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Under thirty on LinkedIn: an examination of outcomes and use

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Dissertation presented as partial requirement for obtaining the master's degree in Information Management specializing in Marketing Intelligence

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UNDER THIRTY ON LINKEDIN: AN EXAMINATION OF OUTCOMES AND USE

by

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Marketing Intelligence

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ABSTRACT

This study intended to understand whether young adults under 30 perceived the outcome of LinkedIn use as beneficial and whether it impacted their continuance intention to use the platform. The Delone & McLean Information System Model and the Task-Technology Fit Model were combined to understand the connection between the task of looking for a job and using LinkedIn to do so and whether that choice and subsequent use will impact the net benefits one will gain with said usage and their continuance intent to keep using the platform. An online survey was done on 255 respondents. The results reveal that users perceive LinkedIn as an optimal platform for the intended job-related task, and its outcome positively affects continuance intention to use.

KEYWORDS

LinkedIn; Delone & Mclean model; Task-Technology Fit model; Outcome; Continuance Intention

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1. INTRODUCTION

Social Network Services are a plethora of extremely reciprocal platforms (Sei-Ching Joanna Sin, 2015)that enable users and groups to self-express, through the creation of content (Barker et al., 2015), communicate amongst personal ties, as well as develop new acquaintances, share and debate ideas and seek information and entertainment (Quinn, 2016; van Dijck, 2013). This new type of information and communication technology (ICT) has had a swift spread due to its advantageous platform design valuing interactivity (Kane et al., 2013), making it a groupware technology (C. Xu et al., 2012) and has become an imperative means of keeping up with extensive and, usually, very different networks of people who offer the user social support (Quinn, 2016). Social networks have profoundly transformed the way people create, communicate, cooperate, consume, and produce information (Aral et al., 2013). Since they differ from other traditional offline and online media, such as journals, websites, and search engines, in the sense that they have an inimitable advantage of creating, sharing, and diffusing information in a viral form, driving the increasing velocity at which information is spread, digitally (Luo et al., 2013).

Social networks are extremely popular within a younger age gap (Sei-Ching Joanna Sin, 2015). According to Hargittai & Hinnant's (2008) statement, young adults are far more prone to be online than any older demographic, being considered the most connected group. Consequently, according to this behavior, they are also the demographic more prone to search online for employment (more specifically, unemployed young adults with higher education, with computer skills, and with a higher household income).

In the past years, we have seen social network sites being used for a much broader multitude of tasks than initially imagined (Kane et al., 2013). The rise of certain social network platforms, such as career-oriented social networks, confirms this fact. One of the key priorities of these types of platforms is for users to apply to job openings. Consequently, the suggestion of having suitable openings is an indispensable part of these types of social networks (Chamoso et al., 2018). Within the category of career-oriented social networks, LinkedIn is the world's biggest career-oriented network (Komljenovic, 2019), self-reporting an estimate of 645 million users worldwide (Clement, 2020). As of July 2020, the distribution of LinkedIn users worldwide, by age group, show a massive dominance of users between the age of 25 to 34 years old, with a percentage of 63.6%, loosely followed by the age group of 18 to 24 (accounting for 18.3% of total user population) (both user groups comprise graduates as well as young professionals) (Clement, 2020), being the ladder the demographic expanding at the quickest rate, accounting for a quarter of LinkedIn's entire advertising audience (Kemp, 2019). More specifically, in the United States, the second biggest group of LinkedIn users is the 18 to 29 years old age group, making up 30% of the demographics (Pew Research Center, 2021). This data shows a massive potential, from a young adult perspective, regarding LinkedIn but also an effective dominance of users under thirty years old, who use the platform.

As Davis et al., (2020, p.1) argue, "very little is known about the benefits of using such social networking platforms, especially LinkedIn, which was designed for professional purposes.". The research done on these types of platforms has chiefly focused on uses and gratifications (Basak & Calisir, 2014), user motivations and patterns (L. Zhang & Pentina, 2012), psychological determinants (Guillory & Hancock, 2012; Lee et al., 2016; van Dijck, 2013), job search processes (M. A. Johnson & Leo, 2020), amongst others. However, none have mentioned if there are any impacts between obtaining a job through a career-oriented social network and the continuance intention to use the system. As a result, this paper intends to fill the research gap on understanding whether users perceive the outcome of LinkedIn usage as beneficial for their careers and if it helps them or not, either to obtain employment or to continue using the system. Two theoretical models were combined: the DeLone and McLean Information System (IS) Success Model (DeLone & McLean, 2003) and the Task-Technology Fit Model (Goodhue & Thompson, 1995) to answer these questions. Hence the research questions are as follows:

RQ1: What are the drivers that lead to LinkedIn's Net Benefits?

RQ2: To what extent does Use explain Net Benefits, which in turn explain continuance intention?

In answering these questions, the remainder of the paper is organized as follows: a theoretical background section devoted to understanding previous research on the referred topic, followed by a section dedicated to the theories used, research model, and hypotheses; the fourth section will be dedicated to data collection, and the fifth section will approach the results of the said empirical approach. Finally, the final section will include the discussion of results and their implications, along with conclusions, limitations, and further research.

2. LITERATURE REVIEW

2.1. SOCIAL NETWORKS

While some authors consider ICTs to be technologies that facilitate data and information analysis, retention, and evaluation, as well as data and information transmissions and communication over the Internet and other means (Weber & Kauffman, 2011), other scholars define it as a general-purpose technology (GPT), which refers to breakthroughs that have the potential to affect a wide variety of societal sectors. Fundamentally, ICTs can be viewed from these viewpoints as a diversified set of technologies that enable the processing of information and involve electronic transmission, which can be used to fulfill a broad variety of daily tasks and have a continuously changing landscape (Goncalves et al., 2018). Undoubtedly, ICTs play a significant part in the current society (Goncalves et al., 2018). These types of technologies, which are used for myriad functions, seem to have been the main driver of production and economic development in the global economy (X. Xu et al., 2014). Indeed, they have entirely transformed the fabric of social and economic life since the 1990s by altering business strategies and patterns of consumption, lowering transaction fees and space-time constraints, and allowing for the rapid and widespread dissemination of information and knowledge (Song et al., 2020).

Recent decades have observed the growth, spread, and universal acceptance of a new type of ICT function, widely referred to as social media or social network sites (Kane et al., 2013). This type of Internet-based platform facilitated social interaction, collaboration, consumption, and creation (Barker et al., 2015; Kane et al., 2013) and, as a consequence, impacted consumers lives, and, more importantly, how they connect and relate (Chamoso et al., 2018), constituting one of the most influential effects of information technology on companies, governments and entities (Goncalves et al., 2018) both within and beyond business limits (Aral et al., 2013). The success of particular social networks, such as Facebook and Twitter, has brought significant changes to the information environment because there are several forms of social network platforms, each one targeting users' unique needs (Chamoso et al., 2018; Sei-Ching Joanna Sin, 2015). Social networking provides both benefits and obstacles in the daily search for information (Sei-Ching Joanna Sin, 2015).

