Découvrir le potentiel de l'omniprésence technologique pour l'apprentissage et le développement de carrière à l'heure de la 4eme révolution industrielle

Nicolas Bazine

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Par **Nicolas BAZINE**

Découvrir le potentiel de l'omniprésence technologique pour l'apprentissage et le développement de carrière à l'heure de la 4eme révolution industrielle

Sous la direction de Adalgisa BATTISTELLI et Marie-Christine LAGABRIELLE

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Membres du jury :

M. AMADIEU, Franck	Professeur	Université Toulouse Jean Jaurès	Examinateur
Mme VAYRE, Emilie	Professeure	Université de Lyon 2	Rapporteur
Mme DELOBBE, Nathalie	Professeure	Université de Genève	Rapporteur
Mme BATTISTELLI, Adalgisa	Professeure	Université de Bordeaux	Directrice
Mme LAGABRIELLE, Christine	Professeure	Université Toulouse Jean Jaurès	Co-Directrice

Titre: Découvrir le potentiel de l'omniprésence technologique pour l'apprentissage et le développement de carrière à l'heure de la 4eme révolution industrielle

Résumé :

Ce travail doctoral a comme objectif la compréhension des effets engendrés par la 4ème révolution industrielle sur l’apprentissage (Cascio & Montaelegre, 2016; Battistelli & Odoardi, 2018) et sur les carrières (Hirschi, 2018). Plus précisément le cœur de cette recherche vise à saisir comment les changements engendrés par la 4ème révolution industrielle peuvent être un atout pour les individus tant pour apprendre et développer des compétences pour leur carrière professionnelle, spécifiquement la carrière protéenne. En premier lieu, l’examen de la littérature sur la 4ème révolution industrielle nous amené à porter notre attention sur un aspect largement négligé à savoir l’omniprésence technologique. Nous avons développé deux échelles, l’une portant sur l’émergence d’un environnement psycho-technologique (EPT) qui se traduirait par de plus grandes opportunités d’apprentissage et des technologies plus accessibles due à l’omniprésence technologique et l’autre sur l’apprentissage avec les technologies (CAT). Nous avons pu mettre en évidence que la perception de l’EPT était un agent motivationnel pour le CAT. D’une part, l’EPT est associé positivement à la motivation à apprendre et que d’autre part, nous observons une relation indirecte entre le CAT par la motivation à apprendre. Dans un second temps, une analyse en profils latent (LPA) a été réalisée pour mettre en évidence les profils les plus à même de développer leur carrière dans le contexte de la 4ème révolution industrielle. 4 profils ont été mis en évidence, soit ceux d’ « Architecte de carrière protéenne, de Pragmatique, d’Idéaliste et de Non-Investi ». Le premier profil apparait le plus adapté alors que le dernier apparait le moins adapté. Et en dernier lieu, nous avons développé un modèle s’efforçant de comprendre comment les individus peuvent utiliser l’omniprésence technologique pour leur développement de carrière. L’ensemble de ces travaux approfondissent l’état de nos connaissances sur la 4ème révolution industrielle et la façon dont les individus peuvent tirer avantage de l'omniprésence technologique pour leur apprentissage continu et la construction de leur carrière professionnelle.

Mots-clés : Apprentissage, Environnement psycho-technologique, Comportements d'apprentissage avec les technologies, 4ème révolution industrielle, Développement de carrière, Orientation de carrière protéenne,

Title: Uncovering the potential of technological ubiquity for learning and career development in times of the 4th Industrial Revolution

The aim of this research was to understand the effects brought by the 4th revolution on skill development (Cascio & Montaelegre, 2016; Battistelli & Odoardi, 2018) and career (Hirschi, 2018). More precisely, the heart of this research was to examine how the changes brought by the 4th Industrial Revolution can be an asset for individuals to develop skills for their career. To do this, we first reviewed the literature on the 4th Industrial Revolution and focus our attention to an aspect largely neglected by research on the 4th Industrial Revolution: technological ubiquity. We then developed two scales focus on the emergence of a psycho-technological environment which is characterized by more learning opportunities and more accessible technologies due to technological ubiquity and with learning with technologies. In addition, we highlighted that the perception of PTE was a motivational agent for learning with technology. This study demonstrates that PTE has a positive relationship with motivation to learn and that PTE is associated with learning behaviors with technologies through motivation to learn. Then, a latent profile analysis was performed to highlight the profiles most suited to develop their careers in the context of the 4th industrial revolution. 4 profiles has been identified highlighted Protean career Architect, Pragmatic, Idealist and Not Invested. These profiles are from Protean career Architect to Not-invested as the most suited to the least suited. Finally, we developed a model to understand how individuals can use the technological ubiquity for their career development. All of this work deepens our understanding of the 4th Industrial Revolution and how individuals can take advantage of technological ubiquity for their continuous learning and the career building.

Key words: Learning, psycho-technological environment, learning behaviors with technologies, Career development, 4th industrial revolution, Protean career orientation

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Unité de recherche

Laboratoire de psychologie, EA4139, Université de Bordeaux 3 ter, place de la Victoire

33076 Bordeaux cedex

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Texte long français

Introduction

L'avènement de la 4ème révolution industrielle a été synonyme de nombreux changements pour les organisations et les individus. En premier lieu, les organisations ont dues modifier leur fonctionnement et leurs méthodes ce qui bouleversa en profondeur le contenu des métiers pour les employées. Dans ce nouveau contexte, l'apprentissage et les carrières sont des enjeux importants qui nécessitent des connaissances nouvelles pour aider les travailleurs dans leur réussite professionnelle. La particularité de cette 4ème révolution industrielle est l'augmentation exponentielle du nombre de technologies toujours plus performantes connectés entre elles (Cascio & Montaelegre, 2016). L'enjeu est de pouvoir garantir aux entreprises compétitivité, croissance, performance et qualité des biens et des produits, ainsi que la qualité de vie au travail des acteurs concernés. La 4ème Révolution industrielle est donc en train d'activer un changement systématique et radical qui exige aux individus qu'ils s'adaptent en continu, l'une des particularités de la 4ème révolution industrielle étant la rapidité de l'évolution des technologies au sein des organisations (Battistelli & Odoardi, 2018). Cela implique notamment que les travailleurs développent de nouvelles compétences pour qu'ils puissent continuer à effectuer leurs métiers de manière efficace (Campion et al., 2011). Cascio et Montaelegre (2016) soulignent que l'augmentation des technologies connectées entre elles et leur omniprésence peuvent s'avérer un atout pour le développement des compétences et des carrières. Comprendre comment l'omniprésence technologique peut être un atout pour soutenir les individus dans leur apprentissage et dans leur développement de carrière est un enjeu majeur et l'objectif général de cette thèse. Notamment en considérant que les développements théoriques et empiriques sur cet aspect-là sont manquants.

Le chapitre 1 se focalise sur la compréhension de comment l'omniprésence technologique peut s'avérer être un atout pour l'apprentissage et s'efforce de proposer un cadre conceptuel et théorique et d'en définir les caractéristiques. Nous y supposons que l'omniprésence technologique doit être conceptualisée comme un contexte dans la mesure où les technologies sont intégrées dans nos actions quotidiennes. Cet environnement se caractériserait par deux aspects majeurs : l'un relatif aux opportunités d'apprentissage issues des technologies, l'autre relatif à l'accessibilité des technologies pour apprendre. L'hypothèse poursuivie est qu'un tel environnement pourrait représenter un potentiel d'apprentissage et favoriser l'apprentissage.

Dans le chapitre 2, l'objectif consiste à nous assurer de la validité de nos hypothèses théoriques. Pour cela, deux mesures permettant de saisir la perception de cet environnement psycho-technologique (EPT) et des comportements d'apprentissage avec les technologies (CAT) ont été développées. Deux études regroupant 389 étudiants ont été conduites. Dans la première, auprès d'un échantillon de 151 étudiants, deux échelles ont été élaborées via une analyse factorielle exploratoire. Dans la seconde, basée sur un échantillon de 238 étudiants, une analyse factorielle confirmatoire a permis d'attester des propriétés psychométriques des mesures. Cette première validation démontre une bonne fiabilité et validité de nos construits avec de bonnes qualités psychométriques des outils qui représente un premier pas dans la validation théorique de notre proposition.

L'objectif du chapitre 3 est d'examiner plus en profondeur la relation entre EPT et les comportements d'apprentissage avec les technologies (CAT) en mettant avant que l'EPT pourrait agir comme un agent motivationnel. De plus, nous analysons le rôle d'interaction de la conscience technologique (conscience de l'importance des technologies dans le contexte actuel) entre la motivation à apprendre et les comportements d'apprentissage avec les technologies. Pour tester nos hypothèses, nous avons conduit une méthode d'équations structurelles sur un échantillon de 344 étudiants avec une expérience professionnelle. Nos résultats démontrent qu'EPT a une relation positive indirecte avec CAT par la motivation à apprendre. De plus, nos résultats mettent en lumière que la conscience technologique modère la relation entre la motivation à apprendre et les comportements d'apprentissages avec les technologies. Cette étude contribue ainsi à élargir nos connaissances sur le rôle motivationnel de l'EPT et sur son impact sur les comportements d'apprentissage avec les technologies

Le chapitre 4 souligne les effets engendrés sur la carrière par la 4ème révolution industrielle. Tout d'abord, les carrières sont de plus en plus non-linéaires et discontinues (Arthur & Rousseau, 2001). Les carrières traditionnelles définies par la loyauté d'un employé envers son organisation récompensée en contrepartie par le développement de carrières s'efface au profit de carrière plus incertaines et plus autodirigées. Le développement de carrière est passé d'une responsabilité organisationnelle à une responsabilité individuelle (Hall et al., 2018). Dans ce cadre-là, un changement majeur est l'avènement de l'économie de plateforme (Ashford et al., 2018) qui amène une plus grande flexibilité d'une part dans le lien qu'entretiennent l'entreprise et l'employé et d'autre part dans la manière de réaliser son activité professionnelle. Une orientation de carrière protéenne qui correspond, quant à elle, a une attitude individuelle qui amène les individus à définir eux-mêmes leurs carrières indépendamment de l'organisation. Cette orientation semble être un moyen de faire face à ces nouvelles exigences. Deux dimensions définissent cette orientation : l'auto-direction (degré dans lequel une personne assume la responsabilité de sa carrière) et les valeurs (guide des décisions de carrière prises). Cette orientation influe sur trois mécanismes : agentivité, adaptabilité et identité. Et ces mécanismes sont reliés à des comportements favorables au développement de carrière. La littérature a largement mis en évidence les relations qu'entretiennent l'orientation de carrière protéenne et un meilleur développement de carrière (Smale et al., 2018 ; Hirschi & Koen, 2021). Il est à noter que des études s'efforcent de montrer que l'orientation de carrière protéenne constitue un atout dans l'utilisation des technologies pour le développement de carrière (Hirschi, 2018).

Le chapitre 5 s'attarde sur les différentes entre les individus dans leur développement de carrière. La recherche sur le développement de carrière a établi la façon dont l'orientation de carrière, la motivation à apprendre et les perspectives de carrière future prédisent les comportements de carrière (tels que la planification, le réseautage ou le développement de compétences). La perspective centrée sur les variables c'est-à-dire l'analyse de l'effet d'une variable A sur une variable B ignore l'existence de sous populations d'individus développant leur carrière différemment. Or Hall (2002) a souligné, dans le cadre d'une orientation de carrière protéenne, qu'une personne peut montrer des niveaux d'auto-direction et de valeurs différenciés conduisant à des profils singuliers, cela suggère l'existence de différents profils. Pour approfondir ces résultats, nous avons conduit une étude avec une approche « centrée sur l'individu » dont l'objectif est de comprendre comment ces facteurs combinés peuvent caractériser des d'individus et leur probabilité de réussir leur développement de carrière. Une analyse en profil latent, réalisée parmi un échantillon de de 767 individus afin d'identifier l'existence de profils distincts. 4-Quatre profiles ont été identifiés. Le premier profil idéaliste correspond aux personnes montrant des hauts niveaux de PCO et des bas niveaux de motivation à apprendre. Le deuxième profil orientation a été nommé orientation de carrièrre protéenne architecte dans la mesure où il correspond aux individus qui sont fortement engagés dans leur développement de carrière et qui présentent des hauts niveaux d'orientation de carrière protéenne comme de motivation à apprendre. Le troisième profil « Pragmatique » correspond à des individus avec des niveaux modérés pour chaque indicateur. Enfin le profil « non-investi » correspond à des individus démontrant des bas niveaux dans chaque indicateur. Nos résultats témoignent que les orientations de carrière protéenne architecte semblent les plus à même de développer leur carrière dans ce contexte en démontrent les plus aux niveaux de comportements de carrière proactifs et de comportements d'apprentissages avec les technologies. Cette étude est parmi les premières à explorer les différents profils de développement de carrière et met en avant de nouvelles connaissances sur la nature mais aussi la façon dont différents individus développent leurs carrières.

