.669	1

In Table 4.2, one can observe the tests for the convergent and discriminant validity of the scales. The Average Variance Extracted (AVE) that is the average quantity of variance in variables that a construct is able to explain is always close to or exceeding 0.50, and Composite Reliability exceeds 0.73. These values for Composite Reliability imply that the questions of each construct are still holding together in the Confirmatory Factor Analysis. In this table, Maximum Reliability (MaxR(H)) is also reported. Common Methods Bias was tested during the Confirmatory Factor Analysis, where it was compared the unconstrained and the fully zero constrained common method factor models that was significant with chi-square difference of 72.4, and a degrees of freedom difference of 25.

Table 4.2 – Results for the convergent and discriminant validity of scales

	1	**2**	**3**	**4**	**5**	**6**	**7**
CR	.780	.905	.793	.873	.738	.757	.874
AVE	.542	.576	.495	.696	.485	.509	.776
MaxR(H)	.781	.930	.948	.962	.966	.969	.975
Perceived Seriousness	.736	.073	.067	.047	.177	.140	-.007
Perceived Ease of Use & Perceived Usefulness		.759	.470	.814	.221	.635	.877
Health Belief & Concerns			.704	.419	.673	.606	.559
HIT Reliability				.834	.273	.645	.789
Subjective Norm					.697	.522	.289
HIT Self-Efficacy						.714	.737
Intention to use							.881

Nevertheless, the common latent factor was removed for the sake of the maximum interactions of the model. A Cook's distance test was done regarding multivariate assumption and no abnormalities were found. The final model obtained is represented in Figure 4.1.

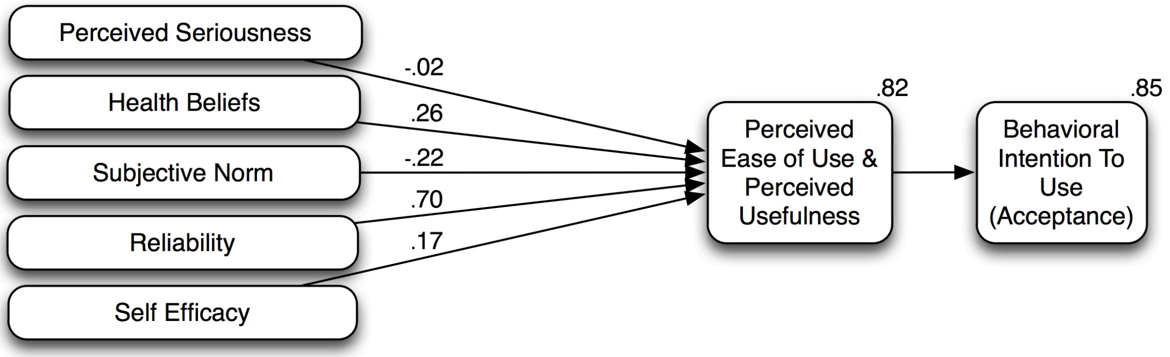

Figure 4.1– Finalized Extreme Users Model

4.5 Discussion

Through an online survey it was assessed the use of Activity Trackers, it was assessed HITAM, which could explain this use. It was submitted the constructs of HITAM for statistical analysis and obtained the resulting final model. As expected from an exploratory assessment like this one, the majority of the hypotheses did not prevail, since the original model was not dedicated to extreme users. Although the complete HITAM model did not prevail (J. Kim & Park, 2012), the trimmed valid final model that was derived from the results had a higher level of prevision than the original TAM (Davis, 1989).

The other statistical results while mediocre, are not necessarily surprising given that it was dealing with extreme users who, by definition, are at the extreme end of a distribution.

The study is limited in a number of ways: its sample is biased, as 81.6 percent were males, however this is common in extreme sports. A few items have statistical limitations in their loadings. There is a shared variance between Perceived Ease of Use & Perceived Usefulness with Intention to Use, and with HIT Reliability. Furthermore, there is shared variance between HIT Self-Efficacy with Intention to Use. This in turn is in line with the fact that the independent variables have some redundancy when explaining the dependent variables.

This study supports the notion that Subjective Norm has a negative influence on Perceived Ease of Use & Perceived Usefulness giving AT a utilitarian value to these users. Since Subjective Norm has this effect in the acceptance of these devices, thus other users or social counterparts do not induce Activity Tracker use by extreme users, it was questioned if this should be considered when thinking about the marketability of these devices. Previous studies, which looked at the social aspect of the uses, found it to be important (Clawson et al., 2015; Consolvo et al., 2006; Thevenin, 2001). The results narrow the broadness of social influence, quantifying its competitive and comparative aspects found by other authors (Rooksby et al., 2014). It seems that extreme athletes do not give importance to the social aspect of the use, even though there is a suspicion that the comparisons with their counterparts are important as previously found (Harrison et al., 2015).

As expected, HIT Self-Efficacy has an influence on the model, supporting previous findings on features such as giving credit and awareness to users (Pullin & Newell, 2007), widening the variety of adjustable goals (Venkatesh & Davis, 2000) or a tailored efficacy evaluation (Klasnja et al., 2011).

The described study supports the hypothesis that Perceived Usefulness & Perceived Ease of Use is a stronger determinant of the Behavioral Intention to use Activity Trackers than Health Threat. A major difference regarding the original HITAM is that it is seen that the Health Information, in this case is not an important condition for the validity of ATs acceptance and use by extreme users. Specifically, Health Threat loses its prevailing value in favor of Perceived Ease of Use & Perceived Usefulness, given that, Perceived Susceptibility was initially trimmed, and later Perceived Seriousness was found not to be an influencer. In the light of this, there is the suspicion that it is because extreme athletes' physical condition is above the average. This level of physical condition might reflect that the extreme athletes have a minimum perception of the likelihood of experiencing a condition that would be unfavorable to their health. Therefore, this lack of impact of Susceptibility, and Seriousness found in this study may be because some extreme users considered the issue of Susceptibility and Seriousness to be unimportant, due to their good health. This is backed by the finding of the strong influence of Health Belief in the model, meaning that these users have a strong belief in their good health. Another reason might be that Perceived Susceptibility and Perceived Seriousness focus on disease, but perceived usefulness focus on usefulness of HIT in health support. These are important findings that add to the increasing body of knowledge in the intersection of HCI, Information Systems, and Health Sciences (Klasnja et al., 2011).

The deeper repercussion of this work for further research is that health threat is exhausted by the important role of Reliability, supporting previous findings regarding the need for accuracy in AT (Harrison et al., 2015; Shih et al., 2015). The obtained model clearly shows Reliability as the most influential construct for Extreme Users. This finding advocates that development in Activity Trackers should be made by focusing more on the effective response of the system and not so much on the search for secondary determinants. From this, it can be suggested that designers of AT will need to be the ones to perfect and evolve the intricate details of wearable devices when the engineers do not fulfill nor anticipate results of the devices.

For extreme users, the effect of Perceived Ease of Use on Perceived Usefulness is so strong that the two constructs load as one. Nevertheless, it supports previous findings such as the need of the user to create routines, the need for low maintenance of the devices, devices that speak the user's language, the need to coach the user (Lazar et al., 2015), the dealing with the interweaving among systems, the need to have meaning to the context, and the fact that the user is not a data scientist needing the data to be processed (Rooksby et al., 2014). These loading as one is stimulated by the fact that a significant correlation between Perceived Ease of Use and Perceived Usefulness is precisely the pattern foreseen if Usefulness is mediated between Ease of Use and Intention to Use (Davis, 1989). This brings into question whether for an extreme user a device that is not easy to use immediately becomes useless. This result was unexpected, as it conflicts with the basic idea of the Technology Acceptance Model. This also raises questions about the use of a TAM-like model for predicting and explaining the adoption of emergent information technologies (Röcker, 2010). While surprising, it is necessarily interesting given that it deals with extreme users, and to the best of current knowledge this is the first acceptance model that looks at these specific users.

It is worth mentioning that the resulting model of this paper has similarities with the UTAUT model and that this line of research should be pursued (Venkatesh et al., 2003). This is because the UTAUT constructs: Performance expectancy, effort expectancy, and social influence are conjectured to influence the behavioral intention to use a technology, while behavioral intention and facilitating conditions determine technology use.

The quantitative results from this paper, shown in Figure 4.1– Finalized Extreme Users Model, partly reflect that the work is done with Ultra Trail athletes who are ‘extra-ordinary users in extra-ordinary situations.’ These users do not represent the average user however they are an important market niche and are also used for marketing purposes.

The resulting model fulfills the objectives of model-based design, stated in the introduction. The theoretical bases of models allow the designers to select the accurate model for the design problem. However, designers need to realize and understand when the design problem encompasses matters and features not tackled by the models. Since this contribution, to the best of current knowledge, is new given the obtained dedicated model, designers using the EU design method can utilize this model or a more generic one.

4.6 Conclusion

Research and design opportunities abound in the Activity Trackers sphere, and the goal was to obtain a preliminary understanding of Activity Trackers use by ultra-trail runners. Not only because these users represent a niche market, but also, mainly because they are taken into consideration in a design method.

The main contributions of this article are of two levels. At the first level in the Information Systems field this article presented a unique quantitative acceptance model that although statistically mediocre, models how extreme users accept and use Activity Trackers. At the second level in the Human Computer Interaction field this article presented a unique quantitative instrument that can support the work of the designers using the Extreme Users method while designing Activity Trackers. These contributions together are significant as they show more opportunities for the intersection of these two fields.

In this study, the HITAM model has been examined to explain and predict factors affecting extreme users of Activity Trackers. Health Belief and Concerns, Subjective Norm and Health Knowledge, HIT Self-Efficacy, HIT and Reliability included as antecedents in this model were found to influence extreme users' beliefs and indirectly influencing Activity Trackers use. The resulting model improves on existing models, due to its reinforced specialization in predicting Activity Trackers use by extreme users. Therefore, this study can help Activity Trackers' designers, especially those who work with the Extreme Users method, because it reinforces and unveils more of what makes extreme users use these devices. Such knowledge adds to the improvement of Activity Trackers, through an enhanced aptitude in order to evaluate users beliefs.

One of the long-term aims of this research path is a qualitative evaluation of the performance of Acceptance Models' use with the Extreme Users design method. Future research can be to evaluate Extreme Users with the UTAUT Model, and to evaluate HITAM with an alternative type of extreme users of Activity Trackers, such as the morbidly obese.

The differences and similarities between the model of this study and the model of the previous study are presented in Table 4.3 – Differences and similarities between ATTAM and EUATTAMTable 4.3 – Differences and similarities between ATTAM and EUATTAM

Table 4.3 – Differences and similarities between ATTAM and EUATTAM

EUATTAM	**ATTAM**
Intention to Use	
	Perceived Usefulness
	Perceived Ease of Use
Perceived Ease of Use & Perceived Usefulness	
Health Belief & Concerns	Health Consciousness
Perceived Seriousness	Perceived Severity
	Perceived Susceptibility
	Habit
HIT Reliability	
	Hedonic Motivation
Subjective Norm	Image
HIT Self-Efficacy	Self-Efficacy

	Perceived Data Control

Chapter 5 Athletes vs Health Runners via ATTAM – Paper III

Parts of the content of this chapter were published at:

Sol, R. and Baras, K. (2022). Activity Trackers: Comparing Athlete Runners versus Health Runners through a Dedicated Technology Acceptance Model. In Proceedings of the 10th International Conference on Sport Sciences Research and Technology Support, ISBN 978-989-758-610-1, ISSN 2184-3201, pages 78-85. (icSPORTS 2022).

The conducted study seeks to learn if, why and how two different groups of Activity Trackers users, Athletes and Health Runners, are utilizing these devices for their self-quantification. The study is based on the content analysis of 20 semi-structured interviews, 10 of which were with Athletes. To achieve its goals, the authors use a model based on the Technology Acceptance Model (TAM), a widely adopted technology acceptance theory. Amongst the findings, the construct Perceived Ease of Use showed that Athletes find it hard to program the settings for their training and Health Runners expressed that there is too much information involved. This paper contributes by showing that an all-purpose interface is not suitable and offers new knowledge for methodological discussions as it is, to the best of our knowledge, the first qualitative study to employ a model like the TAM in order to qualitatively interpret the use of Activity Trackers.

5.1 Introduction

Activity Trackers have become mainstream gadgets for consumers in recent years. However, many people still do not achieve the recommended levels of activity for their age groups. For the activity of walking, it has been widely recommended that healthy adults should reach the goal of ten thousand steps per day in order to maintain or improve their health. The development and the commercialization of activity trackers have shown a positive effect in helping many users to reach this goal (Laranjo et al., 2021). Research has shown that users of activity trackers, when steadily checking their step count walk more (Carels et al., 2005), lose more body weight (Akers et al., 2012), and are more in control of their actions (Burke et al., 2011). Nevertheless, a study on the adoption of a specific activity tracker found that half of the users stop using the device after two weeks (Shih et al., 2015).

Several models to describe and capture the use of activity trackers have been created since Li et al.'s seminal work of a model with five iterative stages: preparation, collection, integration, reflection, and action (Li et al., 2010). These authors later refined their model. Epstein et al. expanded that model by including the lapses and interruptions of tracking, and emphasizing the intricacy of integration, collection and reflection (D. A. Epstein et al., 2015). This model was also expanded to count for eudemonia and changing goals (Niess & Woźniak, 2018). However, these models are not quantitative, not dedicated exclusively to activity trackers, do not have a health-oriented component, and fall short in incorporating Data Control and

Privacy issues. To address these shortages, a quantitative model was created, that has eleven factors that influence the acceptance and usage of Activity Trackers (Sol & Baras, 2016). Nevertheless, constructs such as Subjective Norm or Attitude failed to be part of this model.