2.1.1. Previous research on Social Networks

Early studies on the motivations of social networks' use have shown that it is primarily driven by social desires (Lee et al., 2016). Social networks are often used for functions, including leisure, checking for information, and fellowship (Quinn, 2016; van Dijck, 2013). It encourages users to retain friendships, communicate with others, and establish and retain loose links, enabling a comparatively more significant number of connections to be held at once. It also allows individuals to build their profiles (Kane et al., 2013) and display a comprehensive collection of information about themselves (such as achievements, beliefs, projects, daily routines, etc.), which, consequently, results in a deep understanding of what we can learn about others, and vice-versa, as well as a vast network of people users can learn from (Vogel et al., 2015). Nevertheless, there are differences to consider when regarding specific types of social networks (namely the several available forms of social network platforms, as each one targets users' unique needs, which then affect the type of interaction the user is searching for (Chamoso et al., 2018; Sei-Ching Joanna Sin, 2015). As they serve different purposes, and their communities of users are very distinct. They each have their specific customer segments in incentive, intent, interaction, and interpretation of usage (Chang et al., 2017).

Social networks provide access to many user benefits, including facilitated teamwork between linked friends, increased ease of human interaction, enhanced employee engagement between an organization and its clients, and the advancement of multi-channel online retail (Chang et al., 2017). The success of specific social networking services, such as Facebook and Instagram (Statista, 2020), has brought significant changes to the information environment. Social networks have now become pervasive in society (Vogel et al., 2015), representing approximately a quarter of consumers' Internet time, massively exceeding gaming and emailing (Luo et al., 2013), with major social networks such as Facebook, LinkedIn, and Twitter being used by hundreds of millions of people (Kane et al., 2013).

Social networks are unparalleled in their ability to let users create, communicate and disseminate content in viral form, allowing them to be content creators, commentators, or reviewers in the online community they are inserted in (Chang et al., 2017) (these distinctive features create a social contagion effect that fuels the unprecedented pace of digital knowledge distribution (Luo et al., 2013)). However, social networking provides both benefits and obstacles in the daily search for information (Sei-Ching Joanna Sin, 2015), as well as in one's well-being. Users can uncover the advantages of social networks, such as developing ideas, social support, knowledge improvement, and dissemination of innovations. However, on the other hand, they also face risks such as danger and lack of influence over personal information (Chang et al., 2017).

Prevalent social networks have culminated in reliance on technologies and inappropriate use, suggesting that inappropriate and unreasonable use of social network sites have been common for a significant proportion of people, leaving severe detrimental impacts on themselves and institutions (Cao & Yu, 2019). In both at home and at work, social network sites are regularly accessed. While individuals should retain a cognitive separation between personal life and professional life, all of these elements are part of their personality overall (Brooks, 2015). As a result, individuals' social network presence leads to adverse consequences. These unfavorable circumstances include social comparison behaviors, anxiety, depression, social network fatigue, and fear of missing out (Dhir et al., 2018; Jang et al., 2016).

Moreover, techno tension, which is positively related to the use of social networks (Brooks, 2015), technostress and adverse impact on task success, also caused by the use of social networks (Cao & Yu, 2019), which is then correlated with lower happiness (Brooks, 2015) and far too much online sharing can cause saturation and confusion of information, disrupting employee attention, and impeding decision-making capabilities (Cao & Yu, 2019). The loop of social networks can decrease users' enjoyment when not getting the support and constructive input they are seeking. Prolonged use of a system can also result in higher strains. These consequences can lower the well-being of a person (Brooks, 2015).

2.2. CAREER-ORIENTED SOCIAL NETWORKS

Social networks have grown and incorporated the working world, increasing the resources and opportunities for consumers to work, consequently changing the way work and talent are paired. The rise of career-oriented social networks, such as LinkedIn, Monster, and Xing (which specialize in building professional connections between users), is a prominent example of how social networks intertwine with the job market (Aral et al., 2013; Chamoso et al., 2018). This type of recruitment method focused on web-based information, particularly obtained from social networks, is entitled E-recruitment (Domeniconi et al., 2016).

Social networks, in general, contain a variety of connections, accommodating friends, relatives, and business colleagues. Users recognize there are clear distinctions between both types of platforms: whereas private-oriented social networks, such as Facebook, are intended to share personal data (such as photos, interests, beliefs and/or political viewpoints) and communicate with other users, career-oriented social networks comprise online CVs, position descriptions and career knowledge, as they intend to bind professionals, post and exchange business-related information and refer one user to another (Buettner, 2016).

More specifically, LinkedIn is one of the most prominent career-oriented social networks that has proliferated over time (Clement, 2020). As the most prominent global professional network, LinkedIn wants to build economic prospects for all in the job market. Pairing positions with professionals is one of their most important activities, improving work accuracy and recruiting productivity (Li et al., 2020; Utz, 2016). The social network component of LinkedIn offers a unique feature of job search that enables users to participate in comparison processes with friends, family, and professional contacts (M. A. Johnson & Leo, 2020). Notwithstanding the growing popularity of social networking sites like LinkedIn, few academic studies have examined the potential professional advantages of using these platforms (Davis et al., 2020a).

2.3. PREVIOUS RESEARCH ON CAREER-ORIENTED SOCIAL NETWORKS

When using a specific social network platform, it is possible to refer to useful indicators that separate each of them (Buettner, 2016). Previous studies have shown distinct user drivers between the career-oriented social network XING and the private-oriented social network StudiVZ. Investigations have found systemic disparities between LinkedIn and Facebook, in terms of drivers and actions, as well as disparities in behavior between common LinkedIn users and Orkut, Myspace and Hi5 (all three being private-oriented social networks) users (Buettner, 2016).

This aspect demonstrates that drivers that lead users to approach and effectively use these types of career-oriented social networks have already been previously studied and mentioned by several authors, as demonstrated in the table below:

Broad Driver	Specific Drivers	Description	Author(S)
Psychological			
Five-Factor Model	Extraversion	0.246. it was considered a good predictor for usage.	(Buettner, 2016)
	Emotional Stability	0.160. it was considered a good predictor for usage.	(Buettner, 2016)
	Openness to Experience	0.122. it was considered a good predictor for usage	(Buettner, 2016)
Tangible			
	Communication	Universities rely on their LinkedIn groups to communicate with alumni	(Komljenovic, 2019)

