IUL School of Social Sciences

Department of Social and Organizational Psychology

Nothing to hide, nothing to fear: The moderating effect of fear on AI empowered technology intention of use

Alexandre Marcos Vidreiro Rilho

Dissertation submitted as partial requirement for the conferral of the Masters degree in Social and Organizational Psychology

Supervisor: Nelson Campos Ramalho, PhD, Assistant Professor

ISCTE – University Institute of Lisbon

October, 2019

IUL School of Social Sciences

Department of Social and Organizational Psychology

Nothing to hide, nothing to fear: The moderating effect of fear on AI empowered technology intention of use

Alexandre Marcos Vidreiro Rilho

Dissertation submitted as partial requirement for the conferral of the Masters degree in Social and Organizational Psychology

Supervisor: Nelson Campos Ramalho, PhD, Assistant Professor

ISCTE – University Institute of Lisbon

October, 2019

Acknowledgements

The current dissertation represents the cumulative result of a several year academic journey, with countless hours of work, learning, enjoyment and trials, negative and positive emotions and experiences. This journey's conclusion would not be achievable without the presence and support of a key number of important people.

Firstly, I would like to thank Professor Nelson Ramalho for his valuable guidance, knowledge, availability and insight during this investigation, and also my colleagues, Filipa Matias and Miguel Longle, for their joined efforts on this particular subject of investigation and all-around contributes to this new artificial intelligence and psychology body of research.

Secondly, because no degree is without its hardships, I thank my closest friends for all the shared moments and companionship through these years. Thank you Pedro Gomes, Daniel Pereira, Margarida Jarego, Cláudia Trindade, Raquel Brandão, Marta Diogo and Robyn Ribeiro for all the good memories and laughs, through the good and bad, and for making my time in this institution feel like a second home.

Last but not least, I want to thank my family, Isabel Vidreiro, Carlos Rilho and Maria Vidreiro, for their continued trust and support.

Abstract

In today's world, technology enabled by artificial intelligence has been the subject of many myths regarding its hidden functions and the threat it poses to privacy and individual freedom. Fear is a powerful motive for human behavior when facing real or perceived threats. Fear is still poorly studied in the relationship between consumers of smart technology and their intention to use it, namely in the field of consumer technology acceptance within the emergence of AI empowered products. This study aims to explore the role that fear plays in reducing or reinforcing the intention to use technology with artificial intelligence, namely an AI empowered device that has very much become a part of us, the smartphone. With a sample of 211 smartphone users, the results show that fear hampers the willingness to use this technology as regards to social networks, even if its' use is taken as fun, and that an interface being perceived as easy-to-use positively influences the acceptance of biometrics AI apps by means of a perception of utility.

Keywords: artificial intelligence; fear; intention of use

Resumo

No mundo de hoje, a tecnologia potenciada por inteligência artificial tem sido tema de muitos mitos sobre as suas funções ocultas e a ameaça que ela representa para a privacidade e liberdade individual. O medo é um motivo poderoso para o comportamento humano no contacto com ameaças reais ou percebidas. O medo ainda é pouco estudado na relação entre os consumidores de tecnologia inteligente e a sua intenção de uso, nomeadamente no campo da aceitação da tecnologia no surgimento de produtos com inteligência artificial. Este estudo tem como objetivo explorar o papel que o medo desempenha na redução ou no reforço da intenção de usar a tecnologia com inteligência artificial, concretamente, no que concerne um dispositivo com inteligência artificial que se tornou parte do quotidiano, o *smartphone*. Com uma amostra de 211 utilizadores de smartphones, os resultados mostram que o medo trava a disposição de usar esta tecnologia para aplicações de redes sociais, mesmo que o seu uso seja considerado divertido, assim como uma perceção de facilidade de utilização do interface influencia positivamente a aceitação de aplicações biométricas de IA por meio de uma perceção de utilidade.

Palavras-chave: inteligência artificial; medo; intenção de uso

Table of Contents

Contents

List of Abbreviations

AI – Artificial Intelligence

BI – Behavioral Intention

CFA – Confirmatory Factor Analysis

CFI – Comparative Fit Index

CR – Composite Reliability

FARAI - Fear of Autonomous Robots and Artificial Intelligence

CPFS – Cyber-Paranoia and Fear Scale

C-TAM – Consumer Technology Acceptance Model

EoU – Ease of Use

IT – Information Technology

RMSEA – Root Mean Square Error of Approximation

TAM – Technology Acceptance Model

TLI - Tucker-Lewis Index

Introduction

Throughout history and time advancements in technology have propelled humanity to new heights and enhanced civilization, human capability, communication and development, both individually and as a society. A few hundred years ago, results that were only attained by hundreds of people doing handwork could then be achieved with much greater speed and efficiency by much fewer numbers, and although the marvels of the industrial revolution and subsequent developments in technology have launched the world into a new era, with an ever growing and technology-bound global population come all sorts of new challenges in the fields of usage, applications, ethics and universal rights.

One such challenge is that of securing privacy and individual freedom when dealing with a human-computer interface, namely a device that is now part of our very selves in a modern and developed society, the smartphone. With recent technological advancements came a new breed of mobile phones. No more are phones mere devices used solely to place calls or send a text message. In today's world smartphones are equipped with a plethora of functions, some more transparent than others, and with the more recent addition of Artificial Intelligence (AI) on our everyday devices comes a concern with privacy and fear that our lives in data are to be passed, sold and used in the name of profit or some unspoken interest.

In this day and age, AI empowered technology has been a target for popular and urban myths concerning its hidden functions and the threat it poses to privacy and individual freedom. Fear is a powerful motive for human behavior when facing real or perceived threats. Fear is still understudied in the relation between smart technology consumers and buying decision. However, AI also brings with it a halo of modernity, wonder, and sophistication. Therefore, the current dissertation is set to explore and shed light on the role that fear plays in detracting or boosting technology use intentions according with their perceived AI features.

Chapter I – Literature Review

1.1. Artificial Intelligence

Intelligence has proved to be a rather difficult trait to define and replicate. Over time, many attempts were made with the aim of mirroring, in a computer, the kind of intelligent behavior that is so characteristic of human beings. Some of which relied on symbol manipulation, learning through directives and emulating the human brain as the most effective way to replicate, on a digital platform, the versatility, adaptability and robustness the human brain exhibits on information processing (Oliveira, 2019). Namely, our species' unique ability to interpret external data, manipulate symbols and create languages in order to communicate and articulate complex and abstract ideas is what led to the creation of culture and technology. Analogously, in this section of literature review we explore the emergence of Artificial Intelligence in the image of human information processing, usually defined as a system's ability to interpret external data correctly, to learn from such data, and to use that knowledge to achieve specific goals and tasks through flexible adaptation (Kaplan & Haenlein, 2019). Through a 1950's lens, period where AI was first established as an academic subject, today's technological world would seem like something out of a science fiction book. From image recognition to self-driving cars, interfaces and smartphones, AI empowered technology has an ever growing prominence in a constantly changing, constantly self-modernizing society.

In its dawn, AI may probably find its origins in Isaac Asimov's Three Laws of Robotics, which, in his science fiction short story regarding an engineered robot, postulated the following:

(1) a robot may not injure a human being or, through inaction, allow a human being to come to harm;

(2) a robot must obey the orders given to it by human beings except where such orders would conflict with the First Law;

(3) a robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

Asimov's work became a staple and inspiration for robotics enthusiasts, scientists, philosophers and engineers all over the world, as well as a reference for discussion and implications regarding Artificial Intelligence and developments in computer science.

Contemporarily, English mathematician Alan Turing, influenced by his experience cracking the seemingly impossible German Enigma code during the war, thought about the possibilities and limits of machine intelligence, and devised the famed Turing Test, which postulated the circumstances in which a machine could be considered intelligent, that is, "when a human is interacting with another human and a machine and unable to distinguish the machine from the human, then the machine is said to be intelligent." Notably, to this day no form of AI has been able to pass the Turing test.

The term Artificial Intelligence, however, first derived from a conference held by Marvin Minsky and John McCarthy, in 1956, the *Dartmouth Summer Research Project on Artificial Intelligence*. This event gathered great minds in the field of mathematics and computer science, some of which are now considered the founders of AI. From the *Dartmouth Research Project* hailed the definition of AI as the problem of "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy, Minsky, Rochester, & Shannon, 1955). Subsequently, research and investment in AI fell short in the following decades, as the excitement and wonder began to waver, somewhat attributed to the book *Perceptrons* by Marvin Minsky and Seymore Papert (1969), in which the authors identified fundamental limits of the AI developed at that time (Erisman & Parker, 2019), such as computers lacking the necessary processing capability to match the effort required by an artificial neural network. The concept of artificial neural networks derived from psychologist Donald Hebb's search for methods of achieving true AI, dating back to the 1940's. Hebb proposed a theory of artificial learning which would replicate the process of neurons in the human brain (Hebb, 1949). Even though research began on Artificial Neural Networks, the constraints evidenced by Minsky & Papert (1969) led to negativity and disenchantment regarding the overemphasized promises of AI and substantial declines in research funds.

As technology and computing processing capabilities gradually became more powerful in the subsequent decades, Artificial Neural Networks re-emerge in the specific form of Deep Learning in 2015, and set new standards by beating the human world champion on a game considerably more complex than chess (Silver et. al, 2016). In the wake of its' resurgence, Artificial Neural Networks and Deep Learning today make up the cornerstone of most applications we know under the label of AI. They are the basis of image recognition algorithms used by Facebook, speech recognition algorithms that fuel smart technology and self-driving cars (Kaplan & Haenlein, 2019).

Contrastive to standard computer programs, AI learning systems function differently. The program is given some guidelines, examples of good output derived from input, and the learning system, through identifying statistical patterns in the data, figures out how to produce good output from the received input. Notably, although the person behind the system does not specify what the patterns are (even sometimes one might not fully understand them), the system discovers a way to deliver a good outcome, much like a child learns, through trial and error, failure, repetition, and then, success (Erisman & Parker, 2019). Such Deep Learning systems constitute the basis of artificial intelligence in the modern world.

To classify different types of AI, Kaplan & Haenlein (2019) borrow from literature which regards 3 skills or competencies for remarkable performance, these being cognitive intelligence (e.g., pattern recognition and systematic thinking), emotional intelligence (e.g., flexibility, self-confidence, self-awareness), and social intelligence (e.g., empathy, teamwork) (Boyatzis, 2008, Hopkins & Bilimoria, 2008; Luthans, Welsh, & Taylor, 1988; McClelland & Boyatzis, 1982, Stubbs Koman & Wolff, 2008). Based on these competences, there are considered to exist three types of AI systems, outlined in Figure 1.1.

	Expert Systems	Analytical AI	Human-Inspired AI	Humanized AI	Human Beings
Cognitive Intelligence	×	✓	✓	✓	✓
Emotional Intelligence	×	×	✓	✓	✓
Social Intelligence	×	×	×	✓	✓
Artistic Creativity	×	×	×	×	✓
		Supervised Learning, Unsupervised Learning, Reinforcement Learning			

Figure 1.1 – Types of AI systems

In a psychological approach, intelligence is regarded as a generally innate feature. Social and emotional intelligence, however, are attributed to skills that are learned and honed, which AI systems are able to replicate, in the sense that these can be trained to recognize these patterns, (e.g. through expression and face analysis) and adjust their responses accordingly.

Contrary to real AI, expert systems developed in the 90's lack the ability to learn autonomously from external data, and represent a different approach altogether since they assume that human intelligence can be formalized through rules and hence reconstructed in a top-down approach (also called symbolic or knowledge-based approach). If an expert system were programmed to recognize a human face, then it would check for a list of criteria (e.g., the presence of certain shapes, of a nose, of two eyes) before making a judgment based on embedded rules (Kaplan & Haenlein, 2019).

Real AI, however, uses a bottom-up approach (also called connectionist or behavior-based approach) by imitating the brain's structure (e.g., through neural networks) and using large amounts of data to reach an autonomous conclusion or output, such as a child would learn to recognize a face, not guided by a set of rules but by seeing many faces and, consequently, being able to recognize one as such.

This enables vastly more complex problem-solving than what could be dealt with via expert systems. Authors Kaplan & Haenlein (2019) state:

1.

   Analytical AI has merely cognitive intelligence features. It generates a cognitive depiction of the world and learns based on past experience to advise future resolutions. Most AI systems used by firms today fall into this group, such as image recognition software and autonomous vehicles.

2.

   Human-Inspired AI has features both from cognitive and emotional intelligence In addition to cognition, this type of AI is able to comprehend and process basic emotions.

3.

Humanized AI embodies all kinds of formerly stated competencies. Although this type of AI would be what we would truly call conscious, one such entity that autonomously experiences existence in a central manner is for now still unattainable.

Regarding AI learning from previous experience, there are three categories of learning processes: supervised learning, unsupervised learning, and reinforcement learning.

1.

Supervised learning connects given inputs to established desired outputs. This is one of the less opaque methods for users since humans are able to understand and accompany the process to some extent. Even elaborate methods such as neural networks are included in this category.

2.

In *unsupervised learning,* the outputs aren't specified, only the inputs, leaving it up to the AI system to deduce a positive outcome from gathered data, with said output resulting from the algorithm itself. As such, humans must be more trusting and dependent on the AI system itself to make choices that produce positive outputs, which can leave some people feeling uneasy. One such example is speech recognition in portable devices, which can be powered via unsupervised learning.

3.

In *reinforcement learning,* the AI is given an output variable to be maximized and a sequence of choices that can be made to influence the output (e.g. the system becoming proficient in a complex game, learning by trial and error from a set of initial rules, and reaching a level where it' even able to beat top players, such was the case in AlphaGo).

Contemplating the current state of AI the doubt emerges of whether there are any skills that remain unique of human beings and beyond the grasp of AI. This question is difficult to answer given the tremendous progress AI has experienced over the past decade (Kaplan &

Haenlein, 2019). It would however seem that humans may continuously have an advantage regarding art, expression, and creativity.

This evermore present technological wonder, however, isn't without its' challenges and opportunities. The potential is limitless for innovation through breakthroughs in algorithmic machine self-learning and autonomous decision-making, sparking a revolution and potential disruption in areas such as finance, healthcare, production, retail and logistics (Dwivedi et al. 2019).

The reality of AI overcoming human constraints in the intellectual and processing field gives way to an unfathomable change to come regarding productivity and efficacy. AI empowered systems within organizations are expanding rapidly, transforming business and manufacturing, extending their reach into what would normally be seen as exclusively human domains (Daugherty & Wilson, 2018; Miller, 2018). These systems have evolved to where self-driving cars, human-AI interfaces, medical diagnosis and app use are entirely run by artificial intelligence.

Additionally, to make things more complex, the Deep Learning system which powers most AI technology and machine learning today is inherently opaque, in the sense that while we can assess the output of these AI systems as positive or not, the inner machinations of the system's process in achieving these results remain blurry to us. This non-transparency may be deliberate (e.g. an organization wanting its algorithm to remain secret) or not, with some scenarios more acceptable than others.

Some researchers, such as Müller and Bostrom (2016), predict that AI systems are likely to reach overall human ability by 2075. In the face of this new, seemingly unstoppable force in technological progress and achievement, it proves of great importance to keep in mind that we, as a species, are yet to be fully aware of many of the ethical and world-changing considerations associated with AI and big data and its wider impact on human life, culture, sustainability and technological transformation (Duan, Edwards, & Dwivedi, 2019; Pappas, Mikalef, Giannakos, Krogstie, & Lekakos, 2018).

