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Developing digital skills intention: A test of a UTAUT variant model

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Master's in social and Organizational Psychology

Supervisor:

Doctor Nelson Campos Ramalho, Associate Professor, Iscte – University Institute of Lisbon

July 2021

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CIÊNCIAS SOCIAIS
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“You become responsible, forever, for what you have tamed. I am who I am, and I have the need to be”.

Antoine de Saint-Exupéry – The little prince

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Abstract

The plethora of research and models on technology acceptance testify the critical role that digital skills play today. This proliferation of models has been taken place ever since Davis (1989) proposed the TAM which was subsequently changed into C-TAM, UTAUT (Venkatesh et al., 2003), and most recently Meta-UTAUT (Dwivedi et al., 2019). Although the proposed models assumedly intend to extend and correct some issues in the previous models (including new boundary conditions), their alleged added value (e.g. better explanatory power, better psychometric properties) is yet to be proven. The rationale supporting the most recent version (Meta-UTAUT) is questionable as the model becomes a saturated one, i.e. a model where all constructs seem to be associated with each other, and the cumulative effect of moderators is never claimed. To ascertain this, we compared – with the exact same dataset – the two most popular (UTAUT vs. meta-UTAUT) against a novel variant that previews multiple-interactions. Based on a sample of 206 individuals, the models are contrasted as regards model fit, and explained variance. Findings show the three models have equivalent model fit. Also, that the UTAUT model has strong explanative power, the Meta-UTAUT slightly outperformed UTAUT and also that the proposed model slightly outperforms both in explained variance. Findings suggest a novel theoretical configurational approach may emerge in this field of research.

Keywords: Behavioral Intention; Determinants; Digital Skills; UTAUT; Organizational behavior; Human Factors Engineering

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Resumo

A multiplicidade de investigações e modelos sobre a aceitação da tecnologia testemunham o papel crucial que as competências digitais desempenham atualmente. Esta proliferação de modelos surgiu com o TAM (Davis, 1989) que foi posteriormente transformado em C-TAM, UTAUT (Venkatesh et al., 2003), e mais recentemente Meta-UTAUT (Dwivedi et al., 2019). Embora os modelos propostos supostamente pretendam alargar e corrigir algumas questões dos modelos anteriores (incluindo novas condicionantes), o seu alegado valor acrescentado (por exemplo, melhor poder explicativo, melhores propriedades psicométricas) ainda não foi provado. A lógica que suporta a versão mais recente (Meta-UTAUT) é questionável à medida que o modelo se torna saturado, ou seja, um modelo onde todas as construções parecem estar associadas umas às outras, e o efeito cumulativo dos moderadores nunca é reivindicado. Para verificar isto, comparamos - com exatamente o mesmo conjunto de dados - os dois mais populares (UTAUT vs. meta-UTAUT) com uma variante nova que prevê interações múltiplas. Com base numa amostra de 206 indivíduos, os modelos são contrastados no que diz respeito à adaptação ao modelo, e explicada a variância. Os resultados mostram que os três modelos têm um ajuste de modelo equivalente. Para alem disso, verificamos que o modelo UTAUT tem um forte poder de explicação, o Meta-UTAUT tem um desempenho ligeiramente superior ao do UTAUT e também que o modelo proposto tem um desempenho ligeiramente superior a ambos na variância explicada. Os resultados sugerem que uma nova abordagem teórica pode emergir neste campo de investigação.

Palavras-chave: Intenção Comportamental; Determinantes; Habilidades Digitais; UTAUT; Comportamento Organizacional; Engenharia de Fatores Humanos

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Glossary

CEDEFOP – European Centre for the Development of Vocational Training

DC – Digital Competencies

DeSeCo – Definition and Selection of Competencies

DS – Digital Skills

ICTs – Information and Communication Technologies

IS – Information Systems

IT – Information Technology

NAEP - National Assessment of Educational Progress

OECD – Organisation for Economic Co-operation and Development

TAM – Technology Acceptance Model

UTAUT – Unified Theory of Acceptance and Use of Technology

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Introduction

As the world evolves, we evolve with it to become the best version of ourselves. Evolution brings many challenges and new ways of living that can stem from different reasons, such as "globalization, aging or climate change" (Joint Research Centre, 2019). The impact of digitalization and technologies in our daily lives – how it is reshaping the marketplace, communications, and even our way of education – gained a critical place in the ongoing public debate about such changes. According to the same source, new technologies spread across workplaces faster than ever – in Europe, the use of computers at work expanded exponentially in the last 15 years.

As the world of technologies evolves in the workplace, many jobs are being transformed and becoming more and more automatic while reshaping the jobs themselves and the content and methods of work, repetitive jobs and tasks are being progressively substituted by automatic machines (Bisello et al., 2019). Non-routine tasks (manual or cognitive) have less probability of being replaced because they are harder to codify. In that sense, workers, and future workers (students preparing for the job market), need to adapt to all these circumstances and anticipate changes (Joint Research Centre, 2019). Thus, it is reasonable to assume Digital Skills (DS) are a top priority for knowledge-based societies. This has been recognized as such by, e.g., the European Commission because there is a need for workers with skilled digital knowledge that can produce, and distribute ideas and information (van Laar et al., 2019).

However, as recently claimed by YouGov (2018) in a Vodafone study across 15 countries, 1 out of 5 people aged 18-24 admitted they feel underprepared for the digital economy. One of the key dimensions of preparedness is the intention towards developing DS. These are "a set of basic knowledge, skills, abilities, and other characteristics that enable people at work to efficiently and successfully accomplish their job tasks regarding digital media at work" (Oberländer et al., 2020, pp. 5).

Amongst the challenges research on DS faces, is the search for which skills fall within the class of DS? In recent effort to build common ground, Oberländer et al. (2020) endeavoured to conduct a systematic literature review (25 in total by their criteria) to offers a comprehensive view of the possibilities regarding which types of skills fall within the umbrella of DS. Among these skills.

Another challenge for DS research pertains to the establishment of a model that explains the promotion of DS learning and use. This requires a behavioral model that identifies the determinants of such learning. Van Laar et al. (2019) made an essential contribution to this by examining the level of DS (e.g., information, communication, collaboration, critical thinking, creativity, and problem-solving) among workers and identifying their determinants (such as potentially personal, motivational, and social determinants).

Although such purpose is unquestionably relevant, the specific choice of the behavioral model underlying the studies may be subjected to question. Such is the case for studies that adopted or adapted the TAM model (Davis, 1989), a well-known model in IT behavioral research that aims to measure the use and acceptance of technology. If such model has the merit of having pioneered the field, it has the disadvantage of having witness the birth of newer models that claim to overcome its limitations. Namely, its alleged lack of comprehensiveness regarding psychological processes comprehending the attitude of intention.

C-TAM (Taylor & Todd, 1995) is a good example of such models. It was developed specifically to explain consumer behavior related to technology acceptance and has introduced the well-known dimension that comprehends affection into the model as it pertains to attitudes. Therefore, attitudes comprehend a cognitive, affective, and action dimension. Another model, the UTAUT model (Venkatesh et al., 2003), has also gained an outstanding place in IT behavioral literature as it explicitly was designed to integrate all extant theories adding to the baseline TAM model some novel dimensions. Lately, Dwivedi et al. (2019) revised UTAUT (Meta-UTAUT) and recovered attitude as a key mediator and proposing new associations between constructs. Scholars claim cumulative knowledge but, from a closer view, the evolution of models does not offer such evidence of the claimed cumulativeness. For example, the changes made from TAM to UTAUT and from UTAUT to Meta-UTAUT seem not to follow a consistent path.

This situation may explain why older models (e.g. TAM) endure despite the existence of competitor models. We reason that either scholars overlooked newer models, or they discard their alleged added value. The former seems unlikely, as any literature review would highlight all models. The latter would be more in line with our own literature review that showed direct comparisons between models are very scarce if not inexistent and, likewise, the newest version is very much a saturated model, meaning all constructs are related with each other, which is theoretically unclear.