Le chapitre 6 a pour objectif de mettre en évidence que les technologies peuvent être un atout pour le développement de carrière. Pour cela, nous avons analysé la relation entre l'orientation de carrière protéenne et les comportements de carrière avec une focale sur le rôle médiateur de (1) l'EPT et (2) des CAT. Une modélisation par équations structurelles a été conduite pour analyser les relations supposées auprès d'un échantillon d'étudiants et ce sur deux temps de mesure. Nos résultats confirment le rôle médiateur de l'EPT et des comportements d'apprentissage avec les technologies. Cette étude avance nos connaissances en démontrant comment les technologies peuvent être aidante pour l'avancement de carrière. L'orientation de carrière protéenne permettrait ainsi de reconnaitre les opportunités présentes dans l'environnement technologique, opportunités stimulant les comportements d'apprentissage avec les technologies et conduisant au développement de comportements de carrière. Cette étude amène également des informations pour les conseillers en gestion de carrière dont l'activité est de favoriser le développement de carrière des consultants ou des salariés qu'ils reçoivent, en ayant à l'esprit le rôle bénéfique que peuvent jouer les technologies dans leur évolution professionnelle.

Pour conclure, le travail présenté entend mettre en évidence comment les changements apportés par la 4ème révolution industrielle, s'ils modifient largement le cadre et les activités de travail, s'avère être une ressource pour les individus. Cette thèse apporte plusieurs implications théoriques et pratiques et constitue un premier pas dans la compréhension de comment la 4ème révolution peut s'avérer une ressource ou atout pour les individus en se focalisant sur l'omniprésence technologique.

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Introduction

The advent of the 4th Industrial revolution is synonym of changes and upheavals in the professional context (Petrillo, et al., 2018) but also in society (Schwab, 2017). The massive introduction of disruptive technologies and the automatization in the organizations are starting to be well documented. However, the understanding of how technologies affect the experiences at work and the life in organizations are still lacking. The great challenge of 4th industrial revolution for all type of organizations is be ensure competitiveness, growth, performance and quality on the one hand, and to provide to employees with a better quality of life at work, personal development and satisfaction on the other. Parker (2014) points out that the evolution of work is an opportunity to provide employees with motivating jobs and assume their well-being and satisfaction.

Technologies are bringing about changes in the way which organizations create and capture value, when, where and how people do their work, and the ways in which individuals interact and communicate with each other. The 4th Industrial revolution is currently activating a systematic and radical change which requires individuals to adapt continuously. « This revolution can be defined in three points: fasting (characterized by an exponential and non-linear speed where each technology generates an interconnected world); breadth and depth (a combination of different technologies which provokes a paradigm shift in social and economics domains, business affairs but also in an individual plan: it is not only the “What” and the “How” which are upheavals but also the “Who” we are. The systemic impact (involve a transformation of whole system of country, organizations and any aspects of society” (Schwab, 2017; p.13 cited by Battistelli & Odoardi, 2018; p. 35).

In addition, technologies are becoming more necessary than before, almost every task depends on technologies at work, and they change the way organizations work. Every sector (industry, services, etc..) is concerned by the changes of the 4th industrial revolution. « We are witnessing a paradigm shift in the way we work, communicate, care, learn and perform any task, including environmental conservation » (Battistelli & Odoardi, 2018, p. 36). The specificity of the 4th industrial revolution is that the technologies are not only a set of tools which allow individuals to carry out tasks faster or more efficiently, but they transform important parts of work and now some technologies can be considered such as an employee. For instance, the actual collaborative robots (cobots) suitable for working alongside individuals can be considered as teammates (Coovert and Thompson, 2014; Davenport & Kirby, 2015). One of multiple examples is the implementation of robots in the police in Dubai, in 2017, initially intended for the reporting crime and the payment of fines from citizens, the objective for the police organization is to have, by 2030, twenty-five percent of their workforce in the form of officers robotic. The advancement of Artificial Intelligence allows the development of new robots which make increasingly complex tasks and can deal with uncertain situations in an efficient way. There are robots that are more adapted to the working environment with multimodal interfaces that allow them to communicate more efficiently with other human members of the team (Redden et al., 2014). This evolution raises many questions about the right and capacity of robots, but nevertheless, they play an increasing role in the dynamics of organizations. This is just one example showing that one cannot consider only as a tool, but rather as an environment or system in which individuals and technologies are in multiple and mutual interaction.

Technologies are producing a new type of control, coordination and collaboration in professional tasks, which will trigger new forms of work through internet networks such as teleworking, virtual team, and working with robots etc. (Hoch & Kozlowski, 2014, Charalampous et al., 2018). The interaction between humans and technologies has been the focus of concerns of engineers and computers scientists for a long time. From their part, psychologists strive to contribute to the understanding of this interaction through the development of theories, models and research that will significantly help individuals and organizations. On the other hand, organizations can be able to design a working environment that enables to individuals to be more creative, proactive, involved and motivated. Organizations will be led to change strategies and management with the aim of fostering the continuous learning. But also, to recognize the value of competences and provide sufficient resources to ensure safety, health at work and well-being of employees through the creating of sustainable working conditions (Cascio & Montaelegre, 2016). Successful transformation of organizations relies on the ability to integrate technologies into the productive, human and social system, giving meaning to employees, fostering their professional growth and improving innovation and performance (Battistelli & Odoardi, 2018; Khanaga, et al., 2017).

The 4th industrial revolution has attracted great attention from manufacturing companies, engineer research, work and organizational psychologists and service systems. Many authors and researches have discussed about the nature of the fourth industrial revolution and which technologies of this revolution are having an impact on the economic and social world. For instance, Cascio & Montaelegre (2016) argue that mobile informatics, cloud, big data, machine learning, sensors, intelligent manufacture, advanced robotics, drones are the technologies that have changed the workplace and society. But Schwab (2017) emphasized that they are Artificial Intelligence (AI), robotics, Internet of things, 3D print, nanotechnologies, biotechnologies, energy storage, quantum informatics that have changed the workplace. Salkin et al. (2018) argue that the 4th industrial revolution is characterized by the deployment of multiple technologies in a system (e.g., organization, university, team) and propose a framework to understand how the technologies are integrated and connected.

According to the conceptualization of Salkin et al. (2018), the 4th industrial revolution captures the interconnectedness of technologies to define a new world that is “hyper connected and saturated in which everyone’s Internet is connected to everyone else’s Internet

(Wooldridge, 2015, p. 29). To support this point, Gubbi et al. (2013) indicate that the number of interconnected technologies has increased significantly and this significant growth has facilitated their integration by creating a fusion between the physical and digital world. This phenomenon provokes the proliferation and *ubiquity* of advanced technologies in our daily lives (e.g. NICTs, artificial intelligence, Internet of Things). Cascio and Montaelegre (2016) underline that now, technologies are omnipresent in all aspects of life such as work, education, family and leisure time. This technological ubiquity has produced the digitalization of the world (Colbert et al., 2016) which reflects that, now technologies are an integral part of our lives and that human activities are more dependent of them for the realization of any daily actions (Barley et al., 2017).

Technological ubiquity has been accompanied by an increase of training through the use of technologies. For instance, in 2012, in the United States, training using technologies including e-learning, online learning, MOOC, mobile learning etc. accounted for 39% of training in professional context (Miller, 2013). An important change brought out by technological ubiquity is that individuals can now learn and develop knowledge and skills regardless of time and place. Internet (Wikipedia, Scholar, MOOC), smartphone, GPS, video game, virtual reality, simulations have given employees and students access to educational resources anywhere and anytime, inside or outside their organization (Cascio & Montaelegre, 2016). Traditional forms and designs of training conceived activities where learners must follow the instruction and realize activities step by step during the process of acquiring skills and knowledge (Noe et al., 2014). With the new forms of learning, individuals are potentially becoming active agents of their own learning (Beier & Kanfer, 2009; Bell & Kozlowski, 2008). Moreover, technological ubiquity provides more opportunities for individuals to develop knowledge and skills and learning contents is more accessible, varied and easier to share (Dachner et al., 2021). However, learning with technologies is not inherently more effective than other instructional methods. Consequently, literature strives to understand the benefits and the limitations of learning with technologies (Bell & Kozlowski, 2008). Even if, few studies show that technologies could be an opportunity for the learning and skills development (Noe et al., 2014), the evidence suggests that technologies give access to learning content more easily and in greater numbers (Beier, 2019). The increasing number of learning opportunities due to technologies could be considered such as learning potential. Furthermore, McFarland and Ployhart (2015) emphasized the importance of social media such as Facebook, Twitter, LinkedIn, and Youtube in sharing knowledge or communicating in order to acquire new knowledge. Social media are the perfect example of the advantages of these new tools because they are not tools designed to provide knowledge nor to facilitate the acquisition of skills but their flexibility allows that (Balakrishan & Can, 2016). The use of social media have been considered as a resource for individuals' learning (Behringer,et al., 2017) and their use have the potential to transform organizational behavior (innovation, proactivity). For example, Robertson and Kee (2017) found that the amount of time employees spend interacting with their colleagues on Facebook had a positive effect on job satisfaction. Martin et al. (2015) demonstrated that social media use was effective in improving employee voice behavior. Bala, et al. (2019) found that use of social media in the workplace had a positive effect on innovative behavior. Cai et al. (2020) have demonstrated that the use of social media is a resource for newcomers' socialization and highlight that they can use social media to seek information and advice from their colleagues to improve their performance. But also, the authors demonstrate that the use of social media is associated with better interpersonal relationship among employees. These different studies have highlighted the multiple benefits of social media at work.

Some consequences of the changes of the 4th industrial revolution require highly skilled employees (Manyika et al., 2012) who are able to adapt and develop new skills in order to be an effective workforce (Campion et al., 2011; Pulakos et al., 2000). In addition, Cascio and Montaelegre (2016) emphasized an increase in the complexity of work and organizations. This aspect is highlighted by the study of Wegman et al. (2018) which shows how technological evolution affects job characteristics and in particular increases job complexity. One solution to this challenge is to improve the supply of skills, for example, through better education. But the attention must also be given to the side of the organizations that should design the work that requires both a greater use of skill and a possibility to develop skills more easily (Osterman & Shulman, 2011, Payne & Keep, 2003). Promoting learning and development is also important at the individual's level. Individuals need to develop sufficient cognitive, self, social, and affective capacities to interact adaptively in dynamic and unpredictable environments (Lord et al., 2011). The digitalization and technological ubiquity have considerably affected the content of work, careers and also learning (Parker, 2014). Learning is among the central questions of how technologies and technological ubiquity have transformed the acquisition of knowledge and skills (Beier, 2019). And theoretical and empirical studies on the impact of technological ubiquity on learning and work are still lacking in the literature.

Moreover, the changes of the 4th industrial revolution are profoundly affecting careers. The consequences of changes in work, occupations and organizations have led to the disappearance or modifications of many current occupations and the emergence of new jobs. At the same time, new occupations, new industries, and fundamentally new ways of working and managing the careers are likely to emerge (Brynjolfsson & McAfee, 2014) and numerous studies have pointed out that technologies can play a huge role in career development (Lent, 2018).

A major stake of the 4th industrial revolution for work and organizational psychologists' scholars is to understand how this revolution is affecting career orientations and behaviors. It seems clear that the 4th industrial revolution could therefore be one of the most important issues in shaping the future nature of career choices, career development and career counselling (Hirshi, 2018).

Therefore, our knowledge on how changes affect individuals is still lacking, notably research on technological ubiquity and learning (Cascio & Montaelegre, 2016), or research on career development in the digital age. This PhD thesis strives to fill this gap. The general aim of this PhD thesis is to demonstrate that the changes brought about by the 4th industrial revolution can be useful resource for professional development and career development and enable individuals to thrive in their careers. To do so, we propose a theoretical framework to understand technological ubiquity and how this environment can be helpful for developing skills. Then, we also address the fact that the changes brought about by the 4th industrial revolution can be useful for career development. As highlighted by Venable (2010), the research area remains unexplored and requires to be investigated. We deepen how 4th industrial revolution has shaped the careers in Chapter 4. Our findings aim to provide to practitioners, researchers and individuals, with some knowledge and advice to facilitate the setting of actions that enable professional and career development.

The doctoral thesis consists of four studies based on two theoretical frameworks. The first chapter is a theoretical introduction in the view to present how technological ubiquity have modify learning. The second chapter focuses on the development of two measures which captures two aspects of learning in the technological ubiquity. The first measure captures the perception of a psycho-technological environment such as learning potential which reflects that the ubiquity of technologies provides more opportunities to learn and more accessibility. The second measure is about learning behaviors with technologies and captures how individuals use technologies to learn. The third chapter strives to demonstrate that the perception of PTE as a motivational agent. To do so, we develop a model that link PTE and learning behaviors with technologies through motivation to learn. The fourth chapter provides a theoretical introduction of the impact of 4th industrial revolution on career. In the fifth chapter, we examine and determine which profiles are the most adapted to thrive in career at time of the 4th industrial revolution. We apply a latent profile analysis to identify the most suited career development profile. The findings show several profiles and demonstrate that certain profiles are more adapted to the requirements of career at 4th industrial revolution. The sixth chapter focuses on how the protean career orientation and psycho-technological environment allow developing career and acquiring knowledge. More specifically, the results demonstrate protean individuals are more able to recognize opportunities offer by technological ubiquity in order to develop their career.