1.1.1. AI in Smartphones

During the last years, deep learning and AI became one of the main tendencies in the mobile business (Ignatov et al. 2019), as a natural consequence given that from the 1990s onwards mobile devices were getting empowered with more and more software for intelligent data processing, such as face and eyes detection, eye tracking, voice recognition, barcode scanners, accelerometer-based gesture recognition, analytical text recognition, handwritten text recognition, along with others.

In the year 2010 the circumstances took a massive leap when mobile devices started to get better processors and more powerful hardware, more adequate for machine and deep learning processes. Coincidentally, there was a fast development of the deep learning field, consisting of a number of new approaches and models that were attaining a fundamentally new staple of performance for many practical undertakings, such as image organization, photography and speech processing, neural language comprehension, among others. Since then, the formerly available hand-crafted systems were progressively replaced by substantially more powerful and proficient deep learning techniques, carrying us to the present situation of AI applications on smartphones.

Today, several deep learning models can be found in virtually any mobile device. Among the most prevalent tasks are diverse processes like image organization, image improvement and super-resolution, object tracking, optical character recognition, face detection and recognition, as well as augmented reality. An additional important group of tasks realized by mobile devices is related to various language processing problems, such as natural language translation, sentence completion, voice assistants and interactive chatbots.

Furthermore, many tasks deal with time series processing, *e.g.*, human activity recognition, gesture recognition, sleep monitoring, adaptive power management, music tracking and classification. (Ignatov et al. 2019).

A plethora of deep learning algorithms are likewise embedded directly into smartphones firmware and used as supplementary means for assessing numerous factors and for intelligent data processing.

Although running many advanced deep learning models on smartphones was at first a challenge, the situation has drastically changed in recent years.

Notably, the incredible progress in mobile AI hardware since last year is undeniable, taking the AI capabilities of smartphones to a substantially higher level. In the next two to three years all mid-range and high-end devices will be powerful enough to run the vast majority of ordinary deep learning models developed by the research community and industry. Consequently, this will result in even more AI developments pursuing mobile devices as the main platform for machine learning distribution.

1.2. Fear

Fear has been extensively studied in Psychology and has been a fundamental emotion that models human behavior (Phelps & LeDoux, 2005). The stimuli that enact fear vary and such mechanism is taken as adaptive and facilitating survival (Bentz & Schiller, 2015). However, fear itself can also be hazardous in the sense that is can be displaced from real threats and hamper individuals' ability to cope with unknown objects and jeopardize their survival (Beckers, et al., 2013). Fear of novelty is a known barrier to technology acceptance and adaption (Lee, Rhee & Dunham, 2009).

1.2.1. 1.2.1. Fear of Artificial Intelligence

Although fear has been widely explored as a fundamental individual emotion, some would argue that a new type of collective, societal fear and distrust is taking place on a cultural level. This could effectively be a contributing factor for explaining an increased fear of novelty and change itself in a constantly evolving, fast paced world. However, the simple "flight or fight" response to fear is often looked upon with the most naturalistic view, while in reality its occurrence depends heavily on situational factors (Tudor, 2003). There is the possibility that, in the face of danger, one lacks the adequate cognitive map to identify it as perilous and menacing, whilst in spite of that still feel afraid when confronted with an unknown artifact, either by its mystery or unpredictability. Even so, it is imaginable that our cognitive mechanism motivates us to explore this novel, intriguing thing rather than avoid it, to wallow in it rather than flee from it.

Naturally, different types of fears and concerns emerge on individuals when faced with the concept of AI, some being the replacement of jobs and employment, qualified work, displacement of workers and/or inadequately prepared political systems and institutions (Smith & Anderson, 2014), with the increasingly growing perception that breakthroughs in AI and robotics will fundamentally transform the workplace in the following decades (Brynjolfsson & McAfee, 2014), (Ford, 2015), as the result of a new industrial revolution marked by transformative and fast paced technological change (Berg, Buffie & Zanna, 2018). Additionally, there is a prevalence of fear concerning security and privacy invasion threats with the use of technology (Taipale, 2005). Particularly associated with smartphones hidden functions, algorithms and ethical use, individuals above all fear privacy intrusions and malicious activities (Gates et al. 2014), mostly regarding the realization of the amount of personal information collected by apps (Boyles, Smith & Madden, 2012), mobile malware intentionally developed to breach platforms (Fortinet, 2014), location and movements tracking without the users' knowledge (Diaz, 2012), and transmission of that information with third parties without disclosure or consent (Thurm & Kane, 2010), as well as service providers' information collection regarding calls and text messages, which, obliviously to the user, may then be shared with third parties in the form of big data (e.g. for advertisement purposes).

Others take concerns on the subject of Artificial Intelligence a step further. In the last decades, notable figures took cautionary and alarming stances regarding AI development (Johnson & Verdicchio, 2017). Personalities such as Stephen Hawking and Elon Musk noted that the development of Artificial Intelligence may very well result in a catastrophic and out of control super intelligent system which would have disastrous consequences to human beings and society in general, even calling it our biggest existential threat (Kurzweil, 2014), a scenario that would very much mirror Icarus when he flew too close to the sun.

In sum, there is no shortage of negative predictions derived from AI emergence, whether being in interpersonal relations, unemployment, crumbling of economies and societal systems, weapon development and the escalation of conflict, and, lastly, humanity's subversion and ultimate (ironically self-engineered) demise (Vasile, 2018).

Thus, as autonomous technology begins to be ever more pervasive in all aspect of our lives, in contexts such as work, leisure, health, industrial and military, so too emerges a necessity to understand and anticipate individuals' reactions, expectations and thoughts regarding human-technology interactions. Yuhua and Seungcheol (2017) examined fear of artificial intelligence based on the fear concept's sociological characteristics and its ability to elicit strong emotional responses, introducing the novel concept *of Fear of Autonomous Robots and Artificial Intelligence* (FARAI), as a way to further explore the collective expectation/apprehension regarding human-robot interaction. The study suggested that individuals' responses to autonomous robots and artificial intelligence were found to be empirically indistinguishable. Consequently, FARAI corresponds to the likelihood that individuals anticipate a higher magnitude of negative experience (i.e., to the point where they anticipate being fearful) when interacting with an autonomous robot and/or artificial intelligent machine (Yuhua & Seungcheol, 2017). As such, self-reported FARAI was considered as a measure for the purposes of the present research.

1.3. Cyber-Paranoia

Considering today's concerns and anxieties regarding personal privacy and the secure use of technology, it is understandable that delusions regarding technology and computer-related fears are ever more common and widespread, fears which can range from the comprehensively realistic to the plain paranoid (Mason, Stevenson & Freedman, 2014).

The fast paced development and use of technology has numerous research ties to delusions and paranoid thinking. Some authors have brought to light an excessive level of fear in respects to modern technology and security issues in the modern world, such as Stewart and Segars (2002) who coined this term *computer anxiety*, suggesting that this can influence the intention of using cyber-technology.

Consequently, Mason, Stevenson and Freedman (2014) have sought to assess cyber-related feelings, attitudes, beliefs, and behaviors that stem uniquely from distrust, fear, and paranoia, and coined these extreme unrealistic fears regarding threats via information technology as *cyber-paranoia*, thus constructing and validating a new measure, the Cyber-Paranoia and Fear Scale, in order to assess these exacerbated fears regarding threat perception in cyber-technology. Ever since the use of information technology, namely the internet and

GPS/tracking technology became more prevalent and of common-use, the literature has shown an ever-growing number of reports of paranoid delusions with technology as a central theme (Catalano et al., 1999; Compton, 2003; Lerner et al., 2006; Nitzan et al., 2011).

Additionally, the fact that Stewart and Segars (2002) suggest that the intent to use cyber-technology can be influenced by this type of fear made us consider the use of the Cyber-Paranoia and Fear Scale as a valuable measuring tool for the purposes of this study, regarding the novelty and wonder that is artificial intelligence in recent technology.

1.4. Technology Acceptance Model

Ever since before the turn of the century researchers have tried to pinpoint and better understand the factors that influence technology acceptance in this increasingly technology-dependent world. One such theory for technology acceptance relied on the TAM, the Technology Acceptance Model, which was broadly used in management of information systems (Davis, 1989). This model was an adaptation of the theory of reasoned action (Fishbein & Ajzen, 1975) and was meant to parsimoniously explain the determinant factors for technology acceptance and use whilst also being broad enough to apply to usage behavior over a large array of different technologies. (Davis, Bagozzi & Warshaw, 1989). According to the TAM, an individual’s behavioral intention to use a certain type of technology is determined by the individual’s attitude regarding that technology. Attitude which, in itself, is determined by the perceived usefulness and perceived ease of use of said technology.

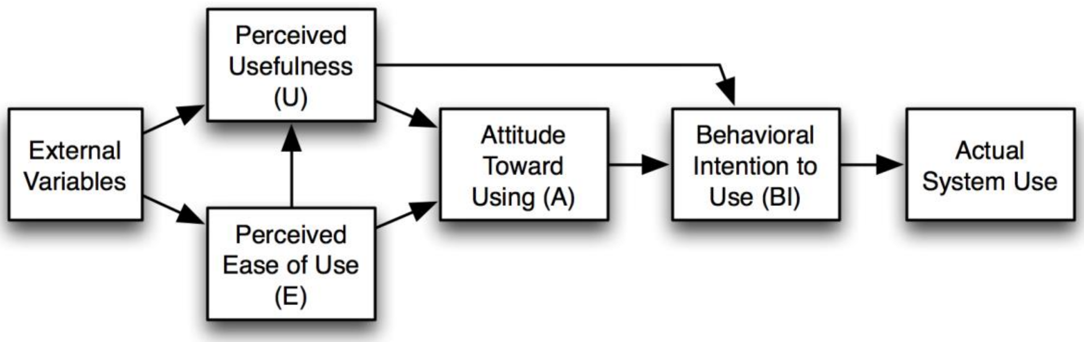


Fig. 1.2 – Technology Acceptance Model (Davis, 1989)

The TAM, however, being all the more focused on cognition rather than affect, proves to be lacking in regards to fully explaining consumer behavior in adopting new technology, in which individuals base their adoption on rejection of technology on the way they think as well as how they feel (Bruner & Kumar, 2007). As such, a hedonic factor seems to be an important factor in the model when considering a consumer context (Childers et al., 2001; Dabholkar and Bagozzi, 2002).

Consequently, a response to a better understanding of the consumer context in technology acceptance came in the form of the Consumer Technology Acceptance Model (c-TAM), developed by Bruner & Kumar (2003), which also regarded fun as a predicting factor for behavioral intention to use a type of technology.

By considering affective factors as well as cognitive ones, the c-TAM relates to fear in the aspect that fear itself is an affective response and alert system which functions as an inhibitor of behavioral action, and, more importantly for the purposes of this study, behavioral intent. As stated before, in order to fully understand the consumer context in technology acceptance we must explore and grasp the contribute of emotions. As fear is a powerful emotion and motive for human behavior, we formulated the following hypotheses regarding fear and technology acceptance.

1.5. Hypotheses

The integration of all hypotheses is depicted in figure 1.3.

.

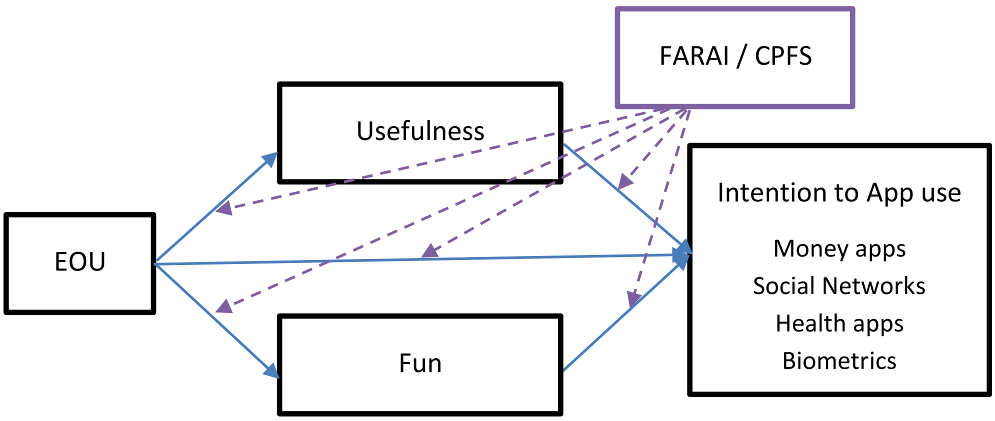


Figure 1.3 – Research model

For clarity sake, we will depict separately the cognitive path (mediated by usefulness and moderated by FARAI in Figure 1.4) as well as the affective path (mediated by fun and moderate again by FARAI in Figure 1.5).

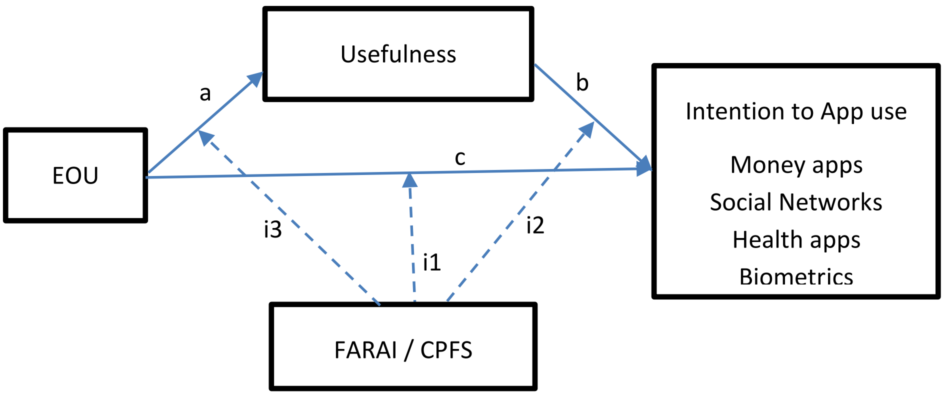


Figure 1.4 – Research model for cognitive path (usefulness)

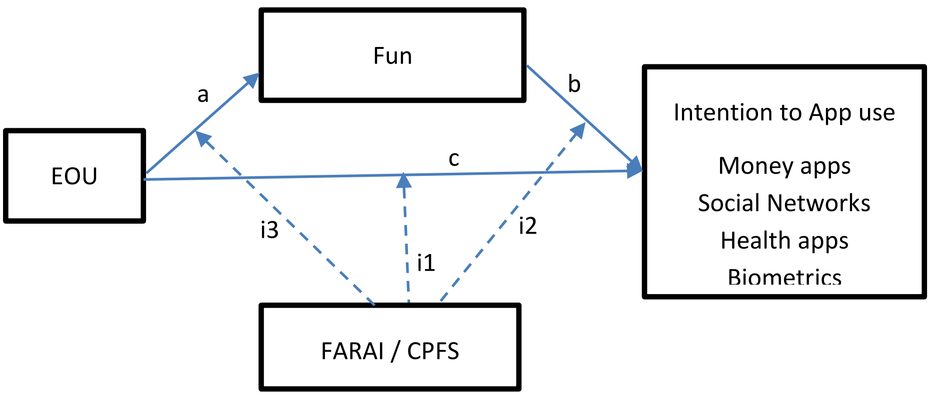


Figure 1.5 – Research model for affective path (fun)

Hypothesis 1 concerns the mediating role usefulness and fun play between EOU and behavioral intentions. Therefore, we hypothesize that:

Hypothesis 1a: **Usefulness mediates** the positive relationship between **EOU** and **behavioral intention** to use money-related apps (1a.1), social-related apps (1a.2), health-related apps (1a.3) and biometrics apps (1a.4).