Considering this, the overarching objective of this research is to conduct an explicit comparative analysis of UTAUT and Meta-UTAUT as well as exploring an alternative UTAUT-based model to explain DS development intention. This alternative stem from our own criticism to extant models.

This is ideally done in an empirical study with the exact same dataset. We reason that the most suitable model is the one (under the premise that all psychometric quality criteria are met) that accounts for higher explained variance in the dependent variable, in this case, the behavioral intention to use DS. Therefore, the primary motive for this thesis is to add value to extant literature because it is an evolving topic that agglomerates different viewpoints and conceptual models yet to be discovered.

Chapter I - Literature Review

1.1 – Digital Transformation

Humanity always interacted with the surrounding environment; that is how we can transmit information, create relationships and knowledge. To do this, we count on our cognition (how we process information) and create an interaction that allows us to respond to it. If we do this every day, even before the technologies, what we can achieve with operative systems can surpass imagination. We interact as we do, but with a programmed machine that does the work for us - this is what we call *Cognitive Ecology* (Lévy, 1991), the capability of just using the necessary amount of cognition because the machine helps us do the rest - so we use just some of the cognitive mechanisms. The magnitude of these changes is astonishing when we realize how our lives were changed by mobile banking, online shopping, by working with people in video calls, or even giving classes through a computer. Years ago, none of this would be possible or considered until the rapid evolution of the digital tools that allow us to live our days as we do now.

Therefore, the impact that we feel in our daily lives tells us that we have entered the 4th revolution - the era of technologies and systems. This revolution consists on the development of "information technologies combined with robotization, automation of tasks, the Internet, 3D printing, driverless cars, and safety and defence programs" that allow us to interact and improve our way of life (Degryse, 2016, pp. 19). For example, these changes are creating new forms of employment, which have an impact on working conditions and in the labor market - like ICT-based mobile work, where we can work from across the world. A CEDEFOP (2017) study concludes that Europe lives a time where people feel the changes that digitalization can bring, for example, 47% watched their jobs changing methods and practices; besides, 43% watched an evolution in the technologies that they use in their work. One of the challenges is the irrational fear for our jobs and how they can be replaced - mostly the routine production tasks because they are easier to codify. Nonetheless, even these tasks require the "ability to communicate, solve problems, and mediate information" (Vooght & Roblin, 2012, pp. 300). In this way, digitalization brought a new battleground for competitive advantage, where "fast and first" is the crucial element for companies that need to develop the capacity to respond as fast as possible to their customer needs (Vasilescu et al., 2020). Although organizations that want to survive need to rely on digital transformation, there is not much space for discussing digitalization's efficacy in the corporate area (Sousa & Rocha, 2019). In that sense, organizations struggle to cope with new emerging customer segments, cultural diversity in a global marketplace, market volubility, raised customer expectations about the quality of products and services, and the impact of the Internet on an organization's core business. One of the "must happen changes" is a coping mechanism for the digitalization era. Organizations need to strategically manage their business environment by developing their workers' digital skills (Sousa & Rocha, 2019).

In this sense, the reality for someone born after the year 2000 or, even after, is entirely different - the mindset is not "Look at where we are now?", but more "This is not fast enough!". We comprehend that there is the facilitation of younger generations working with datasets and technologies, but do they know how to use them effectively? Can younger people achieve what they pretend in using the available tools?

1.1.1 – 21st century skills development

There is a lack of understanding or clarity about the nature of 21st century skills, which originates from authors using the same words but with entirely different meanings. As Dede (2009, pp. 1) claimed, "the capabilities that people need for work, citizenship, and self-actualization" differ from those of the 20th century due to the emergence of information and communications technologies. Therefore, the 4th technology revolution appears to demand knowledgeable workers to provide solutions when the protocol fails.

Usually, 21st century skills are generally characterized as "being transversal, multidimensional and associate with higher-order skills and behaviors" (Dede, 2009, pp. 300) that can serve different fields of expertise to cope with complex problems and unpredictable situations (Vooght & Roblin, 2012).

There has been an effort made by different institutions and experts to uncover the essential skills required for the 21st century. For example, under the program DeSeCo, the OECD referred to "information as a product: restructuring and modeling on information and developing own ideas" (pp. 397) as primary skills. Likewise, under the program P21 skills, the USA distinguished creativity, innovation, critical thinking, and problem-solving as essential skills of the 21st century (Ahonen & Kinnunen, 2015; Sousa & Rocha, 2019). The National (USA) Assessment of Educational Progress also claims it is crucial to assess technology and engineering literacy. In line with this, Vooght and Roblin (2012, pp. 308) state that there are “strong agreements on the need for competencies in the areas of communication, collaboration, ICT-related competencies, and social and/or cultural awareness”. These authors also acknowledge the important role of creativity, critical thinking, and problem-solving among others. We reason then that there seems to be a consensus on the idea that ICT is at the core of each of the frameworks because it implies a new set of competencies to manage, evaluate, and produce information, so necessary in these times.

As mentioned, digital technology in the workplace has been altering many systems with the introduction of software, robots, and AI-powered machines. One of the consequences of such changes pertains to the labor market. The ubiquity of ICT and non-cognitive skills seems to be evident and Europe is expected to most jobs required by 2025 have at least a moderate level of DS (Joint Research Centre, 2019).

Despite the acknowledged importance of digital skills, a study that surveyed EU citizens about their self-evaluation of DS found that the majority recognized having but “meager digital skills” and “low usage of the Internet” (Vasilescu et al., 2020, pp.1). The authors also concluded that this was more visible in older participants. Thus, although youngsters use more digital skills, they may not have think that they need to evolve and develop their DS for the labor market. So, what if our younger workers do not have the level of DS that our labor market requires?

1.1.2 – Digital Skills

The definition of digital skills is, most of the time, not converging into one concept or construct because of the extensive research on the matter. Usually, digital competence is the most used term. However, some authors prefer to use the term digital competencies (e.g., Oberländer et al., 2020), others digital literacy (e.g., Martin, 2005, p. 131), and others such as Calvani et al. (2008) prefer digital competence. The big difference between the definitions concerns their comprehensiveness, what knowledge they entail, and how technical they are. For example, in the first concept, Digital Competencies include basic skills such as searching for information online and more complex abilities, like analyzing, interpreting, and applying the information in relevant life contexts (Oberländer et al., 2020).

For this study, we adopted Oberländer et al. (2020, pp. 5) definition because it offers a broader scope of DS: "Digital competencies at work are a set of basic knowledge, skills, abilities, and other characteristics that enable people at work to efficiently and successfully accomplish their job tasks regarding digital media at work". Therefore, we use the name of Digital Skills as a surrogate of Digital Competencies.

Alongside terminological variations so do competencies' frameworks vary. To understand what is underneath the DS scope, van Laar et al. (2019) and Oberländer et al. (2020) conducted a systematic review to define the set of competencies that fall under the DS scope. They compiled 75 and 25 articles, respectively, to merge and define different DS. So, after a revision of the two articles, we concluded that Oberländer et al. (2020) proposal fits better into the categories of van Laar et al. (2019). We, therefore, opted to use van Laar et al. (2019) DS profile set. For clarity's sake, we will identify and characterize each of the ten DS to offer a more rigorous account of its understanding in this study. They are as follows:

a) ***Information management*** refers to using ICT to define and search (formulate a research statement to facilitate the search for information); select or access (find and retrieve information from a variety of online sources); organize or manage (organize information to be able to find it later) to make informed decisions about a given task (van Laar et al., 2017; Van Deursen & Van Dijk, 2009). For example, it is critical to use search engines effectively and efficiently amongst the variety of online information and the proliferation of databases (Ananiadou & Claro, 2009; Punie & Ala-Mutka, 2007). Likewise, workers must manage their documents, files, and other forms of digital information as part of their work activities. They need to know how to save files in the right place, be consistent in naming digital files and organize digital files via hierarchical folder structures.

b) ***Information evaluation*** includes judging the usefulness, relevance, and reliability of digital information (Hatlevik et al., 2018). For example, workers need the skills to check whether the information found is correct and valid and is up to date using available digital tools.