According to the International Data Corporation, worldwide shipments of wearables grew 9.9% during the third quarter of 2021 reaching 138.4 million units (IDC, 2021). Within these millions of users, one may be able to predict and identify that diversity can be found in types of use of trackers. Actually, researchers have already noticed gender differences (Shih et al., 2015), differences between health runners and pleasure runners (Temir et al., 2016), others look to naïve users (Rapp & Cena, 2016) and yet others looked at extreme users (Sol & Baras, 2021). This research aimed to find and compare aspects that impact acceptance and use of activity trackers by Athletes whose focus is to better performance in competitions and Health or Recreational Runners whose focus is to be healthy.

The model used takes into consideration Data Control, unlike previous technology acceptance models in the field (J. Kim & Park, 2012). This is a construct of importance, when only 31% of workers disagree to let their employer make use of wearable devices to monitor their performance at work, with 44% in favor (PWC, 2021). Especially, when research shows that third-party vendors are collecting detailed data from users (Ho et al., 2014).

A quantitative model was applied to qualitatively elucidate why people are more or less likely to adopt and use all kinds of activity trackers. Recommendations are proposed about how that model can enhance analyses of activity trackers use.

5.2 Particular Literature Review

In this section, the literature related to the use of Activity Trackers is reviewed. Technology Acceptance research is analyzed to understand its associations, relevance and definitions. The acceptance and use of activity trackers is due to numerous reasons and motives, some of which appear to conflict. Individual users may start tracking their activity because they have a specific goal in mind (D. Epstein et al., 2014). These goals can be a healthier life or a beautiful physical appearance, or both, the later being an excuse to reach the former (Kay et al., 2013). Nevertheless, there are users who begin to use Activity Trackers having no objective in mind and use the device to help them set a specific goal. This goal becomes more defined as the usage moves from the discovery phase to the maintenance phase of pondering (Li et al., 2010). Others begin tracking simply moved by interest and curiosity in quantitative data (Lindqvist et al., 2011). Many users receive the device as a gift, but when having the chance to choose specific tracking devices they base their choices on online reviews, marketing campaigns, specific features, portability, or follow an advice given by friends or family members (Kaye et al., 2014). Goal setting is only one idea to support and persuade health-related behavior change, others include feedback, reminder notifications, and social comparison (Shih et al., 2015). To become aware of one's performance and to regulate performance concerning the defined objectives, users also tend to check the data as soon as it is gathered (Fritz et al., 2014). Users tend to change their habits, goals, and devices and the related applications or dashboards are unprepared to deal with this. When tracking, users tend to change devices frequently or use several devices at the same time, which leads to problems in assessing and consolidating data (Rooksby et al., 2014).

5.3 Methodology

The study consisted of semi-structured interviews to twenty activity trackers users that were recruited via convenience sample. The participants were informed and gave their free consent (see Appendix E). In total, the group of participants consisted of 20 activity tracker users. Of the 20 users interviewed for this study, 10 were female and 10 were male. To help ensure that there would be a variety of experiences amongst participants, interviewees were recruited from amateur running competitors and from the general public, being 10 self-identified competition-running athletes (four females) and 10 self-identified health runners (six females) who were not so easy to reach in the convenience sample. The athletes ranged in age from 22 to 45 [average (Av) 35.5, standard deviation (SD) 7.5, median (M) 36], and had the devices from 1 to 150 months (Av=51.1, SD=52.9, M=30). The Health Runners ranged in age from 26 to 48 (Av=34, SD=8, M=31.5), and had the devices from 12 to 50 months (Av=24.5, SD=13.7, M=21). The summary of the demographics is in Table 5.1 – Demographics of the participants. The participants were from Western Europe. Nineteen interviews were conducted face to face and one through Skype video call. Of the 20 interviews 18 were conducted in the participants' native language. The interviews used 22 trigger questions shown in Appendix D. However, the interview protocol was used in a flexible manner according to the flow of the conversation. The average time of the interviews was 18 minutes with a minimum of 12 minutes and a maximum of 34 minutes. Respondents were first asked for the activity trackers they knew about. In Appendix D one can verify that Athletes were more prone to use dedicated devices while Health Runners were more prone to use software applications in smartphones. Afterwards the respondents were asked for what purposes they used the activity trackers. To make the interview more focused, next it was asked the participants to elaborate on their use of the device that they defined as the most frequently used for quantifying physical activity. In addition to finding out about general trends in activity trackers use and acceptance, the interest was in learning if activity trackers changed user's attitudes. As part of the interview process the participants were asked, for example, whether society recognizes activity trackers as part of the promotion of one's image. All interviews were digitally recorded using Word Audio Notes and then manually transcribed. The confidentiality and anonymity of all participants were safeguarded by making the names of study interview participants only known to the interviewer, using aliases for the interviewees in the transcriptions.

Table 5.1 – Demographics of the participants

	Group	**Months of use**	**Gender**	**Age**	**Education**
P1	Health	36	Female	28	Master
P2	Health	12	Male	32	Master
P3	Health	24	Female	48	Master
P4	Health	24	Female	26	Master
P5	Health	12	Male	30	Master
P6	Health	42	Female	40	Master
P7	Health	15	Male	33	Master

P8	Health	50	Female	26	Bachelor
P9	Health	12	Male	46	Master
P10	Health	18	Female	31	Master
P1	Athlete	24	Female	34	Master
P2	Athlete	36	Male	41	Master
P3	Athlete	36	Male	45	Master
P4	Athlete	24	Female	38	Master
P5	Athlete	150	Male	44	Master
P6	Athlete	24	Male	30	Master
P7	Athlete	144	Male	29	Master
P8	Athlete	1	Female	22	Master
P9	Athlete	60	Male	41	Master
P10	Athlete	12	Female	31	Master
Average	-	51.1	-	35.5	
Standard Deviation	-	52.9	-	7.5	
Median	-	30	-	36	

To analyze the transcripts, the activity trackers technology acceptance model (Sol & Baras, 2016) was applied. This study conducted an extensive review and analysis of noticeable technology acceptance and use models including Davis' Technology Acceptance Model (TAM) (Burke et al., 2011), Kim & Park's Health Information Technology Model (J. Kim & Park, 2012), and Venkatesh et al., Unified Theory of Acceptance and Use of Technology (Venkatesh & Davis, 2000). Their resulting model confirms PU and PEoU as strong predictors of Behavior Intention to use. Although these kinds of models are usually applied to analyze and explain the quantitative data collected through a survey instrument, the current study has taken a different approach. To the best of our knowledge, this is the first qualitative study that deploys this quantitative model to study activity trackers use, which is an evolving line of research.

The results of the study are presented in the following sections. Firstly, the model is applied to analyze the interview data and compare it with previous work. Next, the model's applicability is discussed in terms of explaining activity trackers use and finally recommendations are made that are supported by the model. The concluding section summarizes the results.

5.4 Employing the Model to Understand Runners Use of Activity Trackers

Here the Activity Tracker Technology Acceptance Model is applied to cluster the interview data with each of the eleven constructs shown in Figure 5.1. In the following sections, the participants are identified as, for example: P9H12M18, meaning: Participant number (P1 to

P10), runners group (H = Health, A = Athlete), number of months using activity trackers, gender (F = Female, M = Male) and age.

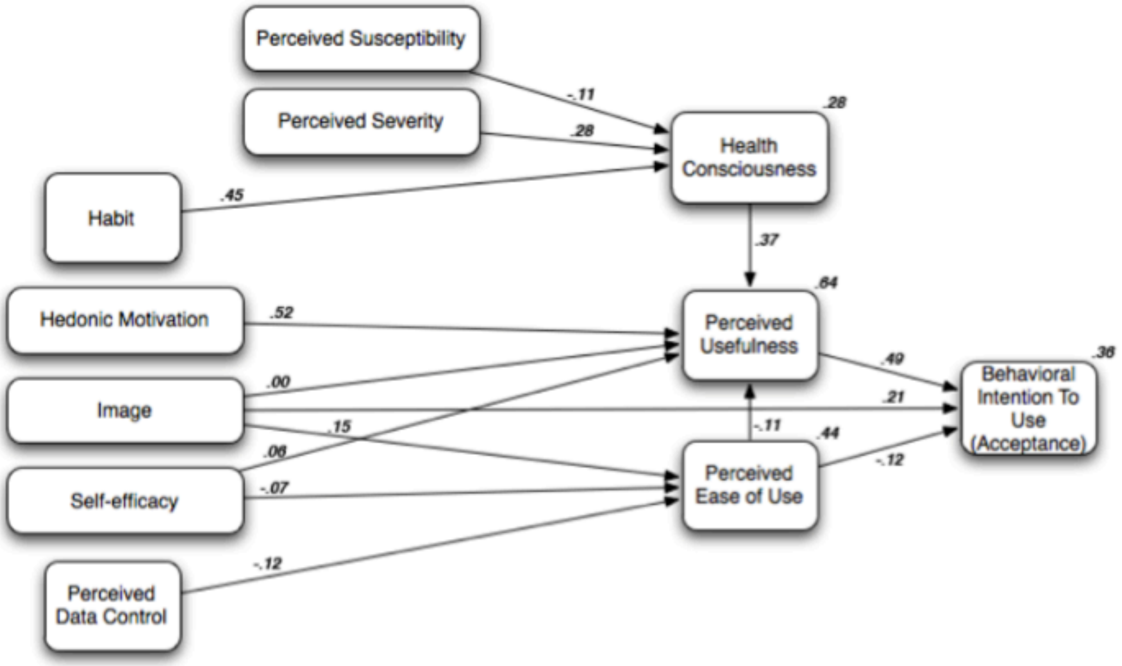

Figure 5.1– Activity Trackers Technology Acceptance Model (Sol & Baras, 2016)

5.4.1 Perceived Usefulness

When characterizing the Perceived Usefulness construct statements such as ”Using Activity Trackers is beneficial for you”, were used. All participants mentioned that being aware of the information collected by this kind of devices was particularly useful and stated that they do not use all the information. Nevertheless, Athletes were focused on the immediacy for trainings, as said by P1A24F34: “I think it allows you to act on the spot and I think that's the relevance, knowing where you are and being able to correct it on the spot, or else correct it in the coming weeks.” It was also noticed that the Athletes were inclined towards a perspective of near future actions when using the devices, as emphasized by the following quote by P1A24F34: “What changed the most was having more information and with it being able to plan my activity.” This supports the idea that the devices should facilitate these plans and inclinations more. Athletes also reported a focused experience, as expressed by P5A150M44: “It gives the necessary data to experience what I want. That's why I don't take full advantage of the program.” This points to the fact that some users are operating the technology in a limited way. Similarly, young Health Runners like P5H12M30 corroborate: “I don't think there's the need to buy dedicated device for activity tracking.” A few Health Runners were more concerned with using the devices for an assortment of situations, like P10H18F31 put it: “It doesn't have the possibility for me to record a group class. It’s got a set of activities, and it doesn't have what I need.” Overall, it was supported by this construct that these devices are useful, however it was also realized that there are specifics that are distinctive between the two groups. While both groups reported issues that are important, these issues are quite different and need specific design solutions.

5.4.2 Perceived Ease of Use

When characterizing the Perceived Ease of Use construct questions such as “Which were the most difficult aspects when using Activity Trackers?” were used. All participants mentioned that the devices were easy to use. Nevertheless, Athletes find it hard to program the settings for their trainings, like P8A1F22 noted: “What is more complicated to do is, for example, the programing of the training scheme.” Which was corroborated by P9A60M41: “Not in the use part, but in the configuration.” Whereas Health Runners were more concerned, again, with using the devices for specific sports, like P1H36F28 put it: “If I want to ride a bike, I can't, I have to put the watch on my ankle otherwise it won't register my steps.” There were concerns about the understanding, meaning and clarity of the information provided, like P5H12M30 stated: “You don't know in practical terms what that means.” It is important to notice that users are not specialists in analyzing data, so the data displayed would need to be translated for the user. Overall, it was supported that these devices are easy to use, however some issues were reported, and these were different between the two groups.

5.4.3 Perceived Data Control

When characterizing the Perceived Data Control construct questions such as “What do you think about your control of the information“ were used. In both groups there were users who did not care and there were users who were worried. The Athletes who cared were more concerned about the security perspective than with the data itself, as described by P1A24F34: “Hack the data, you can see what time the person is not at home. To rob houses is good.” This point was corroborated by P9A60M41: “Any person that follows me in the social app of the tool, easily finds out where I live, since my training start always in the same place. That's what worries me the most.” Most of the Health Runners stated that they knew that they were not in control of the data and that they did not introduce much personal information. Nevertheless, they did not care that this kind of data was available and exposed, except for participant P2H12M32 who said: “I know that the data is not locally stored and have access to the raw files. Especially in the case of Google Fit, I knew that the data was in Google servers, and since they have everything, my email, my calendar, and my physical performance, I felt a bit scared and stopped using Google Fit and GPS tracking." To summarize, users are aware that their personal information can be seen, as found before, nevertheless overall most users in both groups are not overly concerned or worried about data control. The differences between the two groups were noticeable but were minor.

5.4.4 Self-efficacy

When characterizing the Self-efficacy construct questions such as "How do you feel when managing the information?", were used. All users considered themselves quite efficient users of the devices, as stated by P7H15M33: "I'm not using it one hundred percent in all features. But the ones I use, I use it very well." However, P3H24F40 noted: "I think there is too much information to manage." Again, it is highlighted that information must be relevant for the users or it will be considered superfluous.

To summarize, the major difference between the two groups is that Health Runners think there is too much information.

5.4.5 Image

When characterizing the Image construct questions such as "What do you think about other people who use Activity Trackers?", were used. Both groups in the sample gave medium importance to Image. However, the idea of the device being an iconic trend was mentioned by P1A24F34: “Theoretically this turns out to be a cult.” The importance of the social aspect is underlined here. On top of this, for Athletes, one having a device was associated with a more competitive person, as expressed by P4A24F38: “They are people that have other goals, they are committed to progress in their training to reach one goal after another… improve their performances in the competitions they enter.” Similarly, Health Runners mirrored others, as expressed by P1H36F28: “They are smart like me and want to improve their health.” Nevertheless, P4H24F26 said: “I think the devices are ugly, I don't like to wear a black thing.” This denotes the importance of visual design and the consideration of gender differences or preferences. Overall, both groups are of the opinion that other people who use the devices have the same objectives as themselves.