	Information	LinkedIn is a crucial source of information about alumni, hence why universities use LinkedIn's services and products	(Komljenovic, 2019)
	Social aspects of employment	The social facets of jobs gratify LinkedIn clients. They are receptive to their identity online. They need to see how others depict themselves and are curious about how they could look,	(Brewer, 2018)
	External networking	There is a greater number of connections with users who rank high on the external network construct. Before they begin accessing LinkedIn, they presumably already have broader offline networks, which should be reflected in their online networks. Networking is a significant driver of the use of LinkedIn for informational benefits.	(Utz & Breuer, 2019)
	Self-promotion	This construct consists of six items pertaining to presenting and communicating oneself to someone else, namely having direct contact with the professional community, reaching out to employers and business executives, getting in touch with others, following firms, staying in touch with contacts, and promoting himself/herself.	(Basak & Calisir, 2014; Chang et al., 2017)
	Group activities	Users of LinkedIn can join and engage in groups that share interests, begin or follow a discussion in a group, and add a comment to a discussion. Via groups, users can meet like-minded experts.	(Basak & Calisir, 2014; Chang et al., 2017)
	Job and Job affairs	Users of LinkedIn receive information about the active community, look for work, and can monitor these issues via the website.	(Basak & Calisir, 2014; Brewer, 2018; Chang et al., 2017)
	Professional networking	The primary tasks of LinkedIn are to develop a professional network and establish new links.	(Basak & Calisir, 2014; Chang et al., 2017)
	Finding old and new friends easily	Based on the recommendations of people they know, using the search tool, and browsing alumni pages affiliated with an employer or institution, LinkedIn users discover connections on the platform.	(Basak & Calisir, 2014; Brewer, 2018; Chang et al., 2017)
	Follow-up	Members of LinkedIn can track their contacts' career development, access job details, and view CVs in a similar way to visiting other members' profiles or seeing their newsfeed updates.	(Basak & Calisir, 2014; Chang et al., 2017)

Profile-viewer data	The statistics of the users who accessed your profile and the number of times your profile was viewed are kept by LinkedIn. Thanks to this feature, users will see who has been browsing through their profiles and how often their profiles have been viewed in the last 90 days.	(Basak & Calisir, 2014; Chang et al., 2017)

Table 1: Career-oriented Social Network Drivers of Use

According to (C. Xu et al., 2012), users actively select their social networks based on their desires. Thus, it is possible to consider that the gratification one might acquire can be regarded as an outcome of said selection and usage. We can consider two main streams of thought regarding outcomes of ICT and social network use. These avenues being: psychological (Vogel et al., 2015) or non-instrumental (C. Xu et al., 2012) and tangible (Helsper et al., 2015; Sei-Ching Joanna Sin, 2015) or instrumental (C. Xu et al., 2012). Psychological outcomes observe the consequences social networks' usage might have on an individual's mental state (Dhir et al., 2018; Jang et al., 2016), whereas tangible outcomes study concrete gratifications one can obtain by using social networks. Notwithstanding, and as previously stated, outcomes can be considered either positive or problematic.

As for career-oriented social networks, this exact congruence also occurs. A plethora of studies has been published regarding outcome factors from these types of platforms. The authors Basak & Calisir, (2014) & Brewer, (2018) were able to identify several, which, in their studies, were regarded as both uses for the platforms and gratifications from using the platforms. However, in the context of outcomes, these were incorporated into three major groups, namely Jobs and Job Affairs (in which this category encompasses the factors 'Finding out job opportunities', 'Jobs you might be interested in,' 'Following the career progression of my contacts' and 'Viewing job ads posted by companies'). Secondly, Social Aspects of Employment (which includes 'Searching for jobs,' 'Seeing who's viewed my profile,' and 'Viewing resumes of others') and, thirdly, Finding Old and New Friends Easily (including 'User-friendly search engine,' 'Finding friends, alumni, etc.,' 'Ease of use' and 'Suggestion of people you know') (Brewer, 2018).

3. CONCEPTUAL MODEL AND HYPOTHESES

3.1. DELONE AND MCLEAN MODEL OF INFORMATION SYSTEMS SUCCESS

The DeLone and McLean Model of Information Systems Success (also known as the D&M IS Success Model) is an interactive model for the success of Information Systems' conceptualization and operationalization (DeLone & McLean, 2003). The development of the D&M IS Success Model in 1995 was motivated by the process of comprehension of Information Systems (DeLone & McLean, 2003). However, based on further study, that initial model was revised by the authors in 2003, and the introduction of service quality was the primary change to the updated version (Tam & Oliveira, 2016). This method only has three components: the development of a system, its effective use, and the repercussions of said usage.

DeLone & McLean, (2003) posit that the main drivers of IS success, including users' perceived benefits and satisfaction, are determined by the system's quality and information (Seol et al., 2016). It consists of six interrelated IS success constructs: information, system and service quality, intention to use, use, user satisfaction, and net benefits (Dong et al., 2014). These six success dimensions are suggested to be interrelated rather than separate based on both mechanism and causal factors (DeLone & McLean, 2003).

The model can be interpreted as follows: an Information System is first generated, possessing different characteristics that can be described as displaying varying degrees of system, information, and service quality (DeLone & McLean, 2003). These constructs impact intention to use and user satisfaction (the user, when experiencing these attributes, will be either satisfied or disappointed with the system or its informational items (DeLone & McLean, 2003)), which then impacts net benefits (Dong et al., 2014).

The three dimensions of quality: information quality, system quality, and service quality, should be calculated – or monitored for – independently, considering the resulting 'use' and user satisfaction will be influenced independently or collectively (DeLone & McLean, 2003).

3.2. TASK-TECHNOLOGY FIT MODEL

The Task-Technology Fit model, by Goodhue & Thompson, (1995), is a commonly used analytical model for evaluating how information technology contributes to success, determining the impact of use, and assessing the match between tasks and technology features (Wu & Chen, 2017). Both the task and technology characteristics will influence the fitness of the task technology, which influences the user's performance and usage (Wu & Chen, 2017). Goodhue and Thompson claim that the degree of fitness of task-technology, defined as the extent to which information system capabilities complement the tasks that the user wants to perform, is a crucial factor in explaining the success level of the construct' performance impacts' (Goodhue & Thompson, 1995). The optimistic scenario is that the more technology suits particular work characteristics, the greater the technology's chance to lead to better performance (Larsen et al., 2009).

The theory notes that, in order for the information system to have a positive effect, the technology has to be, firstly, used, and secondly, well suited to the activities that it supports (Goodhue & Thompson, 1995). People can use said technology to assist them in carrying out their tasks.

Characteristics of the user (training, software experience, motivation) could affect how quickly and well the technology is used (Goodhue & Thompson, 1995).

The Task-Technology Fit model is aligned with the one suggested by DeLone & McLean, (2003) in that both usage and consumer behaviors towards technology contribute to individual performance and benefits. It goes beyond the DeLone and McLean model in two significant respects. Firstly, it highlights the importance of the Task-Technology Fit in illustrating how technology contributes to success impacts. Secondly, it is more explicit about the ties between the structures, offering a better theoretical framework for reasoning about various issues linked to the effect of information systems on performance. These include: Comprehending the effect of user interaction on performance, creating improved diagnosis of IS issues (Goodhue & Thompson, 1995), amongst others.

The Task-Technology Fit offers a clearer view of the interrelationship between the user and task-specific fit, which influences the user's decision as to whether or not to use an information system. The function of individual characteristics and task characteristics is a crucial element of the function performance chain (Yu & Yu, 2010).