Chapter 1 : Technological ubiquity as context for learning

1. Theoretical background of the technological ubiquity for learning

Generally, researches have studied the specificity of each technology in a specific setting producing numerous “minitheories”. With technological ubiquity, the use of technologies is integrated in our daily actions (Cascio & Montaelegre, 2016), this has caused a paradigm shift in the analysis of how technologies influence learning. Nowadays, technologies cannot be considered simply as a tool as they represent a context due their interconnedness. Accordingly, in this thesis, drawing on Johns (2006), we analyze technological ubiquity as a context characterized by situational opportunities and constraints for learning. Johns (2006) framework for understanding context suggests that the contextual features affect the cognition, affect and behaviors of individuals embedded within this context. This conceptualization of context by Johns is clearly aligned with multilevel theorizing and principles (Kozlowski & Klein, 2000) and emphasized that context operates as a cross-level effect in which situational variables at one level affect variables at another level. But this conceptualization is patchy and the social cognitive theory of Bandura indicates that individuals behave not as in the deterministic way. Contextual features are not sufficient to activate a behavior but depend of a triadic. Based on the social cognitive theory (Bandura, 1989), individuals are neither autonomous agents nor simply mechanical conveyers of animating environmental influences. In this research, personal factors and technological ubiquity operate as interacting determinants.

The first aspect of this environment is the opportunity to learn. This aspect is of great importance because some research has noticed that the construction of knowledge will increasingly rely on the availability and use of technologies and emphasizes that access to sufficient materials and the opportunity to experiment with new ways of learning is essential (Kozlowski & Hults, 1987; Noe & Wilk, 1993). Moreover, Farr and Middlebrooks (1990) underline the importance of having sufficient resources to develop relevant skills. Individuals need opportunities and resources in order to experiment to explore and experiment to discover and apply better strategies to enhance learning (Bell & Kozlowski, 2008; Debowski, et al., 2001; Keith & Frese, 2008; Noe, 2008). As noted above, technological ubiquity provides a wealth of content, in terms of quantity and diversity for learning due to technological diversity facilitating the construction or improvement of specific skills by the individual (Dachner et al., 2019). Moreover, each technology has some strengths and weaknesses for developing skills (Beier, 2019). The integration of multiple technologies in the learning process provides the possibility to compensate the weakness of some technologies using the strength of others. For example, MOOC provides amount of relevant information to develop knowledge and skills but the learning process is lonely (Beier, 2019). The integration of social media can allow individuals to share, discuss with videos to limit the loneliness of this learning method.

Opportunities to learn offered by technological ubiquity also concern their flexibility. Derouin et al. (2005) pointed out that e-learning allows better flexibility, for example, it offers training to employees and students on demand, anytime and anywhere and E-learning is self-pacing. Self-pacing, therefore, permits trainees to work on training tasks as quickly or as slowly as they prefer. At the current period students and employees have multiple other sources, spaces, and times for learning (Noe et al., 2014; Heidari, et al., 2021). E-learning has caused a major shift in the conception of learning, which has evolved from a passive to an active mode (Katz-Navon et al., 2009). Individuals can now exercise more personal control over their own learning, they are seen as active decision makers responsible for their own learning (Noe 1986; Noe et al., 2014). When given greater responsibility over learning, effective learning experiences require individuals to choose to participate in, continue, and apply the knowledge and skills learned from training (Brown et al., 2016). Learning with technology requires individuals to improve their personal control over their own learning, including through the use with use of multimedia instruction on the Internet or other technologies (Caprara et al., 2008).

In addition to richness and flexibility, technological ubiquity has produced more opportunities to learn by facilitating the process of sharing information and knowledge and communication has become continuous. Interaction is facilitated because each person has several technological tools interconnected 24/24 and 7/7. For instance, a student or a worker equipped with different technologies (laptop, smartphone, etc…) can connect with others and access multiple networks through the use of technologies and Internet (Uemukai et al., 2004) and foster the process of sharing knowledge and information. Additionally, computers can provide students and workers with an important amount of information via tools like chatbot or Internet when they need.

The second aspect is the accessibility. This environment is characterized by the fact that learning becomes easier through the accessibility and ease of use technologies (Sakamura & Koshizuka, 2005). The access to learning contents has become more available with technological ubiquity by freeing itself from the constraints of time and place (Beier, 2019). In addition, UX researchers have made significant efforts to develop technologies that any person can use (Tao et al., 2020). These authors point out that individuals require convenient and efficient technological tools to engage in their daily activities (i.e., learning, communication) and their current activities can be encountered by tools which are costly in terms of time, efforts, and easiness to use to achieve their actions.

Based on partly on the literature of learning potential (Nikolova et al., 2014), and partly on work on context of Johns, (2006), we considered that the contextual features of technological ubiquity (opportunities to learn and accessibility) as a learning potential and this context technological ubiquity can activate learning behaviors and facilitate learning.

Nikolova et al. (2014) highlight that the perception to have opportunities to learn is essential for learning. We claim that technological ubiquity have produced the perception that thanks to technologies, individuals can develop knowledge and skills. This new Psycho-Technological Environment (PTE) is derived from the individual perception of the merging of the physical and digital worlds due to the technological ubiquity (Colbert et al., 2016; McFarland & Ployhart, 2015). PTE is characterized by the interactions between human and technology and is defined by a set of opportunities and constraints affecting behaviors and beliefs (Johns, 2006; McFarland & Ployhart, 2015).

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Chapter 2 Article 1 : Environnement psycho-technologique (EPT) et comportements d'apprentissage avec les technologies (CAT) : développement et adaptation française de deux mesures[1]

RESUME

La 4ème révolution industrielle et l'omniprésence des technologies ont largement modifié le contexte professionnel notamment l'apprentissage. Nous postulons l'émergence d'un environnement psycho-technologique qui se traduirait par davantage d'opportunités d'apprentissage et des technologies plus accessibles. A notre connaissance, aucune mesure ne permet de saisir la perception de cet environnement psycho-technologique (EPT) ni des comportements d'apprentissage avec les technologies (CAT). L'objectif de cet article est donc de pallier ce manque d'outils par la construction d'échelles francophones. Pour cela, deux études regroupant 389 étudiants ont été conduites. Dans la première, auprès d'un échantillon de 151 étudiants, deux échelles ont été élaborées via une analyse factorielle exploratoire. Dans la seconde, basée sur un échantillon de 238 étudiants, une analyse factorielle confirmatoire a permis d'attester des propriétés psychométriques des mesures. Cette première validation démontre une bonne fiabilité et validité de nos construits avec de bonnes qualités psychométriques des outils.

Mots-clés : Apprentissage, Environnement psycho-technologique, Comportements d'apprentissage avec les technologies, Potentiel d'apprentissage, 4ème révolution industrielle

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[1] 33

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ABSTRACT

The 4th industrial revolution and the omnipresence of technologies have largely modified the work context and more specifically the learning process. We postulate the emergence of a new psycho-technological environment which is characterized by more opportunities to learn and more accessible technologies. To our knowledge, no measurement can capture the perception of psycho-technological environment (PTE) and learning behaviors with technologies (LBT). The aim of this study is therefore to compensate for this lack of tool with the development of French-language. Two studies that combine 389 students were conducted. In the first study, based on a sample of 151 students, two scales were developed via an explanatory factorial analysis. In the second study, based on a sample of 238 students, a confirmatory factorial analysis confirmed the psychometric qualities of our scales. This first validation study shows good validity and fiability with the good psychometric qualities of our scales.

Key words: Learning, psycho-technological environment, learning behaviors with technologies, learning potential, 4th industrial revolution

2.1 Introduction

L'avènement de la 4ème révolution industrielle a profondément bouleversé le monde professionnel (Petrillo et al., 2018). Dans les nombreux changements introduits, l'omniprésence des technologies, définies comme l'ensemble des outils électroniques (Cascio & Montealegre, 2016) est particulièrement significative. On dénombre ainsi davantage de technologies que d'habitants sur terre et désormais la quasi-totalité des individus ne peuvent plus travailler sans les utiliser (Mohindru et al., 2019). Cette omniprésence des technologies a provoqué l'émergence d'un nouvel environnement psycho-technologique où les mondes physique et électronique ont fusionné (Colbert et al., 2016; McFarland & Ployhart, 2015). Selon le cadre théorique de Johns (2006) ce nouvel environnement psycho-technologique, caractérisé par l'interaction entre les technologies et l'individu, peut être défini comme un ensemble d'opportunités et de contraintes qui affectent les comportements et les pensées (McFarland & Ployhart, 2015 ; Ryan & Derous, 2019).

De cette situation, émerge incontestablement l'importance d'investiguer comment l'omniprésence de ces technologies a bouleversé les comportements individuels et plus particulièrement ceux relatifs à l'apprentissage (Battistelli & Odoardi, 2018 ; Cascio & Montaelegre, 2016), apprentissage représentant un des aspects les plus largement affectés par l'arrivée des nouvelles technologies (Dunn & Kennedy, 2019 ; Noe et al., 2014) avec la transformation de ses modalités, de son déroulement et de ses résultats (Bell et al., 2017). Par exemple, l'omniprésence des technologies dans l'environnement a permis d'avoir un plus grand nombre de contenus de formation autant en termes de quantité que de diversité (Dachner et al., 2020). De plus, ces contenus de formations sont beaucoup plus accessibles en s'affranchissant des contraintes de lieux et de temps (Beier, 2019). Cette grande variété de contenus et de manières renouvelées d'acquérir des connaissances et des compétences a permis une personnalisation de l'apprentissage en le rendant entre autres plus flexible (Brown et al., 2016). Grâce à cela, les individus peuvent élargir leurs expériences d'apprentissages (He & Zhu, 2017). Certains auteurs parlent d'apprentissage « additionnel » qui se rajoute à l'apprentissage « pur » permettant d'obtenir du soutien, de maintenir sa motivation ou encore de développer des stratégies pour apprendre grâce aux moyens technologiques (Heflin et al., 2017). Cet apprentissage additionnel est rendu possible grâce à ces nouveaux procédés qui facilitent la collaboration, le partage et la création de connaissances (Song & Lee, 2014).

Cet article entend contribuer à la littérature scientifique en plusieurs axes. Tout d'abord, cette recherche s'inscrit dans une compréhension contextuelle des technologies en identifiant la perception du contexte technologique (EPT) par les individus. Elle vise à répondre à l'appel de Johns (2018) en portant une focale sur l'aspect contextuel souvent négligé au profit d'une analyse plus individuelle des technologies (Beier, 2019 ; Bell et al., 2017). En s'efforçant de donner un cadre et une définition conceptuelle des changements apportés par les technologies nous soulignons que l'omniprésence des technologies agit en tant que potentiel d'apprentissage (Nikolova et al., 2014). En accord avec les travaux de Nikolova et al. (2014), cela implique que l'omniprésence technologique constitue un levier pour l'apprentissage.

En deuxième contribution, cet article présente une première validation de mesures en français, permettant de rendre compte de deux aspects différenciés liés à l'omniprésence technologique : d'une part, la perception de l'environnement psycho-technologique et d'autre part, les comportements d'apprentissage utilisant les technologies (Cascio & Montaelegre, 2016). Pour ce qui concerne les comportements d'apprentissage avec les technologies, la mesure vise à mettre en lumière deux dimensions : une utilisation des technologies comme *outil* d'apprentissage et une comme *soutien* de l'apprentissage (Dunn & Kennedy, 2019).

Une troisième contribution est de pouvoir proposer des outils pour le développement de l'apprentissage professionnel dans les organisations qui passera par le développement de climat d'apprentissage avec les technologies. Ces outils sont une première marche de compréhension sur la façon dont les individus perçoivent et se comportent vis-à-vis des technologies, dans l'optique de créer des climats d'apprentissages

2.2 Cadre conceptuel

2.2.1 Environnement psycho-technologique

L'environnement psycho-technologique comme opportunité pour apprendre est née du constat que les technologies digitales élargissent le nombre de ressources, les moyens d'apprendre, et que leur facilité d'accessibilité augmente leur utilisation (Beier, 2019). Ces changements engendrent donc des opportunités nouvelles pour apprendre et se former (Dunn & Kennedy, 2019 ; Noe et al., 2014). L'accessibilité se traduit comme la facilité ou la flexibilité d'accès à du contenu d'apprentissage non limité par des contraintes géographiques ni par des contraintes temporelles (Bell & Kozlowski, 2009), soit la possibilité d'avoir un accès aux ressources de quelque endroit qu'on le souhaite et quand on le souhaite (Weiser, 1999). Nous supposons logiquement que l'omniprésence des technologies va accroitre le potentiel d'apprentissage d'un environnement qui peut se définir par la perception individuelle qu'il nous offre plus ou moins d'opportunités pour apprendre (Cangialosi et al., Odoardi, & Battistelli, 2020 ; Nikolova et al., 2014). La considération des ressources et des opportunités de ce nouvel environnement s'exprimera en termes de cognitions, croyances, émotions et perceptions de la part des individus (James & James, 1989).