c) ***Communication*** refers to the capacity of transmitting information to others, ensuring that the meaning is expressed effectively (van Laar et al., 2017). The competency is subdivided into 1) *Communication expressiveness* referring to being able to shape interpersonal impressions and fostering satisfactory online interactions. For example, choosing the right location to post and carefully consider its contents is crucial to getting a message across and accomplishing what one wants from online interactions (Van Deursen et al., 2014). 2) *Communication contact-building* refers to make and maintain contacts (Van Deursen et al., 2014). For example, using digital networks, communities, or platforms to engage in professional conversations. 3) *Communication networking* refers to mobilizing online contacts to achieve a specific goal (Wolff & Moser, 2010). 4) *Communication content-sharing* is the ability to share online content, from status updates, photos, and videos to writing comments and blogs (Brandtzaeg et al., 2010) *e)* ***Collaboration*** concerns developing a social network and operate within teams to exchange information, negotiate agreements, and make decisions with mutual respect toward achieving a common goal (van Laar et al., 2017). Furthermore, this competency extends to responsibility, planning, interdependence, and knowledge sharing with team members. For example, working with diverse and interdisciplinary teams of people with complementary expertise and roles (Mishra & Kereluik, 2011). Also, working on the same documents, doing video calls across the world, supporting others' work, and participating in online discussions or forums is essential.

f) ***Critical thinking*** is the ability to make informed judgments and choices regarding obtained information and communication using reflective reasoning and sufficient evidence to support claims. Likewise, it refers to being open to ideas that challenge some of one's own beliefs and consider various arguments before formulating a point of view (van Laar et al., 2019). For example, be actively open to new ideas by being critical and, if necessary, modifying one's thinking considering convincing evidence. Moreover, it implies considering multiple perspectives and being able to decide whether objective data support the content to establish substantiated arguments or reasoning (Higgins, 2014; Petrucco & Ferranti, 2017).

g) ***Creativity*** refers to generating new or previously unknown ideas or treating familiar ideas in a new way and transforming them into a product, service, or process recognized as a novel within a particular domain (van Laar et al., 2017). For example, workers are expected to use ICTs to generate innovative ideas, perspectives, and approaches to give a creative turn to existing processes.

h) ***Problem-solving*** is the ability to find solutions to a problem via using ICTs to "cognitively process and understand a problem situation in combination with the active use of knowledge" (van Laar et al., 2017, pp. 583). Components such as flexibility and effectiveness are crucial to getting different solutions for the same problem. For example, workers need to problem-solve, often using the Internet to generate and integrate information about the problem and solve the problem according to the acquired information (Greiff & Funke, 2017).

Independently of the interest individuals state about their DS development, the intention to apply them precedes the actual need to develop such skills. UTAUT (Venkatesh et al., 2003) is a model that can account for the factors that explain such intention to use DS.

1.2 - UTAUT model

Since technologies are a reality in our lives, there has been an interest to build acceptance models in the use of technologies. Davis (1989) was one of the first authors and his model is one of the more commonly used models - called TAM (Technology acceptance model). This model predicts that *perceived usefulness* (meaning, the utility in using technologies) and *perceived ease of use* (meaning, how easy it is to use technology) would positively affect the intention of using technology, and therefore, their actual use (Venkatesh & Davis, 2000). However, this model has suffered changes, many of them referring to the addition of new constructs or new relationships between constructs. For example, C-TAM-TPB (Taylor & Todd, 1995) adds new constructs, namely "*Attitude,*" "*Subjective Norm,*" and "*Perceived Behavioral Control*" to better explain the acceptance and use of technologies. In total, according to Venkatesh et al. (2003) eight different models compete to explain the use of technologies, which implies many different constructs, relationships, and even a non-congruent model in the academic community.

Regarding the display of models created, the UTAUT model (Venkatesh et al., 2003) emerges as an alternative theoretical model for explaining the acceptance and use of information systems to build a unified view among all the models available. This model comprises eight theoretical models Reasoned Theory (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT). In adapting all models into one, Venkatesh et al. (2003) opted to use four determinants (performance expectancy, effort expectancy, social influence, facilitating conditions) and four moderators (gender, age, experience, and voluntariness of use) to gain comprehensiveness into explaining the behavioral intention and use of technologies.

UTAUT itself is not exempt from criticism. For example, Dwivedi et al. (2019) elaborated a recent alternative to this model: the meta-UTAUT model. The two significant issues and changes between UTAUT and meta-UTAUT are the "*Attitude*" construct and moderators - because, as Dwivedi et al. (2020) explain, "the model posits that the attitude construct has, both direct as well as indirect, (via behavioral intention) effects on use behavior" (pp.14). In a single year, the meta-UTAUT model has been widely used, counting 71 fully downloadable articles, 20 citations regarding the conceptual model and research design, and 15 studies that cited meta-

UTAUT in the introduction section and used to build new constructs and models. At the moment this section is being written, it counts now with 623 citations in scholar google.

1.2.1 – Attitude & Moderators

Research shows that attitude is a potential determinant of 21st century DS (Sinnaeve et al., 2011; Van Deursen & Van Dijk, 2015). As stated in previous models of IS/IT acceptance, such as TRA (Ajzen and Fishbein 1980; Fishbein and Ajzen 1975), TPB (Ajzen, 1991), and DTPB (Taylor & Todd 1995), "attitude" was included and claimed to play a mediating role. Therefore, one of the foremost critics arising from the UTAUT model is that Venkatesh et al. (2003) did not include the attitude construct "in order to better explain intention parsimoniously" (Venkatesh et al., 2003, pp. 428). The authors contend that "attitude" will not directly influence intention while in the presence of other constructs namely “effort expectancy” and “performance expectancy”. The main reason for this is that they believe affective reactions may operate via two other constructs (Venkatesh et al., 2003; Venkatesh & Davis, 2000).

In that sense and to revise the UTAUT model, Dwivedi et al. (2019) proposed a new theoretical model with two fundamental changes. The first one is the recovery of the "attitude," as he believes that the relationship between attitude and behavioral intention is significant because people form intentions to perform behaviors towards which they have a positive attitude. Dwivedi et al. (2019) highlights that attitudes include an affective component that translates to a cognition, therefore, an action – in this case, the intention. Likewise, in revising the model, scholars observe that the moderators do not always apply to all contexts, omitting some relationships that may be potentially important, being the solution to withdraw them (being the significant second change). This may be a solid reason to explain why the moderators are often ignored in applying the UTAUT model (Dwivedi et al., 2019). Still, there seem to be some differences e.g. pertaining to gender (Sobieraj & Kramer, 2020) but these do not necessarily cumulate into an interaction effect as gender may not moderate the relationship at all (e.g. Petersen et al., 2020).

Overall, many proposed variants of technology acceptance models were designed to progressively integrate theory and refine conflicting empirical findings on missing or redundant predictors. However, extant models grew in complexity, and for parsimony's sake, some options have been made – although tacitly – that can alter the status of the variables. Fundamentally, there has been variation as regards assuming an additive effect as compared to a multiplicative effect.

1.3 – Proposed Model

If we consider one of the fundamental models that generated UTAUT, namely TPB (Ajzen, 1991), the predictors are computed based on a multiplicative effect of underlying components. For example, attitude is computed based on the product of behavioral beliefs and outcome evaluation. Likewise, the subjective norm is the result of the product between normative beliefs and motivation to comply. Lastly, perceived behavioral control results from the product between control beliefs and perceived power. So, there is this unique thinking that expressed the coexistence of multiplicative effects rather than additive effects. This multiplicative nature of the model dynamics is also expressed in TPB applications such as the one tested by Azjen (1991), where perceived behavior control moderates the effect between intention both with attitude and subjective norm. In a variant design of UTAUT, Diaz and Loraas (2010) claimed effort expectancy interacts with attitude and anticipated emotions to explain behavioral intentions. Findings supported their conceptual model showing interaction effects do occur in several of the direct relations.