Hypothesis 1b: **Fun mediates** the positive relationship between **EOU** and **behavioral intention** to use money-related apps (1b.1), social-related apps (1b.2), health-related apps (1b.3) and biometrics apps (1b.4).

Hypothesis 2 concerns the moderating effect that FARAI and Cyber-paranoia play in the paths linking directly EOU to BI. Therefore we hypothesize that:

Hypothesis 2a: FARAI will moderate the direct effect between EOU and Behavioral Intentions to use AI empowered apps, in such a way that the direct effect is weaker as FARAI increases.

Hypothesis 2b: Cyber-paranoia will moderate the direct effect between EOU and Behavioral Intentions to use AI empowered apps, in such a way that the direct effect is weaker as Cyber-paranoia increases.

Hypothesis 3 concerns the moderating effect that FARAI and Cyber-paranoia play in the paths linking EOU to BI via both cognitive and affective paths. Therefore we hypothesize that:

Hypothesis 3a: FARAI will moderate the indirect effect between EOU and Behavioral Intentions to use AI empowered apps through usefulness, in such a way that the indirect effect is weaker as FARAI increases. This moderation can occur either in path a (EOU->Usefulness) and/or b (Usefulness-> BI).

Hypothesis 3b: FARAI will moderate the indirect effect between EOU and Behavioral Intentions to use AI empowered apps through fun, in such a way that the indirect effect is weaker as FARAI increases. This moderation can occur either in path a (EOU->Usefulness) and/or b (Usefulness-> BI).

Hypothesis 3c: Cyber-paranoia will moderate the indirect effect between EOU and Behavioral Intentions to use AI empowered apps through usefulness, in such a way that the indirect effect is weaker as Cyber-paranoia increases. This moderation can occur either in path a (EOU->Usefulness) and/or b (Usefulness-> BI).

Hypothesis 3d: Cyber-paranoia will moderate the indirect effect between EOU and Behavioral Intentions to use AI empowered apps through fun, in such a way that the indirect effect is weaker as Cyber-paranoia increases. This moderation can occur either in path a (EOU->Usefulness) and/or b (Usefulness-> BI).

Due to the multiple dimensions of BI, as stated .a1 refers to money related apps, .a2 refers to social related apps, .a3 refers to health related apps, and .a4 refers to biometrics apps. Therefore, future sub-hypotheses will be referred to as e.g. 3a1, 3b3, etc.

Chapter II – Method

2.1. Procedure

For the purposes of this study, an online questionnaire was created on qualtrics and subsequently distributed by online link via e-mail, social media and other work and academic groups, such as LinkedIn and the university's public Facebook page, to smartphone users aged 18 and up. In the first page of the questionnaire data and identity anonymity and confidentiality were guaranteed via an informed consent, to which the collected data was only to be used purely for research and academic purposes. If not granted by the participant, the questionnaire would end at this point. Additionally, an introduction to the general theme of the study and relevant information was provided. The questionnaires' data was exported directly from the platform. The whole data gathering process occurred approximately during a two-month period. Participants were eligible if they stated they owned a smartphone which was measured by means of a single control question placed upfront.

2.2. 2.2. Sample

A sample of 211 individuals was gathered for this study, of which 70.8% are female. The participants' age ranges between 18-69 years-old, with an average of 30.16 years-old (sd=11.73) and own a smartphone (averaging 6.9 years, s.d.=3.5, ranging 1 to 24 years). On Marital Status, a larger portion of individuals are single, representing 72.8% of the total sample. The majority (79.2%) does not work in an IT related job.

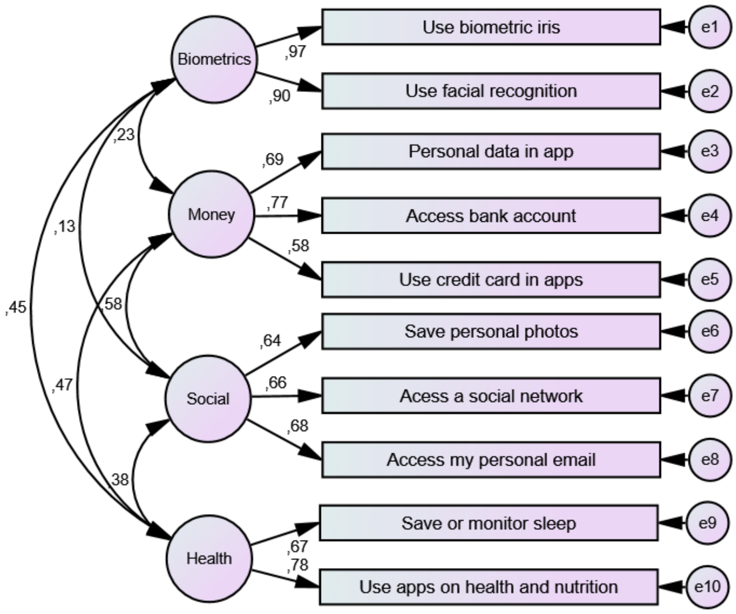
2.3. 2.3. Data analysis strategy

Data analysis followed a twofold strategy where variables were tested for their psychometric quality (i.e. that they are both valid and reliable) and then, after guaranteeing these conditions, the analysis focused on hypothesis testing.

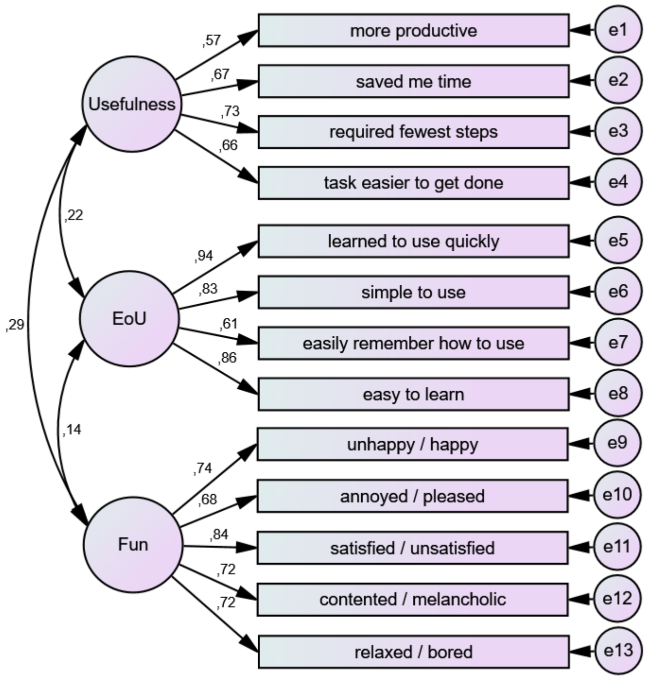
A given measure is considered psychometrically sound when it has good fit indices in a Confirmatory factor analysis, and cumulatively has both convergent and (when applicable) divergent validity. A confirmatory factor analysis goodness of fit is judged on the basis of indices as proposed by Hair et al. (2010) as follows: χ^2/df below 3.0 and with a non significant p-value, Comparative Fit Index (CFI) above .92, Tucker-Lewis Index (TLI) above .92), Root Mean Square Error of Approximation (RMSEA) below .06. This indicates construct validity. Additionally, the measures are expected to comprehend factors that have convergent validity, i.e. where average item loading achieve at least 50% variance, which means the Average Extracted Variance (AVE) should be .50 or higher. Also, whenever the factor solution counts with more than a single factor, divergent validity should be tested. It is expected that a solution with divergent validity show higher average factor loadings in each factor than the respective interfactor correlations. Lastly, measures are expected to be reliable, i.e., either show a Cronbach alpha or a Composite Reliability of .70 or higher. According with Fornell and Larcker (1981: 46) whenever AVE fails to reach the threshold, we can judge the suitability of the factor based on CR's threshold.

2.4. Measures

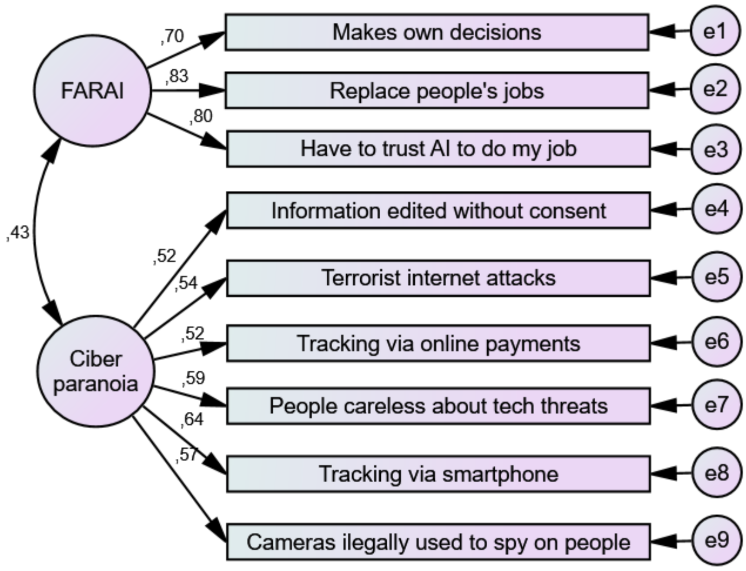
Behavioral intention of use was a measure built for this study on the basis of a focus group conducted which indicated consensus around 15 items. The original design thus, comprehended 15 items covering five groups of smartphone applications use, namely: 1) money-related (3 items, e.g. online banking), 2) social contacts related (4 items, e.g. social networks), 3) health-related (2 items, e.g. health status monitoring), 4) biometrics related (4 items, e.g. fingerprint access), and 5) GPS related (2 items, e.g. tracking on base of GPS). By conducting a CFA with this solution we found the fit indices unsuitable (χ^2/82=2.237, p<.001; CFI=.897, TLI=.849, RMSEA=.077). By using Lagrange multipliers as well as applying rules for psychometric quality as stated in section "Data analysis strategy" we excluded several items and the final factorial solution kept four of the five initial factors. The resulting model showed good fit indices (χ^2/31=1.323, p=.108; CFI=.984, TLI=.972, RMSEA=.039) and the structure of the factors is the following: 1) money-related (3 items, "Int1_Place my personal data in a smartphone application", "Int2_Access my bank account", and "Int11_Use applications that require a credit card", AVE=.468, CR=.72), 2) social contacts related (3 items, "Int8_Acess your personal email", "Int7_Acces a social network", and "Int3_Store personal photos", AVE=.43, CR=.70), 3) health-related (2 items, "Int4_Store or save monitoring my sleep" and "Int6_Use applications to monitor my health and feeding habits", AVE=.52, CR=.69), and 4) biometrics related (2 items, "Int14_Use biometric identification via iris or retina" and "Int15_Use facial recognition", AVE=.89, CR=.94).



Technology acceptance was measured with C-TAM that comprehends three dimensions: ease of use (EoU, 5 items, e.g. “I quickly learned how to use it”), usefulness (5 items, e.g. “Requires a lesser number of steps to do the tasks I want to”), and fun (6 items, e.g. “dissatisfied/satisfied” or “angry/calm”). The CFA showed unsuitable fit indices (χ^2/101=2.493, *p*<.001; CFI=.898, TLI=.862, RMSEA=.084). By using Lagrange multipliers as well as applying rules for psychometric quality as stated in section “Data analysis strategy” we excluded three items (one per dimension). The resulting model showed good fit indices (χ^2/62=1.649, *p<.001*; CFI=.966, TLI=.957, RMSEA=.056). The solution has convergent validity (for all factors): AVE_{EoU}=.436, CR_{EoU}=.754; $AVE_{Usefulness}$=.671, $CR_{Usefulness}$=.889; AVE_{fun}=.550, CR_{fun}=.859).



Cyber-paranoia and Fear were measured with Cyber-paranoia and fear scale (CPFS, Mason, Stevenson and Freedman, 2014) as well as with Fear of Autonomous Robots and Artificial Intelligence scale (FARAI, Yuhua & Seungcheol, 2017). CPFS comprehends two factors (paranoia and fear) that were measured with 5 items each (e.g. "People do not worry enough about threats from their use of technology", and "I avoid using the internet on personal matters so as not to have my details accessed") asking the respondent to indicate in a 6 point Likert scale from 1 (strongly disagree) to 6 (strongly agree) how much they agreed to the each item. Because this scale targets fear of threats via misuse of information technology it leaves aside fear of technology itself, as a potential autonomous and intelligent entity, therefore we opted to include FARAI scale that comprehends 4 items structured into a single factor (e.g. "Autonomous technology replacing people in the workforce"). Respondents were requested to answer in a 4 point Likert scale from 1 (not fearful at all) to 6 (very fearful). By conducting a CFA with this solution we found the fit indices unsuitable (χ^2/74=2.347, p<.001; CFI=.888, TLI=.862, RMSEA=.080). Additionally, the inter-correlation magnitude (r=.73). between CPFS factors might indicate factor fusion. Therefore, we conducted a CFA on the overall two-factor solution joining CPFS and FARAI. Fit indices remained unsuitable but by using Lagrange multipliers as well as applying rules for psychometric quality as stated in section "Data analysis strategy" we excluded several items and the final factorial solution showed good fit indices (χ^2/26=1.482, p=.054; CFI=.973, TLI=.962, RMSEA=.048). The structure of the factors is the following: FARAI (3 items, "Autonomous technology can make its own decisions and take its own actions", "Autonomous technology replacing people in the workforce", and "People trusting Artificial Intelligence to do work"), AVE=.606, CR=.82), and CPFS (6 items, "I worry about others editing my information without my consent", "Terrorists will find new ways to use the internet to plan new attacks on the general public", "Online payments allow the authorities to monitor my travel and purchases", "People do not worry enough about threats from their use of technology", "People should worry that their movements can be monitored via their smartphone", and "Cameras are illegally used to spy on people"), AVE=.319, CR=.737). Because cyber-paranoia AVE is very far from acceptance level, we opted to exclude it from further analyses.



Control variables were included in the study to determine if they have an effect on the relationship between the independent and dependent variables and also to ascertain if participants were eligible to the study. Among these, we included if participant had an IT related occupation (dummy coded 1= Yes and 2=No), if they use a smartphone (dummy coded 1=Yes, and 2=No), for how long was using a smartphone (in years), the percentage of people around using smartphone, the degree one fells aware of AI use in own smartphone (1=does not incorporate anything close to AI" to 7 "Incorporates a lot of AI, even more than people think"). Additionally, we included gender (dummy coded for 1="Male" and 2="Female"), age (coded as continuous variable), education (1="<9 years schooling", 2="9th grade", 3="12th grade", 4="Degree", 5="Master", 6="PhD"), and civil status (1="Single", 2="Married", 3="Divorced", and 4="Widowed").

Also, we checked for the self-reported perception of awareness of AI features in own smartphone by means of a Likert scale (1=does not incorporate anything close to AI" to 7 "Incorporates a lot of AI, even more than people think"), and the mean was 4.98 (s.d.=1.46) which indicated there was enough perceive AI to move on with the analyses.

2.5. Design

The current investigation is a study of quantitative and exploratory nature, intended to test the relationship between the user's awareness of AI on their smartphone, their possible fears and concerns regarding said AI and the behavioral intention of use regarding these technological devices. The data was collected through scale measured variables which allow ordering and quantifying differences (Maroco, 2010).

Chapter III – Results

3.1. Descriptive and bivariate statistics

For parsimony sake, descriptive and bivariate statistics are shown in Table 3.1. It shows that in most cases the full scale range of all variables was observed which indicates heterogeneity among sampled individuals. C-TAM variables (ease-of-use, usefulness, and fun) all show averages above the midpoint of the scale, thus indicating that technology seems to be more favorable dealt with than the opposite. FARAI is also, to some surprise, above midpoint scale (m=2.41, sd=.88) which suggests individuals tend not to unconditionally judge AI empowered technology thus reinforcing the appropriateness of this research topic. By far, amongst the types of applications, it is social networks that gather the highest mean (M=4.32, sd=.77) making it the most intended smartphone application use. Both money related and health related applications fall short from it, with median values below the scale midpoint (towards unlikely pole) and biometrics is strikingly low (M=1.69, sd=1.24) which can derive from being yet an unusual feature in many smartphones.