En se basant sur les éléments précédents, nous pouvons supposer que la perception de l'environnement psycho-technologique s'articule autour de deux dimensions : *opportunités* et *accessibilité*. Le premier facteur renvoie à la perception que l'environnement, caractérisé par l'omniprésence technologique, offre davantage d'*opportunités* (EPT-opportunités) (He & Li, 2019) et de diversité dans les formes d'apprentissage et qu'il peut ainsi s'avérer être une ressource ou une plus-value (Noe et al., 2014). Cette perception se base sur le constat que les technologies offrent des méthodes d'apprentissage innovantes (coopération, gamification, etc.) et une richesse de contenus jamais égalée (Warschauer, 2007). La méta-analyse de Sung et al. (2016) renforce cet aspect en soulignant que l'apprentissage est stimulé par des environnements où sont intégrées plusieurs technologies avec des utilisations multiples. La deuxième dimension a trait à l'*accessibilité* (EPT-accessibilité) qui désigne la perception des individus selon laquelle les technologies semblent accessibles et faciles d'utilisation (Maurer et al., 2003). Beier (2019) met en lumière que les technologies peuvent limiter plusieurs contraintes liées à l'apprentissage telles l'accès aux ressources, l'endroit où on apprend, le partage de contenus, etc.

2.2.2 Comportements d'apprentissages avec les technologies

Les comportements d'apprentissage avec les technologies (CAT) se définissent comme tous les comportements visant à un changement relatif du répertoire des connaissances et des compétences d'une personne par la création de nouvelles, ou par leur transformation dans les structures conceptuelles par le biais d'utilisations des technologies (Noe, et al., 2014 ; Weiss, 1990). Ces comportements se distinguent par la possibilité de gérer son processus d'apprentissage en adaptant le rythme de l'apprentissage à ses besoins et en ayant accès à un plus vaste répertoire de contenus pour apprendre (Brown et al., 2016 ; Derouin et al., 2005). Les technologies entendent de plus favoriser les interactions avec les autres, adapter l'apprentissage à travers de nouvelles modalités et donner plus de feedback sur le processus d'apprentissage (Beier, 2019). Par conséquent, il est également possible de spécifier les comportements d'apprentissage avec les technologies en deux dimensions. La première dimension renvoie au fait que les technologies permettent d'acquérir des connaissances et de développer des compétences (He & Zhu, 2017 ; Noe et al., 2014) ; en cela, nous pouvons considérer que les technologies constituent un « media » pour apprendre. La littérature a mis en avant qu'une technologie peut être envisagée comme un *outil* d'apprentissage (CAT-outil) car elle permet l'accès aux informations, aux données, et en général, aux ressources utiles à la personne pour ses acquisitions (Bell & Kozlowski, 2009). La deuxième dimension traduit le fait que les technologies forment un *soutien* (un *intégrateur*) pour l'apprentissage ; elles renforcent et élargissent potentiellement l'apprentissage (Fernandez-Lopez et al., 2013). Si la flexibilité et l'élargissement des opportunités offertes par les technologies répondent à certains besoins individuels comme l'accès à des ressources soutenant l'apprentissage (Dyson et al., 2015), elles offrent aussi la possibilité de développer des stratégies d'apprentissage (Van Laar et al., 2019), comme la recherche de feedback (Chan et al., 2015 ; Hwang & Arbaugh, 2009) ou encore l'augmentation de la collaboration (Rashid & Asghar, 2016).

2.2.3 Aperçu des études

Dans cette ligne, nous avons construit une première échelle (EPT-Environnement psycho-technologique questionnaire) qui mesure les deux dimensions citées à savoir les *opportunités* d'apprentissage ainsi que l'*accessibilité* des technologies. Une deuxième échelle a été développée (CAT-comportements d'apprentissage avec les technologies questionnaire) qui mesure, quant à elle, les comportements d'*outil* d'apprentissage ainsi que de *soutien* de l'apprentissage.

Lors de la validation d'outils, Gerbing & Hamilton (1996) suggèrent une méthode de validation en deux étapes. En ce sens, deux études ont été menées pour valider la construction des outils de mesure proposés dans cet article. L'étude 1 correspond à la première étape qui consiste à évaluer les mesures avec un premier échantillon à l'aide d'une analyse factorielle exploratoire pour en vérifier la structure (Hurley et al., 1997). L'étude 2 a pour objectif de réaliser une analyse factorielle confirmatoire pour valider le construit produit par l'analyse factorielle exploratoire et s'assurer de la validité de nos deux outils de mesure (Kline, 2015).

ÉTUDE 1

2.3 Méthode

Participants

L'échantillon de cette étude est composé de 151 étudiants Français sur 501 contactés (30,13%), appartenant à l'Université de Bordeaux et ayant une expérience professionnelle. Le recrutement des participants a été réalisé au cours de l'année 2019/2020 via une invitation par email à participer à l'étude. L'échantillon comprend 103 femmes (68,2%) et 48 hommes (32.8%) d'une moyenne d'âge de 24,2 années (*ET* = 6,8). Concernant leur niveau d'étude, 6,0% ont un niveau Baccalauréat, 3,3% ont un niveau Bac+1, 13,2 % Bac+2, 9,9 % Bac+3, 30,5 % ont un niveau d'étude Bac+4, 26,5% Bac+5 et enfin 10,6% ont un niveau Bac+8. Les filières d'étude sont de 56 (37,08%) en Sciences techniques et ingénierie, de 61(40,39%) en Sciences Humaines et sociales et de 34 (22,53%) en Sciences médicales.

Mesures

Perception de l'environnement psycho-technologique (EPT). La génération des items s'est faite grâce à l'analyse et l'adaptation des mesures de Nikolova et al. (2014) et de Maurer et al. (2002) sur l'environnement de travail comme source d'opportunité d'apprentissage. Pour la 1ere dimension *Opportunité,* nous avons adapté les trois items de la dimension *facilitation du climat d'apprentissage* de la mesure de Nikolova et al. (2014) en suivant notre cadre théorique. La mesure de Nikolova et al. (2014) est également composé des dimensions *climat d'appréciation d'apprentissage* et *erreur évitement climat* que nous avons ignoré car ne correspondant pas aux objectifs de la mesure. Nous avons ensuite intégré des items que nous avons générés pour compléter la mesure. Ces items ont été générés suite à un pré-test, basé sur un examen de la littérature et une pré enquête avec un groupe d'étudiants. Ces items nous ont permis de compléter la mesure dans l'optique de la rendre plus adaptée à notre objectif de recherche sur l'environnement technologique (offres attrayantes, nouvelles manières d'apprendre, etc..). Les items de la seconde dimension *accessibilité* ont été générés à partir de l'échelle de Maurer et al. (2002) qui considère que les ressources de formation sont non-contraignantes d'accès et d'utilisation. Par conséquent, nous avons adapté ce point avec le fait que les technologies soient faciles d'utilisation et disponibles. Au final, 12 items sur 20 ont été conservés : 7 items concernent la perception des technologies comme opportunité d'apprentissage et 5 la perception des technologies comme accessibles. Les items supprimés après analyses statistiques montraient une inconsistance en termes de validité de contenu (Haynes et al., 1995). L'échelle de réponse utilisée, de type Likert, va de 1= Pas du tout à 5=Tout à fait. Les items sont indiqués dans le tableau 1.

Comportements d'apprentissages avec les technologies (CAT). Les items ont été générés par une traduction et une adaptation de l'échelle d'He & Zhu (2017), dans la mesure où elle se concentre sur les différentes formes de comportements d'apprentissage avec les technologies que nous souhaitons évaluer. A la suite d'un ensemble de pré-tests des items auprès de doctorants et d'étudiants (Haynes et al., 1995), 11 items sur 20 ont été conservés : 4 items représentatifs de *CAT-outil* et 7 du *CAT-soutien*. L'échelle de réponses utilisée, de type Likert, va de 1= Pas du tout à 5=Tout à fait. Les items sont présentés dans le tableau 2.

Résultats

Environnement psycho-technologique (EPT)

Pour évaluer la structure de notre mesure, nous avons eu recours à une analyse factorielle exploratoire via Mplus 8.4 (Muthen & Muthen, 2017). L'estimateur WLSMV a été choisi pour sa robustesse dans le cadre des analyses factorielles (Muthen et al., 1997) et une rotation oblique (Geomin) a été effectuée dans la mesure où nos deux dimensions *Opportunités* et *Accessibilité* sont théoriquement reliées (Tabachnick & Fidell, 2012).

Après vérification de l'adéquation des données avec un indice Kayser Meyer Olkin à .859 et une sphéricité de Bartlett avec un p<.000, une analyse factorielle a été réalisée (Kaiser, 1970). Pour déterminer le nombre de facteurs, nous avons opté pour la règle de l'eigenvalue supérieure à 1 ainsi que pour une analyse parallèle afin d'augmenter la consistance dans l'extraction des facteurs (Ford, McCallum, & Tait, 1986 ; Hayton, Allen, & Scaparello, 2004 ; Tucker, Koopman, & Linn, 1969). Ces deux méthodes orientent vers l'extraction de deux facteurs avec une variance expliquée de 55.478%. En suivant les recommandations de Kline (2015), l'ajustement de notre échelle en deux facteurs a été vérifiée ($\chi 2$ (43) = 112,409 ; $p < .000$; RMSEA = .10 ; CFI = .95 ; TLI = .93 ; SRMR = .06). Ce modèle d'ajustement présente de bons indices malgré le RMSEA. Chen, Curran, Bollen, Kirby et Paxton (2008) relèvent qu'un RMSEA supérieur à 0.10 devrait être rejeté mais que cet indice ne doit pas être considéré seul. De plus, ces chercheurs ont mis en évidence que pour des échantillons inférieurs à 200 le RMSEA pouvait s'avérer moins performant sans être forcément le signe d'un non ajustement.

Le modèle en deux facteurs ($\chi 2$ (43) = 112,409 ; $p < .000$; RMSEA = .10 ; CFI = .95 ; TLI = .93 ; SRMR = .06) s'ajuste mieux que le modèle en un seul facteur ($\chi 2$ (54) = 299,249 ; $p < .000$; RMSEA = .17 ; CFI = .84 ; TLI = .80 ; SRMR = .12). La mesure présente en outre une bonne cohérence interne (Cortina, 1993) avec un alpha de Cronbach de .87 pour l'échelle complète et, respectivement, de .86 et .78 pour les dimensions *Opportunités* et *Accessibilité*. Nos deux dimensions présentent enfin une corrélation inter dimensions égale à .581 ($p < .000$) et chaque item des saturations supérieures à .50 (Brown, 2015).

Tableau 2.1 Analyse factorielle exploratoire Environnement Psycho-Technologique (EPT)

Items	Facteurs	
	1	2
Facteur 1 : **EPT-opportunités**		
L'utilisation des technologies digitales est un bénéfice réel pour le développement de connaissances et de compétences	.801	
Les technologies digitales sont une plus-value pour l'apprentissage	.749	
Les technologies digitales m'offrent d'avantages d'opportunités pour apprendre	.728	
Les technologies digitales m'offrent de nouvelles manières	.727	

d'apprendre		
Les technologies digitales me fournissent des offres plus attrayantes pour apprendre	.724	
Les technologies digitales en général me permettent d'apprendre autant pour mon travail, pour mes études que pour ma vie personnelle	.637	
L'utilisation de certaines technologies digitales pour l'apprentissage me permet d'avoir accès à de nouvelles formes d'apprentissage	.628	
Facteur 2 : **EPT-accessibilité**		
Les technologies digitales pour l'apprentissage sont faciles à maitriser		.846
Pour développer des compétences et des connaissances, je n'ai aucune difficulté à utiliser les technologies digitales		.744
Les technologies digitales pour l'apprentissage sont faciles et pratiques à utiliser		.702
Les technologies digitales pour l'apprentissage ne sont pas contraignantes d'utilisation		.640
Les technologies digitales dédiées à l'apprentissage sont facilement accessibles		.582
Eigenvalues	5.043	1.613
Variance expliquée %	32.34	23.14
Variance expliquée totale %		55.48

Note. N=151. Méthode d'extraction WLSMV avec Rotation Geomin.