5.4.6 Hedonic Motivation

When characterizing the Hedonic Motivation construct questions such as ”How do you feel using Activity Trackers?”, were used. Participants felt good when using the devices. However, Athletes felt good when using but also before using the devices, as described by P5A150M44: “The more goals one reaches, which are the data that the device also gives, the more desire to go training.” Whereas Health Runners felt well when running, such as P7H15M33 put it: “I find it more motivating during exercise. Not necessarily before doing the exercise.” This was corroborated by P3H24F48: “Not that it's going to make me get up one day and run on purpose just because of the device.” This can indicate that Athletes are pre-motived to run while Health Runners need support to encourage behavior change. To summarize, there is a key difference between the groups.

5.4.7 Habit

When characterizing the Habit construct questions such as ”Using an Activity Tracker is or is not a habit for you?”, were used. For Athletes using the device, this can be more than a habit they can be craving for it. Nevertheless, Health Runners who do not make use of the device as a habit blamed the recharging of the device batteries for their inconsistent use of the device, as said by P1H36F28: “What annoys me sometimes is putting the watch on charge, I don't want to get up without it counting those steps.” This point was corroborated by P4H24F26: “For me it's boring every three days to remember that the battery is going to fail.” This shows that the device needs to be able to encourage and give assistance in the implementation of habits. To summarize, the differences between the two groups are noticeable but were minor.

5.4.8 Perceived Susceptibility to Chronic Diseases/Perceived Severity of Chronic Diseases/Perceived Threat - Health Consciousness

In the interviews the three health related constructs were indistinctive. When characterizing the Perceived Susceptibility to Chronic Diseases construct questions such as: What kind of injury have you had?”, were used. When characterizing the Perceived Severity of Chronic Diseases construct questions such a: “How do you react to the possibility of having an injury?“, were used. When characterizing the Perceived Threat-Health Consciousness construct questions such a: ”What kind of attitudes do you take concerning your health?”, were used. All participants mentioned paying special attention to their diet, alcohol intake, and sleep. In both groups there were users with conflicting practices. Health Runners are more inclined not to think that they could have a health problem, most Athletes, on the other hand have this in mind all the time and consider how this can impact their occupation. As P3A36M45 noted: “I go to competitions carefully to avoid serious injuries. With care, with calm, because I see many competitors especially downhill, and I get scared to see them going downhill so fast. I'm often overpassed, because that scares me.” Similar attitude was viewed in a Health Runners, as described by P1H36F28: “In the gym there are exercises that I know I cannot do, I only do if I have someone next to me.” To summarize, the differences between the two groups were noticeable but were minor.

5.4.9 Behavioral Intention to Use (Acceptance)

When characterizing the Behavioral Intention to Use (Acceptance) construct questions such as “In the long run do you think you will still use the device or not?“, were used. All participants stated that they will continue to use the device, except P9H12M46: “If I can achieve a weight loss goal without needing to use it, I will not use it.”

5.5 Discussion

The findings suggest that certain model constructs were revealed to be important in studying acceptance and use of activity trackers. The primary performance booster that participants saw in activity trackers was the ability to show data that one had never been able to see before. Other common useful practices of using activity trackers included motivational support and comparison with others and oneself.

It was found that for this small sample population, Perceived Usefulness, Perceived Ease of Use, Image, Hedonic Motivation, and Habit were strongly associated with the acceptance and use of Activity Trackers and show significant differences between groups. Perceived Usefulness and Perceived Ease of Use constructs showed that Athletes experienced difficulties and problems with configuring the settings for their training, corroborating the design idea of facilitating micro plans (Gouveia et al., 2018) and that users are using the technology in a limited way (Didziokaite, 2017). It also showed differences among ages especially in young runners (Janssen et al., 2020). Additionally, the study showed that Health Runners felt that they were faced with too much information or complex information and wanted the possibility to track different exercises. A similar issue with the volume of information has been described in previous work stating that users are not data scientists (Rooksby et al., 2014) and that the information is not in the user’s language (Lazar et al., 2015). Perceived Data Control showed conflicting differences within the two groups, however generally speaking users are conscious that their personal information can be highly sensitive, as previously established (Lupton, 2017). However, most of the interviewees did not have many concerns in sharing their data. The Self-efficacy construct showed that both groups are efficient users. Nevertheless, it is seen here the need of personal relevance of the data (D. Kim et al., 2016). The Image construct showed that both groups in the sample gave ordinary importance to image. Also, it is underlined here the long viewed importance of the social aspect of these devices (Clawson et al., 2015; Consolvo et al., 2006; Patel et al., 2015), also, the importance of aesthetics and form (Harrison et al., 2015) and the significance of gender differences (Shih et al., 2015). The Hedonic Motivation construct showed that both groups felt good when using the devices. Athletes find motivation before and during running, in accordance with previous findings (Rapp & Tirabeni, 2020). The Health Runners denoted a previously identified need for behavior change strategies (Klasnja et al., 2011) and the two groups showed the need for egocentric design (Elsden et al., 2015). The Habit construct showed that Athletes could be addicted to use while Health Runners use the battery recharge as an excuse not to use it. Thus, it is noticed the importance of the previously identified idea of implementing routines (Lazar et al., 2015) and adherence (Tang et al., 2018). As for Perceived Susceptibility to Chronic Diseases, Perceived Severity of Chronic Diseases, Perceived Threat - Health Consciousness, and Acceptance showed no major differences between groups or conflicting differences within the groups.

By the end of conducting this research it was clear that an all-purpose interface is not suitable. The novelty of the findings suggests specific design considerations: designers should look at the ease of use and usability of the overall settings, the need for easy-to-use training plans and training settings. In order to accomplish this, it is proposed that the software has different modes that would be selected by different types of users: pleasure runners, health runners, athletes, etc. Another possibility would be to associate the modes to the three classes of tracker motivations: behavior change, instrumentation, and curiosity. One limitation of this work is that it does not make a clear split between intention to use activity trackers and the actual use. This is because most of the interviewees were users of at least one activity tracker. Finally, it is anticipated that the establishment of specific models for each group may be a necessity to better explain the acceptance and use of activity trackers by these users.

5.6 Conclusion

There is an ample number of studies looking into users of activity trackers. However, only a few have compared different groups of users. This study was based on 20 semi-structured interviews with Health Runners and Athlete Runners. They offered a diverse variety of information on how users are integrating activity trackers into their lives, their benefits, difficulties, and future tendencies. This study shows that the Activity Trackers Acceptance Model can be employed in this context and makes suggestions for its future application. Participants that use activity trackers in their daily lives found them useful for emotional support, social parallelism and competition, and, surprisingly interesting for the data the device provides.

This study revealed that there were significant differences regarding the difficulties of the users experience. Athletes had issues with configuring the settings for their training, whereas Health Runners found too much or too complex information and wanted the possibility to track different exercises. There were also significant differences regarding motivation. The devices motivated Athletes before and during running while Health Runners were motivated by the devices only when running. Both groups thought that the people who use these devices had the same goals as themselves. Health Runners used the excuse of having to regularly recharge the device battery as the reason for not making the use of the device a daily habit in their lives. Even with a small number of users, and by utilizing the model constructs it was possible to gain new insight into the differences of how these two groups use and accept activity trackers in this initial investigation. This study brings more light to the value of looking more closely at specific types of users and how their documented experiences and use of these devices can be analyzed and applied to the understanding of the use of activity trackers. More such studies need to be carried out in order to gain and maximize data pertaining to the abundant diversity that exists with regards to user experiences, which can then also impact future designs of activity trackers.

Chapter 6 ATTAM via Artificial Neural Networks – Paper IV

Parts of the content of this chapter were published at:

Sol, R. and Baras, K. (2022). An Integrated Neural Network and Structural Equation Modeling Approach for Modeling Activity Trackers Use. In Proceedings of the 6th International Conference on Computer-Human Interaction Research and Applications, ISBN 978-989-758-609-5, ISSN 2184-3244, pages 49-58. (CHIRA 2022).

Best Student Paper Award.

The objective of this study is to enhance a Technology Acceptance Model (TAM) with an Artificial Neural Network (ANN) approach in order to obtain substantially accurate results when compared to Structural Equation Modeling (SEM). This study looked at another paper that created a TAM dedicated to activity trackers (AT) obtained via SEM from a questionnaire to 247 participants. This study uses the constructs of that paper in an ANN as the input units and the Root Mean Square of Errors to indicate that the ANN method achieves high prediction accuracy than SEM. The results provide conclusive evidence that Perceived Usefulness is the most significant factor affecting AT acceptance. Perceived Ease of Use and Image affect acceptance, however their impact is much lower. Hedonic Motivation and Habit were found to have a significant relationship with TAM while Self-Efficacy showed mixed results. This confirmation could be useful for future designs of activity trackers.

6.1 Introduction

Wearable devices such as activity trackers have become important in monitoring health behavior, for recreation, and socialization, and thus are a viable and significant research topic in Human Computer Interaction. Confirming this trend is the International Data Corporation in a press release, stating that worldwide shipments of wearables grew 9.9% throughout the third quarter of 2021 reaching 138.4 million units (IDC, 2021). The improvement and the commercialization of activity trackers have helped many users to reach the recommended goal of ten thousand steps per day in order to maintain or improve their health (Akers et al., 2012). However, a study on the acceptance of a particular activity tracker device discovered that half of the users stop using the device after two weeks (Shih et al., 2015).

One possibility to help solve design issues that lead to loss of interest or decrease of device usage, is the use of models. Even though some researchers think of them as excessively theoretical. In fact, researchers working with interfaces that had often been skeptical, started to acknowledge that models could be helpful in the design of interfaces (Myers et al., 2000). Since Li et al.'s seminal work, researchers have been trying to describe the use of trackers through a model (Li et al., 2010). Li et al. presented a model with five iterative stages: preparation, collection, integration, reflection, and action; later the model was refined by these authors. Also, Epstein et al. looked at that model and expanded on it by including the lapses and interruptions of tracking, and highlighting the intricacy of integration, collection and reflection (D. A. Epstein et al., 2015). Narrowing the scrutiny, Sol and Baras obtained a model dedicated to activity trackers use (Sol & Baras, 2016) that is used in this chapter. The most important advantage of this model is that it is quantitative. It was obtained by expanding the Technology Acceptance Model (TAM), with health oriented constructs, data control, and other constructs. TAM assumes that user acceptance can be described by two ideas: Perceived Usefulness (PU), and Perceived Ease of Use (PEoU) which determine Intention to Use through Attitude (Davis, 1989).

A TAM based model for activity trackers, as most of the research on technology acceptance models is done simply with Structural Equation Modeling (SEM) methods, or other models, for example, the Ubiquitous Computing Acceptance Model (Spiekermann, 2007), and the Health Information Technology Acceptance Model (J. Kim & Park, 2012). SEM is a sophisticated multivariate technique that can be used to scrutinize multiple dependence associations between variables simultaneously. It is useful for hypothesis specification and testing, can suggest novel hypotheses that were not considered initially. Nevertheless, SEM may lead frequently to an oversimplification of the complexities involved as it is simply detecting linear relationships (Ringle et al., 2012). To address this issue, undertaking a second step using an Artificial Neural Network (ANN) allows for further scrutiny and examination.

An ANN is "*a massively parallel distributed processor made up of simple processing units, which have a neural propensity for storing experimental knowledge and making it available for use*" (Haykin, 2004). Contrary to SEM an ANN is not suitable for hypotheses testing, but further to linear relationships can also deal with non-liner relationships. Moreover, an ANN has the capability to assess non-compensatory processes (Svozil et al., 1997). Additionally, an ANN is more robust and can offer greater prediction accuracy than linear models (Tan et al., 2014). This study uses the constructs of the TAM based model for activity trackers as the input units of an ANN in order to obtain a more accurate view of the acceptance and use of these devices.

In the following sections, the study is contextualized with the literature review, and the model is presented. Next, the methodology is described, and the results of ANN analysis are discussed. Finally, the conclusion and the envisioning of possible future research are presented.

6.2 Particular Literature Review

In this section, the literature related to activity trackers is reviewed. There is also a gaze into Artificial Neural Networks research to understand its relations, importance and classifications. The acceptance and use of activity trackers is due to many reasons and motives, several of which seem to clash. Users may begin tracking their activity since they have a certain goal in mind (D. A. Epstein et al., 2015). Still, there are users who start to use activity trackers with no goal in mind and use the device to help them set an objective. This objective becomes clearer as the usage changes after transitioning from the discovery phase to the maintenance phase of pondering (Li et al., 2010). Other users start tracking merely moved by concern and curiosity of the quantitative data (Lindqvist et al., 2011). Nonetheless, goal seating is just one notion to help and persuade health-related behavior change.

For example, when the user wants to implement a habit in daily life, one of the best ways is for the activity tracker to help implementing routines (Lazar et al., 2015).

An egocentric perspective for these devices (Elsden et al., 2015) can be looked at as a form of hedonic motivation, as is individual encouragement (Patel et al., 2015), the acknowledgement of effort (D. Kim et al., 2016), and giving credit (Consolvo et al., 2006).

When looking at image one can look into the lifestyle of the user (Consolvo et al., 2006) or to the aesthetics and form of the devices (Harrison et al., 2015). Other notions embrace social comparison (Harrison et al., 2015), social competition and collaboration (Patel et al., 2015).

Users manage to change their goals, habits, and devices; however the applications or dashboards are ill equipped to allocate this change. For tracking, users tend to change devices often or even use several devices in parallel, which leads to complications in measuring and associating data (Rooksby et al., 2014). This issue has many impacts as it increases the difficulty to provide a tailored efficacy evaluation (Klasnja et al., 2011) that is important for the users' self-efficacy.