Overall, the pattern of correlations between socio-demographic variables included in the research model suggests a surprisingly high self-reported degree of familiarity with embedded AI technology in smartphones (70%) which occurs mainly in younger, male, and more schooled individuals. More educated individuals are also those that reported higher levels of awareness.

Some socio-demographic variables are associated to some key variables included in the research model. As expected, more aged individuals report less ease-of-use as well as less intention to use smartphone based applications. Gender has a single case of significant association that occurred with FARAI indicating women reported higher levels. Education level has also a single case of association with intention to use social networks where more educated individuals and those that report stronger intentions. As a age-related variable, marital status, is also negatively associated to intention to use both money and health related applications.

Table 3.1. Descriptives and bivariate statistics

	Min-max	mean	sd	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	18-69	30.16	11.73	1													
2. Gender	1-2	70.8%fem	-	-,029	1												
3. Education	-	-	-	-,169*	,077	1											
4. Marital status	-	-	-	,692**	,047	-,232**	1										
5. ITprofessional	1-2	79.2% no	-	,047	,342**	,080	,024	1									
6. Familiarity	0-100	69.9%	11.73%	-,304**	-,194**	,174*	-,326**	-,236**	1								
7. Awareness	1-7	4.98	1.46	-,118	,002	,251**	-,170*	-,099	,123	1							
8. CTAM_Usefulness	1-5	3.82	.73	-,037	-,032	,240**	-,035	-,163*	,175*	,094	1						
9. CTAM_EoU	2.5-5	4.66	.55	-,487**	,107	-,021	-,233**	-,109	,362**	,118	,190**	1					
10. CTAM_Fun	1-5	3.40	.41	-,091	,056	,075	-,044	-,108	,062	,084	,320**	,153*	1				
11. FARAI	1-4	2.41	.88	,012	,206**	-,072	,021	,010	-,220**	,028	-,090	,022	-,025	1			
12. BI_moneyrelated	1-5	2.65	1.01	-,314**	-,142	,099	-,185*	-,197**	,251**	,235**	,217**	,274**	,178*	-,027	1		
13. BI_socialnetwork	1.33-5	4.32	.77	-,415**	,128	,219**	-,312**	-,007	,219**	,217**	,233**	,299**	,155*	,032	,422**	1	
14. BI_healthrelated	1-5	2.14	1.16	-,202**	-,025	,006	-,111	-,107	,129	,123	,179*	,180*	,131	,073	,338**	,277**	1
15. BI_biometrics	1-5	1.69	1.24	-,126	-,092	,005	-,027	-,084	,107	,073	,135	,051	,176*	-,091	,205**	,101	,347**

* p<0.05; ** p<0.01

For nominal variables statistics were computed with either Pearson χ^2, φ coefficient, Cramer's V, or η value.

The inexistence of significant correlations between both FARAI and BI and FARAI and C-TAM variables suggests its external role and not so much a possible antecedent which reinforced our conviction of its potential effect as a moderator. Likewise, the existence of several positive associations between C-TAM variables and BI is in line with the hypothesize relationships, thus encouraging further testing of the model.

3.2. Hypothesis testing

Table 3.2. Path coefficients and interactions

Mediator	Criterion variable	Direct effect	Indirect effect	Interaction Effect FARAI			R^2
				Path a	Path b	Path c	
Usefulness	Money	.279 CI95 [-.030; .590]	.055 CI95 [-.004; .146]	.100 CI95 [-.119; 320]	.105 CI95 [-.205; .416]	. 079 CI95 [-.131; .289]	19.4%
Usefulness	Social networks	.209 CI95 [-.010; .429]	.042 CI95 [-.005; .110]	.100 CI95 [-.119; 320]	.004 CI95 [-.144; .154]	.218 CI95 [-.002; .438]	28.9%
Usefulness	Health	.078 CI95 [-.284; .441]	.062 CI95 [-.006; .165]	.100 CI95 [-.119; 320]	.191 CI95 [-.005; .437]	-.049 CI95 [-.413; .314]	13.8%
Usefulness	Biometrics	-.104 CI95 [-.501; .293]	.079 CI95 [.002; .200] 1a4	.100 CI95 [-.119; 320]	-.105 CI95 [-.274; .164]	.050 CI95 [-.348; .449]	6.8%
Fun	Money	.329 CI95 [.020; .639]	.007 CI95 [-.022; .067]	.201 CI95 [-.278; .681]	.025 CI95 [-.067; .118]	.123 CI95 [-.192; .438]	7.9%
Fun	Social networks	.261 CI95 [.044; .477]	-.002 CI95 [-.030; .021]	.201 CI95 [-.278; .681]	-.075 CI95 [-.139; -.010] 3b2	.275 CI95 [.058; .495] 2b2	29.3%
Fun	Health	.151 CI95 [-.212; .515]	.003 CI95 [-.037; .046]	.201 CI95 [-.278; .681]	-.031 CI95 [-.140; .077]	.027 CI95 [-.343; .397]	10.8%
Fun	Biometrics	-.054 CI95 [-.446; .337]	.028 CI95 [-.030; .119]	.201 CI95 [-.278; .681]	-.067 CI95 [-.184; .049]	.067 CI95 [-.331; .466]	7.0%

Predictor variable: Ease-of-use, Path a (EOU*FARAI->Mediator), Path b (Mediator*FARAI->Criterion), Path c (EOU*FARAI->criterion)

Note: For parsimony sake, significant associations with correlates are not shown (can be seen at appendix section)

Findings concerning the direct, indirect and interaction effects are mostly non-significant to the exception of a direct effect found between blabla and two interaction effects found for FARAI between EoU and Social as well as between fun and social.

(Int1) The interaction found between FARAI and EoU in explaining BI-Social has a coefficient of .275 that is shown to be meaningful as bootstrapped confidence interval is [CI95 .058; .495]. Graph A depicts the interaction which indicates that the direct effect is meaningful when the moderator is removed from the equation (.216 CI95 [.044; .477]) as well as when the moderator is one standard deviation above mean (.502 CI95 [.177; .826] cf. Table 3.2).

Graph A – Interaction FARAI*EoU -> Social

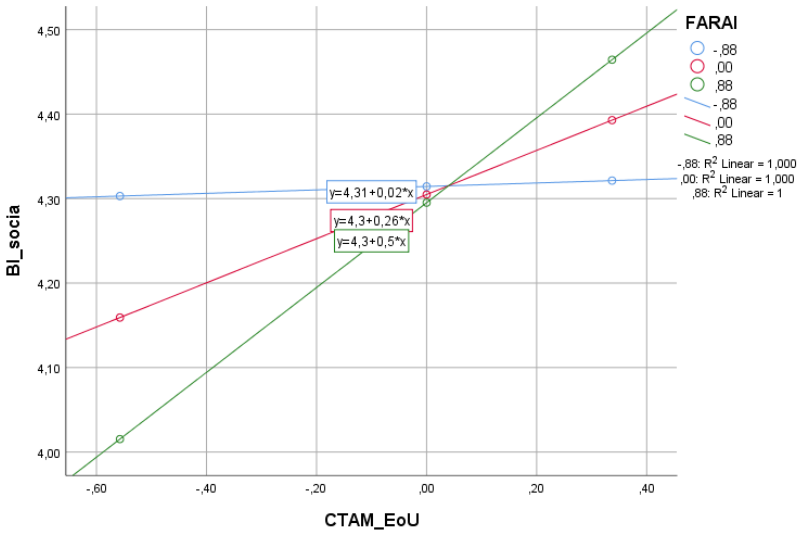


Table 3.3 - Conditional effects of EOU at values of FARAI

FARAI	Effect	se	t	p	LLCI	ULCI
-.8756	.0204	.1270	.1605	.8727	-.2302	.2710
.0000	.2613	.1096	2.3829	.0183	.0449	.4777
.8756	.5021	.1644	3.0546	.0026	.1777	.8266

Neyman-Johnson table shows the association between EoU and BI Social is significant when FARAI is lower than 2.09 (Table 3.4)

Table 3.4 - Johnson-Neyman table for FARAI*EOU -> Social

FARAI	Effect	se	t	p	LLCI	ULCI
-1.3714	-.1160	.1641	-.7073	.4803	-.4399	.2078
-1.2214	-.0748	.1517	-.4930	.6226	-.3741	.2246
-1.0714	-.0335	.1402	-.2390	.8114	-.3102	.2432
-.9214	.0078	.1298	.0598	.9524	-.2485	.2641
-.7714	.0490	.1210	.4054	.6857	-.1897	.2878
-.6214	.0903	.1138	.7932	.4288	-.1344	.3150
-.4714	.1316	.1089	1.2085	.2285	-.0833	.3465
-.3214	.1728	.1063	1.6255	.1059	-.0370	.3827
-.1873	.2097	.1063	1.9739	.0500	.0000	.4195
-.1714	.2141	.1064	2.0125	.0457	.0041	.4241
-.0214	.2554	.1091	2.3417	.0203	.0401	.4706
.1286	.2966	.1141	2.5990	.0102	.0714	.5219
.2786	.3379	.1213	2.7849	.0060	.0984	.5774
.4286	.3792	.1303	2.9100	.0041	.1220	.6364
.5786	.4204	.1407	2.9884	.0032	.1427	.6982
.7286	.4617	.1522	3.0331	.0028	.1612	.7622
.8786	.5030	.1646	3.0548	.0026	.1780	.8280
1.0286	.5442	.1778	3.0612	.0026	.1933	.8952
1.1786	.5855	.1915	3.0577	.0026	.2075	.9635
1.3286	.6268	.2056	3.0480	.0027	.2209	1.0327
1.4786	.6680	.2202	3.0345	.0028	.2335	1.1026
1.6286	.7093	.2350	3.0188	.0029	.2455	1.1731

(Int2) The interaction found between FARAI and fun in explaining BI-Social has a coefficient of -0.075 that is shown to be meaningful as bootstrapped confidence interval is [CI95 -.139; -.010]. Graph B depicts the interaction which indicates that the direct effect is meaningful when the moderator is removed from the equation (.216 CI95 [.044; .477]) as well as when the moderator is one standard deviation above mean (.502 CI95 [.177; .826] cf. Table 3.5).

Graph B – Interaction FARAI*Fun -> Social

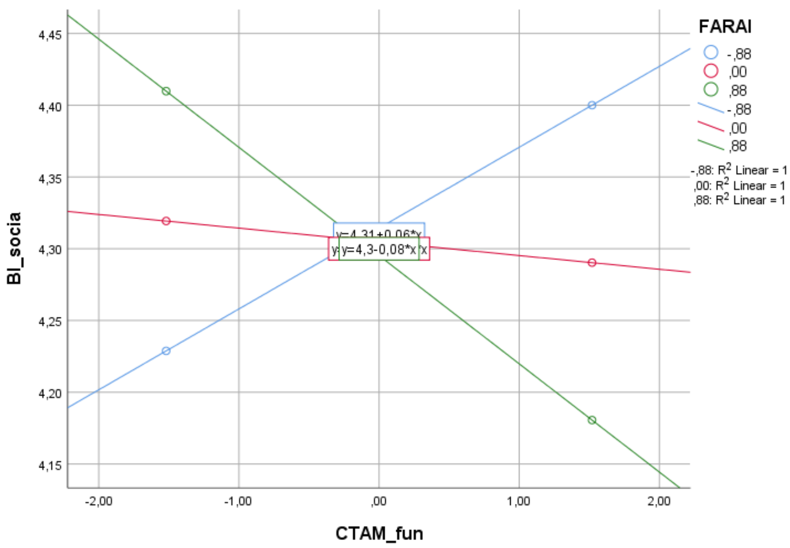


Table 3.5 - Conditional effects of Fun at values of FARAI

FARAI	Effect	se	t	p	LLCI	ULCI
-.8756	.0563	.0441	1.2764	.2035	-.0308	.1435
.0000	-.0095	.0344	-.2776	.7817	-.0773	.0583
.8756	-.0754	.0454	-1.6626	.0982	-.1650	.0141

Neyman-Johnson table shows the association between fun and BI Social is significant when FARAI is higher than 3.88 (Table 3.6)

Table 3.6 - Johnson-Neyman table for FARAI*Fun -> Social

FARAI	Effect	se	t	p	LLCI	ULCI
-1.3714	.0937	.0558	1.6782	.0951	-.0165	.2038
-1.2214	.0824	.0520	1.5834	.1152	-.0203	.1851
-1.0714	.0711	.0484	1.4675	.1441	-.0245	.1667
-.9214	.0598	.0451	1.3257	.1867	-.0292	.1488
-.7714	.0485	.0421	1.1527	.2506	-.0346	.1316
-.6214	.0372	.0394	.9436	.3467	-.0406	.1151
-.4714	.0259	.0373	.6958	.4875	-.0476	.0995
-.3214	.0146	.0356	.4109	.6817	-.0557	.0850
-.1714	.0034	.0347	.0970	.9228	-.0650	.0718
-.0214	-.0079	.0343	-.2308	.8177	-.0757	.0599
.1286	-.0192	.0347	-.5533	.5808	-.0878	.0493
.2786	-.0305	.0358	-.8523	.3952	-.1011	.0401
.4286	-.0418	.0375	-1.1153	.2663	-.1157	.0322
.5786	-.0531	.0397	-1.3372	.1829	-.1314	.0253
.7286	-.0644	.0424	-1.5190	.1306	-.1480	.0193
.8786	-.0756	.0454	-1.6653	.0977	-.1653	.0140
1.0286	-.0869	.0488	-1.7820	.0765	-.1832	.0094
1.1786	-.0982	.0524	-1.8747	.0625	-.2016	.0052
1.3286	-.1095	.0562	-1.9486	.0530	-.2204	.0014
1.3886	-.1140	.0578	-1.9739	.0500	-.2280	.0000
1.4786	-.1208	.0602	-2.0078	.0462	-.2396	-.0020
1.6286	-.1321	.0643	-2.0554	.0414	-.2589	-.0052

These findings mostly do not support the majority of hypotheses as to the exception of a single case, no indirect meaningful effects were found to operate in the model. The exception is the indirect effect usefulness plays in the relationship between EOU and the intention to use biometrics. The relatively weak effect (.079) does correspond to a total mediation (direct effect not meaningful) where an interface being perceived as easy-to-use does influence the acceptance of biometrics by means of a perception of utility. All other stated mediations were not supported by results. This lends support only to hypothesis 1.a.4.

The absence of mediations does not preclude testing moderation effects precisely because not considering such interactions can mask the true relationship between variables. Such was the case of the effect found for FARAI interacting with EOU in explaining intention to use social networks apps via path c (.275, CI95 .058; .495) which is in line with hypothesis 2b2 in the sense that there is an interaction but shows the reverse valence, which lead us to state h2b2 is not supported by findings. However, for being counterintuitive it deserves special attention in the discussion.

Conversely, the effect found for FARAI interacting with fun in explaining intention to use social networks apps via path b (-.075, CI95 -.139; -.010) does support hypothesis 3b2 which means FARAI does hamper the ability to enact willingness to use social networks apps by making it more enjoyable (fun).