There are many other cases where predictors are theorized as operating in a multiplicative rather than additive fashion. For example, in exploring this multiplicative effect in motivation theories, Arnold (1981) explicitly contrasted it with the additive effect, finding support for its existence between valence and expectancy in explaining individual motivational force. The author thus ruled out the additive model. Extending this study into the context of educational psychology, Trautwein et al. (2012) found support for the interactive effect of expectancy with value beliefs (attainment, intrinsic, utility, and cost) in explaining academic achievement.

Transferring this rationale to UTAUT, one should mind that mathematically, the interaction effect between AxB is indistinguishable from BxA. However, theoretically, it is essential to ascertain which is the predictor and which is the moderator. We reason that performance expectancy is most suitably a predictor. It is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in a job" (Venkatesh et al., 2003, pp.447). The theoretical background of this variable comes from usefulness perceptions (TAM), extrinsic motivation (MM), job fit (MPCU), relative advantage (IDT), and outcome expectations (SCT). It is found in all of them that, performance expectancy construct is the strongest predictor of intention, as the previous model also observed (Venkatesh et al., 2003; Chang, 2012). Since perceived usefulness (performance expectancy) is such a fundamental driver of usage intentions, it is likely that it affects the DS use intention. Therefore, we hypothesize:

H1: Performance expectancy is positively associated to Digital Skills use intention.

However, being defined as "the degree of ease associated with the use of the system, so the degree to which a person believes that using ICTs would be free of effort" – effort expectancy involves the self-perception of the difficulty of learning the use of technology (Venkatesh et al., 2003, pp. 459; Davis, 1989). This construct reflects the "Perceived ease of use" from the TAM model (Davis, 1989) and is conceived as a facilitator of technology use intention (Davis, 1989; Taylor & Todd 1995; Heerwegh et al., 2016). This suggests that developing a feeling of control over technologies can contribute to 21st century DS (Venkatesh & Davis, 2000). Following Diaz and Loraas (2010) lead, we reason that the multiplicative model can apply to these two variables as it makes sense to think the performance expectancy is leveraged by effort expectancy. Namely, following previous UTAUT reasoning, the most favorable configuration to quickly adopt a new technology occurs when the expected performance is high, and the option is not overly effortful. Therefore, we hypothesize:

H2: Effort expectancy interacts with the positive relation between performance expectancy and Digital Skills use intention in such a way that the lower the expected effort, the stronger the association.

Likewise, social influence is suitably seen as a contextual variable that interferes with the way these variables interact. Social influence is the "degree to which a user perceives that significant persons believe technology use to be important" (Diaz & Loraas, 2010, pp.64). The original construct, "subjective norm," as defined in TAM, emerges like an explicit or implicit notion that the individual's behavior is influenced by how they believe others will view them of having used the technology. Diaz and Loraaz (2010, pp.75) claimed that "it is important for supervisors to focus on the importance of learning and utilizing technology if they want to encourage learning (especially) when the technology is perceived to be difficult to learn because these viewpoints will impact potential users' attitudes, which in turn impacts intent."

Approaching the social influence (i.e., the subjective norm) as a context variable that facilitates or hampers the exhibition of socially relevant behavior, several studies have successfully shown social influence moderates the direct effect upon behavioral intention, such as in the case of eating healthy food (Povey et al., 2000), recycling intentions (Wan et al., 2017)

Amidst technology acceptance research, social influence has been found to moderate attitude in relation to e-learning technologies use (Cheung & Vogel, 2013). Therefore, we hypothesize:

H3: The social influence will moderate the conditional effect of effort expectancy in the relation between performance expectancy and digital skills use intention such that the higher the social influence, the stronger the conditional effect of effort expectancy in the relation between performance expectancy and digital skills use intention.

This set of hypotheses is assumedly presented as a variant to the extant UTAUT models reviewed, namely UTAUT and meta-UTAUT. Albeit not made explicit, the hypotheses of those models (mainly, the direct effects towards behavioral intention) are tacitly tested in comparing the proposed model and those. They are briefly depicted in the graphical representations of those models and are not written in this study to avoid being wordy.

To account for this comparative purpose, we claim that our UTAUT model variant will have more explanative power of the behavioral intention to use DS than the mentioned models. Therefore, putting all hypotheses together, this is the proposed conceptual model for this research (Figure 1).

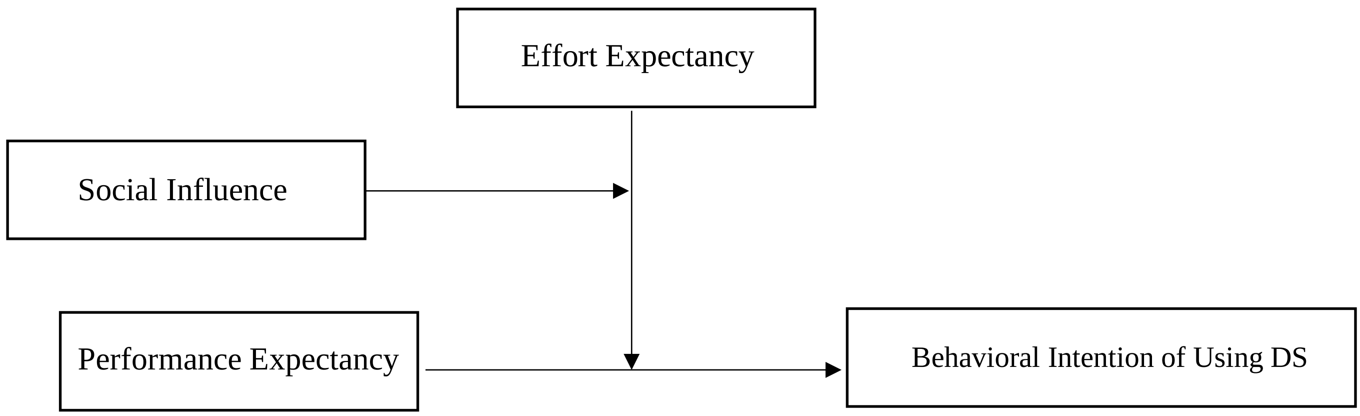

Figure 1: Proposed Model

Chapter II – Method

This section shows the procedure for data collection, the sample, the measures as well as the data analysis strategy.

2.1 - Data Analysis Strategy

Data analysis followed a two-step procedure, starting by testing the psychometric quality of the measures followed by hypothesis testing. To test the psychometric quality, we conducted confirmatory factor analysis (CFA) with AMOS 26 software. The model fit was judged on Hair et al. (2014) criteria where the chi-square p-value should not reject H0, the Confirmatory Fit Index (CFI) should attain at least. 95; The Tucker Lewis Index should attain at least .95; The Root Mean Squared Error of Approximation (RMSEA) should fall below .08 (with a bootstrapped interval at 90% have a non-significant PClose value). The reliability was measured with Jöreskog Composite reliability and with Cronbach alpha which should attain at least .70.

Additionally, constructs are considered to have convergent validity when the average variance extracted (AVE) reaches at least .500 (Fornell & Larcker, 1981). In the cases where a model has two or more latent variables, discriminant validity was judged on the HTMT values (Henseler et al., 2015), targeting values below .85. Hypotheses were tested on Process Macro 3.5 (Hayes, 2018) that conducts simultaneous tests of effects with a bootstrapping procedure. Following Hayes (2018) recommendations, we set the procedure to calculate confidence intervals for 95% with 5000 repetitions. Any given effect is considered significant if the value zero is not comprehended between the lower and upper bounds.

2.2 - Procedure

Data were collected by an online survey via Qualtrics that states the questionnaire's aim, inviting to participate and ensuring confidentiality and anonymity as well as the voluntary nature of the study (making explicit, participants could withdraw from the survey at any time without any consequence). Because the target population is used to social networks and digital outlets, we reasoned its use as a media to reach potential participants would be suitable. Therefore, we sent invitations in a snowball procedure as it is most suitable to reach the same cohort participants (Patton, 1990). To mitigate the possible bias that first contacts in this sort of procedure may have, we started by sending the first invitations to different social networks (Linkedin, Facebook, Instagram) and groups of students. The invitation clearly stated that only students 18 or more years old would be eligible to participate.