4. RESEARCH MODEL AND HYPOTHESES

In the D&M IS Success Model, the constructs focus only on the system's quality and how it influences one to use it. However, it does not mention the reason why a user chooses that system in the first place. In other words, what is the nature of the user's task that leads them into choosing said system? However, this study will not include the 'Task Characteristics' and 'Technology Characteristics,' as these aspects have been extensively studied, and the confirmed relationships to Task-Technology Fit have been proven. Instead, it will only consider this latter variable as it is a critical construct to acknowledge.

Nevertheless, the D&M and Task-Technology Fit models complement each other, meaning that their synthesis helps recognize the effect of individual performance and the discipline of information systems (Tam & Oliveira, 2016). In addition, the limitations of the two models can be adjusted, as each one possesses differing views on the effect of usage and individual performance (Tam & Oliveira, 2016).

The final construct added to the model will be 'Continuance intention to use, which has been integrated into previous studies regarding both the D&M IS Success Model and the Task-Technology Fit Model (Dong et al., 2014; Larsen et al., 2009). Even though this construct is not incorporated in any of the original models, it aims to clarify why IS users want to keep using (or stop using) a system since, ultimately, the users' ability to continue using the information system is influenced by their perceptions of its utility and satisfaction (continuance intention) (Larsen et al., 2009).

4.1. HYPOTHESES

Information Quality includes the desired characteristics of importance, precision, timeliness, completeness, comprehension, and usability of system outputs. It also assumes a key position in cultivating a favorable outlook about the advantages of using specific information technologies (Tam & Oliveira, 2016). The quality of the information on social network pages relates to the quality of interaction that information produced. It involves features like completeness, ease of interpretation, customization, and significance. The quality of the information is critical for internet services widely perceived as sources of valuable knowledge. A high degree of complete, comprehensive, authentic, timely, appropriate, and reliable content is likely to satisfy users' informational needs (Seol et al., 2016). The more information quality a website or information system has, the more popular it will be due to more frequent users. This angle is particularly true as the information system continually incorporates daily material, be it posts, news, or opinion items. A high level of information quality enhances the objectivity or at least the intersubjectivity of the website or information system. In addition, the quality of information was evaluated in terms of precision, meaning, significance, timeliness, completeness, and usability (Dong et al., 2014). Information quality influences if a user will indeed use a system, hence the hypothesis:

H1: Information quality has a positive influence on LinkedIn Use.

In the D&M IS Success Model, System Quality evaluates technological success (DeLone & McLean, 2003). System quality is evaluated in terms of ease of use, functionality, reliability, versatility, accessibility, performance, and relevance (Dong et al., 2014). In terms of social networks, a high system quality offers more accessible and collaborative spaces through user-friendly features, audiovisual services, and user customization. Social networks need features such as reliability, consistency, and system speed in real-time, as well as collaborative connectivity between users (Seol et al., 2016). A high-quality IS could allow users to have a more rewarding and enjoyable experience. If the social network is unreliable or sluggish, users cannot feel comfortable interacting with one another, and this disruption may deter them from enjoying the space (Seol et al., 2016). More system efficiency is expected to lead to greater use (Tam & Oliveira, 2016) and improved net benefits. Hence the hypothesis:

H2: System Quality has a positive influence on LinkedIn Use.

Service Quality was the third construct added by the authors in the renewed model (DeLone & McLean, 2003). It is the quality of social contact between the customer and a business; it represents the firm's confidence, compassion, and responsiveness. Service quality is critical because low quality of service will alienate users. Online quality of service is especially relevant because businesses strive to offer comprehensive resources that consumers require (information, offline complaint procedures, and real-time responses). A high level of service quality can respond efficiently, easily, and sensitively to customers' needs (Seol et al., 2016). Effectively, LinkedIn supplies users with a Help Center in which it provides support for various tasks and problems one might have while using the platform. There is public information and detailed step-by-step descriptions on how to resolve issues, and the possibility to leave a message, should the task or problem one might have, not be available on the site (*LinkedIn Help*, n.d.). However, since LinkedIn is a social network platform, it does not constitute an e-commerce website since it does not sell anything but provides services (including but not limited to LinkedIn premium); therefore, the hypothesis is as follows:

H3: Service Quality does not impact LinkedIn Use.

Task-technology Fit results from when a technology grants functionality and assistance that 'suits' the specifications of a task. Specifically, Task-Technology Fit is the interaction between the specifications of the mission, the individual skills, and the technology features. A positive Task-Technology Fit and subsequent outcome happen if the users recognize that the technology serves the task they intend to complete (Tam & Oliveira, 2016). This view is seen in the middle model in which the fit, sometimes, defines use (Goodhue & Thompson, 1995).

Perceived Task-Technology Fit, which in this case is the fitness between the task of looking for a job and the LinkedIn system, is anticipated to be a fundamental prerequisite to LinkedIn use and the outcome. Thus we propose the following hypotheses:

H4: Task-Technology Fit has a positive impact on LinkedIn Use.

H5: Task-Technology Fit has a positive impact on Net Benefits.

Usage is the practice of using technology to complete tasks. This construct is defined by Goodhue & Thompson, (1995) as a binary state of use or non-use. The authors stated that the model should not focus on how long someone has used the system (for a particular, specified purpose) as the period of use might be attributable to the scale of one's task and/or task-technology fit of the system, but rather on the option of use of the system (Goodhue & Thompson, 1995).

Once a user takes on the activity of using LinkedIn, the net benefits can be various, amongst which we encompass the practical discovery of a job. Without effective use, there can be no outcome. Therefore, we hypothesize that:

H6: LinkedIn Use positively impacts the Net Benefit of finding a job.

The option of calculating the impacts will depend on the system(s) being assessed and their purpose. Instead of complicating the model with various success determinants, DeLone & McLean, (2003) aggregated all impact determinants into one construct entitled 'Net Benefits' (incorporating both individual and organizational impacts). The choice of wording for 'Net Benefits' arose since the initial word 'impacts' can be beneficial or negative, leading to a potential misunderstanding of whether the effects are good or poor. Further, the inclusion of 'net' in 'net benefits' is significant as no effect is exclusively positive, with no negative effects (DeLone & McLean, 2003).

Since different entities may have diverging views as to what benefits them, in this particular study, we consider 'Net Benefits' to be the job a user gained from LinkedIn. This benefit will have an impact on whether or not said user will want to continue to use the system (i.e., the user is happy with the 'net benefit' because they feel the system provided them with a good opportunity, or they feel as though the outcome did not match their expectations of the system).

If the IS or program is to be persisted, it is presumed that the 'net benefits' from the point of view of the end-user or supporter are positive, thereby affecting and enhancing the resulting 'usage' and 'user satisfaction.' These natural cycles are still relevant, even if the 'net benefits' are negative. The lack of positive benefits is likely to result in diminished utilization and potential discontinuation of the system (DeLone & McLean, 2003).