Chapter IV – Discussion and Conclusion

The present study investigated an integrated model that brings together C-TAM (Bruner & Kumar, 2003) and the deeply rooted and powerful human emotion that is fear. As stated, fear is a fundamental modeler of human behavior (Phelps & LeDoux, 2005), and a known barrier to technology acceptance and adaption (Lee, Rhee & Dunham, 2009). The use of C-TAM in this study is more in line with the nature of fear itself as an affective factor and with consumer behavior, as it includes both cognitive and hedonic channels (Bruner & Kumar, 2003).

Out of our hypotheses, stemming from the research regarding fear as an inhibitor of cyber-technology intention of use (Stewart & Segars, 2002), we could confirm that usefulness mediates the positive relationship between EOU and behavioral intention to use biometrics, an interface being perceived as easy-to-use does influence the acceptance of biometrics by means of a perception of utility, thus confirming hypothesis 1.a.4.

Additionally, findings show that fear indeed moderates the indirect effect between EOU and Behavioral Intentions to use AI empowered apps through fun, in such a way that the indirect effect is weaker as fear increases, namely in the particular case of social media apps, which may relate to security and privacy concerns regarding personal information on these networks (Mason, Stevenson & Freedman, 2014).

Worthy of note are the results regarding hypothesis 2b2, which hypothesizes that cyber-paranoia would moderate the direct effect between EOU and Behavioral Intentions to use AI social networks' empowered apps, in such a way that the direct effect is weaker as Cyber-paranoia increases.

Our findings, however, in a somewhat counterintuitive manner suggest the reverse valence, meaning a stronger direct effect as Cyber-paranoia increases. This relation could concern modern dependency on social networks (Griffiths, Kuss & Demetrovics, 2014) and the effect this type of social interaction or perceived threat has in paranoid thinking (Green & Phillips, 2004), and is deserving of future research.

Regarding the absence of support for our remaining hypotheses, a shortage of measures concerning affective factors in relation to AI, as well as the general awareness to this novelty (as something not palpable that runs in the background of our everyday lives and devices) very likely played a key role in our findings. These will be discussed in the following paragraph.

As mentioned, the present study wasn't without its limitations and constraints, some of which for example regarding the scarceness of literature exploring Artificial Intelligence in relation to psychological (both cognitive and affective) factors. This situation is likely to undergo a massive change in years to come, as human-AI relations will become ever more prevalent in the workplace, health, military, homes and all around way of life of humans in the modern world, sparking a need for an increased and comprehensive body of research and investigation on this topic.

Consequently, the lack of quantity and well-established measures concerning emotional responses to AI in current research was also a factor that limited our choices and approach to this investigation, with an additional necessity to adapt the available materials (e.g. FARAI, Yuhua & Seungcheol, 2017) to the Portuguese language for the purposes of this study. Arguably, the construction of a measure to evaluate fear responses regarding advances in AI, more concretely in smartphones, may be a matter of a thesis by itself, and something worthy of pursuing in further, future research.

One other subject worthy of further discussion and investigation is the degree of awareness and consciousness of AI presence in smartphones by the general population, as well as AI as a whole.

Continuing our trajectory of technological development and ascension, the wide range of applications of AI in the form of autonomous decision making systems will, in the upcoming decades, fundamentally change many aspects of our daily lives in deeply impactful and transformative ways.

With the exponential increase of intelligence in artificial systems and machines a shift and adaptation in human skills is projected, with some human tasks rendered irrelevant or disappearing completely.

As a result, a new age of profound deliberation on basic rights, privacy, freedom and ethics concerning the human and AI factors and roles in society is very well set to take place in our lifetimes.

Bibliography

Beckers, T., Krypotos, A. M., Boddez, Y., Effting, M., & Kindt, M. (2013). What's wrong with fear conditioning? *Biological psychology, 92*(1), 90-96.

Bentz, D., & Schiller, D. (2015). Threat processing: models and mechanisms. *Wiley interdisciplinary reviews: cognitive science*, *6*(5), 427-439.

Berg, A., Buffie, E. F., & Zanna, L. F. (2018). Should we fear the robot revolution?(The correct answer is yes). *Journal of Monetary Economics, 97*, 117-148.

Boyatzis, R., & Boyatzis, R. E. (2008). Competencies in the 21st century. *Journal of management development*.

Boyatzis, R., Hopkins, M. M., & Bilimoria, D. (2008). Social and emotional competencies predicting success for male and female executives. *Journal of management development*.

Boyles, J. L., Smith, A., & Madden, M. (2012). *Privacy and data management on mobile devices.* Pew Research Center.

Bruner II, G. C., & Kumar, A. (2005). Explaining consumer acceptance of handheld Internet devices. *Journal of business research*, *58*(5), 553-558.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: work, progress, and prosperity in a time of brilliant technologies.* New York: W.W. Norton & Company.

Catalano, G., Catalano, M. C., Embi, C. S., & Frankel, R. L. (1999). Delusions about the Internet. *South. Med. J.* 92, 609–610

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of retailing*, *77*(4), 511-535.

Daugherty, P. R., & Wilson, H. J. (2018). *Human+ machine: reimagining work in the age of AI*. Harvard Business Press.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

Diaz, K. (2012). Franken bill aims to curb “stalking” apps. *McClatchy-Tribune Business News*.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Galanos, V. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*.

Green, M. J., & Phillips, M. L. (2004). Social threat perception and the evolution of paranoia. *Neuroscience & Biobehavioral Reviews*, *28*(3), 333-342.

Griffiths, M. D., Kuss, D. J., & Demetrovics, Z. (2014). Social networking addiction: An overview of preliminary findings. In *Behavioral addictions* (pp. 119-141). Academic Press.

Erisman, A., & Parker, T. (2019). Artificial Intelligence: A Theological Perspective. *Perspectives on Science & Christian Faith*, *71*(2).

Ford, M. (2015). Rise of the Robots: Technology and the Threat of a Jobless Future. *Basic Books*

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of marketing research*, 382-388.

Fortinet (2014). Threat Landscape Report.

Gates, C. S., Chen, J., Li, N., & Proctor, R. W. (2014). Effective risk communication for Android apps. *IEEE Transactions on Dependable and Secure Computing*, 11(3), 252-265.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5-14.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). *Multivariate data analysis*, Prentice hall Upper Saddle River, NJ.

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. Guilford Publications.

Hebb, D. O. (1949). *The Organization of Behavior: A Neuropsychological Theory* (New York, NY: John Wiley).

Ignatov, A., Timofte, R., Kulik, A., Yang, S., Wang, K., Baum, F., & Van Gool, L. (2019). AI Benchmark: All About Deep Learning on Smartphones in 2019. *arXiv preprint arXiv:1910.06663*.

Johnson, D.G., & Verdicchio, M. (2017). AI anxiety. *J Assoc Inf Sci Technol,* 68(9)

Kaplan, A., & Haenlein, M. (2019). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons*.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25.

Lee, D., Rhee, Y., & Dunham, R. B. (2009). The role of organizational and individual characteristics in technology acceptance. Intl. Journal of Human–Computer Interaction, 25(7), 623-646.

Liang, Y. & Lee, S.A. (2017). Fear of Autonomous Robots and Artificial Intelligence: Evidence from National Representative Data with Probability Sampling. International Journal of Social Robotics, 9(3), 379-384.

Luthans, F., Welsh, D. H., & Taylor III, L. A. (1988). A descriptive model of managerial effectiveness. *Group & Organization Studies*, *13*(2), 148-162.

Mason O.J., Stevenson, C., & Freedman, F. (2014). Ever-present threats from information technology: the Cyber-Paranoia and Fear Scale. *Front. Psychol.* 5:1298.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI magazine*, *27*(4), 12-12.

McClelland, D. C., & Boyatzis, R. E. (1982). Leadership motive pattern and long-term success in management. *Journal of Applied psychology*, *67*(6), 737.

Miller, T. (2018). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*.

Minsky, M. (1982). Semantic information processing.

Minsky, M., & Papert, S. A. (2017). *Perceptrons: An introduction to computational geometry*. MIT press.

Müller, V. C., & Bostrom, N. (2016). Future progress in artificial intelligence: A survey of expert opinion. In *Fundamental issues of artificial intelligence* (pp. 555-572). Springer, Cham.

Oliveira, A. (2019). *Inteligência Artificial.* Lisboa, Portugal: Fundação Francisco Manuel dos Santos.

Pappas, I. O., Mikalef, P., Giannakos, M. N., Krogstie, J., & Lekakos, G. (2018). Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies.

Phelps, E. A., & LeDoux, J. E. (2005). Contributions of the amygdala to emotion processing: from animal models to human behavior. *Neuron*, *48*(2), 175-187.

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., & Dieleman, S. (2016). Mastering the game of Go with deep neural networks and tree search. *nature*, *529*(7587), 484.

Smith, A., & Anderson, J. (2014). AI, Robotics, and the Future of Jobs. *Pew Research Center*, *6*.

Stewart, K. A., and Segars, A. H. (2002). An empirical examination of the concern for information privacy instrument. *Inf. Syst. Res.* 13, 36–49.

Stubbs Koman, E., & Wolff, S. B. (2008). Emotional intelligence competencies in the team and team leader: A multi-level examination of the impact of emotional intelligence on team performance. *Journal of Management Development*, *27*(1), 55-75.

Taipale, K. A. (2005). Technology, Security and Privacy: The fear of Frankenstein, The Mythology of Privacy and The lessons of King Ludd. *Yale Journal of Law and Technology*, *7*(1).

Thurm, S., & Kane, Y. I. (2010). Review—What they know: A Wall Street Journal investigation: Your apps are watching you—A Journal investigation finds that iPhone and Android apps are breaching the privacy of smartphone users. *Wall Street Journal*, C1.

Tudor, A. (2003). A (macro) sociology of fear? Sociol Rev 51(2):238–256

Turing, A. M. (2009). Computing machinery and intelligence. In *Parsing the Turing Test* (pp. 23-65). Springer, Dordrecht.

Vasile, G. (2018). Why Are We Afraid of Artificial Intelligence (Ai)? *European Review of Applied Sociology*, 11(7), 6-15.

Appendices

Annex A – Cyber Paranoia and Fear Scale Items

Items

Increasing computer usage is changing children's brains for the worse
It's only a matter of time until the global web is brought down with dire consequences
I avoid using the internet on personal matters so as not to have my details accessed
I worry about others editing my Facebook page (or similar) without my consent
I worry about the effects of electromagnetic waves from mobile phones/phone masts
Terrorists will find new ways to use the internet to plan new attacks on the general public

Payment cards such as Oyster cards allow the authorities to monitor my travel and purchases
Companies that store data on customers are very vulnerable to theft of my private details
People do not worry enough about threats from their use of technology
People should worry that their movements can be monitored via their 'smartphone'
Closed circuit television cameras (CCTV) are illegally used to spy on people

Annex B – Statistics

Usefulness **Money**

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_mon_1
    X  : CTAM_EoU
    M  : CTAM_Use
    W  : FARAI

Covariates:
Q40(time owned)  Q36(age)  Q45(gender)  Q37(education)  Q46(civil status)     Q38(IT)

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_Use

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3763      ,1416      ,4693     3,1896     9,0000   174,0000      ,0013
```

```
Model
              coeff         se          t          p       LLCI       ULCI
constant     -,8542      ,4246    -2,0116      ,0458    -1,6922     -,0161
CTAM_EoU      ,2680      ,1106     2,4242      ,0164      ,0498      ,4863
FARAI        -,0649      ,0599    -1,0824      ,2806     -,1831      ,0534
Int_1         ,1003      ,1114      ,9003      ,3692     -,1196      ,3202
Q40           ,0266      ,0148     1,7918      ,0749     -,0027      ,0559
Q36           ,0058      ,0070      ,8333      ,4058     -,0079      ,0195
Q45          -,0326      ,1268     -,2575      ,7971     -,2829      ,2176
Q37           ,2353      ,0657     3,5795      ,0004      ,1056      ,3650
Q46           ,0094      ,1313      ,0714      ,9431     -,2497      ,2685
Q38          -,2238      ,1408    -1,5898      ,1137     -,5017      ,0540

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0040      ,8105     1,0000   174,0000      ,3692
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_Use   .
BEGIN DATA.
     -,5574     -,8756     -,0447
      ,0000     -,8756      ,0558
      ,3370     -,8756      ,1165
     -,5574      ,0000     -,1504
      ,0000      ,0000     -,0010
      ,3370      ,0000      ,0893
     -,5574      ,8756     -,2562
      ,0000      ,8756     -,0578
      ,3370      ,8756      ,0621
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_Use BY       FARAI    .

***************************************************************************
OUTCOME VARIABLE:
 BI_mon_1

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4404      ,1940      ,9177     3,7626    11,0000   172,0000      ,0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,7043      ,6030     6,1434      ,0000     2,5141     4,8944
CTAM_EoU      ,2798      ,1573     1,7791      ,0770     -,0306      ,5902
CTAM_Use      ,2060      ,1064     1,9356      ,0546     -,0041      ,4160
FARAI         ,0073      ,0842      ,0868      ,9309     -,1588      ,1734
Int_1         ,1055      ,1576      ,6692      ,5042     -,2057      ,4167
Int_2         ,0793      ,1067      ,7437      ,4580     -,1312      ,2899
Q40           ,0052      ,0210      ,2466      ,8055     -,0362      ,0465
Q36          -,0250      ,0098    -2,5641      ,0112     -,0443     -,0058
Q45          -,3451      ,1774    -1,9457      ,0533     -,6953      ,0050
Q37           ,1028      ,0955     1,0759      ,2835     -,0858      ,2914
Q46           ,0962      ,1836      ,5242      ,6008     -,2661      ,4586
Q38          -,1726      ,1986     -,8691      ,3860     -,5646      ,2194

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_Use x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0021      ,4479     1,0000   172,0000      ,5042
M*W      ,0026      ,5531     1,0000   172,0000      ,4580
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)
```

```
Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_mon_1   .
BEGIN DATA.
     -,5574     -,8756     2,5394
      ,0000     -,8756     2,6438
      ,3370     -,8756     2,7070
     -,5574      ,0000     2,4943
      ,0000      ,0000     2,6502
      ,3370      ,0000     2,7445
     -,5574      ,8756     2,4492
      ,0000      ,8756     2,6566
      ,3370      ,8756     2,7820
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_mon_1 BY       FARAI    .
----------
    Focal predict: CTAM_Use (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_Use   FARAI      BI_mon_1   .
BEGIN DATA.
     -,7210     -,8756     2,5454
      ,0000     -,8756     2,6438
      ,7210     -,8756     2,7423
     -,7210      ,0000     2,5017
      ,0000      ,0000     2,6502
      ,7210      ,0000     2,7987
     -,7210      ,8756     2,4580
      ,0000      ,8756     2,6566
      ,7210      ,8756     2,8552
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_Use WITH     BI_mon_1 BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,1874      ,1804     1,0387      ,3004     -,1688      ,5436
      ,0000      ,2798      ,1573     1,7791      ,0770     -,0306      ,5902
      ,8756      ,3722      ,2345     1,5868      ,1144     -,0908      ,8351

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_Use    ->    BI_mon_1

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0246      ,0448     -,0360      ,1403
      ,0000      ,0552      ,0394     -,0049      ,1468
      ,8756      ,0980      ,0670     -,0092      ,2515
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_Use