2.2.1 – Sample

The sample comprises 276 responses; 70 were eliminated because there were missing values. Therefore, the sample comprises 206 students, with 68.4% females (1 missing), averaging 20.86 years old (SD=5.24). Most students are in courses that fall in the Law, Social sciences, and services (24.6%), Economics, management, and accountancy (13.8%), Technology and Engineering (13.3%), and Humanities (12.3%), Sciences (10.8%), Education science (10.3%), Health (8.9%) and the remaining areas account for Sports, Agriculture and natural resources, and Architecture (totalling 6%).

2.3 – Measures

Except where noticed, all scales were answered on a 7-point Likert scale ranging from "*Strongly disagree*" to "*Strongly agree*".

Performance expectancy is defined as " the degree to which an individual believes that using the system will help him or her to attain gains in job performance" and was measured with 3 items from Venkatesh et al. (2003, pp.447) scale ("*I would find digital skills useful in my job*.", "*Digital skills enable me to accomplish tasks more quickly.",* "*Digital skills increase my productivity*."). The scale is reliable (CR=.806; α =.787) as has convergent validity (AVE=.581).

Effort expectancy is defined as " the degree of ease associated with the use of the system" and was measured with 3 items from Venkatesh et al. (2003, pp.450) scale ("*It would be easy for me to become digital skillful*.", "*I would find learning digital skills easy*", "*Learning how to apply digital skills is easy for me*."). The scale is reliable (CR=.900; α= .898) as has convergent validity (AVE=.750).

Social Influence is defined as the "degree to which an individual perceives that important others believe he or she should use the new system" and was measured with 3 items from Venkatesh et al. (2003, pp. 451) scale ("*People who influence my behavior think that I should learn digital skills*", "*People who are important to me think that I should learn digital skills*.", "*My colleagues have been endorsing learn digital skills*". The scale is reliable (CR=.864; α= .854) as has convergent validity (AVE=.864).

Facilitating Conditions are defined as the "degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" and was measured with 3 items from Venkatesh et al. (2003, pp. 453) scale ("*I have the knowledge necessary to learn digital skills*.", "*Learning digital skills is not compatible with other learning I must do*.", "*I have a specific person (or group) that is available to help me learning digital skills.*"). This scale has suboptimal reliability (CR=.668, α=.412) and by analyzing the interitem correlations, the last item was removed to show a reliable scale (CR=.837; r_{SB}=.837) which also has convergent validity (AVE=.720).

Attitude is defined as "an individual's overall effective reaction to using a system" and was measured with 3 items from Venkatesh et al. (2003, pp.455) scale ("*Digital skills make work more interesting.*", "*Learning digital skills is fun.*", "*I like learning digital skills*."). The scale is reliable (CR=.892; α= .887) as has convergent validity (AVE=.735).

Although the preceding four variables are not theoretically organized around the same construct, they are theoretically designed at the same level, as predictors, and seemingly associated to each other. Thus, it is possible that issues pertaining to discriminant validity may affect the robustness of models that use them simultaneously. Therefore, we have tested for this with HTMT (Henseler et al., 2015). The matrix showed values for all cases that ranged from .251 to .701 thus not reaching the threshold for strict analysis (.85). Hence, the variables have discriminant validity and pose no issues at this level.

Behavioral Intention (of using digital skills) is defined as the degree of an individual intent to use a system and was measured with Venkatesh et al. (2003) 3-item scale ("*I intend to use the digital skills in the next couple years.",* "*I predict I would use digital skills in the next couple years*.", "*I plan to use the digital skills in the next couple years*."). The scale is reliable (CR=.925; α= .921) as has convergent validity (AVE=.805).

Digital Skills Development Intention were measured based on van Laar et al. (2019) scale in a total of 10 items that represent each of the ten dimensions previewed in the model. The items were designed for this study and are as follows: 1) To what extent do you wish to further develop your information management skills? (save, naming and organizing files), 2) To what extent do you wish to further develop your online information assessment skills? (checking the reliability and updating of information on the website), 3) To what extent do you wish to further develop your online expressiveness skills? (be effective using the internet), 4) To what extent do you wish to further develop your internet content-sharing skills? (messages, blogs, discussion forums), 5) To what extent do you wish to further develop your contact-building skills? (creating new collaborations by establish online contacts), 6) To what extent do you wish to further develop your networking skills? (connect, build and using online contacts), 7) To what extent do you wish to further develop your collaboration skills? (collaborations, establishing contacts), 8) To what extent do you wish to further develop your critical thinking skills? (arguments, examples, and justifications), 9) To what extent do you wish to further develop your creative skills? (creating creative process, manage ideas and be original), and 10) To what extent do you wish to further develop your problem-solving skills? (find online solutions). A CFA showed poor fit to the data ($X^2(35)$ =216.389, p<.001; CFI=.842; TLI=.797; RMSEA = .159 CI90 [.139; .180] PClose=.000). From applying Lagrange Multipliers, a 6-item solution was found that has good fit ($X^2(9)$ =14.038, p = .121; CFI=.990; TLI=.983; RMSEA = .052 CI90 [.000; .102] PClose=.417) and is also reliable (CR=.864; Cronbach alpha=.862) as has convergent validity (AVE=.518). The scale comprises the above-mentioned items number 1, 2, 3, 8, 9 and 10.

Sociodemographic variables comprised age (in years) and gender (1=male, 2=female) as well as the education area (Sciences (e.g. Astronomy, Biology, Ecology, Mathematics, Physics, Chemistry); Health (e.g. Medicine, Nutrition, Nursing, Pharmacy, Physiotherapy); Technologies (e.g. Multimedia, Biotechnology, Informatics, Engineering) ; Agriculture and Natural Resources (e.g. Agronomy, Veterinary, Environment and Territory); Architecture, Fine Arts and Design; Education Sciences and Teacher Training; Law, Social Sciences and Services (e.g. Anthropology, Political Science, Communication, HRM, Marketing, Journalism, Psychology, Sociology, Tourism); Economics, Management and Accounting; Humanities, Secretariat and Translation (e.g. Counseling, History, Languages, Secretariat, Translation); Physical Education, Sport and Performing Arts (e.g. Film, Dance, Sport, Music, Theatre). Due to the relevance that a possible background in IT has for the topic under study, we dummy coded all domains of knowledge where all but Technology was coded as 1 (Non-IT) and Technology was given a code 2 (IT). Although this is not certain, we found it necessary to account for any IT or IT-related domain of expertise in the sample.

2.4 - Measurement model and Common method variance

Whenever measures are self-reported, they have a subjective nature. Mostly, when predictors and outcomes in a model have been collected at the same time (cross-sectional design) and from the same person (common source), findings could be biased by what has been known as common method variance (Podsakoff et al., 2003). To mitigate the previously mentioned issue, it is possible to deploy strategies, both before data collection and after, such as designing a multi-wave data collection, using objective measures, and using different sources for variables within the model. Considering the time available to conduct this study as well as the complexity of the conceptual model and judging on extant research's study design concerning UTAUT (Venkatesh et al., 2003), we opted for a cross-sectional design. As a matter of ethics and to lower the chances of common method bias, we offered clear instructions, removed anything that could indicate social desirability (no right or wrong answers), and offered anonymity guarantees. Likewise, we tested Harman's single factor and Podsakoff et al. (2012) recommendations to compare the measurement model established in the research against its alternatives, especially with a single factor model. If common method bias occurs, then it is expectable that a single factor would show fit indices similar to the one proposed.

Harman's test consists of conducting an exploratory factor analysis with all the items simultaneously and judging the resulting solution if there is an indication of a common factor. Findings showed a five-factor solution accounting for 69.5% variance (before rotation) and with a first factor explaining less than half that variance (32.8%). This indicates that no common method bias occurred in this study. The proposed model also has the best fit compared with alternative models joining variables sequentially linked in the model both backwards (from digital skills development intention to the predictors) as forwards (the reverse). In all cases, both the chi-square comparisons were significant as well as all the CFI differences went above the threshold of 0.01 established by Cheung and Rensvold (2002).