When one approaches data control, the information that activity trackers are gathering can be extremely sensitive (Lupton, 2017) and the risk of third-party recording is real (Elsden 2015).

When looking at how to improve the usefulness of activity trackers different researchers produced several design ideas, one of which was the facilitating of micro-plans (Gouveia et al., 2018), another was to give meaningfulness in context (Rooksby et al., 2014), yet another was to provide a wide variety of adjustable goals (Clawson et al., 2015), or to appeal to identity (Lazar et al., 2015), and another was the idea of adherence (Tang et al., 2018).

The idea that the devices have to “speak“ the language of the users (Lazar et al., 2015) because users are not data scientists (Rooksby et al., 2014), and the need for devices to remind them (Shih et al., 2015) are ways to improve the usability of activity trackers. Nevertheless, these devices are still being used in a rather limited manner (Didziokaite, 2017).

Numerous statistical techniques are parametric, such as SEM and Multiple Regression Analysis (MRA), requiring a great statistical background, while artificial neural networks are non-parametric models, which can provide higher prediction accuracy (Tan et al., 2014). An ANN uses a considerable interconnection of simple computing units called neurons or nodes as inputs, hidden, and outputs layers with connection values called synaptic weights that are adaptable via an iterative process. A classic ANN consists of several layers: one input layer, one or more hidden layers and one output layer (Negnevitsky, 2005). In ANNs for technology acceptance typically only one hidden layer is used (Tan et al., 2014). There are several types of ANNs, but the most common is feed forward back propagation multilayer perceptron (FFBP). In this kind of network, belonging to supervised learning ANNs, the knowledge stored in the network by iteratively subjecting it to patterns of known inputs and outputs (Negnevitsky, 2005). The difference between desired and actual output, is calculated and propagated back, in order to change the synaptic weights and by doing so minimize the estimation error (Haykin, 2004).

A node uses a function **f** defined as a weighted sum of its inputs based on the following equation where the **w** are the weights, and the **x** are the inputs, the bias is **b** and the output is **z** (Haykin, 2004).

$$z = f(w_1x_1 + w_2x_2 + b) \tag{6.1}$$

There are many activation functions for the output layer, however Sigmoid, shown in the following equation, is generally used in a technology acceptance context (Tan et al., 2014).

$$f(x) = \frac{1}{1 + e^{-x}} \tag{6.2}$$

The root mean square of errors (RMSE) is used to predict accuracy and is calculated using the following equations (Tan et al., 2014).

$$MSE = \frac{SSE}{n} \tag{6.3}$$

Where SSE is the sum of squared error, and MSE is the mean squared prediction error.

$$RMSE = \sqrt{MSE} \tag{6.4}$$

6.3 Model Obtained via SEM

In order to obtain the model for activity tracking use, via Structural Equation Modeling, the paper targets a population of actual activity trackers users. These users were recruited from social media and on a micro work site. A survey with 80 questions adapted from prior research in the TAM field was deployed. The items of the survey were considered using a seven-point Likert Scale, amid between “Strongly Disagree” and “Strongly Agree.” Specifically, the strength and significance of direct effect of nineteen independent variables on behavioral intention were determined. Of a total of 17 tested relationships, 11 were statistically significant.

There was a total of 247 users, mostly from Western Europe and North America, that completed the survey, from these 144 were male (58.3 percent) and 103 were female (41.7 percent). The average age was 33 with a standard deviation of 10.6.

The sample size of 247 has exceeded the recommended minimum sample size of 111 obtained from G*Power with an effect size of 0.3, an alpha level of 0.05 and a power of 0.95 (Faul et al., 2009). In Table 6.1, the definitions of the constructs that make up the model are displayed.

Table 6.1 – Definitions of the constructs present in the model

Construct:	**Definition:**
Perceived Susceptibility of Disease	“The perception of the likelihood of experiencing a condition that would adversely affect one's health” (Jayanti & Burns, 1998)
Perceived Severity of Disease	“The beliefs a person holds concerning the effects a given disease or condition would have on one's state of affairs” (G. Hochbaum et al., 1952)
Habit	“The extent to which people tend to perform behaviors automatically because of learning”

	(Limayem et al., 2007)
Health Consciousness	“The degree to which health concerns are integrated into a person’s daily activities” (Jayanti & Burns, 1998)
Hedonic Motivation	“The fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use” (Brown & Venkatesh, 2005)
Image	“The degree to which use of an innovation is perceived to enhance one’s image or status in one’s social system” (Moore & Benbasat, 1991)
Self-Efficacy	“The judgment of one’s ability to use a technology (e.g., computer) to accomplish a particular job or task” (Compeau & Higgins, 1995)
Perceived Data Control	“The degree to which a person feels they have control over the use of, and access to, the data collected” (Lindqvist et al., 2011)
Perceived Usefulness	“The degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989)
Perceived Ease of Use	“The degree to which a person believes that using a

	particular system would be free of effort" (Davis, 1989)

The previously found model was obtained using maximum likelihood parameter estimation. Descriptive statistics, and Exploratory Factor Analysis were conducted using IBM SPSS version 23. The structural equation model was built-in with maximum likelihood estimation routines in IBM SPSS Amos 23.

The Kurtosis analysis found normality issues, with values higher that two, in item two of the construct Perceived Usefulness, item two of the construct Perceived Ease of Use, item one of the construct Intention to Use, and in all items of the construct Behavioral Intention. However, these constructs passed in the Exploratory Factor Analysis. In Figure 6.1, the path diagram of the activity tracker acceptance model with the respective path coefficients is shown.

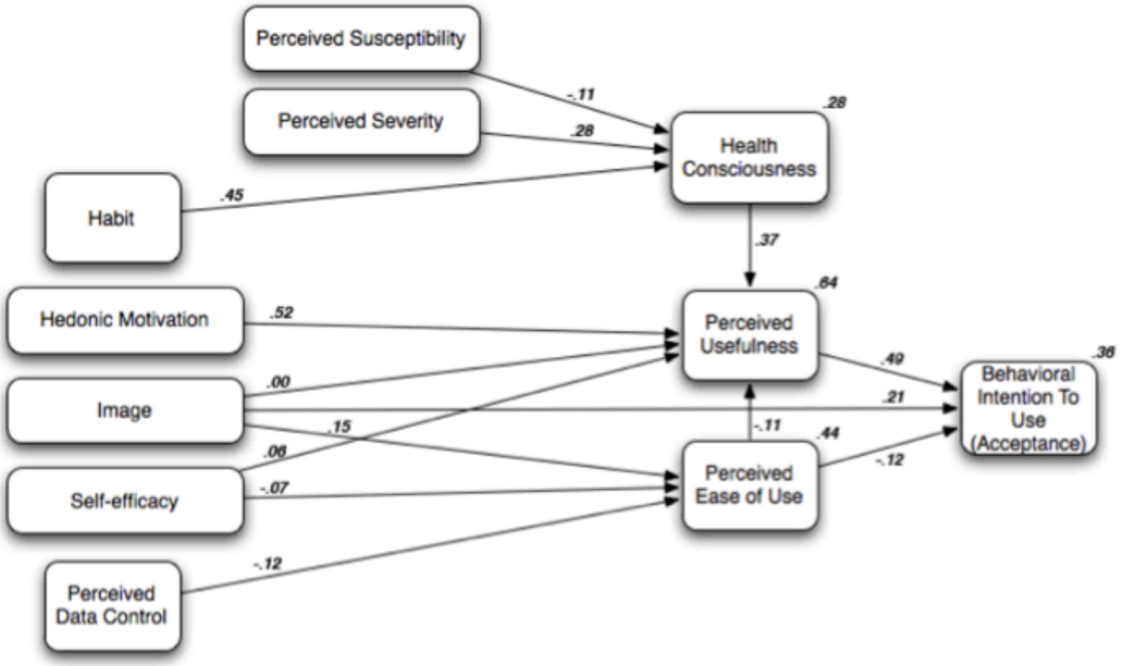

Figure 6.1– Path Diagram of the Activity Trackers Acceptance Model obtained via SEM with respective path coefficients (Sol & Baras, 2016).

6.4 Methodology

In this work, an Artificial Neural Network is applied to analyze, complement and verify the SEM approach and measure the effectiveness of the constructs that prevailed for the acceptance of activity trackers.

A Multilayer Perceptron (MLP) back propagation feed-forward (BPFF) method is used. The MLP is the most used and widespread ANN method (Liébana-Cabanillas et al., 2017). The ANN contains three layers: the input layer, the hidden layer, and the output layer. In this work, the ANN is created using IBM SPSS 24. The model obtained from SEM is divided into four ANN models with one output variable. Model A has the output as the construct Health

Consciousness and has three inputs Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit. Model B has the output as the construct Perceived Usefulness and has five inputs Health Consciousness, Hedonic Motivation, Image, Self-Efficacy, Perceived Ease of Use. Model C has the output as the construct Perceived Ease of Use and has three inputs Image, Self-Efficacy, and Perceived Data Control. Model D has the output as the construct Behavioral Intention to Use (BIU)/ Acceptance and has three inputs Perceived Usefulness, Image, Perceived Ease of Use. The nodes (hidden neurons) are automatically generated by SPSS and the activation function used for both hidden and output layers was Sigmoid Function. Of the total, 90% of the samples were assigned to the training procedure and the remaining 10% were used for the testing procedure. To avoid the risk of over-fitting, a ten-fold cross-validation process was employed. The root mean square of errors (RMSE) was used to assure the predictive accuracy of the four ANNs. The next section analyzes the results of the ANN.

6.5 Artificial Neural Networks Results

An ANN is helpful in discovering both linear and non-linear relationships without requiring any distribution assumptions like linearity, normality, or homoscedasticity as in Structural Equation Modeling (Leong et al., 2013). By doing so, an ANN can provide higher prediction accuracy (Tan et al., 2014).

As shown in Table 6.2, the RMSE values for the training data and the testing data are low, representing a higher predictive accuracy and better data fit.

Table 6.2 – RMSE values of ten artificial neural networks

	Model A		**Model B**		**Model C**		**Model D**	
Input Neuron	Perceived Susceptibility to Disease (PSusD), Perceived Severity to Disease (PSevD), Habit		HC, Hedonic Motivation (HM), Image, Self-Efficacy, Perceived Ease of Use		Image (I), Self-Efficacy (SE), Perceived Data Control (PDC)		Perceived Usefulness, Image, Perceived Ease of Use	
Output Neuron	Health Consciousness (HC)		Perceived Usefulness (PU)		Perceived Ease of Use (PEoU)		Behavioral Intention to Use (BIU)/ Acceptance	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN 1	0.114	0.134	0.072	0.073	0.104	0.096	0.075	0.057
ANN 2	0.117	0.107	0.077	0.077	0.101	0.099	0.072	0.058
ANN 3	0.118	0.116	0.083	0.055	0.100	0.120	0.072	0.067
ANN 4	0.119	0.106	0.076	0.056	0.104	0.094	0.074	0.076
ANN 5	0.119	0.104	0.078	0.077	0.105	0.102	0.087	0.054
ANN 6	0.115	0.129	0.087	0.072	0.102	0.104	0.073	0.071

ANN 7	0.117	0.080	0.080	0.063	0.105	0.159	0.071	0.062
ANN 8	0.116	0.107	0.079	0.049	0.111	0.130	0.079	0.053
ANN 9	0.130	0.108	0.073	0.066	0.100	0.114	0.069	0.083
ANN 10	0.117	0.072	0.069	0.067	0.103	0.079	0.078	0.057
Mean RMSE	0.118	0.106	0.077	0.066	0.103	0.110	0.075	0.064
Standard Deviation	0.005	0.019	0.005	0.010	0.003	0.022	0.005	0.010

In Table 6.3, is shown the results of the sensitivity analysis that assessed the strength of the predictive power of each of the input neurons. In order to have the normalized importance of these neurons in percentage it is divided the relative importance by the maximum importance.

Table 6.3 – Neural network sensitivity analysis

	Model A	**Model B**	**Model C**	**Model D**
Output	Health Consciousness (HC)	Perceived Usefulness (PU)	Perceived Ease of Use (PEoU)	Behavioral Intention to Use (BIU)/ Acceptance
	Relative Importance	Relative Importance	Relative Importance	Relative Importance

ANN	PSusD	PSevD	H	HC	HM	I	SE	PEoU	I	SE	PDC	PU	I	PEoU
1	0.324	0.240	0.437	0.040	0.671	0.065	0.113	0.112	0.301	0.429	0.270	0.730	0.218	0.052
2	0.326	0.256	0.417	0.070	0.603	0.050	0.123	0.154	0.352	0.356	0.291	0.731	0.166	0.103
3	0.298	0.238	0.464	0.237	0.514	0.025	0.097	0.127	0.358	0.306	0.336	0.690	0.174	0.136
4	0.350	0.161	0.488	0.062	0.603	0.035	0.071	0.229	0.411	0.331	0.258	0.651	0.213	0.136
5	0.298	0.248	0.454	0.091	0.584	0.023	0.052	0.250	0.311	0.423	0.266	0.360	0.188	0.453
6	0.379	0.251	0.370	0.168	0.367	0.033	0.170	0.264	0.324	0.419	0.257	0.694	0.149	0.157
7	0.315	0.217	0.467	0.060	0.567	0.096	0.117	0.161	0.335	0.376	0.289	0.754	0.193	0.053
8	0.311	0.252	0.437	0.039	0.601	0.041	0.029	0.289	0.237	0.503	0.260	0.579	0.174	0.247
9	0.223	0.106	0.671	0.023	0.651	0.018	0.102	0.205	0.304	0.299	0.397	0.723	0.195	0.082
10	0.255	0.275	0.470	0.049	0.604	0.054	0.146	0.146	0.380	0.353	0.267	0.525	0.405	0.070
Average	0.308	0.224	0.468	0.084	0.577	0.044	0.102	0.194	0.331	0.380	0.289	0.644	0.208	0.149
Average	68%	50%	99.8%	16.4%	100%	7.7%	18.9%	35.2%	83.3%	93.4%	72.5%	97.9%	33.3%	25.9%

Habit (H) was found to be the key determinant in predicting Health Consciousness (HC) followed by Perceived Susceptibility to Disease (PSusD) and lastly Perceived Severity to Disease (PSevD) in model A. In model B, the order of importance towards Perceived Usefulness (PU) in descending order is Hedonic Motivation (HM), followed by Perceived Ease of Use (PEoU) and Self-Efficacy (SE) and the least important were Health Consciousness (HC) and Image (I). For model C, Self-Efficacy (SE) is the most prominent predictor for Perceived Ease of Use (PEoU), followed by Image (I) and lastly Perceived Data Control (PDC). Finally, Perceived Usefulness (PU) constituted the most effective in term of predicting Behavioral Intention to Use (BIU)/ Acceptance, followed by Image (I) and lastly Perceived Ease of Use (PEoU).