Accordingly, when a user is satisfied with the job obtained through LinkedIn, it is very likely they will have a positive perception of the system and, therefore, keep an ongoing usage behavior with the system, or the contrary. Based on the aforementioned conclusion, we also hypothesize:

H7: LinkedIn Use has a positive impact on Continuance intention to use LinkedIn

H8: Net Benefits have a positive impact on Continuance intention to use LinkedIn.

The complete research model with the hypotheses is outlined below:

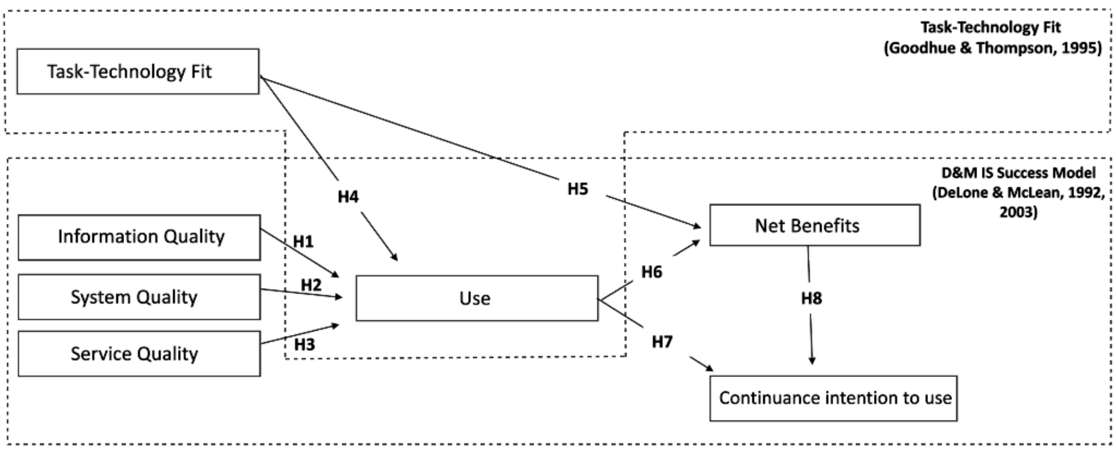

Figure 1: Research Model and Hypotheses

5. DATA

The data was gathered using an online survey through Qualtrics Survey Solutions. A pilot test was first carried out in the first semester of 2021 on a group of 30 young adults who are social network platform users in Portugal and validated using the SMART PLS program (Hair et al., 2021) to test the tool. This initial study sought to improve the questions and delete unclear and/or ambiguous items in order to refine the survey content and structure. Preliminary evidence presented reliable and valid scales. Following the pre-test, the questionnaire was sent through email and social media platforms in order to reach the target, namely, young adult users of LinkedIn in Portugal. The instrument (please see Appendix 1) was adapted from the literature and adjusted to suit the subject matter, to maintain the content validity of the scale used (Chang et al., 2017). All items for each question were measured with a seven-point range scale, from "strongly disagree" (1) to "strongly agree" (7).

IP addresses were recorded and checked to ensure that there were no duplicate respondents. A total of 412 responses were collected. However, 119 responses were removed due to incompleteness, leaving 293 valid and complete responses. The survey addressed LinkedIn users. We assessed common method bias in two ways. First, we used Harman's single-factor test proposed by Podsakoff et al., (2003), in which the first factor explains 29.9% of the covariance amongst all constructs, well below the threshold of 50%. Secondly, we added a theoretically irrelevant marker variable with a maximum shared variance of 19% with any other construct, which is a reasonable value (R. E. Johnson et al., 2011; Lindell & Whitney, 2001). Therefore, we conclude that common method bias does not affect our data (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003). A total of 163 (55.63%) respondents are women, 128 (43.69%) respondents are men and 2 (0.68%) input other. Detailed descriptive statistics are detailed in Table 2.

n=293

Age	Frequency	Percentage (%)
18-20	7	2.39%
21-25	192	65.53%
26-30	56	19.11%
31-35	9	3.07%
>35	29	9.90%
Education	**Frequency**	**Percentage (%)**
High School	55	18.77%
Bachelor's degree	135	46.07%
Master or postgraduate degree	97	33.11%
Doctorate degree	6	2.05%
Occupation	**Frequency**	**Percentage (%)**

Student	61	20.82%
Working student	60	20.48%
Working	149	50.85%
Unemployed	23	7.85%
Occupation	**Frequency**	**Percentage (%)**
Student	61	20.82%
Working student	60	20.48%
Working	149	50.85%
Unemployed	23	7.85%

Table 2: Respondents' Demographics

Even though the data collected encompasses multiple ages, the data analysis only considered the gap between 18 and 30, henceforth referred to as 'Under 30', which accounts for 255 responses. The sample is in line with what was expected since it is substantial and made up of respondents entering the labor market or in it for a short time, as shown in Table 3. Detailed descriptive statistics for this specific data group are detailed in table 3.

Distribution= 255		
Gender	**Frequency**	**Percentage (%)**
Male	107	41.96%
Female	146	57.26%
Other	2	0.78%
Education	**Frequency**	**Percentage (%)**
High School	46	18.04%
Bachelor's degree	122	47.84%
Master or Post Graduate degree	84	32.94%
Doctorate	3	1.18%
Occupation	**Frequency**	**Percentage (%)**
Only Student	58	22.75%
Working student	58	22.75%
Only Working	123	48.23%
Unemployed	16	6.27%

Table 3: Data Group's Gender

6. RESULTS AND DISCUSSION

Structural equation modeling (SEM), specifically partial least squares (PLS) path modeling, was used to estimate and verify the relationship between constructs. The PLS technique was chosen for this study since this approach is explicitly designed for prediction, which is suitable for these forms of models; it does not demand a large sample size or a normal distribution and is recommended for a detailed analysis of an intricate model with causal-formative indicators (Hair Jr et al., 2016). SmartPLS 3.0 was used to evaluate the results (Ringle et al., 2015). The sample size (n = 255) is adequate for this research since there are more than 40 observations for each connection for the dependent construct with more independent constructs linked to it. We employed the bootstrapping procedure with 5,000 resamples to test the statistical significance of the structural model. The analysis was divided into two sections: the analysis of the measurement model and the analysis of the structural model. The measurement model and the structural model make up the SEM. The measurement model analyzes latent variables or composite variables, and a structural model uses path analysis to evaluate all potential relationships (Jarvis et al., 2003).

6.1. MEASUREMENT MODEL

The first section includes the assessment of internal consistency, convergent validity (indicator reliability and average variance extracted (AVE)), and discriminant validity for the reflective constructs (Hair Jr et al., 2016). The composite reliability criterion was evaluated to ensure internal consistency.

The results for Cronbach Alpha were all higher than the threshold value of 0.700, meaning excellent reliability, as one can observe in Table 5. The Composite Reliability results are also above 0.700, indicating excellent reliability, as shown in Table 5. The reliability of the good indicator was also assessed using the cross-loadings criteria (which states that each indicator loading should be greater than all of its cross-loadings (Chin, 1998)). As established in Table 4, each item loads highest on its associated construct (and is greater than 0.70), establishing discriminant validity.