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.
```

```
------ END MATRIX -----
```

Usefulness	Social networks

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_socia
    X  : CTAM_EoU
    M  : CTAM_Use
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_Use

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3763      ,1416      ,4693     3,1896     9,0000   174,0000      ,0013

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,8542      ,4246    -2,0116      ,0458    -1,6922     -,0161
CTAM_EoU      ,2680      ,1106     2,4242      ,0164      ,0498      ,4863
FARAI        -,0649      ,0599    -1,0824      ,2806     -,1831      ,0534
Int_1         ,1003      ,1114      ,9003      ,3692     -,1196      ,3202
Q40           ,0266      ,0148     1,7918      ,0749     -,0027      ,0559
Q36           ,0058      ,0070      ,8333      ,4058     -,0079      ,0195
Q45          -,0326      ,1268     -,2575      ,7971     -,2829      ,2176
Q37           ,2353      ,0657     3,5795      ,0004      ,1056      ,3650
Q46           ,0094      ,1313      ,0714      ,9431     -,2497      ,2685
Q38          -,2238      ,1408    -1,5898      ,1137     -,5017      ,0540

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0040      ,8105     1,0000   174,0000      ,3692
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_Use   .
BEGIN DATA.
     -,5574     -,8756     -,0447
      ,0000     -,8756      ,0558
      ,3370     -,8756      ,1165
     -,5574      ,0000     -,1504
      ,0000      ,0000     -,0010
      ,3370      ,0000      ,0893
     -,5574      ,8756     -,2562
      ,0000      ,8756     -,0578
      ,3370      ,8756      ,0621
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_Use BY       FARAI    .

**************************************************************************
```

```
OUTCOME VARIABLE:
 BI_socia

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5383      ,2898      ,4607     6,3806    11,0000   172,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,8207      ,4272     8,9433      ,0000     2,9774     4,6639
CTAM_EoU      ,2094      ,1114     1,8795      ,0619     -,0105      ,4294
CTAM_Use      ,1591      ,0754     2,1102      ,0363      ,0103      ,3079
FARAI         ,0229      ,0596      ,3842      ,7013     -,0948      ,1406
Int_1         ,2183      ,1117     1,9540      ,0523     -,0022      ,4387
Int_2         ,0049      ,0756      ,0643      ,9488     -,1443      ,1540
Q40           ,0303      ,0149     2,0390      ,0430      ,0010      ,0596
Q36          -,0206      ,0069    -2,9773      ,0033     -,0342     -,0069
Q45           ,0730      ,1257      ,5805      ,5624     -,1751      ,3210
Q37           ,1511      ,0677     2,2327      ,0269      ,0175      ,2847
Q46          -,0787      ,1301     -,6047      ,5462     -,3354      ,1781
Q38           ,1361      ,1407      ,9670      ,3349     -,1417      ,4138

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_Use x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0158     3,8181     1,0000   172,0000      ,0523
M*W      ,0000      ,0041     1,0000   172,0000      ,9488
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Conditional effects of the focal predictor at values of the moderator(s):

      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,0183      ,1278      ,1434      ,8862     -,2340      ,2707
      ,0000      ,2094      ,1114     1,8795      ,0619     -,0105      ,4294
      ,8756      ,4005      ,1662     2,4102      ,0170      ,0725      ,7285

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,0681    59,2391    40,7609

Conditional effect of focal predictor at values of the moderator:
      FARAI     Effect         se          t          p       LLCI       ULCI
    -1,3714     -,0899      ,1645     -,5465      ,5854     -,4145      ,2348
    -1,2214     -,0571      ,1522     -,3755      ,7078     -,3576      ,2433
    -1,0714     -,0244      ,1409     -,1733      ,8626     -,3024      ,2536
     -,9214      ,0083      ,1307      ,0637      ,9493     -,2496      ,2663
     -,7714      ,0411      ,1220      ,3367      ,7367     -,1997      ,2818
     -,6214      ,0738      ,1150      ,6416      ,5220     -,1533      ,3009
     -,4714      ,1065      ,1102      ,9664      ,3352     -,1111      ,3242
     -,3214      ,1393      ,1079     1,2912      ,1984     -,0736      ,3522
     -,1714      ,1720      ,1081     1,5918      ,1133     -,0413      ,3853
     -,0214      ,2048      ,1108     1,8475      ,0664     -,0140      ,4235
      ,0681      ,2243      ,1136     1,9739      ,0500      ,0000      ,4486
      ,1286      ,2375      ,1160     2,0479      ,0421      ,0086      ,4664
      ,2786      ,2702      ,1232     2,1935      ,0296      ,0271      ,5134
      ,4286      ,3030      ,1322     2,2925      ,0231      ,0421      ,5638
      ,5786      ,3357      ,1425     2,3553      ,0196      ,0544      ,6171
      ,7286      ,3685      ,1540     2,3919      ,0178      ,0644      ,6725
      ,8786      ,4012      ,1664     2,4104      ,0170      ,0727      ,7297
     1,0286      ,4339      ,1795     2,4168      ,0167      ,0795      ,7883
     1,1786      ,4667      ,1932     2,4153      ,0168      ,0853      ,8480
     1,3286      ,4994      ,2073     2,4086      ,0171      ,0901      ,9087
     1,4786      ,5321      ,2218     2,3989      ,0175      ,0943      ,9700
     1,6286      ,5649      ,2366     2,3873      ,0181      ,0978     1,0319

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_socia   .
BEGIN DATA.
     -,5574     -,8756     4,2776
```

```
      ,0000     -,8756     4,2878
      ,3370     -,8756     4,2940
     -,5574      ,0000     4,1911
      ,0000      ,0000     4,3079
      ,3370      ,0000     4,3784
     -,5574      ,8756     4,1047
      ,0000      ,8756     4,3279
      ,3370      ,8756     4,4629
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_socia BY       FARAI    .
----------
    Focal predict: CTAM_Use (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_Use   FARAI      BI_socia   .
BEGIN DATA.
     -,7210     -,8756     4,1762
      ,0000     -,8756     4,2878
      ,7210     -,8756     4,3994
     -,7210      ,0000     4,1931
      ,0000      ,0000     4,3079
      ,7210      ,0000     4,4226
     -,7210      ,8756     4,2101
      ,0000      ,8756     4,3279
      ,7210      ,8756     4,4457
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_Use WITH     BI_socia BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,0183      ,1278      ,1434      ,8862     -,2340      ,2707
      ,0000      ,2094      ,1114     1,8795      ,0619     -,0105      ,4294
      ,8756      ,4005      ,1662     2,4102      ,0170      ,0725      ,7285

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_Use    ->    BI_socia

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0279      ,0340     -,0253      ,1116
      ,0000      ,0426      ,0301     -,0056      ,1104
      ,8756      ,0581      ,0497     -,0124      ,1759
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_Use

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Usefulness Health

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_healt
    X  : CTAM_EoU
    M  : CTAM_Use
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_Use

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3763      ,1416      ,4693     3,1896     9,0000   174,0000      ,0013

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,8542      ,4246    -2,0116      ,0458    -1,6922     -,0161
CTAM_EoU      ,2680      ,1106     2,4242      ,0164      ,0498      ,4863
FARAI        -,0649      ,0599    -1,0824      ,2806     -,1831      ,0534
Int_1         ,1003      ,1114      ,9003      ,3692     -,1196      ,3202
Q40           ,0266      ,0148     1,7918      ,0749     -,0027      ,0559
Q36           ,0058      ,0070      ,8333      ,4058     -,0079      ,0195
Q45          -,0326      ,1268     -,2575      ,7971     -,2829      ,2176
Q37           ,2353      ,0657     3,5795      ,0004      ,1056      ,3650
Q46           ,0094      ,1313      ,0714      ,9431     -,2497      ,2685
Q38          -,2238      ,1408    -1,5898      ,1137     -,5017      ,0540

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0040      ,8105     1,0000   174,0000      ,3692
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_Use   .
BEGIN DATA.
     -,5574     -,8756     -,0447
      ,0000     -,8756      ,0558
      ,3370     -,8756      ,1165
     -,5574      ,0000     -,1504
      ,0000      ,0000     -,0010
      ,3370      ,0000      ,0893
     -,5574      ,8756     -,2562
      ,0000      ,8756     -,0578
      ,3370      ,8756      ,0621
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_Use BY       FARAI    .
```

```
**************************************************************************
OUTCOME VARIABLE:
 BI_healt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3723      ,1386     1,2548     2,5154    11,0000   172,0000      ,0058

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,4988      ,7051     3,5440      ,0005     1,1070     3,8905
CTAM_EoU      ,0782      ,1839      ,4253      ,6712     -,2848      ,4412
CTAM_Use      ,2321      ,1244     1,8655      ,0638     -,0135      ,4778
FARAI         ,0791      ,0984      ,8042      ,4224     -,1151      ,2734
Int_1        -,0492      ,1843     -,2670      ,7898     -,4131      ,3147
Int_2         ,1910      ,1247     1,5318      ,1274     -,0551      ,4372
Q40           ,0700      ,0245     2,8562      ,0048      ,0216      ,1184
Q36          -,0234      ,0114    -2,0479      ,0421     -,0459     -,0008
Q45          -,0954      ,2074     -,4601      ,6461     -,5049      ,3140
Q37          -,0299      ,1117     -,2681      ,7890     -,2505      ,1906
Q46           ,1296      ,2147      ,6038      ,5468     -,2941      ,5534
Q38          -,0143      ,2322     -,0618      ,9508     -,4727      ,4440

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_Use x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0004      ,0713     1,0000   172,0000      ,7898
M*W      ,0118     2,3463     1,0000   172,0000      ,1274
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_healt   .
BEGIN DATA.
     -,5574     -,8756     2,0213
      ,0000     -,8756     2,0889
      ,3370     -,8756     2,1298
     -,5574      ,0000     2,1146
      ,0000      ,0000     2,1582
      ,3370      ,0000     2,1845
     -,5574      ,8756     2,2079
      ,0000      ,8756     2,2275
      ,3370      ,8756     2,2393
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_healt BY       FARAI    .
----------
    Focal predict: CTAM_Use (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_Use   FARAI      BI_healt   .
BEGIN DATA.
     -,7210     -,8756     2,0421
      ,0000     -,8756     2,0889
      ,7210     -,8756     2,1357
     -,7210      ,0000     1,9908
      ,0000      ,0000     2,1582
      ,7210      ,0000     2,3256
     -,7210      ,8756     1,9395
      ,0000      ,8756     2,2275
      ,7210      ,8756     2,5155
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_Use WITH     BI_healt BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************
```

```
Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,1213      ,2110      ,5749      ,5661     -,2952      ,5378
      ,0000      ,0782      ,1839      ,4253      ,6712     -,2848      ,4412
      ,8756      ,0351      ,2743      ,1280      ,8983     -,5062      ,5765

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_Use    ->    BI_healt

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0117      ,0425     -,0710      ,1045
      ,0000      ,0622      ,0454     -,0063      ,1659
      ,8756      ,1421      ,1031     -,0039      ,3840
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_Use

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Usefulness	Biometrics

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_biome
    X  : CTAM_EoU
    M  : CTAM_Use
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_Use

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3763      ,1416      ,4693     3,1896     9,0000   174,0000      ,0013

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,8542      ,4246    -2,0116      ,0458    -1,6922     -,0161
CTAM_EoU      ,2680      ,1106     2,4242      ,0164      ,0498      ,4863
FARAI        -,0649      ,0599    -1,0824      ,2806     -,1831      ,0534
Int_1         ,1003      ,1114      ,9003      ,3692     -,1196      ,3202
Q40           ,0266      ,0148     1,7918      ,0749     -,0027      ,0559
Q36           ,0058      ,0070      ,8333      ,4058     -,0079      ,0195
Q45          -,0326      ,1268     -,2575      ,7971     -,2829      ,2176
Q37           ,2353      ,0657     3,5795      ,0004      ,1056      ,3650
Q46           ,0094      ,1313      ,0714      ,9431     -,2497      ,2685
Q38          -,2238      ,1408    -1,5898      ,1137     -,5017      ,0540

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0040      ,8105     1,0000   174,0000      ,3692
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_Use   .
BEGIN DATA.
     -,5574     -,8756     -,0447
      ,0000     -,8756      ,0558
      ,3370     -,8756      ,1165
     -,5574      ,0000     -,1504
      ,0000      ,0000     -,0010
      ,3370      ,0000      ,0893
     -,5574      ,8756     -,2562
      ,0000      ,8756     -,0578
      ,3370      ,8756      ,0621
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_Use BY       FARAI    .
```

```
**************************************************************************
OUTCOME VARIABLE:
 BI_biome

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2626      ,0689     1,5073     1,1578    11,0000   172,0000      ,3200

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,4365      ,7728     3,1528      ,0019      ,9111     3,9618
CTAM_EoU     -,1041      ,2016     -,5164      ,6063     -,5019      ,2938
CTAM_Use      ,2949      ,1364     2,1620      ,0320      ,0257      ,5641
FARAI        -,1084      ,1079    -1,0044      ,3166     -,3213      ,1046
Int_1         ,0506      ,2020      ,2503      ,8027     -,3482      ,4494
Int_2        -,1050      ,1367     -,7683      ,4434     -,3749      ,1648
Q40           ,0087      ,0269      ,3242      ,7462     -,0443      ,0617
Q36          -,0269      ,0125    -2,1537      ,0327     -,0516     -,0022
Q45          -,1827      ,2274     -,8037      ,4227     -,6315      ,2660
Q37          -,0340      ,1224     -,2773      ,7819     -,2756      ,2077
Q46           ,3122      ,2353     1,3266      ,1864     -,1523      ,7766
Q38           ,0165      ,2545      ,0650      ,9483     -,4859      ,5189

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_Use x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0003      ,0626     1,0000   172,0000      ,8027
M*W      ,0032      ,5903     1,0000   172,0000      ,4434
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_biome   .
BEGIN DATA.
     -,5574     -,8756     1,8667
      ,0000     -,8756     1,7840
      ,3370     -,8756     1,7340
     -,5574      ,0000     1,7471
      ,0000      ,0000     1,6891
      ,3370      ,0000     1,6540
     -,5574      ,8756     1,6276
      ,0000      ,8756     1,5943
      ,3370      ,8756     1,5741
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_biome BY       FARAI    .
----------
    Focal predict: CTAM_Use (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_Use   FARAI      BI_biome   .
BEGIN DATA.
     -,7210     -,8756     1,5051
      ,0000     -,8756     1,7840
      ,7210     -,8756     2,0629
     -,7210      ,0000     1,4765
      ,0000      ,0000     1,6891
      ,7210      ,0000     1,9017
     -,7210      ,8756     1,4479
      ,0000      ,8756     1,5943
      ,7210      ,8756     1,7406
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_Use WITH     BI_biome BY       FARAI    .
```

```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756     -,1483      ,2313     -,6415      ,5221     -,6048      ,3081
      ,0000     -,1041      ,2016     -,5164      ,6063     -,5019      ,2938
      ,8756     -,0598      ,3006     -,1990      ,8425     -,6531      ,5335

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_Use    ->    BI_biome

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0697      ,0705     -,0294      ,2451
      ,0000      ,0790      ,0514      ,0021      ,2000
      ,8756      ,0722      ,0743     -,0429      ,2586
---

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_Use

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Fun　　Money

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_mon_1
    X  : CTAM_EoU
    M  : CTAM_fun
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_fun

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2818      ,0794     2,2353     1,6679     9,0000   174,0000      ,1000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,9074      ,9267     -,9792      ,3289    -2,7366      ,9217
CTAM_EoU      ,2318      ,2413      ,9604      ,3382     -,2445      ,7081
FARAI        -,0649      ,1308     -,4962      ,6204     -,3230      ,1932
Int_1         ,2019      ,2432      ,8302      ,4076     -,2781      ,6819
Q40           ,0800      ,0324     2,4700      ,0145      ,0161      ,1439
Q36           ,0004      ,0152      ,0289      ,9770     -,0295      ,0304
Q45           ,1514      ,2767      ,5471      ,5850     -,3947      ,6975
Q37           ,2218      ,1435     1,5458      ,1240     -,0614      ,5049
Q46          -,1129      ,2865     -,3941      ,6940     -,6784      ,4526
Q38          -,3709      ,3073    -1,2073      ,2290     -,9774      ,2355

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0036      ,6892     1,0000   174,0000      ,4076
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_fun   .
BEGIN DATA.
     -,5574     -,8756      ,0241
      ,0000     -,8756      ,0548
      ,3370     -,8756      ,0733
     -,5574      ,0000     -,1312
      ,0000      ,0000     -,0020
      ,3370      ,0000      ,0761
     -,5574      ,8756     -,2866
      ,0000      ,8756     -,0589
      ,3370      ,8756      ,0788
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_fun BY       FARAI    .

**************************************************************************
OUTCOME VARIABLE:
 BI_mon_1
```