The measurement model fit was compared with alternative models that sequentially fused latent variables (Table 1). Findings show the measurement model has a better fit than all its alternatives, suggesting it is the most suitable.

Table 1

Measurement model comparison

Model	**χ^2 (*df*), *p* value**	**CFI**	**TLI**	**RMSEA**	**CI90, PCLOSE**	**SRMR**	**$\Delta\chi^2$**	**ΔCFI**
Research Model 7Factors	χ^2 (201) = 354.198, χ^2/df = 1.687, *p*<.001	.951	.941	.058	[.047, .068] .108	.0523	-	-
DSDI+BI	χ^2 (216) = 945.256, χ^2/df = 4.376, *p*<.001	.753	.711	.128	[.120, .137] .000	.1666	$\Delta\chi^2$ (15) = 591.058, *p*<.001	.198
DSDI+BI+ATT	χ^2 (221) = 1149.801, χ^2/df = 5.203, *p*<.001	.686	.641	.143	[.135, .151] .000	.1416	$\Delta\chi^2$ (20) = 795.603, *p*<.001	.265
PE+EE+SI+FC	χ^2 (224) = 945.630, χ^2/df = 4.222, *p*<.001	.756	.724	.125	[.117, .134] .000	.1007	$\Delta\chi^2$ (23) = 591.432, *p*<.001	.195
PE+EE+SI+FC+ATT	χ^2 (227) = 1119.166, χ^2/df = 4.930, *p*<.001	.698	.664	.138	[.130, .147] .000	.0998	$\Delta\chi^2$ (26) = 764.968, *p*<.001	.253
PE+EE+SI+FC+ATT+BI	χ^2 (229) = 1386.958, χ^2/df = 6.057, *p*<.001	.609	.568	.157	[.149, .165] .000	.1056	$\Delta\chi^2$ (28) = 1032.76, *p*<.001	.342
Single Factor	χ^2 (231) = 1868.478, χ^2/df = 8.089, *p*<.001	.446	.394	.186	[.178, .194] .000	.1546	$\Delta\chi^2$ (30) = 1514.28, *p*<.001	.505
Independence	χ^2 (253) = 3211.179, χ^2/df = 12.692, *p*<.001	.000	.000	.239	[.231, .246] .000	.2502	$\Delta\chi^2$ (52) = 2856.981 *p*<.001	.951

Note: BI – Behavioral intention; DGDI – Digital skills development intention; Att – Attitudes towards DGD; PE – Performance expectancy; EE – Effort expectancy; SI – Social influence; FC – Facilitating condition

Chapter III – Results

This section will start by showing descriptive and bivariate statistics to proceed to hypotheses testing.

3.1 – Descriptive and Bivariate Statistics

Participants have globally reported themselves as comfortably handling DS (M = 4.08, SE = .04), albeit not from an IT background (87%). Table 2 shows the Descriptive and Bivariate Statistics. They also reported that their immediate social environment moderately pushed them to further developed their DS (M = 4.87, SE = .09), which indeed they intended to (M = 3.94, SE = .06). Concordantly, their attitudes towards using DS are favorable (M = 5.64, SE = .07) as well as their behavioral intention to do so (M = 6.16, SE =.06). The drivers of this behavioral dimension are all leaning towards the right side of the scale, i.e., they all sense it is worthwhile (performance expectancy M = 6.08, SE = .05). It does not require much effort to do so (effort expectancy M = 5.69, SE = .07). Lastly, the facilitating conditions are reported as being present (M = 5.72, SE = .07), meaning they believe they have the required resources, knowledge, and support to develop DS.

As regards bivariate patterns, in most cases, the sociodemographic variables do not correlate with the conceptual model variables. The exception lies in DS mastery that was taken as a control variable precisely due to its expected positive associations with the conceptual model variables. Likewise, due to theoretical motives, the facilitating conditions were taken as a control variable because they are linked to the use of technology and according to Venkatesh et al. (2003) they bypass the psychological process conducive to behavioral intention.

Table 2

Descriptive and bivariate statistics

	Mean	SE	1	2	3	4	5	6	7	8	9	10
1. Gender	69.5%	-	-									
2. Age	20.86	.370	.064	-								
3. IT background	86.7%	.020	-.276**	-.183*	-							
4. DigSkills Mastery	4.080	.042	-.063	-.063	.039	-						
5. Facilitating Conditions	5.725	.071	-.083	.079	.098	.411**	-					
6. Behavioral Intention	6.166	.061	-.026	.109	.087	.365**	.459**	-				
7. Attitude towards DS	5.642	.079	.041	.070	.050	.297**	.537**	.491**	-			
8. Perfor. Expect.	6.080	.059	-.021	.166*	.067	.321**	.474**	.671**	.513**	-		
9. Effort expectancy	5.697	.071	.046	.054	.065	.365**	.608**	.368**	.503**	.417**	-	
10. Social Influence	4.875	.095	.033	.082	.174*	.153*	.325**	.319**	.347**	.305**	.217*	-
11. Digital Skills Dvlo. Int.	3.940	.069	.013	-.066	.013	.158*	.029	.193*	.120	.087	-.017	.191*

Note: Gender = F; IT background = non-it profile; **p* < 0.01; ** *p* < 0.001;

As showed in the previous table (2) the bivariate statistics evidenced some relevant elements. It shows that Behavioral Intention has a moderately high correlation with Attitude Towards use (r =.49, *p* <.001), Effort Expectancy (r =.36, *p* < .001) and Social Influence (r = .31, *p* < .001) as well as a strong correlation with Performance Expectancy (r = .67, *p* < .001). Attitude towards use has a strong correlation with Performance Expectancy (r = .51, *p* <.001), Effort Expectancy (r = .50, *p* < .001), and a moderate correlation with Social Influence (r = .34, *p* < .001). Performance Expectancy has a moderate correlation with both Effort Expectancy (r =.41, *p* < .001) and Social Influence (r = .30, *p* < .001). Effort expectancy has a weak correlation with social influence (r = .21, *p* <.01). At last, Digital Skills Developing Intention has a weak correlation both with Behavioral Intention (r = .19, *p* <.01) and Social Influence (r=.19, *p* < .01).

3.2 – Model Comparison

The first step into comparing the three models starts by contrasting their model fits. UTAUT was found to have acceptable fit indices (X^2(216) =391.427, *p*<.001; CFI=.932; TLI=.906; RMSEA = .063 CI90 [.053; .073] PClose=.018), as well as Meta-UTAUT (X^2(278) =490.875, *p*<.001; CFI=.932; TLI=.907; RMSEA = .061 CI90 [.052; .070] PClose=.022) and the proposed model, including the interaction terms have also acceptable fit indices (X^2(275) =517.592, *p*<.001; CFI=.926; TLI=.891; RMSEA = .066 CI90 [.057; .074] PClose=.002). The Chi-square difference test as well as Cheung and Rensvold (2002) ΔCFI test showed that: Meta-UTAUT has equivalent fit to UTAUT ($\Delta\chi^2$(62)=99.448, *p*=.018; ΔCFI=.000). However the proposed model has contradictory comparison fit indication when compared to UTAUT and Meta-UTAUT because on the one hand the chi-square difference is significant for both cases ($\Delta\chi^2$(59)=126.165, *p*<.001; $\Delta\chi^2$(3)=26.717, *p*<.001, respectively) but on the other hand, the ΔCFI falls below the threshold in both cases (.006). Globally, none of these models have indication of misfit to the point of being rejected and therefore we consider them equivalent.

As a second step we focused on explanative power. Hence, we conducted a hierarchical regression for the three models (UTAUT, meta-UTAUT and the proposed model).

Table 3 shows the findings for Venkatesh et al. (2003) UTAUT model. After controlling for sociodemographic, and digital skills mastery, OLS regression shows that only performance expectancy is a predictor of behavioral intention (β=.525, t=8.425, *p* <.001, CI90 [.422, .679]) accounting for an additional 32.4% explained variance which adds up to 45.4% adjusted $R^{2,}$, (F(4, 193) = 29.858, *p* <.001).