All constructs in all ten ANNs for each model had at least one non-zero synaptic weight connected to the hidden neurons which validates the relevance of the constructs as variables, as Figure 6.2, Figure 6.3, Figure 6.4, and Figure 6.5 show.

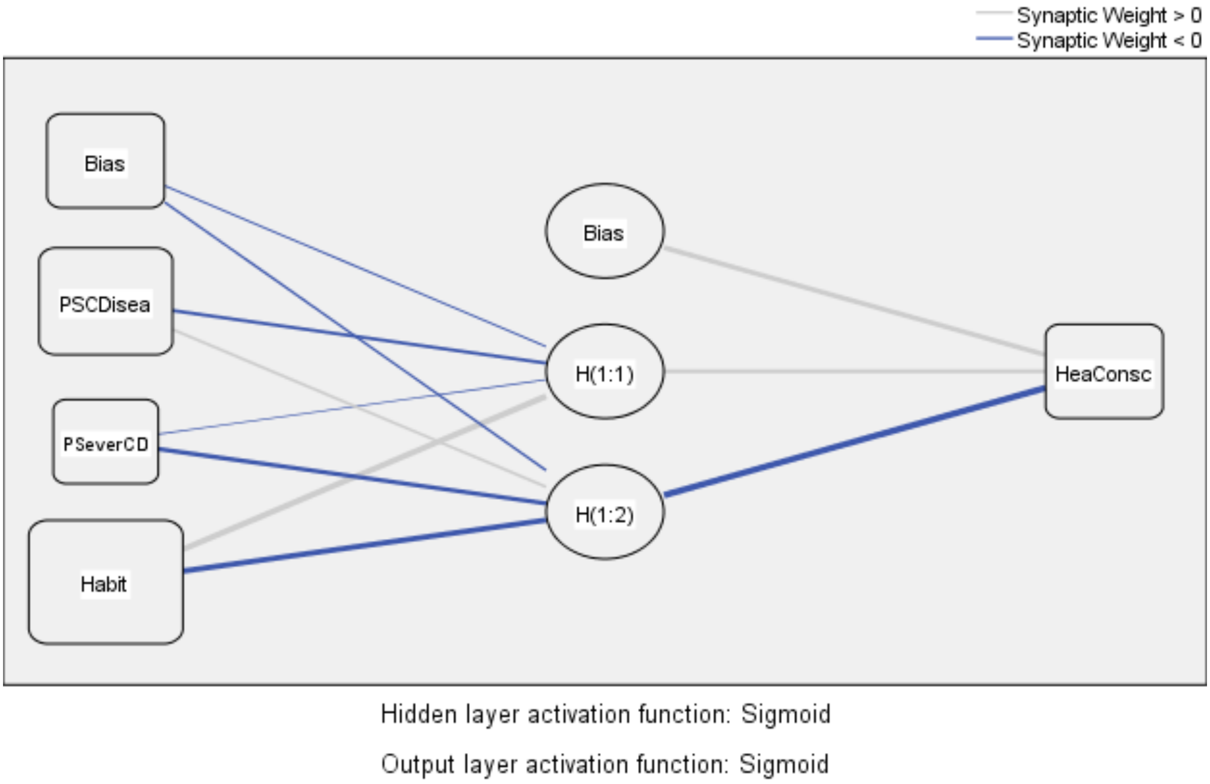

Figure 6.2– Neural Network between Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit with Health Consciousness

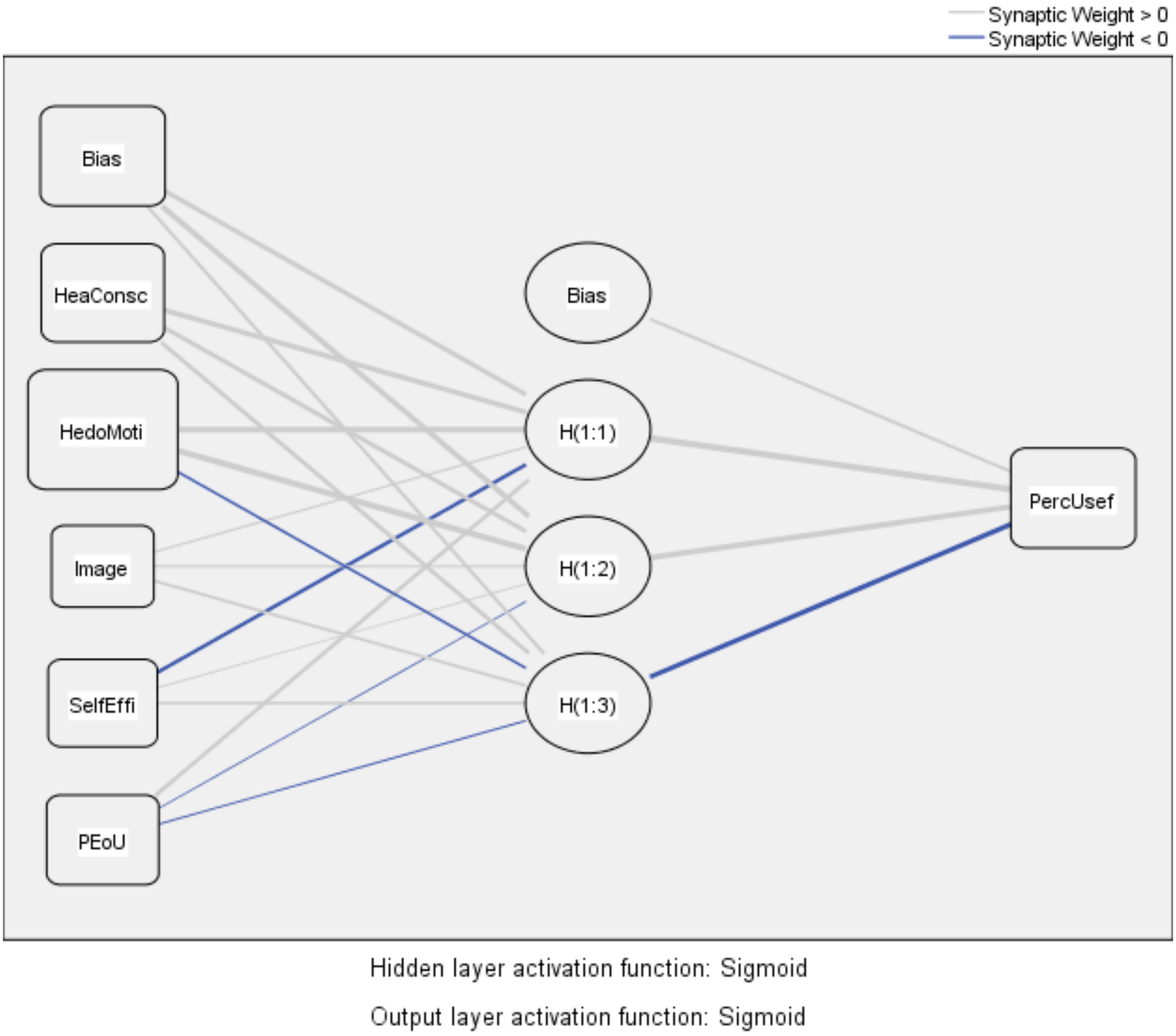

Figure 6.3– Artificial Neural Network between Health Consciousness, Hedonic Motivation, Image, Self-Efficacy, and Perceived Ease of Use with Perceived Usefulness

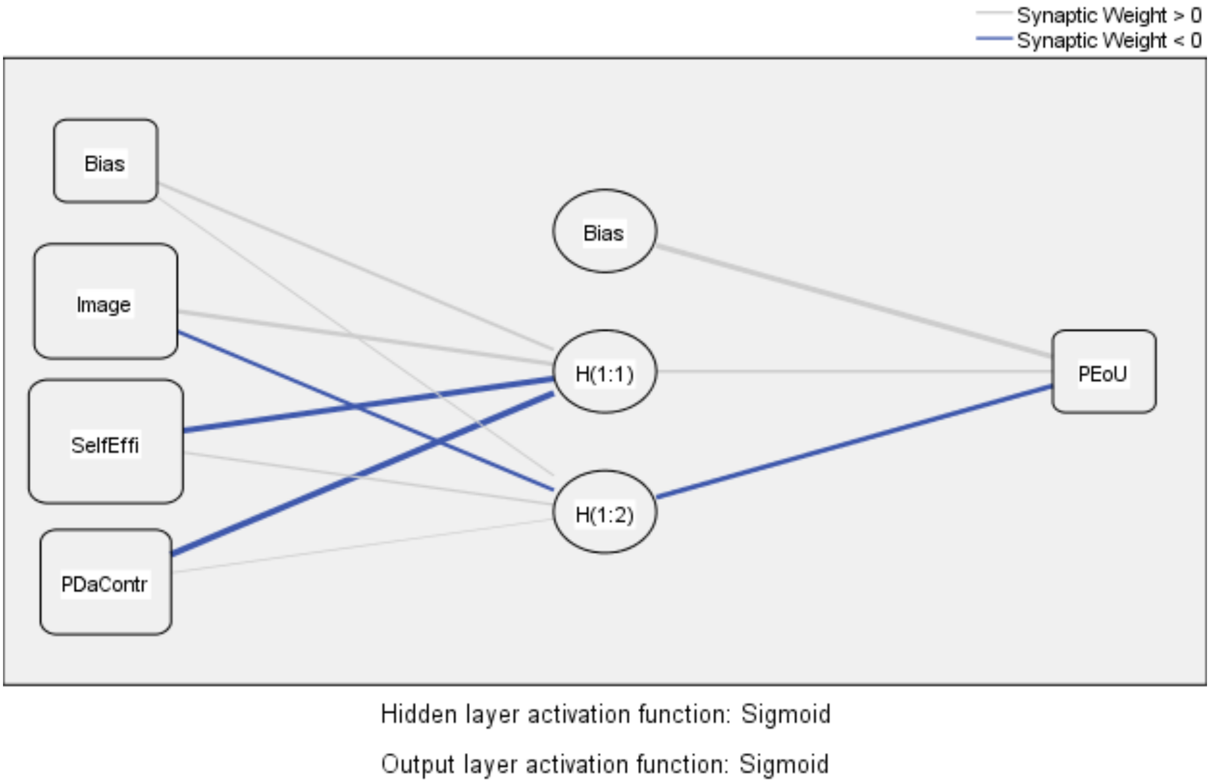

Figure 6.4– Artificial Neural Network between Image, Self-Efficacy, and Perceived Data Control with Perceived Ease of Use

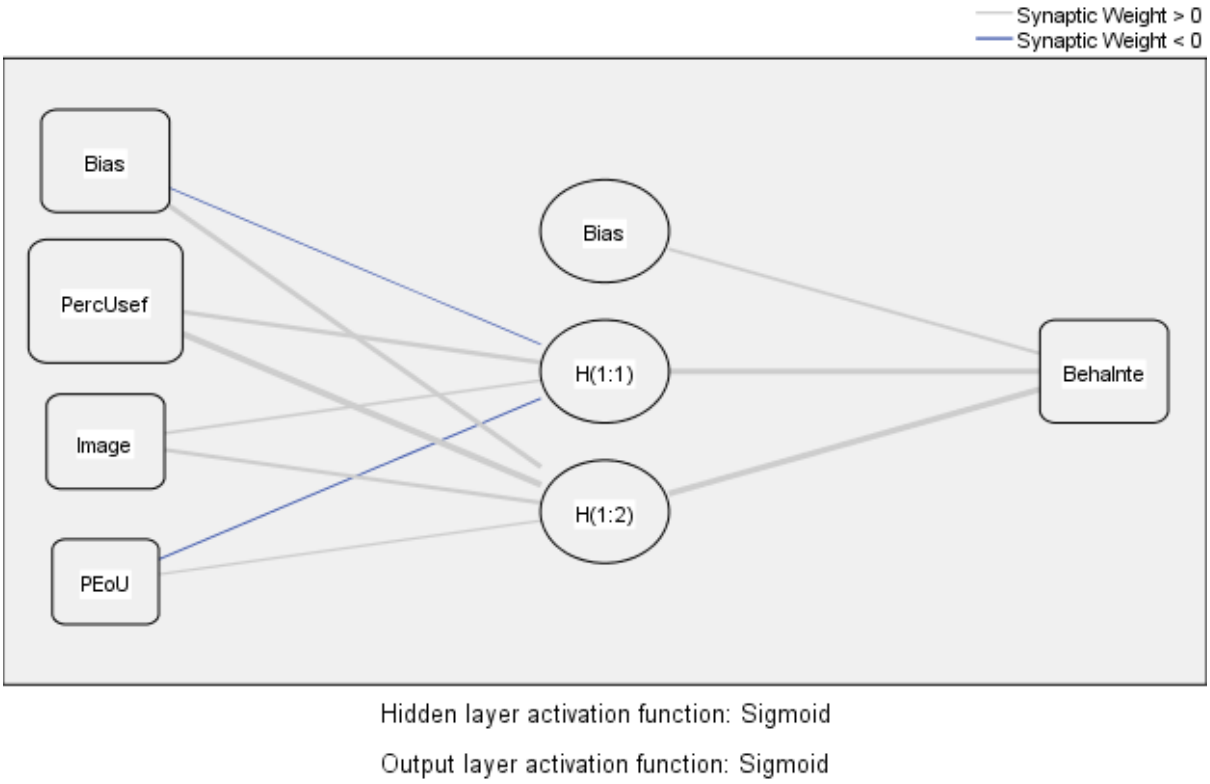

Figure 6.5– Artificial Neural Network between Perceived Usefulness, Image, and Perceived Ease of Use with Behavioral Intention to Use / Acceptance

6.6 Discussion

The Technology Acceptance Model (TAM) is based on many theories and grounded in many studies. In this work, the determinants of activity trackers use include TAM constructs and other constructs such as Image, Hedonic Motivation, Habit and Self-Efficacy. The results show that the research model studied in this work is acceptable. Next, the findings are discussed in more detail.