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4196      ,1761      ,9380     3,3417    11,0000   172,0000      ,0003

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,5757      ,6027     5,9326      ,0000     2,3860     4,7654
CTAM_EoU      ,3299      ,1568     2,1041      ,0368      ,0204      ,6394
CTAM_fun      ,0340      ,0491      ,6916      ,4901     -,0630      ,1309
FARAI         ,0005      ,0860      ,0061      ,9951     -,1692      ,1702
Int_1         ,1231      ,1596      ,7711      ,4417     -,1920      ,4382
Int_2         ,0256      ,0469      ,5453      ,5862     -,0670      ,1181
Q40           ,0064      ,0214      ,3002      ,7644     -,0358      ,0487
Q36          -,0233      ,0099    -2,3566      ,0196     -,0427     -,0038
Q45          -,3541      ,1798    -1,9690      ,0506     -,7090      ,0009
Q37           ,1424      ,0937     1,5204      ,1303     -,0425      ,3273
Q46           ,0935      ,1865      ,5014      ,6167     -,2746      ,4617
Q38          -,2149      ,1999    -1,0749      ,2839     -,6094      ,1797

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_fun x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0028      ,5946     1,0000   172,0000      ,4417
M*W      ,0014      ,2974     1,0000   172,0000      ,5862
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_mon_1   .
BEGIN DATA.
     -,5574     -,8756     2,5220
      ,0000     -,8756     2,6458
      ,3370     -,8756     2,7206
     -,5574      ,0000     2,4623
      ,0000      ,0000     2,6462
      ,3370      ,0000     2,7574
     -,5574      ,8756     2,4027
      ,0000      ,8756     2,6467
      ,3370      ,8756     2,7942
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_mon_1 BY       FARAI    .
----------
    Focal predict: CTAM_fun (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_fun   FARAI      BI_mon_1   .
BEGIN DATA.
    -1,5194     -,8756     2,6282
      ,0000     -,8756     2,6458
     1,5194     -,8756     2,6634
    -1,5194      ,0000     2,5946
      ,0000      ,0000     2,6462
     1,5194      ,0000     2,6979
    -1,5194      ,8756     2,5611
      ,0000      ,8756     2,6467
     1,5194      ,8756     2,7323
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_fun WITH     BI_mon_1 BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
```

```
     -,8756      ,2221      ,1816      1,2234      ,2229     -,1363      ,5806
      ,0000      ,3299      ,1568      2,1041      ,0368      ,0204      ,6394
      ,8756      ,4377      ,2351      1,8617      ,0643     -,0264      ,9018

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_fun    ->    BI_mon_1

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0006      ,0255     -,0373      ,0709
      ,0000      ,0079      ,0217     -,0227      ,0670
      ,8756      ,0230      ,0481     -,0430      ,1452
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_fun

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Fun Social networks

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_socia
    X  : CTAM_EoU
    M  : CTAM_fun
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_fun

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2818      ,0794     2,2353     1,6679     9,0000   174,0000      ,1000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,9074      ,9267     -,9792      ,3289    -2,7366      ,9217
CTAM_EoU      ,2318      ,2413      ,9604      ,3382     -,2445      ,7081
FARAI        -,0649      ,1308     -,4962      ,6204     -,3230      ,1932
Int_1         ,2019      ,2432      ,8302      ,4076     -,2781      ,6819
Q40           ,0800      ,0324     2,4700      ,0145      ,0161      ,1439
Q36           ,0004      ,0152      ,0289      ,9770     -,0295      ,0304
Q45           ,1514      ,2767      ,5471      ,5850     -,3947      ,6975
Q37           ,2218      ,1435     1,5458      ,1240     -,0614      ,5049
Q46          -,1129      ,2865     -,3941      ,6940     -,6784      ,4526
Q38          -,3709      ,3073    -1,2073      ,2290     -,9774      ,2355

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0036      ,6892     1,0000   174,0000      ,4076
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_fun   .
BEGIN DATA.
     -,5574     -,8756      ,0241
      ,0000     -,8756      ,0548
      ,3370     -,8756      ,0733
     -,5574      ,0000     -,1312
      ,0000      ,0000     -,0020
      ,3370      ,0000      ,0761
     -,5574      ,8756     -,2866
      ,0000      ,8756     -,0589
      ,3370      ,8756      ,0788
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_fun BY       FARAI    .