Comportements d'apprentissages avec les technologies (CAT)

La même méthodologie a été utilisée pour valider cette mesure. Notre échelle présente un KMO de .839, ce qui est un bon indicateur (Kaiser, 1970) ainsi qu'une sphéricité de Bartlett p<.000. L'eigenvalue et l'analyse parallèle ont mis en évidence une structure à deux facteurs avec une variance expliquée de 58%. Cette mesure démontre des indices d'ajustement ($\chi 2$ (34) = 135,206 ; p < .000 ; RMSEA = .14 ; CFI = .94 ; TLI = .90 ; SRMR = .07), acceptable pour le SRMR, bons pour le CFI et TLI et le RMSEA devrait être rejeté mais comme précédemment, au regard des autres indices satisfaisants et d'une population inférieure à 200, cela n'indique pas nécessairement le signe d'un non-ajustement (Chen et al., 2008). La mesure présente une bonne cohérence interne de .88 avec, respectivement, pour les dimensions *Soutien* et *Outil* des alphas de .86 et de .79. L'ensemble de nos items montre une saturation supérieure à .50 ce qui nous permet de les conserver dans la structure factorielle ainsi qu'une corrélation inter dimension de : $r = .604$, $p < .000$. Les résultats sont reportés dans le tableau 2.

Tableau 2.2 Analyse factorielle exploratoire Comportements d'Apprentissage avec les Technologies (CAT)

Items	Facteurs	
	1	2
Facteur 1 : **CAT-outil**		
J'utilise les technologies digitales pour étoffer mes connaissances dans mon domaine		.879
J'utilise les technologies digitales pour me tenir informé du développement de ma discipline		.738
J'utilise les technologies digitales pour étoffer ma compréhension des cours		.713
J'utilise les technologies digitales pour étoffer mes connaissances dans une autre discipline		.682
Facteur 2 : **CAT-soutien**		
J'utilise les technologies digitales pour des expériences d'apprentissage nouvelles et originales	.797	
J'utilise les technologies digitales pour rechercher de nouvelles stratégies d'apprentissage	.757	
J'utilise les technologies digitales pour me guider dans la progression de mon apprentissage	.744	
Je vais à la recherche de nouvelles technologies digitales pour m'aider dans mes besoins d'apprentissage	.714	
J'utilise les technologies digitales pour m'engager dans des activités constructives	.698	
Je m'oriente vers les technologies digitales pour rechercher des supports d'apprentissage	.694	
J'utilise les technologies digitales comme maintien de ma motivation dans mon apprentissage	.530	
Eigenvalues	5.595	1.417
Variance expliquée %	32.89	24.98
Variance expliquée totale %		58.68

Note. N=151. Méthode d'extraction WLSMV avec Rotation Geomin.

Discussion

Cette première étude, qui visait à développer et à valider de manière exploratoire et en langue française deux outils de mesure, a mis en avant des structures en accord avec nos postulats conceptuels, tout en respectant les recommandations sur le développement d'outils de mesure (Gerbing & Hamilton, 1996 ; McKenzie et al., 2011). Nos résultats corroborent les structures supposées pour l'environnement technologique avec deux dimensions (EPT) : (1) *EPT-opportunités* pour apprendre et (2) *EPT-accessibilité* des technologies pour apprendre. La deuxième échelle présente deux dimensions des comportements d'apprentissage avec les technologies (CAT) : (1) *CAT-outil* pour développer des connaissances et compétences avec les technologies et (2) *CAT-soutien* comme support à l'apprentissage. Au terme de ce premier travail, il est nécessaire de conduire une étude complémentaire pour vérifier et confirmer la structure factorielle et les qualités psychométriques des mesures initiales (Brown, 2015).

ÉTUDE 2

2.4 Méthode

Participants

L'échantillon de cette seconde étude est constitué de 238 étudiants Français pour 781 contactées (30,47%), appartenant à l'Université de Bordeaux et ayant une expérience professionnelle. Le recrutement des participants a été réalisé au cours de l'année 2020 via une invitation par email à participer à l'étude. L'échantillon, composé de 172 femmes (72,3%) et de 66 hommes (27,7%) a une moyenne d'âge de 26,3 années (ET = 8,0). Concernant leur niveau d'étude, 1,3% ont un niveau Baccalauréat, 5,9% ont un niveau Bac+1, 7,1 % Bac+2, 19,3 % Bac+3, 28,6 % ont un niveau d'étude Bac+4, 29,8% Bac+5 et enfin 8, % ont un niveau Bac+8. Les filières d'étude correspondent pour 61 d'entre eux (23,64%) aux Sciences techniques et ingénierie, pour 132 (51,16%) aux Sciences Humaines et Sociales et pour 65 (25,19%) aux Sciences médicales.

Résultats

Les analyses factorielles confirmatoires ont été réalisées via Mplus 8.4 (Muthen & Muthen, 2017), avec comme estimateur MLR. Les résultats confirment les résultats précédents des analyses factorielles exploratoires avec une structure en deux facteurs, tant pour l'environnement psycho-technologique (*EPT-opportunités* et *EPT-accessibilité*) que pour les comportements d'apprentissage avec les technologies (*CAT-outil ; CAT-soutien).*

Pour la mesure de l'environnement psycho-technologique (EPT), le résultat à deux facteurs présentent des bons indices d'ajustement *(*$\chi 2$ (53) = 116,491; *p* < .000 ; RMSEA = .07 ; CFI = .92 ; TLI = .90 ; SRMR = .05 ; AIC= 7283.886; BIC= 7412.360) contrairement au modèle en un facteur qui fusionnent les deux dimensions *opportunités* et *accessibilité* et qui obtient de mauvais indices *(*$\chi 2$ (53) = 238,219; *p* < .000 ; RMSEA = .12 ; CFI = .77 ; TLI = .72 ; SRMR = .09 ; AIC = 7412.360; BIC = 7555.206). Hu et Bentler (1998) permettent d'affirmer que les indices d'ajustement sont satisfaisants avec un RMSEA à .07, soit une valeur inférieure à .08, seuil minimal pour être considéré comme acceptable. Les indices de CFI et de TLI présentent de bons ajustements, la valeur acceptable étant de .90 (Brown, 2015). Le SRMR présente un indice d'ajustement pareillement acceptable car inférieur à .06 (Browne & Cudeck, 1993). L'Akaike Information Criterion et le Bayesian Information Criterion montrent des niveaux plus faibles que le modèle en un facteur ce qui nous permet d'attester que le modèle théorique retenu est le plus consistant (Brown, 2015).

La même procédure a été réalisée pour l'échelle de comportements d'apprentissage avec les technologies (CAT) et le modèle en 2 facteurs obtient les indices d'ajustement suivants *(*$\chi 2$ (43) = 102,485 ; *p* < .000 ; RMSEA = .07 ; CFI = .94 ; TLI = .92 ; SRMR = .05 ; AIC = 7407.057 ; BIC = 7525.114). Le modèle alternatif en un facteur (*outil* et *soutien*) présente des indices d'ajustement moins acceptables *(*$\chi 2$ (44) = 188,293 ; *p* < .000 ; RMSEA = .11 ; CFI = .85 ; TLI = .81 ; SRMR = .06 ; AIC=7521.335 ; BIC= 7635.920).

Nos construits EPT et CAT étant théoriquement reliés, une structure en 4 facteurs devrait émerger démontrant le lien entre les construits ainsi que la consistance du modèle global (Tabachnik & Fidell, 2012). Ce modèle présente des bons indices d'ajustements *(*χ *2* (224) = 370,004 ; *p* < .000 ; RMSEA = .05 ; CFI = .93 ; TLI = .92 ; SRMR = .05). Les résultats complémentaires des corrélations inter-factorielles, des moyennes (*M*), des écarts-types (*ET*), des alphas de Cronbach sont renseignés dans la matrice de corrélation ci-dessous (tableau 3).

Tableau 2.3 *Matrice de corrélations des facteurs, moyennes, écarts-types et alpha de Cronbach.*

Variables	Moyenne	ET	1	2	3	4
EPT-Opportunités	3.78	.75	(.85)			
EPT-Accessibilité	3.42	.73	.58**	(.78)		
CAT-Acquisition	3.62	.96	.65**	.38**	(.83)	
CAT-Soutien	2.72	.98	.66**	.38**	.74**	(.87)

**$p < .001$

La table des corrélations présente des liens forts entre les deux dimensions des comportements d'apprentissage, ce qui peut indiquer un facteur de second ordre (Marsh & Hocevar, 1988). Suivant Credé et Harms (2015) qui conseillent d'évaluer l'AVE (average variance extracted, Fornell & Lacker, 1981) pour s'assurer de la présence d'un facteur de second ordre, nous obtenons un AVE de .54 pour les comportements d'apprentissage avec les technologies. Cet AVE situé entre .50 et .70 indique effectivement que le modèle peut être considéré comme un facteur de second ordre, autrement dit qui explique aussi bien la variance dans un modèle de second ordre que dans un modèle de 1er ordre. Les deux modèles, et de 1er ordre ($\chi 2$ (43) = 102,485 ; p < .000 ; RMSEA = .07 ; CFI = .94 ; TLI = .92 ; SRMR = .05) et de second ordre ($\chi 2$ (42) = 100,101 ; p < .000 ; RMSEA = .07 ; CFI = .94 ; TLI = .92 ; SRMR = .05), présentent des indices d'ajustement similaires. Ces résultats soulignent, avec un facteur de second ordre, que c'est la combinaison des deux dimensions qui produisent le construit et donc ne peut pas être considéré séparément.

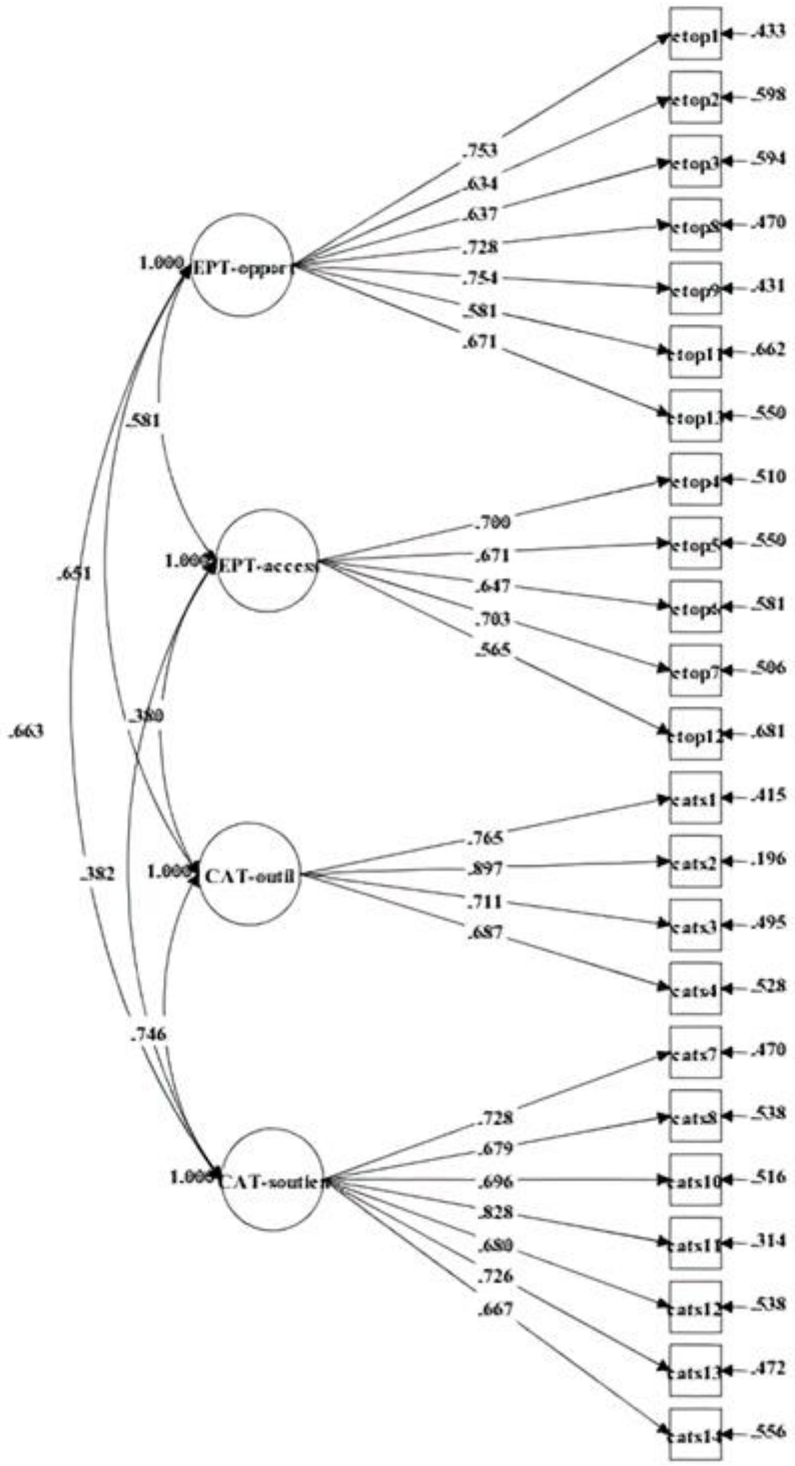
Tableau 2.4 Indices d'ajustement statistique pour chaque modèle

Modèles	χ 2	*ddl*	RMSEA	CFI	TLI	SRMR	AIC	BIC	SB Δ χ **2**
ETP 2 Facteurs	116.491	53	0.07	0.92	0.90	0.05	7283.886	7412.360	χ (1)= 121.728**
ETP 1 Facteur	238.219	54	0.12	0.77	0.72	0.09	7412.360	7555.206	
CAT 2 Facteurs	102.485	43	0.07	0.94	0.92	0.05	7407.057	7525.114	χ(1)=53.047**
CAT 1 Facteur	188.293	44	0.11	0.85	0.81	0.06	7521.335	7635.920	
Modèle 4 facteurs	370.004	224	0.05	0.93	0.92	0.05	14577.283	14837.703	χ(6)=450.566**
1 Facteur	820.857	230	0.10	0.71	0.69	0.09	15875.983	16087.792	

***p*<.001; *Δ* χ 2: χ 2 Satorra-Bentler

La littérature recommande pour plus de robustesse l'utilisation de la méthode Satorra-Bentler quand on compare des modèles d'ajustement entre eux (Pavlov et al., 2020 ; Satorra & Bentler, 2001). Le modèle ETP en deux facteurs *vs* modèle ETP en un facteur présentent un *Satorra-Bentler Δ* χ *2*= 121,728, *ddl*=1, *p*<.01 qui confirme de la robustesse de ETP en deux facteurs. Le modèle CAT en deux facteurs *vs* CAT en un facteur présentent un *Satorra-Bentler Δ* χ *2*= 53,047, *ddl*=1, *p*<.01 qui confirme également la robustesse de CAT en deux facteurs. Le modèle en 4 facteurs *vs* modèle en un facteur présentent un *Satorra-Bentler Δ* χ *2*= 450,566, *ddl*=6, *p* <.01. Nous avons également calculé l'Akaike Information Criterion et le Bayesian Information Criterion qui montre des niveaux plus faibles comparativement au modèle en un facteur. Ces résultats nous permettent d'attester que notre modèle théorique semble le plus robuste. Les différents indices d'ajustements statistiques sont résumés dans le tableau 4.