Average Variance Extracted (AVE) was used to test the convergent validity of the reflective constructs. The AVE should be greater than 0.50, indicating that the latent variables account for more than half of the variance of their indicators. As it is possible to observe in Table 5, AVE for each construct is way above the recommended threshold value, corroborating convergent validity (Fornell, C., & Larcker, 1981). The square root of the AVE measure on each construct was used to assess the discriminant validity of the measures used in greater depth, in which it must surpass the calculated correlations shared between the construct and other constructs in the model (Fornell, C., & Larcker, 1981). Since the square root of AVE on each construct, which are the diagonal items in Table 5, was higher than the correlation of the construct with other constructs, which are the associated off-diagonal items in Table 5, the discriminant validity for the constructs used in our analysis was appropriate.

Finally, the Heterotrait-Monotrait Method (HTMT) (Henseler et al., 2015) was tested to understand the statistical differentiation between constructs. All values are below the more liberal threshold value of 0.900 (Gold et al., 2001), as seen in Table 6, meaning discriminant validity has been established.

Constructs		TTF	SYSQ	INFQ	SERQ	USE	NETBEN	CONT
Task-Technology Fit	TTF_1	**0.857**	0.589	0.615	0.434	0.411	0.625	0.540
	TTF_2	**0.905**	0.645	0.675	0.556	0.443	0.627	0.547
	TTF_3	**0.917**	0.656	0.723	0.556	0.451	0.663	0.550
	TTF_4	**0.871**	0.645	0.687	0.510	0.478	0.717	0.559
System Quality	SYS_1	0.635	**0.911**	0.712	0.468	0.503	0.634	0.521
	SYS_2	0.662	**0.917**	0.756	0.506	0.432	0.660	0.510
	SYS_3	0.677	**0.903**	0.777	0.524	0.456	0.686	0.544
	SYS_4	0.633	**0.910**	0.733	0.463	0.493	0.641	0.538
Information Quality	INF_1	0.670	0.744	**0.891**	0.561	0.442	0.677	0.548
	INF_2	0.649	0.772	**0.867**	0.523	0.408	0.630	0.510
	INF_3	0.699	0.688	**0.894**	0.524	0.449	0.636	0.605
	INF_4	0.651	0.661	**0.852**	0.500	0.402	0.628	0.483
Service Quality	SE_1	0.514	0.478	0.537	**0.893**	0.290	0.482	0.321
	SE_2	0.589	0.524	0.619	**0.934**	0.320	0.564	0.413
	SE_3	0.493	0.455	0.508	**0.895**	0.305	0.498	0.379
	SE_4	0.501	0.488	0.513	**0.899**	0.302	0.529	0.381
Use	USE_1	0.469	0.475	0.446	0.280	**0.881**	0.525	0.628
	USE_2	0.426	0.438	0.396	0.262	**0.916**	0.597	0.561
	USE_3	0.430	0.453	0.408	0.276	**0.911**	0.593	0.590
	USE_4	0.457	0.473	0.471	0.373	**0.833**	0.536	0.608
Net Benefits	NET_1	0.666	0.614	0.624	0.517	0.549	**0.895**	0.577
	NET_2	0.524	0.499	0.539	0.433	0.482	**0.819**	0.456
	NET_3	0.752	0.724	0.744	0.577	0.565	**0.930**	0.640
	NET_4	0.664	0.678	0.666	0.493	0.636	**0.891**	0.734
Continuance Intention to use LinkedIn	CONT_1	0.575	0.578	0.607	0.416	0.657	0.680	**0.909**
	CONT_2	0.520	0.442	0.489	0.351	0.551	0.550	**0.893**
	CONT_3	0.590	0.548	0.557	0.383	0.630	0.644	**0.948**
	CONT_4	0.596	0.565	0.605	0.375	0.644	0.669	**0.946**

Table 4: PLS Loadings and Cross-loadings

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	TTF	SYSQ	INFQ	SERQ	USE	NETBEN	CONT
TTF	0.911	0.938	0.790	**0.889**						
SYSQ	0.932	0.951	0.830	0.686	**0.911**					
INFQ	0.893	0.926	0.757	0.747	0.805	**0.870**				
SERQ	0.925	0.947	0.816	0.548	0.510	0.592	**0.903**			
USE	0.909	0.937	0.787	0.474	0.487	0.469	0.314	**0.887**		
NETBEN	0.902	0.932	0.774	0.730	0.691	0.707	0.563	0.631	**0.880**	
CONT	0.940	0.957	0.848	0.595	0.547	0.600	0.388	0.656	0.672	**0.921**

Table 5: Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE) and the square root of AVE of latent variables

Constructs	TTF	SYSQ	INFQ	SERQ	USE	NETBEN	CONT
TTF							
SYSQ	0.743						
INFQ	0.825	0.883					
SERQ	0.593	0.549	0.649				
USE	0.519	0.525	0.518	0.342			
NETBEN	0.794	0.743	0.779	0.612	0.692		
CONT	0.641	0.578	0.648	0.413	0.706	0.713	

Table 6: Heterotrait-Monotrait Method (HTMT) of latent variables

Therefore, the measurement model's internal consistency, indicator reliability, convergent validity, and discriminant validity are confirmed. As a result, the model's structures are statistically distinct, and the reflective and formative constructs can be used to evaluate the structural model.

6.2. STRUCTURAL MODEL

The structural model, which specifies the relationships between latent variables, was calculated after the measurement model was validated. A bootstrapping analysis with 5,000 iterations was calculated to investigate the statistical importance of the weights of sub-constructs, the R-square statistics, and path coefficients for the endogenous latent variables. Since PLS does not produce overall goodness of fit indices, the R2 is the most common way to assess the model's explanatory capacity (Zheng et al., 2013).

Table 7 shows the findings of the structural model. The results can be stated as follows: Information Quality ($\beta = 0.088$, $p = 0.410$) and Service Quality ($\beta = 0.006$, $p = 0.923$) are not statistically significant in explaining use, meaning hypothesis 1 is not supported, and hypothesis 3 is supported, however, albeit mild, System Quality has a positive influence on Use ($\beta = 0.255$, $p = 0.006$), thus supporting hypothesis 2. The model proves 27.6% of the variance in Use. Task-Technology Fit has a positive influence on Use ($\beta = 0.230$, $p = 0.013$) and is statistically significant in explaining Net Benefits ($\beta = 0.556$, $p < 0.001$), meaning both hypotheses 4 and 5 are supported. The model explains 63.7% of the variance in Net Benefits. Use is also statistically significant in explaining both Net Benefits ($\beta = 0.367$, $p < 0.001$) and Continuance Intention to use LinkedIn ($\beta = 0.386$, $p < 0.001$) confirming both hypothesizes 6 and 7. Finally, Net Benefits is statistically significant in explaining Continuance Intention to use LinkedIn ($\beta = 0.429$, $p < 0.001$), as well, thus supporting hypothesis 8. The model explains 54.2% of the variation in Continuance intention to use LinkedIn and 63.7% of the variation in Net Benefits. These results can be seen in Table 7, and the results of the tests performed on the structural model are depicted in Figure 2.