6.6.1 Relationships between Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit with Health Consciousness

As shown in Table 6.4, the construct Habit showed a significant relationship with Health Consciousness with a path coefficient of 0.451 obtained during the Structural Equation Modeling and has the highest normalized importance according to the Model A of the Artificial Neural Network analysis. While to our knowledge this relation is not found in the literature, the fact that both approaches ranked Habit in first place makes one ponder that a Health Conscious person has health habits.

Table 6.4 – Comparison between SEM and ANN analysis (output: Health Consciousness)

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Perceived Susceptibility to Disease	-0.114	3	68%	2	No
Perceived Severity of Disease	0.283	2	50%	3	No
Habit	0.451	1	99.8%	1	Yes

The findings in this study also show that the construct Perceived Severity to Disease with 50% normalized importance is positively related to Health Consciousness. Looking at this result one might consider that if a person is Health Conscious, then that person should have a high degree of awareness of disease and related issues. Nevertheless, the construct Perceived Susceptibility of Disease showed mixed results within the two approaches.

6.6.2 Relationships between Health Consciousness, Hedonic Motivation, Image, Self-Efficacy, and Perceived Ease of Use with Perceived Usefulness

During the SEM the path coefficient between Hedonic Motivation and Perceived Usefulness is 0.515 (see Table 6.5), which is a significant positive correlation with the highest normalized importance given by model B of the ANN. For many studies, the perception of Hedonic Motivation has been viewed as egocentric (Elsden et al., 2015) and an important issue for individual encouragement (Patel et al., 2015), provide motivation (Lazar et al., 2015), acknowledgement of effort (D. Kim et al., 2016) or giving credit (Consolvo et al., 2006).

The construct Perceived Ease of Use was promoted by the ANN when compared to SEM approach, however, the normalized importance was only 35.2%. This result is in line with previous work that demanded reminders to be added to the devices (Shih et al., 2015).

Regarding the construct Sell-Efficacy, the weak influence is corroborated by model B of the ANN. To some extent, this result is partially contradicted by earlier studies that ask for a tailored efficacy evaluation (Klasnja et al., 2011). The ANN demoted Health Consciousness giving a low normalized importance that shows a weak influence in Perceived Usefulness.

Since the normalized importance for Image is less than 10%, one may conclude that the effect of Image in Perceived Usefulness is very small in comparison to Hedonic Motivation. This result seems to contradict past research (Harrison et al., 2015) however one should keep in mind that here one is relating Image to Perceived Usefulness.

Table 6.5 – Comparison between SEM and ANN analysis (output: Perceived Usefulness)

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Health Consciousness	0.372	2	16.4%	4	No
Hedonic Motivation	0.515	1	100%	1	Yes
Image	-0.013	3	7.7%	5	No
Self-Efficacy	-0.060	4	18.9%	3	No
Perceived Ease of Use	-0.110	5	35.2%	2	No

6.6.3 Relationships between Image, Self-Efficacy, and Perceived Data Control with Perceived Ease of Use

The construct Image showed a significant relationship with Perceived Ease of Use obtained during the SEM and even though it does not have the highest normalized importance it is a high value according to Model A of the Artificial Neural Networks analysis. This finding of this research is compatible with the findings of existing studies that state that Image is present as a component of social tracking (Rooksby et al., 2014) and that it exists as both social competition and social comparison (Patel et al., 2015).

The ANN came to empower Self-Efficacy as a relevant construct in its relationship with Perceived Ease of Use opposing a path coefficient of -0.067 that SEM found (see Table 6.6). The ANN result corroborates with previous research that demanded good inter-device reliability (Dontje et al., 2015). Nevertheless, one has to take into consideration that an ANN measure with high predictive accuracy has both a linear and non-linear relationship among variables.

During the SEM the path coefficient between Perceived Data Control and Perceived Ease of Use is -0.115, which is in accordance with the lowest normalized importance ranking but a high value of 72.5% given by model B of the ANN. To some extent, this result is partially supported by earlier studies which emphasize that the personal information collected by self-tracking can be highly sensitive (Lupton, 2017). One should note that these results are influenced by the fact that in Model C the Average RMSE value of the testing is higher than the Average RMSE for training.

Table 6.6 – Comparison between SEM and ANN analysis (output: Perceived Ease of Use)

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Image	0.146	1	83.3%	2	No
Self-Efficacy	-0.067	2	93.4%	1	No
Perceived Data Control	-0.115	3	72.5%	3	Yes

6.6.4 Relationships between Perceived Usefulness, Image, and Perceived Ease of Use with Behavioral Intention to Use / Acceptance

Perceived Usefulness with the highest normalized importance (97.9%) given by Model D of the Artificial Neural Networks approach (see Table 6.7) was found in the Structural Equation Modeling to have a significant relationship in predicting Behavioral Intention to Use / Acceptance. This finding supports prior research, as the suggestions for the designers of activity trackers to facilitate micro-plans (Gouveia et al., 2018), add a wide variety of adjustable goals (Clawson et al., 2015), and have adjustable tracking goals (D. A. Epstein et al., 2015).

The construct Image shows a significant influence in predicting Acceptance in both approaches. The finding of this research is compatible with the findings of existing studies as the influence of activity trackers on lifestyle (Consolvo et al., 2006) and the importance of aesthetics and form (Harrison et al., 2015).

Concerning the SEM the path coefficient from Perceived Ease of use to Acceptance is -0.115, nevertheless the normalized importance given by model D of the ANN was 25.9%. This result is in line with previous work which points out that people are using activity trackers in a rather limited manner (Didziokaite, 2017).

Table 6.7 – Comparison between SEM and ANN analysis (output: Behavioral Intention to Use / Acceptance)

	SEM Path	SEM Ranking	ANN normalized relative importance	ANN Ranking	Rank Matched?
Perceived Usefulness	0.492	1	97.9%	1	Yes
Image	0.207	2	33.3%	2	Yes
Perceived Ease of Use	-0.115	3	25.9%	3	Yes

6.7 Conclusion

This research aimed to study beliefs and behavioral variables that impact the acceptance and use of activity trackers. It looked to an conventional technology acceptance model dedicated to activity trackers that was obtained via Structural Equation Modeling. These constructs of the model are used in an Artificial Neural Network as the input units of four ANNs. The Root Mean Square of Errors with the highest value of 0.118 indicates that the ANNs method achieves high prediction accuracy.

The constructs of the model were divided in four ANNs. Model A had as inputs the constructs: Perceived Susceptibility to Disease, Perceived Severity to Disease, and Habit, while the output was the construct Health Consciousness. Model B had as inputs Hedonic Motivation, Image, Self-Efficacy, Health Consciousness, and Perceived Ease of Use, while the output was Perceived Usefulness. Model C had as inputs Image, Self-Efficacy, and Perceived Data Control, while the output was Perceived Ease of Use. Model D had as inputs Perceived Usefulness, Image, and Perceived Ease of Use, while the output was Behavioral Intention to Use (BIU) / Acceptance.

When comparing the results of SEM and ANN analysis, the main disparity lies in the strength of the effect of the construct Self-Efficacy with regards to Perceived Ease of Use. The ANN analysis increases the importance of Self-Efficacy in the Perceived Ease of Use of activity trackers. Even though with a lower impact, the ANN also increases the importance of Perceived Susceptibility of Disease when related to Health Consciousness. On the other hand, it also decreases, with a not so high impact, the importance of Health Consciousness in Perceived Usefulness.

The ANN were able to emphasize the strengths and weaknesses of the model obtained via SEM. Furthermore, this research shows the relevance of the two-stage approach integrating SEM and ANN techniques to fine-tune technology acceptance models and to present valuable information that can be utilized to increase the acceptance and usability of activity trackers as well as to enhance device designs.

This research is restricted in the sense that it would be interesting to include control variables such as age and gender and compare the results. Also, it used a cross-sectional approach to obtain the responses of the activity trackers users at one point in time. Hence, in a future study one may repeat the questionnaire to the same users in a longitudinal approach to examine the temporal effects.

Chapter 7 Conclusions

The prior chapters discussed the theories and methods of how people accept wearable ubiquitous activity monitoring devices in depth. This chapter wraps up the thesis by focusing on the most important things that have been learned about wearable ubiquitous activity monitoring devices from both a theoretical and an empirical point of view. In addition, it describes the research limitations and discusses how important they are. The final sections cover how the results of the studies can be used to come up with ideas for more research on other interesting parts of how people accept wearable ubiquitous activity monitoring devices.

7.1 Summary of Contributions

The goal of this work was to find a link between wearable ubiquitous activity monitoring devices and technology acceptance theories to improve the ability of those theories to predict how people will accept and use activity trackers. In particular, the four studies took an inward-looking approach with the goal of shedding light on the characteristics of wearable ubiquitous activity monitoring devices. By showing them as a multi-dimensional construct that best explains how they fit in with technology acceptance theories. To set up the structure of the inquiry, a multi-method research strategy was prepared and used. Most of the research methods were quantitative, however, one was qualitative. The real-world data that was collected was analyzed and interpreted considering a set of research questions that came from theorizing about the phenomena.

The construction of two models that predict the activity tracking adoption and usage is the most significant theoretical contribution that can be taken away from this work.

In the first study of this research, an extended TAM model was used in a new setting to look at how people accept and use activity trackers. The results show that adding external factors to the TAM model (like self-efficacy, image, hedonic motivation, etc.) was successful. The results also show that the proposed model of how people accept and use activity trackers has a lot of power to explain and predict. Hence, combining the external factors with the TAM makes sense both from a theoretical and an empirical point of view. The measurement and structural models were also put to the test with structural equation modeling (SEM) and the AMOS statistical package, and one was then retested with ANNs. Additionally, the data for the empirical studies presented were gathered in a variety of ways, such as through e-mail and self-administered surveys in person. When these methods are used together, they are more flexible, faster, and less expensive than traditional ones. This work is built on prior research that had already been done to make predictive models that show how objective and subjective factors are linked to user acceptance and use.

These models may be used in two distinct ways:

First, they may be used to determine if enough users will utilize a given application over time to justify investing in its future development once a first prototype has been created.

Second, they may be used to enhance a design by identifying problems that must be rectified in order to increase user acceptance and use.

7.2 Design Guidelines for Activity Monitoring Devices

A good design should discover the optimal amount of proactivity and transparency for the application in order to be useful. Based on this work's experience with the acceptability and usage of wearable ubiquitous activity monitoring devices, the following criteria are recommended for any activity tracker designers:

The ATTAM may be used to extend the design iteration process by highlighting flaws that must be addressed in order to improve user approval. The model may also be used to see whether Activity Trackers (AT) can achieve adequate user approval in the long run. The ATTAM implies that Image may play a critical role in increasing acceptability of activity monitors. As a result, if people reject activity trackers, designers may need to include image-related elements to gain user acceptability.

To the best of current knowledge, the Extreme Users of Activity Trackers Technology Acceptance Model (EUATTAM) contribution is still unique in that the resulting model is an initial quantitative working main tool for designers employing the Extreme Users design technique. The EUATTAM achieves the model-based design goals described in the introduction. The theoretical foundations of models enable designers to pick the most correct model for the design challenge. However, designers must recognize and comprehend when the design challenge involves issues and aspects not addressed by the models. As a result, EUATTAM may assist Activity Tracker designers, particularly those working with the Extreme Users technique, since it reinforces and reveals more of what motivates extreme users to utilize these devices.

Activity Trackers should be designed with an emphasis on the system's effective reaction rather than the search for secondary factors. One may conclude from this that AT designers will need to be the ones to refine and evolve the subtle elements of wearable devices when engineers do not fulfill or predict device outcomes.

In the design of the devices, designers must have in consideration the finding that the devices motivated Athletes before and during running while Health Runners were motivated by the devices only when running.

According to the conclusion of this research, it was evident that an all-purpose interface is not appropriate. The results' originality highlights special design considerations: designers should address the overall settings' simplicity of use and usability, as well as the requirement for simple training programs and training settings. To achieve this, it is recommended that software includes several modes that may be chosen by different categories of users, such as pleasure runners, health runners, athletes, and so on. Another option is to link the modes to the three types of tracker motivations: behavior change, instrumentation, and curiosity.

7.3 Limitations

Every piece of research has its own flaws. Limitations show up at different points in the research process. They come about because the empirical part of the study is based on circumstances, such as spatial and temporal dimensions, the researcher's beliefs, and the specifics of the phenomenon being studied, especially how it has been treated by the research community in the past. Even though most of the results are statistically significant, positive and helpful, there are limitations that most field studies have.

The studies were done in voluntary settings, so the results may not apply to settings where the subjects are required to do something.

The studies overlooked the number of individuals who stopped using trackers after a few weeks, as most respondents are enduring tracker users. By not considering the dropouts, one might miss out on valuable insights that who stop using trackers after a few weeks could provide.

A key limitation of the ATTAM is that there were statistical limitations in the loadings of some factors, represented by some covariance between the factors.