Figure 2.1 Analyse factorielle confirmatoire du modèle théorique en 4 facteurs



2.4.1 Discussion

L'objectif général de cette recherche était de développer deux outils de mesure permettant de capturer certains aspects de l'apprentissage fortement bouleversés par les nouvelles technologies. Une méthode en deux étapes a été réalisée avec un travail de génération et d'adaptation d'items, puis un travail de validation des échelles construites (Gerbing & Hamilton, 1996). Les résultats des analyses permettent de considérer les outils de mesure présentés comme ayant des indices statistiques suffisamment satisfaisants pour considérer cette première validation comme robuste et ouvrant des perspectives. Les analyses factorielles confirmatoires ont démontré que nos échelles EPT et CAT présentent bien une structure en deux dimensions chacune comme envisagé théoriquement ; de même, la structure en 4 dimensions mise en avant montre de bons indices d'ajustement et soutient le fait que EPT et CAT sont associés (Kline, 2015). Les alphas de Cronbach, dépassant tous .75, s'avèrent convenables (Schmitt, 1996), ce qui suggère une cohérence interne correcte de nos échelles.

Les résultats de cette recherche apportent plusieurs contributions à la littérature. Dans l'objectif de construire des outils de mesure pouvant refléter la perception des individus du rôle des technologies dans l'apprentissage (Noe et al., 2014), nos travaux identifient l'existence de deux types de perceptions relatifs à l'environnement psycho-technologique, d'une part, un environnement offrant davantage d'opportunités pour apprendre (EPT-opportunités) et d'autre part, une accessibilité facilitée aux technologies (EPT-accessibilité). Ces deux dimensions renvoient à la perception d'une augmentation des ressources produites par l'environnement technologique permettant d'apprendre de manière peu contraignante (Cangialosi, et al., 2020 ; Nikolova et al., 2014).

Ensuite, nos résultats ont permis d'identifier comment les individus utilisent les technologies pour apprendre. En démontrant que les comportements d'apprentissage s'expriment en deux dimensions : CAT-*outil*, qui illustre que les individus considèrent les technologies comme un moyen pour acquérir des connaissances et des compétences, et CAT-*soutien*, qui souligne que les individus considèrent les technologies comme un élargissement des possibilités d'apprentissage. Ceci laisse supposer que les individus considèrent les technologies à la fois comme un moyen effectif de développer des compétences et des connaissances (Dunn & Kennedy, 2019), moyen qui permet de personnaliser les apprentissages, et comme une aide pour la recherche de contenus soutenant l'apprentissage (Brown et al., 2016).

2.5 Discussion générale

2.5.1 Implications Théoriques

Au niveau théorique, cette étude met en lumière que l'omniprésence technologique augmente le potentiel d'apprentissage de l'environnement par la perception de davantage d'opportunités pour se former et développer des connaissances (Cangialosi et al., 2020) avec deux aspects complémentaires : des technologies offrant plus de moyens pour apprendre (Dunn & Kennedy, 2019), mais également plus accessibles (Shen & Ho, 2020).

Ensuite, cette étude confirme que les activités d'apprentissage avec les technologies sont plurielles (Uzun & Kilis, 2019) et soutient l'hypothèse qu'elles ont diversifié les moyens par lesquels l'acquisition de compétences et des connaissances se réalisent (Brown et al., 2016). Cela traduit le fait que les individus peuvent rechercher des ressources humaines (collègues, supérieur, professeur) ou matérielles (wiki, MOOC etc..) permettant de soutenir leur apprentissage via les technologies (Klein et al., 2006).

2.5.2 Implications pratiques

Avec les parcours scolaires et les métiers de plus en plus imprégnés et façonnés par les technologies (Parker, 2014), mesurer comment les individus les perçoivent et se comportent avec ces dernières est devenu de plus en plus important. Notamment avec le fait que l'utilisation des technologies pour l'apprentissage ne va pas de soi mais influencé par des caractéristiques psychologiques, socioprofessionnelles ou encore le contexte professionnel (Thompson, 2013). Pour les organisations, l'optique de devenir apprenantes est particulièrement crucial (Derouin et al., 2005). Les échelles élaborées se veulent donc être une ressource additionnelle pour les professionnels et les managers afin d'évaluer la perception des technologies comme source et ressource d'apprentissage, ce qui permettra de les valoriser dans le développement des compétences proposé par les organisations.

2.5.3 Limites

Notre étude possède plusieurs limites avec en premier lieu, une population jeune, essentiellement étudiante, qui, par définition, rencontre moins de difficultés dans l'utilisation des technologies et en a une utilisation plus fréquente (Thompson, 2013). De futures recherches restent donc à réaliser sur des clusters d'âges variés afin de s'assurer de la validité des échelles sans biais lié à l'âge. Une autre limite méthodologique relève de la non vérification de la validité temporelle. Ainsi, l'application d'une méthode longitudinale test retest permettrait de donner plus de consistance à nos résultats. Il sera également nécessaire de s'intéresser à la validité convergente et divergente dans les prochaines études pour s'assurer que l'outil présenté obtient des corrélations satisfaisantes avec les variables qui lui sont théoriquement reliées et qu'il diverge avec les variables qui lui sont opposées (Hinkin, 1995).

2.5.4 Conclusion

En termes de conclusion, cette étude soutient le postulat que les technologies peuvent être considérées comme un atout pour l'apprentissage (Noe et al., 2014). Cela ouvre la perspective d'investiguer les antécédents et les processus qui permettent aux technologies d'être bénéfiques pour les individus car, comme le souligne Martins et al. (2019), il faut certaines conditions contextuelles et individuelles pour que les technologies puissent être un atout pour l'apprentissage et non un désavantage amenant à un stress supplémentaire (Wang, et al., 2019), à un apprentissage ineffectif marqué par de multiples interruptions, associé à un manque de concentration (Dunn & Kennedy, 2019), à un plus faible engagement dans l'apprentissage (Rashid & Asghar, 2016) et à une réduction de la performance (Jena, 2015).

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Chapter 3 Article 2: Learning in the digital age: The motivating role of the context and the digital awareness on learning behaviors with technologies

ABSTRACT

With the advent of 4th industrial revolution and technological ubiquity, learning through technologies is become essential for students and workers. The present study aims to explore the relationship between Psycho-Technological Environment (PTE) and learning behaviors with technologies through motivation to learn. In addition, the interaction effect of digital awareness between motivation to learn and learning behaviors with technologies was examined. To test our hypothesis, we have conducted structural equation modeling on a sample of 344 students having professional experience. Our results showed that PTE-opportunities have a positive indirect relationship with learning behaviors through motivation to learn. Moreover, the results highlighted that digital awareness moderates the relationship between motivation to learn and learning behaviors with technologies. Hence, this research contributes to expanding the current knowledge about the motivational role of the PTE and its impact on learning behaviors with technologies. This study also breaks new ground by uncovering how PTE can promote learning behaviors and offer guidance for organizations (companies and higher education) that aim to foster and encourage individuals to learn with technologies.

Key words: learning potential, technology, learning behaviors, Psycho-technological environment, opportunities, digital awareness

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3.1 Introduction

Learning corresponds to the ability to acquire relevant knowledge and skills and is considered as a core competence for education and working (Nikolova et al., 2014). However, the way we learn has changed with the technological evolution and turned into an increasingly important challenge for organizations, educational and academic institutions and individuals (Noe et al., 2014; Heidari et al., 2021). During the previous decades, due to the evolution of technologies, learning has evolved from a prevalent instructional system, where the learner follows the instructions step by step, to an active form, where learners can shape how they acquire knowledge (Katz-Navon et al., 2009).

With the advent of the 4th industrial revolution and particularly the ubiquity of technology, the way we learn is significantly changing (Battistelli & Odoardi, 2018; Cascio & Montaelegre, 2016). Technological ubiquity refers to the fact that the technologies have penetrated every part of our lives (work, family and leisure time) especially because the number of technologies has exceeded the number of people and individuals can no longer perform any activity without technologies (Mohindru et al., 2020). We claim that technological ubiquity is not only an aspect of technological evolution but represents a context that has the potential to modify the traditional ways of learning (Landers & Marin, 2021). This new Psycho-Technological Environment (PTE) is derived from the individual perception of the merging of the physical and digital worlds due to the technological ubiquity (Colbert et al., 2016; McFarland & Ployhart, 2015). PTE is characterized by the interactions between human and technology and is defined by a set of opportunities and constraints affecting behaviors and beliefs (Johns, 2006; McFarland & Ployhart, 2015).

The PTE has two key features: perception of *opportunities to learn* and a*ccess to learning contents* (Bazine et al., 2020). Opportunities to learn corresponds to that individual have access to the technological environment allowing them to improve actual knowledge and skills (Nikolova et al., 2014). This is characterized by more learning contents in terms of quantity and diversity due to technology diversity which facilitates individual's construction or improvement of specific skills (Dachner et al., 2019). Access to learning contents refers to the contents which are more accessible by freeing themselves of constraints of time and place (Beier, 2019). Beyond this, learning in this new environment stands out because of the wide variety of contents and new ways and tools (technologies) of acquiring knowledge and skills allowing the personalization of learning by making it more flexible (Brown,et al., 2016). Individuals can expand their learning experiences (He & Zhu, 2017) and some authors speak of additional contributions such as providing support, maintaining one's motivation and developing strategies for learning (Heflin et al., 2017). Consequently, learning with technologies seems to be beneficial for individuals (Noe et al., 2014; Bissonnette & Boyer, 2021). Despite, promising progress in the understanding of the impact of specific technologies on learning, several questions remain open including how the technological environment affects learning (Bell et al., 2017).

The current study aims to extend the literature in three ways. First, whereas several studies have highlighted that the perceptions of environment can have a positive relationship with learning behaviors (McFarland & Ployhart, 2015; Nikolova et al., 2014), this research advances our understanding of the PTE such as a motivational agent and try to explain how this new environment could foster learning behaviors.

Second, this study contributes to develop the literature on the role of the environment as an antecedent of learning behaviors (Cangialosi et al., 2020; Nikolova et al., 2014), we address the neglected role of motivation to learn as a mechanism that connects PTE and learning behaviors with technologies. Doing so answers the call to explore the mechanisms linking the environment with learning behaviors (Maurer et al., 2003; Noe, 1986). This approach breaks new ground as the study of the mechanism between environments and learning behaviors remains scarce.

Third, guided by the research of Brougham and Haar (2018) on technological awareness, this study contributes to shedding light on the crucial role of the individual perception and awareness of the technological impact on the workplace and on learning (Brougham & Haar, 2018). The present endeavor strives to understand the moderating role of technological awareness on the relationship between motivation to learn and learning activities.