Hypothesis	Path Coefficient	*P* -value	T -value	Conclusion
H1: INFQ→USE	0.088	**0.410**	0.833	Not supported
H2: SYSQ→USE	0.255	**0.006**	2.815	Supported

H3: SERQ→USE	0.006	**0.923**	0.095	Supported
H4: TTF→USE	0.230	**0.013**	2.489	Supported
H5: TTF→NETBEN	0.556	**0.000**	10.996	Supported
H6: USE→NETBEN	0.367	**0.000**	6.900	Supported
H7: USE→CONT	0.386	**0.000**	5.002	Supported
H8: NETBEN→CONT	0.429	**0.000**	5.422	Supported

Notes: **INFQ:** Information Quality; **SYSQ:** System Quality; **SERQ:** Service Quality; **TTF:** Task-Technology Fit; **NETBEN:** Net Benefits; **CONT:** Continuance Intention to use

Table 7: Structural model results

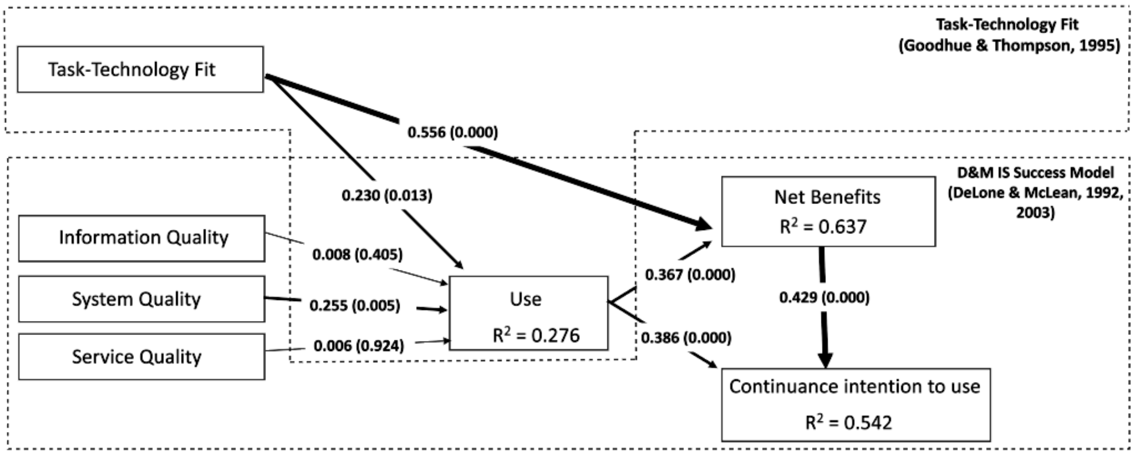

Figure 2: Research Model with hypotheses results

6.3. DISCUSSION

Based on the results obtained, it was possible to infer several points: Task-Technology Fit heavily explains Net Benefits, as well as the fact that Use has a positive influence on the latter, leading to the conclusion that LinkedIn is very well suited for the services (i.e., tasks) it provides as well as for the needs of each individual on the platform (since it meets the benefits they seek), and is not so much influenced by technical factors as postulated by the original model since Information and Service Quality constructs, surprisingly, did not have a decisive effect on LinkedIn use, meaning that it is possible that users do not consider those characteristics as drivers that lead them to choose and consecutively use the platform. These results go against the findings of (Seol et al., 2016), who stated that these constructs are the main dimensions of information system success, for the case of corporate social network cases (in which social interaction quality is paramount) and the authors (Dong et al., 2014), who inferred that the quality constructs play an essential role in the continuous use of a social network. However, Task-Technology Fit and System Quality had a positive, although mild, impact on use, meaning that the quality of the LinkedIn platform and, whether or not, it fits the job-related tasks users want, may weigh more heavily in the decision-making process of a user when deciding the platform. In the same way, this goes against the DeLone & McLean, (2003) stance of the IS success model, which considers system quality, information quality, and service quality to be the three predominant dimensions of information system success. The results obtained on the construct Use is evidence that the system has quality and that it is, in fact, adequate for the career management of its users. This outcome answered the first research question positively that indeed users perceive LinkedIn as an optimal platform for the outcome they seek.

In addition, the model heavily explains Net Benefits, which, in turn, explains the perception in which LinkedIn effectively leads to beneficial outcomes, first through its adequacy, then through use. In turn, Net Benefits heavily explain Continuance Intention to Use (a construct the model explains robustly, as well), meaning that the outcome a user gets (either positive or negative from using the platform) highly influences whether, or not, said user will continue to choose LinkedIn as an optimal platform, and effectively use it. Notwithstanding this finding, Use also had a positive impact on Continuance Intention to use, as such, it is possible to infer that users have the perception that using LinkedIn is beneficial to them, and, therefore, prompting us to confirm the second research question in which the outcome of LinkedIn use leads to a continuance intention in using the platform. These findings fall with the research done by (Davis et al., 2020a), in which the authors also found that LinkedIn usage frequency is linked to a wide range of professional benefits.

The model, finally, heavily explains Continuance Intention to Use and Net Benefits, the latter being highly related to Task-Technology Fit, two constructs that were not initially created together. In fact, both constructs are more highly related than Use is to Net Benefits, two constructs that belong in the same model, leading to the conclusion that the conjunction of both models is highly relevant, and the Task-Technology Fit construct is very effective in predicting Net Benefits.

6.3.1. Theoretical Implications

This study adds to the body of information regarding career-oriented social networks, specifically LinkedIn, from a theoretical standpoint. Although some studies have been made regarding other facets of these types of social networks, this research is among the first attempts at exploring the outcome of looking for a job on LinkedIn and a continuance intention to use the system.

To the best of our understanding, this is also an initial quantitative study in which it combines the Task-Technology Fit and Delone & Mclean model to understand LinkedIn usage, outcomes, and continuance intention. Therefore, contributing to the IS literature in terms of career-oriented social networks' determinants, based on the knowledge that the Task-Technology Fit model is a significant theoretical contribution in understanding how technology is used (Lu & Yang, 2014).

Previous findings suggested that the Delone and Mclean model is a good fit for social networks. While it has been widely utilized in the research of information system applications, it appears that it can also be used for online services (Dong et al., 2014). However, these findings suggest that the Delone and Mclean model might not be the most effective model to adopt for career-oriented social networks, as the results fell short of other studies regarding other types of social networks, such as Facebook (Dong et al., 2014).

The results obtained in this study fall into the same line of thought as the authors Larsen et al., (2009). As a result of their research, they stated that work-centric factors such as perceived task-technology fit and users' usage of information system features might be equally as significant in determining whether or not to continue using an information system. Furthermore, they affirm that the task-technology fit theory variables are essential in assessing users' continuance intention, and Goodhue & Thompson, (1995) proposition in which, indeed the information system has to be used and be a good fit for the assignment it is entailed to do, for it to be used continuously. However, the findings are contrary to those of the authors (Dong et al., 2014) since they stated that system quality, information quality, privacy protection service, and user satisfaction substantially support continuance usage. Our results have not shown this outcome, as well as unlike Tam & Oliveira, (2016), our results only point to a significant effect of task-technology fit and system quality on use and not information quality, as well. This detail indicates that the present study offers new and different insights from previous research conducted on the topics under reference, enriching the existing knowledge.