When taking into consideration Dwivedi et al. (2019) model, Meta-UTAUT, findings should be considered in two instances: in explaining attitude towards the use of digital skills, and in explaining behavioral intention. Meta-UTAUT model is well capable of explaining attitude towards digital skills use with sociodemographic and control variables accounting for 11.6% R^2 and all predictors being significantly associated adding unique 31.1% R^2 (F(4, 193) = 26.150, *p* <.001), this cumulating 40.3% adjusted R^2 as shown in table 4. Focusing on the second part of the model, explaining behavioral intention, to the exception of performance expectancy (β=.485, t=7.513, *p* < .001, CI90 [.375, .642]) and attitudes towards digital skills use (β=.144, t=2.117, *p* = .036, CI90 [.008, .221]), none of the other predictors was significantly associated to behavioral intention. The strongest predictor is again performance expectancy that adds 32.4% R^2 to the sociodemographic and control variables cumulating 45.4% adjusted R^2, while attitude towards digital skills barely add a significant explained variance of 1.2% which is still significant (F(4, 192) = 8.802, *p* = .036). The overall model is capable of explaining 46.4% of behavioral intention.

Our proposed model was also tested with the same data analysis technique. The model design has two fundamental changes: facilitating conditions are now a control variable, and the interaction effects must be accounted for). Likewise, as in Venkatesh et al. (2003) attitudes toward digital skills use, were not considered, as visible in Table 5. The hierarchical OLS regression showed the sociodemographic and control variables accounted for 23.2% adjusted R^2 in a first step. By adding the conceptual model variables (performance expectancy, effort expectancy, and social influence) the model increased its explanatory power to 45.4% adjusted variance (F(3, 193) = 27.540, *p* <.001) and finally, in the third step, when adding the interaction terms (Interaction 1 (Pexp*Eexp); Interaction 2 (Pexp*SocInf); Interaction 3 (Eexp x SocInf); Interaction 4 (Pexp*Eexp*SocInf), the model increased to 49.9% adjusted R^2 (F(4, 189) = 5.274), *p* <.001) due to the significant effect of performance expectancy * social influence (β=.320, t=-3.644, *p* < .001, CI90 [-.308, -.092]) and, most importantly, to the three-way interaction that crossed all these variables (β=.292, t=-2.784, *p* = .006, CI90 [-.114, -.019]).

Overall, in this last step one can confirm that performance expectancy is a significant predictor of behavioral intention (β=.545, t=8.204, *p* < .001, CI90 [.434, .709]) which supports the first hypothesis. Conversely, the interaction between effort expectancy and performance expectancy in explaining behavioral intention was not confirmed in the results (β=.088, t=.859, *p* = .392, CI90 [-.062, .158]) which does not support the second hypothesis. Lastly, the three-way interaction previewed in the third hypothesis was indeed supported by the findings as already detailed in the previous paragraph.

Table 3

Hierarchical Regression Results of Venkatesh (2003)

Variables	Behavioral Intention									
	Model 1					Model 2				
	β	t	*p*	LB	UB	*β*	t	*p*	LB	UB
(Constant)		5.230	.000	1.970	4.354		2.048	.042	.039	2.088
IT	.104	1.505	.134	-.085	.634	.022	.390	.697	-.235	.351
Age	.153	2.289	.023	.004	.048	.015	.283	.778	-.016	.021
Gender	.015	.220	.826	-.234	.292	.003	.056	.955	-.207	.219
DigSkills Master	.358	5.438	.000	.330	.706	.120	2.012	.046	.003	.345
Pexp						.525	8.425	**.000**	**.422**	**.679**
Eexp						.008	.116	.908	-.111	.125
SocInf						.091	1.587	.114	-.014	.133
FacCon						.120	1.653	.100	-.020	.226
Adj. R^2	13.4%					45.4%				
R^2	15.2%					47.6%				
ΔR^2	15.2%					32.4%				
F change	F(4, 197)=8.802, *p*<.001					F(4, 193)=29.858, *p*<.001				

**p* < 0.01; ** *p* < 0.001;

Table 4

Hierarchical Regression Results for Dwivedi et al. (2019)

Variables	Attitude towards digital skills use										Behavioral intention														
	Model 1					Model 2					Model 1					Model 2					Model 3				
	β	t	*p*	LB	UB	*β*	t	*p*	LB	UB	*β*	t	*p*	LB	UB	*β*	t	*p*	LB	UB	*β*	t	*p*	LB	UB
(Constant)		2.725	.007	.587	3.663		-.272	.786	-1.541	1.167		5.230	.000	1.970	4.354		2.048	.042	.039	2.088		2.107	.036	.069	2.100
IT	.081	1.140	.256	-.196	.732	-.019	-.322	.748	-.450	.324	.104	1.505	.134	-.085	.634	.022	.390	.697	-.235	.351	.025	.442	.659	-.225	.356
Age	.101	1.482	.140	-.007	.051	-.023	-.404	.686	-.029	.019	.153	2.289	.023	.004	.048	.015	.283	.778	-.016	.021	.019	.347	.729	-.015	.021
Gender	.083	1.189	.236	-.135	.544	.053	.913	.362	-.151	.411	.015	.220	.826	-.234	.292	.003	.056	.955	-.207	.219	-.005	-.082	.935	-.220	.202
DigSkills Master	.322	4.794	.000	.347	.832	.032	.505	.614	-.168	.283	.358	5.438	.000	.330	.706	.120	2.012	.046	.003	.345	.116	1.951	.052	-.002	.337
Pexp						.276	4.240	.000	.196	.536							**8.425**	**.000**	**.422**	**.679**	**.485**	**7.513**	**.000**	**.375**	**.642**
Eexp						.202	2.860	.005	.070	.382						.008	.116	.908	-.111	.125	-.021	-.312	.755	-.138	.101
SocInf						.144	2.398	.017	.021	.216						.091	1.587	.114	-.014	.133	.070	1.218	.225	-.028	.120
FacCon						.231	3.050	.003	.089	.414						.120	1.653	.100	-.020	.226	.086	1.175	.241	-.051	.199
Attitude																					**.144**	**2.117**	**.036**	**.008**	**.221**
Adj. R^2	9.8%					40.3%					13.4%					45.4%					46.4%				
R^2	11.6%					42.7%					15.2%					47.6%					48.8%				
ΔR^2	11.6%					31.1%					15.2%					32.4%					1.2%				
F change	$F(4, 197)=6.479$, $p<.001$					$F(4, 193)=26.150$, $p<.001$					$F(4, 197)=8.802$, $p<.001$					$F(4, 193)=29.858$, $p<.001$					$F(4, 192)=8.802$, $p=.036$				

*$p < 0.01$; ** $p < 0.001$;

Table 5

UTAUT_Config (Proposed Model)

Variables	Behavioral Intention														
	Model 1					Model 2					Model 3				
	β	t	*p*	LB	UB	*β*	t	*p*	LB	UB	*β*	t	*p*	LB	UB
(Constant)		4.386	.000	1.404	3.699		2.048	.042	.039	2.088		1.048	.296	-.501	1.636
IT	.071	1.073	.284	-.155	.526	.022	.390	.697	-.235	.351	.015	.283	.777	-.241	.321
Age	.107	1.682	.094	-.003	.039	.015	.283	.778	-.016	.021	.024	.450	.653	-.014	.022
Gender	.027	.425	.671	-.194	.301	.003	.056	.955	-.207	.219	.012	.223	.824	-.182	.229
DigSkills Master	.201	2.901	.004	.093	.488	.120	2.012	.046	.003	.345	.075	1.272	.205	-.060	.276
FacCon	.357	5.117	.000	.189	.426	.120	1.653	.100	-.020	.226	.121	1.722	.087	-.015	.223
Pexp						.525	8.425	.000	.422	.679	**.545**	**8.204**	**.000**	**.434**	**.709**
Eexp						.008	.116	.908	-.111	.125	.071	1.068	.287	-.053	.179
SocInf						.091	1.587	.114	-.014	.133	**.179**	**2.930**	**.004**	**.038**	**.195**
Interaction1											.088	.859	.392	-.062	.158
Interaction2											**.320**	**-3.644**	**.000**	**-.308**	**-.092**
Interaction3											.076	1.079	.282	-.045	.152
Interaction4											**.292**	**-2.784**	**.006**	**-.114**	**-.019**
Adj. R^2	23.2%					45.4%					49.9%				
R^2	25.2%					47.6%					52.9%				
ΔR^2	25.2%					22.4%					5.3%				
F change	$F(5, 196)=13.177$, $p<.001$					$F(3, 193)=27.540$, $p<.001$					$F(4, 189)=5.274$, $p<.001$				