3.2 Theoretical framework

3.2.1 The learning potential of Psycho-technological Environment

The learning potential of the PTE refers to the individuals' perception of technologies in the environment that allow individuals to develop knowledge, skills and abilities through the use of technologies (Bazine et al., 2020). This perception represents the learning potential and a key factor to trigger learning behaviors with technologies. In this sense, the learning potential of PTE refers to at least two dimensions, *opportunities* and *accessibility*. *Opportunities* refer to the perception that the environment offers different technological resources and facilitations for learning (Dunn & Kennedy, 2019; He & Li, 2019). The diverse technologies offer innovative learning methods (cooperation, gamification, MOOC, etc.) and richness of contents that has never been seen before (Warschauer, 2007). Thus, these various technologies create a specific environment perceived as being more flexible, rich and favorable for self-learning experience (Brown et al., 2016). Having a greater agency over the learning process such as the ability to personalize learning is considered of great value (Senkbeil & Ihme, 2017). Sung et al. (2016) in their meta-analysis, highlighted that learning is stimulating in an environment where several technologies are integrated with multiple uses.

This integration allows individuals to improve their learning by using technologies that can compensate for the shortcomings of each different learning method (Motsching-Pitrik & Standl, 2013).

As for the second dimension, *accessibility,* it captures the perception that technologies are more accessible, easy to use and can alleviate several constraints such as access to resources, the place where you learn and the possibility to share content (Beier, 2019; Maurer et al., 2003). The individuals, who perceive that situational constraints exist in their environment, develop weak positive attitudes toward learning that result in lower levels of development activity (Noe & Wilk, 1993).

3.2.2 The mediating role of motivation to learn in the relationship between Psycho-technological environment and learning behaviors with technologies.

Noe and Schmitt (1986) have shown the importance of attitudes in the learning context. They have highlighted that the effectiveness of training or learning behaviors depends on the motivation to learn. Moreover, attitudes and motivation of individuals play a key role in the context of online learning where the drop-out rate is important (Hoi & Le Hang, 2021). But also, it is associated to greater results in terms of learning performance (Wang, et al., 2021). Consequently, understanding the characteristics of learning environment is essential to captures the factors that increase motivation to learn (Tsai et al., 2012). Motivation to learn is defined as the specific desire of the learner to acquire new contents (Battistelli et al., 2007; Noe & Schmitt, 1986). Several studies have shown that motivation to learn is related to learning behaviors, skill acquisitions and developmental activities (Colquitt et al., 2000; Noe & Wilk, 1993). Furthermore, Klein et al. (2006) demonstrated the critical importance of motivation to learn specifically in a learning context with technology.

According to Noe et al. (2010), the environment can play a key role in the learner's motivation.

Other scholars have suggested that the environment influences the employees' attitudes and their volition to participate in learning activities (Maurer et al., 2003) and support the idea that motivation to learn can be triggered by the environment (Vanthournout et al., 2014). This view supports the hypothesis of PTE as a motivational trigger.

Individuals are motivated to learn if they have access to sufficient opportunities to learn and have the possibility to experiment with new ways of learning (Kozlowski & Hults, 1987; Noe & Wilk, 1993). Moreover, Farr and Middlebrooks (1990) underline the importance of individual perception of having sufficient resources for developing relevant skills. Several studies have postulated that insufficient resources can be considered as situational constraints because they develop the perception that efforts to engage in developmental activities would be less beneficial (Nikolova et al., 2016). Thus, individuals who have insufficient resources to learn successfully can experience frustration, become dissatisfied in their learning process, are likely to devote less of their time, attention and energy to trying to develop their skills and, they are less confident on the possibility to develop relevant skills (Colquitt et al., 2000). As previously mentioned, one of the characteristics of PTE is that this environment can remove multiple constraints of location and time and lead to a self-learning experience (Beier, 2019). These constraints alleviate can give a greater possibility to learning activities (Derouin et al., 2005).

Drawing on the aforementioned perspectives, we suppose that PTE contributes to enhance motivation to learn.

Hypothesis 1: Psycho-technological environment ((a): opportunities; (b): accessibility) is positively related to motivation to learn

Learning behaviors with technologies refer to behaviors aiming to make a change in knowledge and competency repertoire through the use of technologies, either by elaborating the actual configuration or creating a new one (Noe et al., 2014; Weiss, 1990). These behaviors capture a large panel of actions that contribute to the acquisition of skills through the use of technologies such as mobile, computers, etc. (He & Li, 2019). The specificity of learning behaviors with technologies is the ability to broaden learning possibilities (Shen & Ho, 2020). For instance, technologies allow receiving feedback from long-distance learners including knowledge status, advice on how to improve skills, multitasking, sharing relevant content (Beier, 2019; Fu et al., 2020). Also, individuals can manage the learning process at their pace, needs and goals thanks to a larger repertoire of contents (Brown et al., 2016; Bell & Kozlowski, 2008). Consequently, individuals can use technologies in different ways: as a *media* (tool) or *support* (integrator) (Bazine et al., 2020). The first dimension, *media,* refers to the technologies allowing to acquire knowledge and to develop competencies (He & Zhu, 2017; Noe et al., 2014). Technologies act as a tool/media because they can allow individuals to have access to information, content and generally to resources for learning (Bell & Kozlowski, 2009). The second dimension, *support,* captures the fact that technologies could be a support for the learning process, for example the learner can use technologies to seek feedback from others and adopt the collaboration approach (Chan et al., 2015; Rashid & Ashghar, 2016). The flexibility and the variety of possibilities offered by technologies can respond to the individual's needs (Dyson et al., 2015).

Numerous studies have supported the link between motivation to learn and learning activities (Colquitt et al., 2000). For instance, Noe and Wilk (1993) highlighted that the motivation to learn was positively related to the time spent learning. Lepine et al. (2004) showed that motivation to learn is associated with learning performance. Consequently, motivation to learn has been identified as a strong predictor of learning activities (Major et al., 2006). In addition, few studies have strived to demonstrate the relationship between motivation to learn and learning activities with technologies (de Barba et al., 2016; Huizenga et al., 2009). Garaus et al. (2018) demonstrated that in online learning environments, motivation to learn leads to greater persistence in learning activities. Dunn and Kennedy (2019) reinforced this point by underlining that motivation to learn is related to the engagement in the use of technologies for learning.

In line with this, we suppose that the motivation to learn fosters learning behaviors with technologies and we formulated the following hypothesis:

Hypothesis 2: Motivation to learn is positively related to learning behaviors with technologies ((a): media; (b): support)

According to Colquitt et al. (2000), the environment affects learning activities through a motivational mechanism. The degree to which the motivation to learn affects learning behaviors with technologies depends on the perceptions that the surrounding provides sufficient opportunities and accessibility of contents for learning. PTE motivates individuals to engage in learning behaviors with technologies because opportunities and accessibility have fostered their positive learning beliefs, self-efficacy and attitudes for facilitating individuals' inherent tendencies for growth and development (Maurer et al., 2003; Nikolova et al., 2016).

In doing so, we propose a research model that draws on the learning climate literature and recent studies (Nikolova et al., 2014; Sung & Choi, 2014) to hypothesize that an environment with many resources to learn triggers more learning behaviors through motivation to learn (Kozlowski & Hults, 1987). According to the motivation to learn literature (Noe & Schmidt, 1986; Battistelli et al., 2007; Maurer & Lippstreu, 2008), we further posit that the situational characteristics (quantity of resource, accessibility, easiness of use etc..) act as a driver for motivation to learn and affects the disposition to learn and attitudes towards learning. We suppose that the PTE may enhance learning behaviors with technologies through motivation to learn and we formulated the following hypothesis:

Hypothesis 3: Psycho-technological environment ((a): opportunities; (b): accessibility) is positively related to learning behaviors with technologies-media through motivation to learn

Hypothesis 4: Psycho-technological environment ((a): opportunities; (b): accessibility) is positively related to learning behaviors with technologies-support through motivation to learn

3.2.3 The moderating role of digital awareness

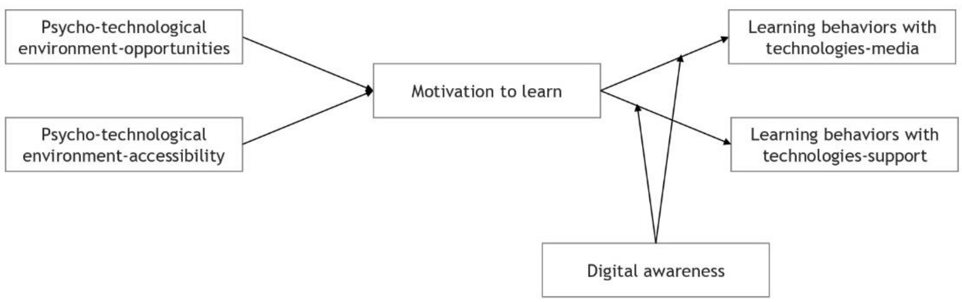
According to Brougham and Haar (2018), digital awareness describes an employee's views about the impact of technologies on his workplace. Brougham and Haar (2017) consider these views critical because individuals who are aware of changes involving technologies are more disposed to anticipate and implement behaviors in line with the actual requirements. Technologies have modified many aspects of work, explicitly the need to develop competencies (Xie, et al., 2019). The necessity of updating knowledge and skills has increased with the arrival of technologies (Bell et al., 2017). Several authors have argued about the fact that in today's world of work, continuous learning is a must (Xie, et al., 2019; Cascio & Montaelegre, 2016; Parker, 2014). Wegman et al. (2018) have explained that the need to continually learn has become a fundamental work characteristic since technologies have been integrated into the workplace.

We recognize that not all individuals perceive technological changes similarly (Brougham & Haar, 2017). This difference may affect the involvement in learning activities notably with technologies (Xu et al., 2019). Because of this, we examine the moderating role of digital awareness and its influence on the relation with motivation to learn and learning behaviors with technologies. Staying consistent with Brougham & Haar (2017), we theorized that digital awareness affects the extent to which individuals make learning behaviors with technologies. Digital awareness may also increase learning behaviors with technologies because individuals who are aware of the importance to learn continuously strive to perform in their jobs by responding to the actual requirements of work (Pan & Seow, 2016). Consequently, we assume that digital awareness may act as a facilitator which allows individuals to orient their effort towards the most effective way to develop necessary skills and knowledge in the digital age.

In sum, individuals with high digital awareness add to their motivation to learn, increase their desire to develop competencies continually to remain employable and competent (Froehlich et al., 2014). We claim that digital awareness could be a moderator of the relationship between motivation to learn and learning behaviors with technologies.

Hypothesis 5: Digital awareness will moderate the relationship between motivation to learn and learning behaviors with technologies ((a): media; (b): support)

Figure 3.1 *Hypothesized model*



3.3. Method

3.3.1 Sample and procedure

The sample of this study is composed of 344 French university students having professional experience. The data was gathered by sending an email with the invitation to answer a survey. Data was collected during the academic year 2019-2020. The sample was composed of 270 (78.5%) women and 74 (21.5%) men with an average age of 24.94 (*SD*=7.59). Students come from Sciences, technology, engineering, and mathematics (STEM) (28.21%), from Human Sciences (43.31%) and from Medical Sciences (28.48%). Finally, the students' education is as follows: 190 master's degree (55.24%), 141 bachelor's degree (40.98%), 13 doctorate's degree (3.78%).

3.3.2 Measures

Psycho-technological environment (PTE)

We assessed the perception of the Psycho-technological environment with the 12-item scale of the measure from the adaptation of Bazine et al. (2020) of the work of He & Zhu (2017), developed in French and ranging from 1 (Not at all) to 5 (Totally). This measure is composed of two dimensions: *Opportunities* and *Accessibility*. A sample item for *Opportunities*: "I have the perception that the use of digital technologies is a real benefit for the development of knowledge and skills; I have the perception that digital technologies offer me a more attractive way for learning "and a sample item for *Accessibility*: "I have the perception that the digital technologies for learning are free to access".

Motivation to learn was measured with the 4-item scale from Battistelli et al. (2007), the French version. Participants were asked to indicate their motivations to learn with technologies and answered each item ranging from 1 (Not at all) to 5 (Totally). An example of item is: "I want to increase my knowledge; I have the desire to improve my skills".

Learning behaviors with technologies were measured with the 11-item scale from the adaptation of Bazine et al. (2020) of the work of He & Li (2019), developed in French ranging from 1 (Not at all) to 5 (Totally). This measure comprises two dimensions *Media* and *Support*. A sample item for *Media*: “I use digital technologies to increase my knowledge in my domain” and one for *Support*: “I actively seek new technologies to help with my learning needs”.

Digital awareness was measured through an adaptation from Stara’s awareness concept (Brougham & Haar, 2017). The measure is composed of 4 items ranging from 1 (Not at all) to 5 (Totally), initially developed in French. Sample items: “The professional context requires of me independently to acquire regularly new knowledge”, “The actual professional context requires to learn continually with new technologies”.

Control variables

Demographic variables included the following collected data age, sex, formation and education level because these variables can be associated to the use of technologies and learning activities (Thompson, 2013). Age, sex and education are commonly associated to the learning activities and the engagement in training (Salas, Tannenbaum, Kraiger, & Smith-Jentsch, 2012) and are related to learning activities with technologies (Dunn & Kennedy, 2019).