The Extreme Users of Activity Trackers Technology Acceptance Model (EUATTAM) statistical results while mediocre are not necessarily surprising given that one is dealing with extreme users who, by definition, are at the extreme end of a distribution. The EUATTAM study is limited in few ways: its sample is biased, as 81.6 percent were males, however this is common in extreme sports, and a few items in the EUATTAM have statistical limitations in their loadings.

One limitation of the interviews is that it does not make a clear split between intention to use activity trackers and the actual use. This is because most of the interviewees were users of at least one activity tracker.

The ANN study is restricted in the sense that it would be interesting to include control variables such as age and gender and compare the results. Also, it used a cross-sectional approach to obtain the responses of the activity trackers users at only one point in time.

The biggest limitation is that the empirical data for these studies came from cross-sectional research, not longitudinal research. This means that the data were collected at one point in time, not at multiple points in time (Hair, 2009). Because each sample is different and has its own qualities, there are more restrictions. In all studies, sampling had to use non-probability methods and reach out to all possible respondents to get the highest response rates possible.

In the end, 247 and 209 respondents completed the survey questionnaires of the exploratory and confirmatory studies, respectively, which is more than the typical maximum of 100 respondents (Shin et al., 2019), resulting in a moderate sample power for statistical analyses. However, a larger sample would have given the results more statistical power. There is also the self-selection bias of those who took part in the empirical research against those who did not. People who did not take part in the study might have had interesting ideas that they did not share, but that could have helped the study's goals.

In terms of the statistical analysis method, the flow of effects could be tested more thoroughly, Structural Equation Modeling (SEM) is similar to multiple regression in that it is based on it and is used for similar things, but in a more powerful way. SEM can be used instead of multiple regression and path analysis, which are not as effective. No matter how the statistics are done, SEM cannot draw causal arrows in models or clear up ambiguities about what causes what. The researcher still needs to have a lot of theoretical knowledge and good judgment. This is a reason this work reanalyzed one of the models via qualitative analyses with 20 interviews and re-reanalyzed the same model via artificial neural networks.

Overall, the limitations above make it hard to say how well the findings can be used in other pervasive information systems and settings. Still, they open the door for more research in a wide range of methodological and theoretical directions that could help mitigate the limitations with the current research, expand on what it has found, and move the field of study forward in its understanding of how technology affects how end users accept and use pervasive information systems.

7.4 Future Research

When research results are used to find other questions that need more explanation or clarification and to look into different ways to add to what has already been found, this is the foundation of scientific advancement. This evolutionary view helps researchers learn more about the things that shape our world, whether they are new or have been around for a long time. It also helped to come up with new ideas.

Hence, every research project should follow this continuity principle by using the results of previous research to shape the current one. This is usually done in the literature review and theory-building processes, but it can also be done in a forward-looking way by suggesting new directions for research. Most of the time, these directions address current problems or findings that need more research. They also point out different points of view that could help researchers learn more about the phenomenon being studied and similar phenomena.

Two things give ideas for more research: the limitations of how this research was done, and the need to go into more detail about the findings about how people accept and use activity trackers through different theoretical lenses.

In the next few paragraphs, some possible directions for future research will be discussed based on what was found in this research.

The next step in this line of inquiry would be to apply an ANN to the data that was generated by the model since the Extreme Users Acceptance Model generates statistical results that are not very powerful.

Second, it would be an interesting challenge to try to reproduce the research with the use of more modern and robust Deep Learning Models that can be used with data from activity trackers users.

Third, it would be interesting to investigate the same research questions about how people feel about activity trackers using a different method than the one used in this study. Specifically, the benefit of longitudinal research suggests that timely replication of the interviews would give up-to-date information on the evolution of perceptions, beliefs, and intents of activity tracker users. This would allow for more nuanced evidence of the effect of beliefs development and prediction of usage intention, and further enhancing the test-retest validity of the scale (Grover & Lyytinen, 2015).

Fourth, it would be interesting to replicate these studies with the individuals who stopped using trackers after a few weeks. These individuals could provide valuable insights.

Despite the fact that twice as many participants as are customarily involved in research of this kind in this area have contributed to this study (Shin et al., 2019), a final next step might be repeating and verifying what has been found up to this point by using a bigger sample size of data and a wider range of respondents might be the last step in expanding the scope of this effort.

Two other avenues of inquiry that were planned for this work but were unexpectedly canceled due to the pandemic of SARSCov2 were:

The first planned method was intended to have the researcher riding a bike accompanying the users when training. The researcher planned to record a video of the users using an Activity Tracker device. After analyzing the videos the researcher should interview the users.

The second planned method was intended to have the users replicate their use of the device in a controlled environment. The researcher planned to record the user while performing a Think Aloud method when using an activity tracker device in the controlled environment.

These two methods would have given a different perspective with useful data to analyze and compare with the data from the surveys.

In conclusion, this research suggests a lot of different directions for future research, either focusing on its theoretical foundations or its methodological framework. Hopefully, it will lead to more theory and research.

7.5 Concluding Remarks

In this thesis, the potential for wearable ubiquitous activity monitoring devices to improve both the user experience and the efficiency of human-computer interaction was examined. Additionally, it was shown that even when users' interpretations are inaccurate, a good interface design might still improve engagement. The adoption and usage of activity trackers were investigated both qualitatively and quantitatively in this research. This research sought to pinpoint crucial elements that influence users' behavioral intentions about activity trackers.

For predicting the acceptability and usage of activity trackers, this research also suggests two research models that were expanded from the Technology Acceptance Model and the Health Information Technology Acceptance Model. According to the quantitative analysis of the Activity Trackers Technology Acceptance Model (ATTAM), users' behavioral intentions toward activity trackers were affected by perceived usefulness, perceived ease of use, subjective norms, and privacy. The research as reported provides evidence in favor of the hypothesis that Perceived Usefulness and Perceived Ease of Use are more significant predictors of behavioral intention to use activity trackers than Health Consciousness. The findings demonstrated that five factors included as antecedents in the model—Hedonic Motivation, Self-Efficacy, Perceived Data Control, Habit, and Image—had a favorable impact on the usage of activity trackers.

The study's conclusions will be helpful to designers as they develop and improve their activity monitors. The ideal method of human-computer interaction is one in which the user is always fully unconscious of what is happening. This study represents one more move in that direction.

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Appendix A – ATTAM Questionnaire

A.1 ATTAM Questionnaire

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
PU	Using an Activity Tracker is useful in managing my daily activity.			
PU	Using an Activity Tracker is advantageous in better managing my activity.			
PU	Using an Activity Tracker is beneficial to me.			
PU	Using an Activity Tracker is valuable to my			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
	activities.			
PEoU	Learning to use an Activity Tracker was easy for me.			
PEoU	My interaction with an Activity Tracker is clear and understandable.			
PEoU	I find an Activity Tracker to be flexible to interact with.			
PEoU	It is easy for me to become skillful at using an Activity Tracker.			
Attitude	I think it is a good idea to use Activity Trackers to monitor my activity.			
Attitude	I find it interesting to use an Activity Tracker for the monitoring of my activity.			
Attitude	The use of Activity Trackers may promote my activity.			
Attitude	In my opinion, the use of an Activity Tracker will			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
	have a positive impact.			
Image	People in my community who use Activity Trackers have less prestige than those who do not.			
Image	People in my community who use Activity Trackers have a high profile.			
Image	Having an Activity Tracker is a status symbol in my community.			
Self-Efficacy	I could complete a task using an Activity Tracker if there was no one around to tell me what to do as I go.			
Self-Efficacy	I could complete a task using an Activity Tracker if I could call someone for help if I got stuck.			
Self-Efficacy	I could complete a task if I had a lot of time to complete the mission for which an Activity Tracker was provided.			
Self-Efficacy	I could complete a task using an Activity Tracker if I had just the built-in help facility for assistance.			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Social Influence	People who influence my behavior think I should use an Activity Tracker.			
Social Influence	I use an Activity Tracker because most of my family/friends do.			
Social Influence	People that I respect are supporting the use of Activity Trackers.			
Social Influence	In general, the community supports the use of Activity Trackers.			
Facilitating Conditions	I have the resources necessary to use an Activity Tracker.			
Facilitating Conditions	I have the knowledge necessary to use an Activity Tracker.			
Facilitating Conditions	An Activity Tracker is not compatible with other systems I use.			
Facilitating	A specific person (or group) is available for			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Conditions	assistance with Activity Tracker difficulties.			
Hedonic Motivation	Using Activity Trackers is fun.			
Hedonic Motivation	Using Activity Trackers is enjoyable.			
Hedonic Motivation	Using Activity Trackers is very entertaining.			
Habit	The use of an Activity Tracker has become an habit for me.			
Habit	I am addicted to using an Activity Tracker.			
Habit	I must use an Activity Tracker.			
Habit	Using an Activity Tracker has become natural to me.			
Trust	I expect that the providers of Activity Trackers will provide trustful services			
Trust	Based on my experience with Activity Trackers I know they are trustworthy.			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Intention to Use	Assuming I have access to an Activity Tracker I intend to use it.			
Intention to Use	Given that I have access to an Activity Tracker I predict that I would use it.			
Output Quality	The quality of the output I get from an Activity Tracker is high.			
Output Quality	I have no problem with the quality of an Activity Tracker's output.			
Results Demonstrability	I have no difficulty telling others about the results of using an Activity Tracker.			
Results Demonstrability	I believe I could communicate to others the consequences of using an Activity Tracker.			
Results Demonstrability	The results of using an Activity Tracker are clear to me.			
Results	I would have difficulty explaining why using an			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Demonstrability	Activity Tracker may or may not be beneficial.			
Perceived Privacy Invasion	The use of an Activity Tracker in my daily life is an invasion of my privacy.			
Perceived Privacy Invasion	I am uncomfortable with the information an Activity Tracker collects.			
Perceived Privacy Invasion	I am concerned about the use of an Activity Tracker in my daily life.			
Perceived Data Control	I am concerned with my ability to control when my data/information is collected by the Activity Tracker.			
Perceived Data Control	I am concerned with my ability to control how frequently my data/information is collected by the Activity Tracker.			
Perceived Data	I am concerned with my ability to control how the			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Control	data/information collected about me is used.			
Perceived Data Control	I am concerned with my ability to control who is given access to the data/information collected about me.			
Personal Innovativeness	If I heard about a new technology, I would look for ways to experiment with it.			
Personal Innovativeness	Among my peers, I am usually the last to explore new technologies.			
Personal Innovativeness	I like to experiment with new technologies.			
Personal Innovativeness	In general, I am hesitant to try out new information technologies.			
PSusD	I have a higher likelihood of taking chronic diseases.			
PSusD	I have a strong possibility of having a chronic disease due to improper daily habits (drinking, smoking,			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
	dietary habit, lack of exercise, etc.).			
PSusD	I would say that I am the type of person who is likely to get chronic diseases.			
PSevD	I am afraid of facing attack or deterioration of chronic diseases.			
PSevD	If I face attack or deterioration of chronic disease, I will have difficulty with my work life (or domestic affairs).			
PSevD	If I face attack or deterioration of chronic disease, it will hinder my personal relationships.			
PSevD	If I face attack or deterioration of chronic disease, I will be long haunted by resultant problems.			
Health Threat	Compared to other people your age, would you that you get sick much more often.			
Health Threat	Compared to other people your age, when you get sick would you say you get much less sick.			

After reading the following description, please put a check mark in the place pertinent to your thinking.

		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Perceived Threat / Health Consciousness	I have the impression that I sacrifice a lot for my health.			
Perceived Threat / Health Consciousness	I consider myself very health conscious.			
Perceived Threat / Health Consciousness	I think that I take health into account a lot in my life.			
Perceived Threat / Health Consciousness	I think it is important to know well how to stay healthy.			
Perceived Threat / Health Consciousness	My health is so valuable to me that I am prepared to sacrifice many things for it.			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
Construct	**Question**	**1**	**…**	**7**
Perceived Threat / Health Consciousness	I often think about my health.			
Perceived Threat / Health Consciousness	I am prepared to do many things to have good health.			
Behavioral Intention	I intend to use the Activity Tracker in the next 12 months.			
Behavioral Intention	I predict I would use the Activity Tracker in the next 12 months.			
Behavioral Intention	I plan to use the Activity Tracker in the next 12 months.			