Note: Interaction 1 (Pexp*Eexp). Interaction 2(Pexp*SocInf). Interaction 3 (Eexp x SocInf). Interaction 4(Pexp*Eexp*SocInf) ; **p* < 0.01; ** *p* < 0.001;

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Chapter IV – Discussion and Conclusion

It is not surprising that the IT developments that we have witnessed in the last decades, namely the so-called 4^{th} revolution, the internet of things, brings challenges to corporations, governments, and individuals. These changes hold great promises, but also, a disruption on the pattens of consumption, production, and employment. The same way that our technological knowledge increases, the work-relevant skills also change. This implies that some abilities, basic skills, and cross-functional skills in line with these changes have a particularly strong demand and active learning and ICT will have a differentiating role on employment opportunities (Leopold et al., 2014). Amongst these, are the digital skills, that have been marked as an important factor in explaining differences in individuals' use of the internet (van Deursen et al., 2014). Mastering such digital skills is reasonably impactful on much more than being able to use the internet. However, such skills, as all other skills, require development and learning, as well as the intention to deploy then.

In this sense, models of acceptance and use of technologies were created to acknowledge this trend of using technology and information in our daily lives. Moreover, these models were adapted and evolved until they reached a phase of maturity represented by UTAUT that claimed to be the unification of every model of technology use and acceptance (Venkatesh et al., 2003). Therefore, UTAUT emerged as a popular answer to the need to integrate the array of theories that were commonly used (e.g. TAM by Davis, 1989) to explain technology acceptance. This was also an answer to Agarwal and Prasad's (1998) call for integrating moderation effects into these sort of models (namely TAM).

In furthering Agarwal and Prasad's (1998) call for incorporating boundary conditions, researchers have included moderators such as gender, age, experience, and voluntariness (Venkatesh et al., 2003; Schehl et al., 2019; Sobieraj & Kramer, 2020). It is however surprising that the interdependence of the predictors among themselves was not built in the model. Because it is reasonable to expect mutual reinforcing effects (e.g., between Effort expectancy and Performance expectancy) in explaining the attitude or behavioral intention this study set itself the objective of testing such model while comparing to the two prevailing models in literature UTAUT and Meta-UTAUT. By doing so, although knowledgeable that such models have been most popular, this study opened the possibility to explore more that additive models. Instead of conceiving predictors as parallel processes, we think it made sense to look for multiplicative models, i.e. integrating interaction effects.

Findings were informative as regards our departing premises. Firstly, the conceptual model that matched UTAUT (Venkatesh et al., 2003) does have explanatory capacity on the behavioral intention, as expected. It is quite strong (45.4% R^2_{adj}) albeit 15.2% did come from control variables, namely age and digital skill mastery. This means, the sole predictor accounted for 32.4%, which is impressive especially because there was no indication of variance inflation due to multicollinearity. Still, the original model does not live up to expectations because effort expectancy, social influence, and the facilitating conditions seem to play no role in explaining behavioral intention, which goes counter to Venkatesh et al. (2003) original proposition. The existence of shared variance across these predictors may partially explain why such has occurred, because the inclusion of two predictors that are closely related make them behave differently as when they are considered alone. Likewise, the relatively younger sample that composed this study may help understanding that facilitating conditions are barely variating to the point of findings large contrasts between individuals. Most of the possible predictors have relative high means and low standard errors, which imply the homogeneous nature of the sample may go counter to findings some significant relations.

When the analysis moved to test Meta-UTAUT model (Dwivedi et al., 2019) findings showed a slightly better scenario. Meta-UTAUT is relatively to Venkatesh et al. (2003) model capable of explaining more variance. However, it still shows that, other than performance expectancy, none of the conceptual model variables seem to be relevant, which mimics the situation observed to Venkatesh et al. (2003) model. The same rationale may apply to explaining why this occurred.

The model we propose has distinct profile from UTAUT (Venkatesh et al., 2003) and Meta-UTAUT (Dwivedi et al., 2019). Because it is mostly focused on comparing with UTAUT, it excluded attitude towards DS development and took facilitating conditions as a control variable. This last option help explaining why the control block accounted for more variance, but it also disentangled possible effects that remain unclear in both UTAUT and Meta-UTAUT. The magnitude of the associations found between facilitating conditions and the conceptual model variables (as seen in Table 5) amply justifies its use as a control variable, but it was surprising also to find so many cases where facilitating conditions were positively associated to conceptual model variables, especially the strong association ($r = .608$, $p < .001$) which is the second to the highest correlation in magnitude. This occurs in those models because the facilitating conditions are direct predictors of behavioral intention.

As explained and expected, performance expectancy is the strongest predictor of behavioral intention, supporting our first hypothesis. However, it is interesting to understand the absence of the moderation effect of effort expectancy in the relationship between performance expectancy and behavioral intention. This is interesting because if a task is effortless the level of performance and the predisposition to develop digital skill should increase (Davis, 1989; Taylor & Todd 1995; Heerwegh et al., 2016). One reason that can explain this outcome is, again, the demographics of our sample, once students (younger population) are technology ready and the effort does not exist. As observed before, in Schepers and Wetzels (2007), results showed stronger effects for students, since they are more technology-ready (effort expectancy) and sensitive to trends, being more easily influenced by technology characteristics and peer opinions (social influence) than non-students or older users.

4.1 - Limitations and future research

There are always several limitations in any research that involve a questionary because the research tool has flaws. For timing and logistics purposes, we had to adapt a questionnaire to assess our research questions. This research tool was a self-report, where participants responded subjectively depending on their interpretation of the questions and perspectives. We are not able to understand or observed the behaviors, which would be much more informative. Therefore, we can only rely on the intention responses, being this one of the main limitations.

In the same line, this study was not designed to target actual behavior (the use of DS) even though the UTAUT model contemplates this step because of time restraints. Nevertheless, it is vital to raise this limitation once that the intent of behavior is different from the actual behavior and possibly, some of the moderators previewed in UTAUT models could exert action at this stage. We suggest that future research add this construct of actual behavior to understand the difference between intention and actual behavior.

The sample size is sufficient to use the data analysis techniques but still far from a comfortable test of hypotheses especially as they would ideally be tested not with multiple hierarchical OLS regression but rather with structural equations modelling. Still, the ratio of observed variables and estimated parameters to the size of the sample precludes using such data analysis techniques. A larger sample can allow such strategy and would benefit future research.

Adding to this, the model fit test for the proposed model may suggest more difficulties into fitting with the data but, in fact, the inclusion of the four interaction terms previewed in the model was done with a composite observed variable for each precisely to keep the ratio to the sample size within workable range. Having worked with laten constructs to represent the interaction terms would hamper the quality of the analysis although it may not have harmed the model fit.

Future research may benefit from focusing more on actual behavior than behavioral intention. For such purpose it would preferably cover a timeline that allows for variation in the use of technology, through a longitudinal research design. Most importantly, from the theoretical point of view, the existence of a tree-way interaction opens the possibility to study different paths or interaction effects beyond the UTAUT model by using multiplicative models. It also changes the status of predictors which can be taken as configurations, and thus, be more reasonably closer to the complex nature of social reality.

We hope this research proposes a different perspective for the acceptance and technology use models and that a configurational approach may prove to be more beneficial than illusive.

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