6.3.2. Managerial Implications

In the fierce rivalry between social network platforms, continuance intention to use has become progressively important (C. B. Zhang et al., 2017). Also, when developing efforts aimed at motivating users to continue using an IS, it is vital to consider the users' perceptions of task-technology fit and their usage of information system features (Larsen et al., 2009). For users, this confirms that choosing LinkedIn is an optimal platform to meet the career management benefits they seek. Notwithstanding this, the importance of social interaction in determining the degree to which users consider a site to be valuable and entertaining should be recognized by management (Seol et al., 2016). According to these findings, understanding the relationship between the outcome of finding a job and the intent to continue using LinkedIn will offer new insights to executives and the actual platform in understanding what drives a user to choose their platform. Also, when considering the best approaches to retain users as well as attract and attain new ones, data can be used to evaluate the person-organization fit for new personality-based digital services like e-recruiting (Buettner, 2016), which, in this case, pertains to LinkedIn. This study can also help marketing, advertisers, and recruiting managers think about how to use the site strategically as they learn how this demographic interacts on the social network, thus, leveraging this knowledge. It is advised that decision-makers base their action plans on the aspects that affect the user to develop effective strategies for advertising on the platform, communicate correctly and effectively to the community of users it is trying to reach. Managers should also examine all elements of social network system quality, information quality, and service quality, as well as monitor their platform condition and consult with social network platform providers to maintain a high-quality system in terms of perceived usefulness (Seol et al., 2016).

7. CONCLUSIONS

This study intended to fill the research gap in understanding if there are any impactful connections between the task of looking for a job and using LinkedIn to do so. Moreover, whether that choice of platform impacts one's Net Benefits and the continuance intention to keep using the platform. Even though researchers have looked into how companies use these types of social networks to assess resumes, plus studies have demonstrated how these sites affect users' psychological well-being, little investigation has looked into whether social networks may help one's personal career (Davis et al., 2020b).

For highly competent professionals, social networking sites are becoming an increasingly powerful tool for job development (Baruffaldi et al., 2017). Hence the fact that LinkedIn has a predominant demographic of young adults (Statista Research Department, 2021). In order to understand how this demographic perceives the outcome of LinkedIn usage as beneficial and whether they intended to continue using the platform, a literature review was conducted in order to identify key concepts of previous work that had been done and the best way to move forward.

While the majority of other studies regarding career-oriented social networks focused on psychological aspects, drivers that lead to use, as well as gratifications, this study focused on the assumption of a fixed outcome and the perception of whether the user considered it as a benefit or not, when evaluating the platform. This type of behavior would then lead to a continuance intention in keeping using the platform or not. By integrating the Delone and Mclean Information System Success Model and the Task-Technology Fit model, which complement each other, the empirical work sought to understand whether if in a first instance, users considered LinkedIn as a platform match to the task of finding a job and whether the platform's characteristics would have an impact on usage. At a later stage, whether LinkedIn usage and the task-technology fit would affect the outcomes one would obtain and, finally, whether that would positively affect a continuance intent to keep using the platform. The results pointed to the confirmation of seven out of eight hypotheses, and the answers to the research questions that show that users consider LinkedIn an excellent social network to find a job and that, because they concur that the outcome is positive, that effectively makes them want to continue to use it. Unlike previous authors who have stated that the revised DeLone and Mclean model variables (such as service quality) have an essential influence on a social network's continuous use, these results point to a different direction regarding LinkedIn, expressly. It is an expectation that this study will be helpful to academics doing future studies on career-oriented social networks since it will provide additional insights into user behaviors and perspectives.

8. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

As with any investigation, the current study had some limitations, which should be considered in further research. The data collected from respondents were gathered at a single point in time. Scholars may be able to determine the relationship between the outcome users obtain from LinkedIn usage and their continuance intention to use, in more depth, through a longitudinal study of the career-oriented social networks' use. The survey was conducted and shared almost exclusively with young Portuguese adults. Future research might investigate how people from diverse cultural backgrounds and nationalities utilize LinkedIn, what benefits they get from it, and if it leads to a continuance intention, as well. Results may vary in circumstances where LinkedIn usage is higher (or lower), depending on perceptions about the use of LinkedIn for job hunting and developing professional networks. This study can also be utilized as a starting point for further study into career-oriented social networks uptake using the Task-Technology Fit model. Understanding users' motivations to use social networks is essential for business and educational contexts, as it may help businesses identify ways to grow by leveraging their users' social needs (Lu & Yang, 2014). Likewise, it would be interesting to see the construct' Continuance intention to use' used more often in these types of models in various research areas, as it has the potential to reveal pivotal insights into user behavior and the success of a platform or information system.

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10.APPENDIX (OPTIONAL)

Annex A: Survey items

Constructs	Items – EN	Adapted from
Task-Technology Fit	TTF_1 - LinkedIn job search services are secure TTF_2 – LinkedIn's account management services are appropriate TTF_3 – LinkedIn services are appropriate TTF_4 – In general, LinkedIn services are sufficient	(Goodhue & Thompson, 1995)
Information Quality	INF_1 – The information provided by LinkedIn is useful INF_2 – The information provided by LinkedIn is easy to understand INF_3 – The information provided by LinkedIn is interesting INF_4 – The information provided by LinkedIn is up to date	(DeLone & McLean, 2003)
System Quality	SYS_1 – LinkedIn is easy to navigate SYS_2 – LinkedIn allows me to find the information I am looking for easily SYS_3 – LinkedIn is well structured SYS_4 – LinkedIn user support provides services on time	(DeLone & McLean, 2003)
Service Quality	SE_1 – LinkedIn's user support is helpful SE_2 – LinkedIn's user support is effective SE_3 – LinkedIn's user support provides personal attention when I have problems SE_4 – LinkedIn user support provides services on time	(DeLone & McLean, 2003)
Use	USE_1 – I use LinkedIn USE_2 – I use LinkedIn to look for jobs USE_3 – I use LinkedIn to apply for jobs USE_4 – I use the LinkedIn features	(DeLone & McLean, 2003)
Net Benefits	NET_1 – LinkedIn saves me time when looking for a job NET_2 – LinkedIn saves me financial resources when looking for a job NET_3 – LinkedIn provides me with a good service NET_4 – Overall, LinkedIn is beneficial for me	(DeLone & McLean, 2003)
Continuance Intention	CONT_1 – I intend to continue using LinkedIn in the future CONT_2 – I will try to use LinkedIn regularly CONT_3 – I plan to continue using LinkedIn frequently CONT_4 – I hope to continue using LinkedIn	(Venkatesh et al., 2012)