A.2 ATTAM Questionnaire Demographics

Age:		**------------------**	**------------------**	**------------------**
Gender:	Male		Female	**------------------**
Education	<= Mid School	<=High School	<= Bachelor	> =PhD

Appendix B – Summary of items and factor loadings with Promax Rotation in ATTAM

	Factor Loadings										
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1 Behavioral Intention				.979							
2 Behavioral Intention				.943							
3 Self-Efficacy					.907						
2 Self-Efficacy					.871						
4 Self-Efficacy					.839						

B-2 – Summary of items and factor loadings with Promax Rotation in ATTAM

	Factor Loadings										
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1 Self-Efficacy					.599						
4 Perceived severity to chronic diseases						.907					
2 Perceived severity to chronic diseases						.902					
3 Perceived severity to chronic diseases						.894					
1 Perceived severity to chronic diseases						.461		.312			

	Factor Loadings										
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1 Perceived Ease of Use							.955				
2 Perceived Ease of Use							.890				
4 Perceived Ease of Use							.819				
3 Perceived Ease of Use							.550				
3 Perceived susceptibility to chronic diseases								.891			
1 Perceived susceptibility to chronic diseases								.827			
2 Perceived susceptibility to chronic								.826			

B-4 – Summary of items and factor loadings with Promax Rotation in ATTAM

	Factor Loadings										
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
diseases											
2 Image									.901		
3 Image									.817		
1 Image									.552		
2 Habit										.945	
3 Habit										.888	
4 Habit										.529	
1 Habit										.455	
1 Hedonic motivation											.828
2 Hedonic motivation											.769
3 Hedonic motivation											.556

Appendix C – EUATTAM Questionnaire

C.1 EUATTAM Questionnaire

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
1	I have much interest in health.			
2	I attentively watch media coverage of health in newspaper, magazine, TV, etc.			
3	I believe that good health management can have good results			
4	I am willing enough to implement health management.			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
5	I now actively implement health management.			
6	My friends or acquaintances influence my behaviour for health management.			
7	When my friends or acquaintances implement health management, I feel a sense of rivalry to do better.			
8	I think I am aware of health or disease to a certain extent.			
9	I think I am aware of health or disease to a certain extent compared with my friends or acquaintances.			
10	I think I am aware of health or disease to a certain extent compared with experts.			
11	I have a higher likelihood of taking chronic disease.			
12	There is a person with chronic disease among my family members.			
13	I have a strong possibility of chronic disease due to improper daily habits (drinking, smoking, dietary habit, etc.).			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
14	I am afraid of facing attack or deterioration of chronic disease.			
15	If I face attack or deterioration of chronic disease, I will have difficulty with my work life (or domestic affairs).			
16	If I face attack or deterioration of chronic disease, it will interfere with my personal relationship.			
17	If I face attack or deterioration of chronic disease, I will be long affected by resultant problems.			
18	I am good at using Activity Trackers, smart phone, etc.			
19	I think I excel others in accessing Activity Trackers, smart phone, etc.			
20	I am confident of health information search and health management via Activity Trackers, smart phone, etc.			
21	I think I am well aware of health information search and health management via Activity Trackers, smart phone, etc.			
22	I think it is interesting to find health information and perform			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
	health management via Activity Trackers, smart phone, etc.			
23	I think it is useful to find health information and perform health management via Activity Trackers, smart phone, etc.			
24	It is credible to use information technology for provision of health information and health management.			
25	Activity Trackers contents for provision of health information and health management are reliable.			
26	Activity Trackers contents for provision of health information and health management are professional.			
27	Activity Trackers findings for provision of health information and health management are of acceptable quality.			
28	Activity Trackers findings for provision of health information and health management are easily understandable.			
29	Whenever I want to find health information, I can access the information via Activity Trackers.			

After reading the following description, please put a check mark in the place pertinent to your thinking.

		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
30	It takes less time to use Activity Trackers than other media for health information search and health management.			
31	It takes less effort to use Activity Trackers than other media for web-based health information search and health management.			
32	It is easy to find health information and learn health management tips using Activity Trackers.			
33	It is convenient to find health information and learn health management tips using Activity Trackers.			
34	It is an economic way to find health information and perform health management using Activity Trackers.			
35	Health information retrieval via Activity Trackers has improved my understanding of symptom, ailment, therapy, and health management of my usual interest.			
36	Health information retrieval via Activity Trackers has improved my capacity for health management.			

After reading the following description, please put a check mark in the place pertinent to your thinking.				
		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
37	I've gone to a doctor or a medical institution based on health information I found via Activity Trackers.			
38	Health information I found via Activity Trackers has influenced my lifestyle for good health (dietary habit, etc.).			
39	I have a positive thinking about the use of Activity Trackers for health information search and health management.			
40	Health information search and health management with Activity Trackers are helpful for me.			
41	Overall, I am satisfied with the use of the Activity Trackers for health information search and health management.			
42	I will continue to perform health information search and health management via Activity Trackers.			
43	I will access regularly to Activity Trackers for health information search and health management.			
44	I will recommend the use Activity Trackers to others as a			

After reading the following description, please put a check mark in the place pertinent to your thinking.

		Never	**…**	**A lot**
	Question	**1**	**…**	**7**
	method for health information search and health management.			

C.2 EUATTAM Questionnaire Demographics

Age:		-------------------	-------------------	-------------------
Gender:	Male		Female	-------------------
Education	<= Mid School	<=High School	<= Bachelor	> =PhD

Appendix D – Interviews

D.1 Triggers of the Interviews

Guiding Question	Construct
Icebreaking Comments	**–**
Which Activity Trackers do you know?	**–**
Have you ever used other device?	**–**
How was it's beneficial for you?	**PU**
Did you use it specifically for diet/performance	**–**
Which were the most difficult aspects using it? (using methods)-(managing and/or using)	**PEoU**
Do you have suggestions to solve these problems?	**PEoU**

Guiding Question	Construct
How was your experience with the information?	**–**
What do you think regarding the veracity of the information?	**Subjective Norm**
What do you think about the fact that the device has your information?	**Perceived Privacy Invasion**
What you think about your ability to control the information?	**Perceived Data Control**
What are your thoughts on using the info for promoting health and diet?	**–**
How do you feel when managing the information?	**Self-efficacy**
Do you recommend and would it be good for your friends to use it?	**–**
What are the impacts of the device in your life?	**Attitude**
What do you think about other people who use the device?	**Image**
Do feel good using the device?	**Hedonic Motivation**
Using the device is a habit for you?	**Habit**
What do you think about the price of the devices?	**–**
What kind of injury have you had?	**Perceived**

Guiding Question	Construct
	Susceptibility to chronic diseases
How do you react to the fear of having an injury?	**Perceived Severity to chronic diseases**
What kind of attitudes do you take concerning your health ?	**Perceived Threat / Health Consciousness**
In the long run do you think you will still use the device?	**Behavioral Intention**
In general how is the experience? Good or bad?	**–**
Revisions and Summary	

D.2 Interviews Demographics

Age:		-------------------	-------------------	-------------------
Gender:	Male		Female	-------------------
Education	<= Mid School	<=High School	<= Bachelor	> =PhD

D.3 Summary of Activity Trackers used

Athletes:	**Health Runners:**
Fitbit	Fitbit Charge 2 HR
Garmet 225 for Runner	Garmet
Nike App	Polar 400
Endomondo	Jawbone
Sportstracker	Apple Watch
Runkeeper	Google Fit
Everyzone	Runtastic
Strada	Fitband Smart
Polar M200	Xiaomi Amazing Fit
RunTracker	Samsung Health
Sunto Ambit	LG Smart watch
Tomtom	Motorola Smart watch
Xiaomi Fit Phase	Endomondo
-	IPhone

	Argos
	Map MyWalk
	MapMyFitness
	MyFitnessPal
	7 Minutes Workout
	Runtracker
	Tomtom Smart 3 Cardio
	Nuven

D.4 Characteristics of a common Activity Tracker

Fitbit Charge 2

General Information and Specifications

Sensors:

A MEMS 3-axis accelerometer, which tracks your motion patterns

An altimeter, which tracks altitude changes

An optical heart rate tracker Materials

Wireless technology: Charge 2 contains a Bluetooth 4.0 radio transceiver.

Haptic feedback: Charge 2 contains a vibration motor, for alarms, goals, notifications, and reminders.

Battery: Charge 2 contains a rechargeable lithium-polymer battery.

Memory: Charge 2 stores most minute-by-minute stats and exercise data for seven days. It stores Smart Track data for three days and summary totals for 30 days. Heart rate data is stored at one-second intervals during exercise tracking and at five-second intervals at all other times

Fitbit Basics

Wear your Charge 2 everyday to track a variety of stats:

Steps taken

Distance covered

Calories burned (total for day including rest)

Active Minutes with strenuous activity

Floors climbed

All day heart rate and zones

Daily Goal: Charge 2 will celebrate when you reach your main goal. By default this is set to 10,000 steps and it resets at midnight. You can change your goal in the Fitbit app settings.

To view your current progress towards your daily goal, press the button to turn on the screen and tap until you see your steps.

Navigation:

The screen of Charge 2 will turn on when you lift and turn your wrist towards you. You can disable this behavior in the Fitbit app.

Press the button or double-tap to turn on the screen then flip through the menus by pressing the button again.

On the clock single-tap to flip through your daily activity stats.

Sleep and Silent Alarms:

Your tracker will automatically track your sleep. Just wear it to bed!

Use the Fitbit app to manually adjust your sleep or set Sleep Goals

Use the Fitbit app to manually adjust your sleep or set Sleep Reminders

Managing Silent Alarms: Setting a bedtime reminder can help you maintain a consistent sleep schedule. Charge 2 will prompt you to unwind 30 minutes before your bedtime target. You can set a bedtime reminder using the app.

Silent Alarms

To wake up in the morning or alert you at a certain time of day, you can set silent alarms that gently vibrate.

Use the Fitbit app to set and manage alarms. You can also manage existing alarms right on your tracker.

To dismiss the alarm, double tap the tracker otherwise it will snooze once for 9 minutes.

Heart Rate

Charge 2 tracks your heart rate all day and during exercise.

See your heart rate on your tracker. When you exercise, the heart icon lets you know which heart rate zone you're in:

In Peak zone

In Cardio zone

In Fat Burn zone

Out of zone

You can customize your heart rate zones in the Fitbit app.

Reminders to Move:

Reminders to Move help you get moving every hour. Throughout your day, try to hit 250 steps each hour.

We use 250 steps because it roughly equals a few minutes of walking. Moving regularly breaks up stationary time and can help improve your well-being.

Personalize your Reminders to Move in the Fitbit app settings.

Tracking Exercise:

Fitbit Charge 2 will automatically detect certain exercises and record them using our SmartTrack feature which automatically recognizes continuous movement at least 15 minutes in length.

You can view the automatically detected exercise in your Fitbit app and adjust the duration for each exercise type.

Real-time Stats: Use the Exercise menu to start a workout. You can tap to cycle through the different exercise types and press and hold the button to start.

During your workout, tap to view different stats. To pause and resume your workout, press the button. When you're done, press and hold the button to end your workout and see your stats.

Track your route: Some outdoor workouts can track your GPS route and give you more accurate real-time stats like pace and distance when your phone is with you.

Make sure Bluetooth and GPS are both enabled to use the Connected GPS feature.

You can customize the activity types in the Fitbit app.

For best results, wait for GPS satellites to lock in on your location before you start.

Notifications:

Charge 2 can receive phone calls, text messages and calendar alerts when near your phone.

Notifications vibrate when your phone receives them. Just lift and turn your wrist towards you or press the button to see them.

You can manage notification settings in your Fitbit app.

Guided Breathing Sessions

The guided breathing sessions on your Charge 2 provide personalized deep breathing exercises that can help you find moments of calm. You can choose between two-minute or five-minute long sessions.

To get started, press the button until you get to the Relax screen, then tap to select a two-minute or 5-minute session.

Press and hold the button to start. Remain still as you begin breathing slowly and deeply, and when prompted, follow the guide (circle on the screen).

The more closely you're able to follow the guide, the more sparkles you'll see throughout the session. Once the session ends, you will see an overall summary of how you did.

All notifications are automatically disabled during the session. If you've set a silent alarm, your tracker will vibrate at the time specified.

Clock Faces:

Charge 2 comes with several clock styles. You can change your clock face in the settings of the Fitbit app. The new style will appear once you sync your tracker.

How to Wear it

Charge 2 is water resistant, splash and sweat-proof, but is not swim-proof. It's important to keep any wearable device clean and dry, so we don't recommend showering with Charge 2.

To track heart rate, your band should lay flat, a finger’s width above your wrist bone.

For better readings during exercise, wear the band higher up on your wrist—about 2-3 finger widths above your wrist bone.

Charge 2 will track your stats more accurately by knowing whether you’re wearing your tracker on your dominant or non-dominant wrist. You can adjust this in Handedness settings.

Changing Wristbands:

The wristband has two separate bands that are removed individually.

To remove or swap the band turn over your Charge 2 and find the band latches - there’s one on each end where the band meets the frame.

To release the latch, press down on the flat metal button on the strap. Then slide the band up to release it from the tracker. Repeat on the other side.

Wear & Care Tips:

Clean your band and wrist regularly with a soap-free cleanser.

If your tracker gets wet, remove and dry it completely.

Take your band off from time to time.

If you notice skin irritation, please remove your tracker. See our full Wear and Care Tips.

The tracker is water resistant, splash and sweat-proof, but is not swim-proof. It's important to keep any wearable device clean and dry, so we don't recommend showering with Charge 2.

Charging:

To charge your tracker plug the charging cable into a USB port. Connect it to your tracker and make sure the gold pins are aligned.

When you first see a low battery indicator on your tracker, you have about a day of battery left. Charging may take up to 2 hours, depending on the current power level. Your fully charged Fitbit Charge 2 has a battery life of up to 5 days. Note that battery life and charge cycles vary with use, settings and many other factors; actual results will vary. (Fitbit, 2016)

Appendix E – Consent Form

E.1 Consent Form for Participation in Research

Study Title: A Predictive Model for the Acceptance of Wearable Ubiquitous Activity Monitoring Devices

Researchers: Ricardo Sol (PhD Candidate)

Supervision: Professor Karolina Baras

Purpose of this study: The purpose of this study is to evaluate user performance whit activity trackers.

Procedures: You have been invited to participate in a survey. The session will take place in a research laboratory on the University of Madeira or via email. You must try to answer the questions as well as possible. The experimental data will be processed in such a way that your anonymity will be preserved.

Participant Requirements: You are eligible for participation if you: are more than 18 years old, are able to read, and use or have used an activity tracker.

Risks: The risks associated with participation in this study are no greater than those ordinarily encountered in daily life.

Benefits: The study will contribute to the understanding of how users use activity trackers.

Confidentiality: By participating in the study, you understand and agree that the researcher may be required to disclose your consent form, data and other personally identifiable information as required by law, regulation, subpoena or court order. Otherwise, your confidentiality will be maintained in the following manner. Data and information gathered during this study may be used by the researcher and published and/or disclosed by the researcher for research purposes. However, your personal information will never be revealed in any publication or dissemination of the research data and/or results.

E.2 Informed Consent Document

I understand that the responsible research team owns all information derived from the study "A Predictive Model for the Acceptance of Wearable Ubiquitous Activity Monitoring Devices". I give my consent for anonymous collection of data about me (results, pictures and videos), which will be stored and processed for scientific evaluation. I understand the significance of this information, and any questions I had were answered satisfactorily. I had enough time to decide on my participation in this study. I hereby consent my participation and the collection of information.

____ ____________

Signature of the Participant Date

____ ____________

Signature of the Researcher Date

A Nossa Universidade

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