**************************************************************************
OUTCOME VARIABLE:
 BI_socia
```

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5413      ,2930      ,4586     6,4807    11,0000   172,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,7277      ,4214     8,8455      ,0000     2,8958     4,5595
CTAM_EoU      ,2613      ,1096     2,3829      ,0183      ,0449      ,4777
CTAM_fun     -,0095      ,0344     -,2776      ,7817     -,0773      ,0583
FARAI        -,0109      ,0601     -,1821      ,8558     -,1296      ,1077
Int_1         ,2751      ,1116     2,4647      ,0147      ,0548      ,4954
Int_2        -,0752      ,0328    -2,2961      ,0229     -,1399     -,0106
Q40           ,0379      ,0150     2,5347      ,0121      ,0084      ,0675
Q36          -,0209      ,0069    -3,0232      ,0029     -,0345     -,0072
Q45           ,0488      ,1257      ,3879      ,6986     -,1994      ,2969
Q37           ,1826      ,0655     2,7875      ,0059      ,0533      ,3119
Q46          -,0498      ,1304     -,3819      ,7030     -,3072      ,2076
Q38           ,0935      ,1398      ,6689      ,5045     -,1824      ,3693

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_fun x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0250     6,0748     1,0000   172,0000      ,0147
M*W      ,0217     5,2722     1,0000   172,0000      ,0229
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Conditional effects of the focal predictor at values of the moderator(s):

      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,0204      ,1270      ,1605      ,8727     -,2302      ,2710
      ,0000      ,2613      ,1096     2,3829      ,0183      ,0449      ,4777
      ,8756      ,5021      ,1644     3,0546      ,0026      ,1777      ,8266

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
     -,1873    47,8261    52,1739

Conditional effect of focal predictor at values of the moderator:
      FARAI     Effect         se          t          p       LLCI       ULCI
    -1,3714     -,1160      ,1641     -,7073      ,4803     -,4399      ,2078
    -1,2214     -,0748      ,1517     -,4930      ,6226     -,3741      ,2246
    -1,0714     -,0335      ,1402     -,2390      ,8114     -,3102      ,2432
     -,9214      ,0078      ,1298      ,0598      ,9524     -,2485      ,2641
     -,7714      ,0490      ,1210      ,4054      ,6857     -,1897      ,2878
     -,6214      ,0903      ,1138      ,7932      ,4288     -,1344      ,3150
     -,4714      ,1316      ,1089     1,2085      ,2285     -,0833      ,3465
     -,3214      ,1728      ,1063     1,6255      ,1059     -,0370      ,3827
     -,1873      ,2097      ,1063     1,9739      ,0500      ,0000      ,4195
     -,1714      ,2141      ,1064     2,0125      ,0457      ,0041      ,4241
     -,0214      ,2554      ,1091     2,3417      ,0203      ,0401      ,4706
      ,1286      ,2966      ,1141     2,5990      ,0102      ,0714      ,5219
      ,2786      ,3379      ,1213     2,7849      ,0060      ,0984      ,5774
      ,4286      ,3792      ,1303     2,9100      ,0041      ,1220      ,6364
      ,5786      ,4204      ,1407     2,9884      ,0032      ,1427      ,6982
      ,7286      ,4617      ,1522     3,0331      ,0028      ,1612      ,7622
      ,8786      ,5030      ,1646     3,0548      ,0026      ,1780      ,8280
     1,0286      ,5442      ,1778     3,0612      ,0026      ,1933      ,8952
     1,1786      ,5855      ,1915     3,0577      ,0026      ,2075      ,9635
     1,3286      ,6268      ,2056     3,0480      ,0027      ,2209     1,0327
     1,4786      ,6680      ,2202     3,0345      ,0028      ,2335     1,1026
     1,6286      ,7093      ,2350     3,0188      ,0029      ,2455     1,1731

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_socia   .
BEGIN DATA.
     -,5574     -,8756     4,3030
      ,0000     -,8756     4,3144
      ,3370     -,8756     4,3213
```

```
     -,5574      ,0000     4,1592
      ,0000      ,0000     4,3048
      ,3370      ,0000     4,3929
     -,5574      ,8756     4,0153
      ,0000      ,8756     4,2952
      ,3370      ,8756     4,4644
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_socia BY       FARAI    .
----------
    Focal predict: CTAM_fun (M)
          Mod var: FARAI    (W)

Conditional effects of the focal predictor at values of the moderator(s):

      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,0563      ,0441     1,2764      ,2035     -,0308      ,1435
      ,0000     -,0095      ,0344     -,2776      ,7817     -,0773      ,0583
      ,8756     -,0754      ,0454    -1,6626      ,0982     -,1650      ,0141

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
     1,3886    91,3043     8,6957

Conditional effect of focal predictor at values of the moderator:
      FARAI     Effect         se          t          p       LLCI       ULCI
    -1,3714      ,0937      ,0558     1,6782      ,0951     -,0165      ,2038
    -1,2214      ,0824      ,0520     1,5834      ,1152     -,0203      ,1851
    -1,0714      ,0711      ,0484     1,4675      ,1441     -,0245      ,1667
     -,9214      ,0598      ,0451     1,3257      ,1867     -,0292      ,1488
     -,7714      ,0485      ,0421     1,1527      ,2506     -,0346      ,1316
     -,6214      ,0372      ,0394      ,9436      ,3467     -,0406      ,1151
     -,4714      ,0259      ,0373      ,6958      ,4875     -,0476      ,0995
     -,3214      ,0146      ,0356      ,4109      ,6817     -,0557      ,0850
     -,1714      ,0034      ,0347      ,0970      ,9228     -,0650      ,0718
     -,0214     -,0079      ,0343     -,2308      ,8177     -,0757      ,0599
      ,1286     -,0192      ,0347     -,5533      ,5808     -,0878      ,0493
      ,2786     -,0305      ,0358     -,8523      ,3952     -,1011      ,0401
      ,4286     -,0418      ,0375    -1,1153      ,2663     -,1157      ,0322
      ,5786     -,0531      ,0397    -1,3372      ,1829     -,1314      ,0253
      ,7286     -,0644      ,0424    -1,5190      ,1306     -,1480      ,0193
      ,8786     -,0756      ,0454    -1,6653      ,0977     -,1653      ,0140
     1,0286     -,0869      ,0488    -1,7820      ,0765     -,1832      ,0094
     1,1786     -,0982      ,0524    -1,8747      ,0625     -,2016      ,0052
     1,3286     -,1095      ,0562    -1,9486      ,0530     -,2204      ,0014
     1,3886     -,1140      ,0578    -1,9739      ,0500     -,2280      ,0000
     1,4786     -,1208      ,0602    -2,0078      ,0462     -,2396     -,0020
     1,6286     -,1321      ,0643    -2,0554      ,0414     -,2589     -,0052

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_fun   FARAI      BI_socia   .
BEGIN DATA.
    -1,5194     -,8756     4,2288
      ,0000     -,8756     4,3144
     1,5194     -,8756     4,4000
    -1,5194      ,0000     4,3193
      ,0000      ,0000     4,3048
     1,5194      ,0000     4,2903
    -1,5194      ,8756     4,4098
      ,0000      ,8756     4,2952
     1,5194      ,8756     4,1806
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_fun WITH     BI_socia BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,0204      ,1270      ,1605      ,8727     -,2302      ,2710
      ,0000      ,2613      ,1096     2,3829      ,0183      ,0449      ,4777
      ,8756      ,5021      ,1644     3,0546      ,0026      ,1777      ,8266

Conditional indirect effects of X on Y:
```

```
INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_fun    ->    BI_socia

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0031      ,0249     -,0230      ,0779
      ,0000     -,0022      ,0121     -,0308      ,0212
      ,8756     -,0308      ,0475     -,1624      ,0189
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_fun

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Fun Health

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_healt
    X  : CTAM_EoU
    M  : CTAM_fun
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_fun

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2818      ,0794     2,2353     1,6679     9,0000   174,0000      ,1000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,9074      ,9267     -,9792      ,3289    -2,7366      ,9217
CTAM_EoU      ,2318      ,2413      ,9604      ,3382     -,2445      ,7081
FARAI        -,0649      ,1308     -,4962      ,6204     -,3230      ,1932
Int_1         ,2019      ,2432      ,8302      ,4076     -,2781      ,6819
Q40           ,0800      ,0324     2,4700      ,0145      ,0161      ,1439
Q36           ,0004      ,0152      ,0289      ,9770     -,0295      ,0304
Q45           ,1514      ,2767      ,5471      ,5850     -,3947      ,6975
Q37           ,2218      ,1435     1,5458      ,1240     -,0614      ,5049
Q46          -,1129      ,2865     -,3941      ,6940     -,6784      ,4526
Q38          -,3709      ,3073    -1,2073      ,2290     -,9774      ,2355

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0036      ,6892     1,0000   174,0000      ,4076
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_fun   .
BEGIN DATA.
     -,5574     -,8756      ,0241
      ,0000     -,8756      ,0548
      ,3370     -,8756      ,0733
     -,5574      ,0000     -,1312
      ,0000      ,0000     -,0020
      ,3370      ,0000      ,0761
     -,5574      ,8756     -,2866
      ,0000      ,8756     -,0589
      ,3370      ,8756      ,0788
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_fun BY       FARAI    .

**************************************************************************
```

```
OUTCOME VARIABLE:
 BI_healt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3299      ,1088     1,2981     1,9090    11,0000   172,0000      ,0411

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,4160      ,7090     3,4074      ,0008     1,0165     3,8155
CTAM_EoU      ,1518      ,1845      ,8228      ,4118     -,2123      ,5159
CTAM_fun      ,0157      ,0578      ,2724      ,7856     -,0983      ,1298
FARAI         ,0475      ,1011      ,4696      ,6392     -,1521      ,2471
Int_1         ,0271      ,1878      ,1443      ,8854     -,3436      ,3978
Int_2        -,0318      ,0551     -,5760      ,5654     -,1406      ,0771
Q40           ,0747      ,0252     2,9642      ,0035      ,0249      ,1244
Q36          -,0222      ,0116    -1,9087      ,0580     -,0451      ,0008
Q45          -,1234      ,2115     -,5831      ,5606     -,5409      ,2942
Q37           ,0083      ,1102      ,0757      ,9398     -,2092      ,2259
Q46           ,1483      ,2194      ,6760      ,5000     -,2848      ,5814
Q38          -,0851      ,2351     -,3617      ,7180     -,5492      ,3791

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_fun x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0001      ,0208     1,0000   172,0000      ,8854
M*W      ,0017      ,3318     1,0000   172,0000      ,5654
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_healt   .
BEGIN DATA.
     -,5574     -,8756     2,0326
      ,0000     -,8756     2,1040
      ,3370     -,8756     2,1471
     -,5574      ,0000     2,0609
      ,0000      ,0000     2,1455
      ,3370      ,0000     2,1967
     -,5574      ,8756     2,0893
      ,0000      ,8756     2,1871
      ,3370      ,8756     2,2463
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_healt BY       FARAI    .
----------
    Focal predict: CTAM_fun (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_fun   FARAI      BI_healt   .
BEGIN DATA.
    -1,5194     -,8756     2,0378
      ,0000     -,8756     2,1040
     1,5194     -,8756     2,1701
    -1,5194      ,0000     2,1216
      ,0000      ,0000     2,1455
     1,5194      ,0000     2,1695
    -1,5194      ,8756     2,2055
      ,0000      ,8756     2,1871
     1,5194      ,8756     2,1688
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_fun WITH     BI_healt BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************
```

```
Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756      ,1280      ,2136      ,5994      ,5497     -,2936      ,5497
      ,0000      ,1518      ,1845      ,8228      ,4118     -,2123      ,5159
      ,8756      ,1755      ,2766      ,6345      ,5266     -,3704      ,7214

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_fun    ->    BI_healt

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0024      ,0246     -,0447      ,0619
      ,0000      ,0036      ,0193     -,0377      ,0464
      ,8756     -,0049      ,0429     -,0906      ,0872
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_fun

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Fun Biometrics

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 59
    Y  : BI_biome
    X  : CTAM_EoU
    M  : CTAM_fun
    W  : FARAI

Covariates:
 Q40      Q36      Q45      Q37      Q46      Q38

Sample
Size:  184

**************************************************************************
OUTCOME VARIABLE:
 CTAM_fun

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2818      ,0794     2,2353     1,6679     9,0000   174,0000      ,1000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,9074      ,9267     -,9792      ,3289    -2,7366      ,9217
CTAM_EoU      ,2318      ,2413      ,9604      ,3382     -,2445      ,7081
FARAI        -,0649      ,1308     -,4962      ,6204     -,3230      ,1932
Int_1         ,2019      ,2432      ,8302      ,4076     -,2781      ,6819
Q40           ,0800      ,0324     2,4700      ,0145      ,0161      ,1439
Q36           ,0004      ,0152      ,0289      ,9770     -,0295      ,0304
Q45           ,1514      ,2767      ,5471      ,5850     -,3947      ,6975
Q37           ,2218      ,1435     1,5458      ,1240     -,0614      ,5049
Q46          -,1129      ,2865     -,3941      ,6940     -,6784      ,4526
Q38          -,3709      ,3073    -1,2073      ,2290     -,9774      ,2355

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0036      ,6892     1,0000   174,0000      ,4076
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      CTAM_fun   .
BEGIN DATA.
     -,5574     -,8756      ,0241
      ,0000     -,8756      ,0548
      ,3370     -,8756      ,0733
     -,5574      ,0000     -,1312
      ,0000      ,0000     -,0020
      ,3370      ,0000      ,0761
     -,5574      ,8756     -,2866
      ,0000      ,8756     -,0589
      ,3370      ,8756      ,0788
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     CTAM_fun BY       FARAI    .

**************************************************************************
```

```
OUTCOME VARIABLE:
 BI_biome

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2653      ,0704     1,5050     1,1839    11,0000   172,0000      ,3014

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,2958      ,7634     3,0072      ,0030      ,7889     3,8028
CTAM_EoU     -,0542      ,1986     -,2727      ,7854     -,4462      ,3379
CTAM_fun      ,1225      ,0622     1,9685      ,0506     -,0003      ,2453
FARAI        -,1354      ,1089    -1,2437      ,2153     -,3504      ,0795
Int_1         ,0673      ,2022      ,3327      ,7398     -,3319      ,4664
Int_2        -,0673      ,0594    -1,1338      ,2584     -,1845      ,0499
Q40           ,0099      ,0271      ,3666      ,7144     -,0436      ,0635
Q36          -,0266      ,0125    -2,1249      ,0350     -,0513     -,0019
Q45          -,2238      ,2278     -,9824      ,3273     -,6734      ,2258
Q37           ,0065      ,1187      ,0545      ,9566     -,2278      ,2407
Q46           ,3526      ,2363     1,4925      ,1374     -,1137      ,8189
Q38           ,0063      ,2532      ,0249      ,9802     -,4935      ,5061

Product terms key:
 Int_1    :        CTAM_EoU x        FARAI
 Int_2    :        CTAM_fun x        FARAI

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0006      ,1107     1,0000   172,0000      ,7398
M*W      ,0069     1,2856     1,0000   172,0000      ,2584
----------
    Focal predict: CTAM_EoU (X)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_EoU   FARAI      BI_biome   .
BEGIN DATA.
     -,5574     -,8756     1,8746
      ,0000     -,8756     1,8116
      ,3370     -,8756     1,7735
     -,5574      ,0000     1,7232
      ,0000      ,0000     1,6930
      ,3370      ,0000     1,6748
     -,5574      ,8756     1,5718
      ,0000      ,8756     1,5744
      ,3370      ,8756     1,5760
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_EoU WITH     BI_biome BY       FARAI    .
----------
    Focal predict: CTAM_fun (M)
          Mod var: FARAI    (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CTAM_fun   FARAI      BI_biome   .
BEGIN DATA.
    -1,5194     -,8756     1,5359
      ,0000     -,8756     1,8116
     1,5194     -,8756     2,0873
    -1,5194      ,0000     1,5069
      ,0000      ,0000     1,6930
     1,5194      ,0000     1,8792
    -1,5194      ,8756     1,4779
      ,0000      ,8756     1,5744
     1,5194      ,8756     1,6710
END DATA.
GRAPH/SCATTERPLOT=
 CTAM_fun WITH     BI_biome BY       FARAI    .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************
```

```
Conditional direct effect(s) of X on Y:
      FARAI     Effect         se          t          p       LLCI       ULCI
     -,8756     -,1131      ,2300     -,4916      ,6236     -,5671      ,3409
      ,0000     -,0542      ,1986     -,2727      ,7854     -,4462      ,3379
      ,8756      ,0047      ,2978      ,0159      ,9873     -,5831      ,5926

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 CTAM_EoU    ->    CTAM_fun    ->    BI_biome

      FARAI     Effect     BootSE   BootLLCI   BootULCI
     -,8756      ,0100      ,0634     -,1115      ,1573
      ,0000      ,0284      ,0372     -,0304      ,1197
      ,8756      ,0260      ,0519     -,0368      ,1714
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: The following variables were mean centered prior to analysis:
          FARAI    CTAM_EoU CTAM_fun

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

Annex C – Questionnaire

AI_Smartphones2

Início do bloco: Bloco de questões por defeito

Q1 No âmbito do Mestrado em Psicologia Social e das Organizações, no ISCTE-IUL Instituto Universitário de Lisboa, foi criada uma equipa de investigação com o objetivo de estudar a utilização de smartphones.

Gostaríamos que nos ajudasse, respondendo a um pequeno questionário que lhe toma, aproximadamente, 10 a 15 minutos.

O questionário é anónimo, com o fim de assegurar a confidencialidade e imparcialidade dos participantes e não lhe trará nenhuma despesa, nem riscos. No mesmo, não existem respostas certas, nem erradas. É a sua opinião, verdadeira, sincera e espontânea que realmente importa. Além disso, a sua participação é, totalmente, voluntária.
Os dados recolhidos destinam-se exclusivamente para fins académicos da presente

investigação, juntamente com os dos restantes participantes.
Caso pretenda informações adicionais e/ou esclarecimentos de dúvidas relativas ao estudo, contacte o professor responsável através do seguinte e-mail: nelson.ramalho@iscte-iul.pt
Caso aceite participar no presente estudo, por favor, preencha o espaço abaixo indicado.
Os dados só serão guardados quando, no final, clicar em submeter, pelo que é muito importante que não desista antes de chegar a este passo.
Gratos pela sua colaboração,

Alexandre Rilho, Filipa Matias, Miguel Longle

Q42 Ao avançar, declaro que tomei conhecimento dos objetivos e procedimentos previstos para a minha colaboração neste estudo e aceito participar.

Quebra de página

Q25 Atualmente tem smartphone?

◯ Sim. Qual? (1) ____

◯ Não (2)

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q40 Há quanto tempo tem um smartphone? (anos)

____

Q47 Entre as pessoas mais próximas de si que percentagem usa smartphone?

____

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q48 Em que medida considera que o seu smartphone incorpora inteligência artificial?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	(7)	
Não incorpora nada sequer parecido com inteligência artificial.	◯	◯	◯	◯	◯	◯	◯	Incorpora bastante inteligência artificial, até mais do que as pessoas pensam.

Fim do bloco: Bloco de questões por defeito

Início do bloco: C-TAM

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q18 Usefullness **Pense na utilidade do seu smartphone**. Indique em que medida concorda ou discorda com as seguintes afirmações.

	Discordo totalmente (1)	Discordo parcialmente (2)	Não concordo nem discordo (3)	Concordo parcialmente (4)	Concordo totalmente (5)
Ajuda-me a ser mais eficaz. (1)	○	○	○	○	○
Ajuda-me a ser mais produtivo. (2)	○	○	○	○	○
Poupa-me tempo por usá-lo. (3)	○	○	○	○	○
Requer um menor número de etapas para realizar o que eu queria fazer. (4)	○	○	○	○	○
Facilitou a tarefa que eu queria realizar. (5)	○	○	○	○	○

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q19 Ease of use **Pense na facilidade de uso do seu smartphone**. Indique em que medida concorda ou discorda com as seguintes afirmações.

	Discordo totalmente (1)	Discordo parcialmente (2)	Não concordo nem discordo (3)	Concordo parcialmente (4)	Concordo totalmente (5)
É fácil de usar. (1)	○	○	○	○	○
Eu aprendi a usá-lo rapidamente. (2)	○	○	○	○	○
É simples de usar (3)	○	○	○	○	○
Eu facilmente me lembro como usá-lo. (4)	○	○	○	○	○
Foi fácil aprender a usá-lo. (5)	○	○	○	○	○

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q21 Considerando as possibilidades que um smartphone pode oferecer hoje, em que medida utiliza ou utilizaria as seguintes funcionalidades?

	Nunca (1)	Algumas vezes (2)	Cerca de metade das vezes (3)	A maioria das vezes (4)	Sempre (5)
Colocar os meus dados pessoais numa aplicação do smartphone (1)	○	○	○	○	○
Aceder à minha conta bancária (2)	○	○	○	○	○
Guardar fotos pessoais (3)	○	○	○	○	○
Guardar ou permitir a monitorização do meu sono (4)	○	○	○	○	○
Dar a conhecer a minha localização através do GPS (5)	○	○	○	○	○
Usar aplicações de monitorização da minha saúde ou alimentação (6)	○	○	○	○	○
Aceder a uma rede social (7)	○	○	○	○	○
Aceder ao email pessoal (8)	○	○	○	○	○
Permitir a integração de toda a informação num browser (9)	○	○	○	○	○
Usar aplicações de GPS para chegar a um endereço (10)	○	○	○	○	○
Usar aplicações que exigem um cartão de	○	○	○	○	○

crédito (11)					
Usar mecanismos de bloqueio do tipo password (12)	○	○	○	○	○
Usar impressão digital (13)	○	○	○	○	○
Usar identificação biométrica pela retina ou iris (14)	○	○	○	○	○
Usar reconhecimento facial (15)	○	○	○	○	○

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q44 Em que medida usar o seu smartphone a/o deixa...

	1 (1)	2 (2)	(3)	(4)	(5)	
Infeliz	○	○	○	○	○	Feliz
Irritado/a	○	○	○	○	○	Calmo/a
Insatisfeito/a	○	○	○	○	○	Satisfeito/a
Melancólico/a	○	○	○	○	○	Contente
Desesperado/a	○	○	○	○	○	Esperançoso/a
Aborrecido/a	○	○	○	○	○	Relaxado/a

Apresentar esta pergunta:

If Atualmente tem smartphone? = Sim. Qual?

Q27 FARAI2 Quão receoso(a) está do seguinte? :

	Nada receoso(a) (1)	Algo receoso(a) (2)	Receoso(a) (3)	Bastante receoso(a) (4)
Que a tecnologia autónoma venha a tomar as suas próprias decisões e acções? (1)	○	○	○	○
Que a tecnologia autónoma venha a substituir trabalhos de pessoas? (2)	○	○	○	○
Que a Inteligência Artificial evolua para além da capacidade de controlo humano? (3)	○	○	○	○
Que eu tenha de confiar na inteligência artificial para realizar o meu trabalho? (4)	○	○	○	○

Q28 Quão frequentemente vê séries e filmes e conteúdos relacionados com ficção científica, fantasia e super heróis?

- Nunca vejo (1)
- É raro ver (2)
- Ocasionalmente (3)
- Frequentemente (4)
- Vejo muito frequentemente (5)

Q29 Cyber-paranoia Em que medida concorda com as seguintes afirmações?

	Discordo fortemente (1)	Discordo (2)	Discordo ligeiramente (3)	Concordo ligeiramente (4)	Concordo (5)	Concordo fortemente (6)
O aumento do uso de telemóveis por crianças tem um efeito negativo no seu cérebro (1)	○	○	○	○	○	○
É apenas uma questão de tempo até que a rede global de internet colapse com graves consequências (2)	○	○	○	○	○	○
Evito usar a internet para assuntos pessoais para ninguém ter acesso à minha informação pessoal (3)	○	○	○	○	○	○
Preocupo-me que outros editem as minhas informações na internet (ex: redes sociais) sem o meu consentimento (4)	○	○	○	○	○	○
Os terroristas encontrarão novas formas de utilizar a internet para planear novos ataques às populações (5)	○	○	○	○	○	○
Pagamento com cartões	○	○	○	○	○	○

permite que as autoridades monitorizem as minhas viagens e compras (6)						
Empresas que armazenam dados sobre clientes são muito vulneráveis ao roubo da minha informação pessoal (7)	○	○	○	○	○	○
As pessoas não se preocupam o suficiente com as ameaças que advêm do seu uso de tecnologias (8)	○	○	○	○	○	○
As pessoas deveriam preocupar-se que os seus movimentos sejam monitorizados através do seu smartphone (9)	○	○	○	○	○	○
Câmeras são ilegalmente usadas de forma a espiar as pessoas (10)	○	○	○	○	○	○

Q30 Em que medida está familiarizado com as tecnologias de um smartphone?

	Nada familiarizado(a). Não conheço nada.	Perfeitamente. Conheço bem as tecnologias usadas.

	0	10	20	30	40	50	60	70	80	90	100
1 ()											

Fim do bloco: Questões de Alex neste bloco

Início do bloco: Sociodemographics

Q51 Para terminarmos segue-se um pequeno conjunto de questões de natureza sociodemográfica apenas para caracterização agregada dos participantes. Recordamos que todo o inquérito tem natureza confidencial e a sua participação é anónima.

Q36 Idade

____

Q45 Sexo

○ Masculino (1)

○ Feminino (2)

Q37 Habilitações literárias

- Até ao 9º ano (1)
- 9º ano completo (2)
- 12º ano completo (3)
- Licenciatura ou equivalente (4)
- Mestrado (5)
- Doutoramento (6)

Q46 Estado Civil

- Solteiro/a (1)
- Casado/a ou em União de facto (2)
- Divorciado/a (3)
- Viuvo/a (4)

Q38 Exerce atualmente ou exerceu uma profissão ligada às Tecnologias de Informação?

- Sim (1)
- Não (2)

Fim do bloco: Sociodemographics