3.3.3 Results

Table 3.1 *Means, Standard Deviations, Coefficient Alphas and Coefficient Omegas, and Correlations Between Variables*

Variables	Means	SD	α	ω	1	2	3	4	5	6
1. PTE Opportunities	3.78	.75	.85	.87						
2. PTE Accessibility	3.38	.80	.85	.85	.43**					
3. LBT -media	3.62	.89	.83	.85	.51**	.27**				
4. LBT- support	2.66	.96	.89	.91	.55**	.27**	.64**			
5. MT Motivation to Learn	3.88	.95	.86	.88	.48**	.27**	.40**	.43**		
6. DA Digital Awareness	3.94	.75	.82	.82	.35**	.09	.28**	.34**	.27**	

Note: N=344, ***p*<.001

The means, standard deviations, and correlations among variables are indicated in Table 1. To estimate internal consistencies, we analyzed and reported in Table 1 Cronbach's alphas and McDonald's omegas (Dunn et al., 2014).

Before examining our model, we verify if demographic variables (age, sex, formation and education) can create differences regarding our interest variables. We perform an analysis of variance (ANOVA) and our results confirm that demographic variables demonstrated any difference among our results (all p>.05).

Confirmatory factor analysis (CFA) through Mplus 8.4 (Muthen & Muthen, 2017) and the MLR estimator was used to examine the theorized 6 factor structure. This analysis indicated that all items loaded significantly on their corresponding latent variables (*p*<.001) and the latent variables loaded significantly on their corresponding second order variables latent variables. The CFA model yielded a good fit to the data: χ 2/df= 1.87, RMSEA=.05, CFI=.92, TLI=.91 and SRMR=.05. Hu and Bentler (1998) allowed us to affirm that fit indices are good with an RMSEA and an SRMR of .05, a value lower than .06, the minimum threshold to be considered a good fit. The CFI and TLI indices show good fits, with acceptable fit superior to .90, generally the rule is to accept a value greater than .90 for an acceptable fit (Brown, 2015).

To assume the robustness of our model, we proceed to a comparison analysis with the use of the Satorra-Bentler method (Pavlov, Shi, & Maydeu-Olivares, 2020; Satorra & Bentler, 2001). The theorized model outperformed simpler models that were obtained by merging two or more factors, such as (a) a five factor that combined LBT-media and LBT-support, χ 2/df= 2.26, RMSEA=.06, CFI=.88, TLI=.87 and SRMR=.06, Satorra-Bentler $\Delta\chi 2$= 134,3084, df=5, and p<.01, (b) a five factor that combined PTE-opportunities and PTE-accessibility, χ 2/df= 2.76, RMSEA=.07, CFI=.83, TLI=.82 and SRMR=.07, Satorra-Bentler $\Delta\chi 2$= 408,5523, df=5, and p<.01, (c) four factor model that combined PTE-opportunities and PTE-accessibility and combined LBT-media and LBT-support, χ 2/df= 3.14, RMSEA=.08, CFI=.80, TLI=.78 and SRMR=.07, Satorra-Bentler $\Delta\chi 2$= 491,2707, df=9, and p<.01, (d) three factor that combined motivation to learn and digital awareness, χ 2/df= 4.01, RMSEA=.09, CFI=.71, TLI=.69 and SRMR=.09, Satorra-Bentler $\Delta\chi 2$= 788,9894, df=1, and p<.01, (e) two factor model that combined LBT, motivation to learn and digital awareness, χ 2/df= 4.89, RMSEA=.11, CFI=.62, TLI=.60 and SRMR=.10, Satorra-Bentler $\Delta\chi 2$= 971,4431, df=14, and p<.01, and (f) one factor model, χ 2/df= 5.66, RMSEA=.11, CFI=.55, TLI=.52 and SRMR=.11, Satorra-Bentler $\Delta\chi 2$= 1102,5147, df=15, and p<.01.

According to Podsakoff et al. (2003), we examine our data could be affected by common method variance. Model fit and correlation between latent factors remained unchanged with add to an orthogonal latent factor named CMV encompassing all the variables items. The CMV factor accounted for 31.5% of the total variance, suggesting that although common method bias was partly present in this study, it is unlikely to affect the validity of the research results (Williams et al., 1989). The probability of common method bias was low.

Table 3.2 Model Measurement Fit Indices for Assessed the Differences between the Variables

Model	Model Description	χ^2	*df*	RMSEA	CFI	TLI	SRMR	AIC	BIC	$\Delta\ \chi^2$
Measurement model (MLR)										
M1	6-model factor	786.409	419	.05	.92	.91	.05	27460.253	27875.042	
M2	5-model factor (combining factor LBT media and support)	959.232	424	.06	.88	.87	.06	27650.833	28046.419	$\chi^2(5)=134.31^{**}$
M3	5-model factor (combining Factor PTE: opportunities and accessibility)	1174.362	424	.07	.83	.82	.07	27890.686	28286.272	$\chi^2(5)=408.55^{**}$
M4	4-model factor (combining LBT: media and support and PTE: opportunity and accessibility)	1345.431	428	.08	.80	.78	.07	28082.700	28462.924	$\chi^2(9)=491.27^{**}$
M5	3-model factor (combining MT and DA)	1732.123	431	.09	.71	.69	.09	28523.485	28892.182	$\chi^2(12)=788.99^{**}$
M6	2-model factor (combining LBT and MT and DA)	2118.781	433	.10	.62	.60	.10	28978.841	29339.862	$\chi^2(14)=971.44^{**}$
M7	1-model factor	2458.383	434	.12	.55	.52	.11	29385.895	29743.074	$\chi^2(15)=1102.51^{**}$

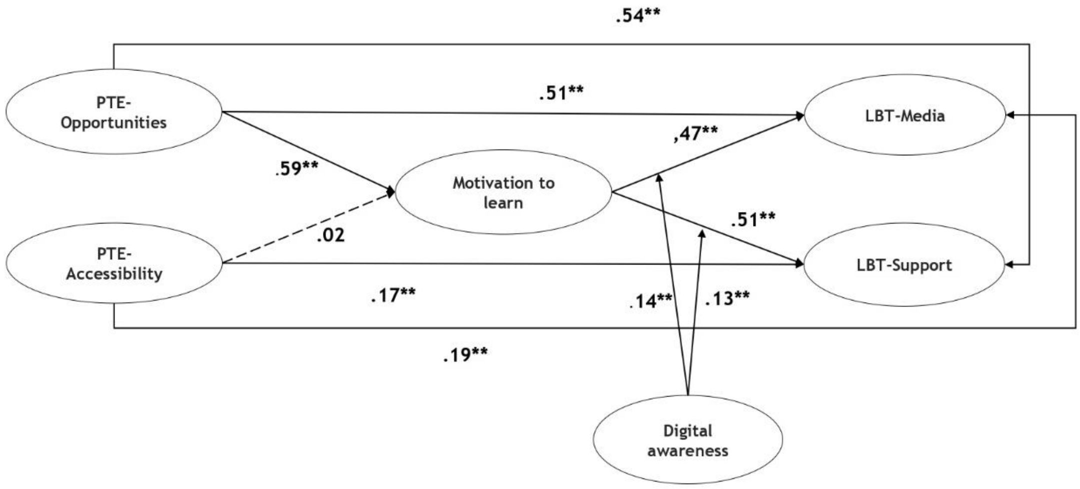
Note: N = 344. ** p < .01. RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR: standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion; PTE = psycho-technological environment; LBT = learning behaviours with technologies; MT = motivation to learn; DA = digital awareness.

3.3.4 Hypothesis testing

The hypothesized structural model based on our hypotheses was examined with Mplus 8.4 (Muthen & Muthen, 2017). Standardized path coefficients associated with the overall hypothesis model is reported in Figure 2. Our results supported Hypothesis 1a which stated that the PTE-opportunities is positively related to motivation to learn (β=.59, p<.001) but Hypothesis 1b did not (β=.02, p=*ns)*.In addition, Hypothesis 2a was confirmed with motivation to learn being positively related to learning behaviors with technologies-media (β=.47, p<.001) and Hypothesis 2b was also confirmed (β=.51, p<.001).Hypothesis 3a predicted the existence of a positive indirect path between PTE-opportunities and learning behaviors with technologies-media through motivation to learn. The indirect effect was estimated with Mplus 8.4 and hypothesis 3a was supported with the indirect effect of PTE-opportunities on learning behaviors with technologies-media via motivation to learn (estimate =.28, 95% CI=.19-.36). Hypothesis 3b did not support the relationship between PTE-accessibility and learning behaviors with technologies-media via motivation to learn (estimate =.01, 95% CI=-.04-.08). Hypothesis 4awas confirmed by an indirect effect of PTE-opportunities on learning behaviors with technologies-support via motivation to learn (estimate =.30, 95% CI=.23-.37), and the hypothesis 4b did not support the relationship between PTE-accessibility and learning behaviors with technologies-support via motivation to learn (estimate =.02, 95% CI=-.05-.09).

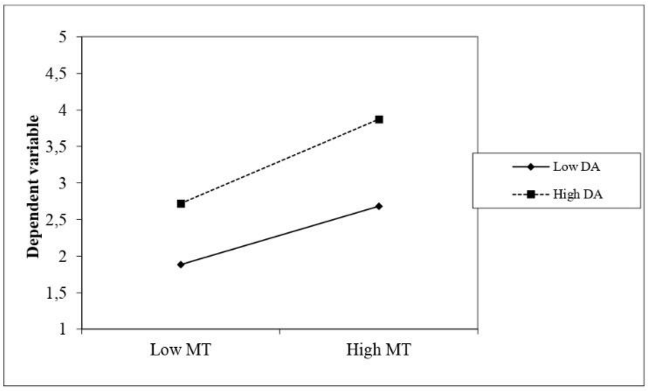
A closer examination of our results indicated that motivation to learn partially mediated the association between PTE-opportunities and learning behaviors with technologies-media because an association was founded (direct effect β =.51, p<.001).Furthermore, the results showed that motivation to learn partially the association between PTE-opportunities and learning behaviors with technologies-support because also an association was founded (direct effect β =.54, p<.001). Therefore, PTE-accessibility was directly associated with learning behaviors with technologies-media (β=.19, *p*<.001) and learning behaviors with technologies-support (β=.17, *p*<.001).

Figure 2.2 *Standardized path coefficients associated with the final model (N = 344)*



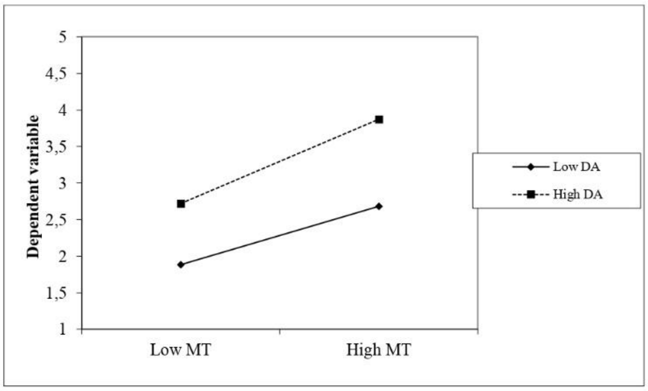
Hypothesis 4 focuses on the moderating role of digital awareness. We proceed by using structural equation modeling and latent variables, using random type, ML and bootstrap (1000). We specified a moderated mediation model of digital awareness on the indirect relationship between PTE and learning behaviors with technologies via motivation to learn has been tested. The "motivation to learn" X "digital awareness" interaction term was statistically significant (β=.14, *p*<.01). In order to examine the form of this interaction, we have plotted the interaction term. Results demonstrate in case of the simple slope test that digital awareness is low, motivation to learn is significantly related to positively and significantly related to learning behaviors with technologies-media (β=.03, *p*<.05). In addition, in the case where digital awareness is high, the relationship is also positively and significantly related to learning behaviors with technologies-media (β=.22, *p*<.001). These results provide support for Hypothesis 5a.

Figure 2.3 *Interaction effect of motivation to learn and digital awareness for learning behaviors with technologies-media*



We applied the same methodology for Hypothesis 4b. The “motivation to learn” X “digital awareness” interaction term is statistically significant (β=.13, *p*<.01). In order to examine the form of this interaction, we have plotted the interaction term. Results demonstrate in case of the simple slope test that digital awareness is low, motivation to learn is significantly related to positively and significantly related to learning behaviors with technologies-support (β=.05, *p*<.05). In addition, in the case where digital awareness is high, the relationship is also positively and significantly related to learning behaviors with technologies-support (β=.24, *p*<.001). These results provide support for Hypothesis 5b.

Figure 2.4 *Interaction effect of motivation to learn and digital awareness for learning*



*behaviors with technologies-suppor*t

3.4 Discussion

The core contribution of this research was threefold. First and foremost, we have shown support that the PTE could be a learning potential that is, a motivational agent. Additional evidence is our results demonstrating that only PTE-opportunities increase the motivation to learn. The second contribution is that we have established two positives indirect paths between PTE-opportunities and learning behaviors with technologies-media and support through motivation to learn. Additionally, we found that motivation to learn partially mediated these two indirect paths. The third contribution is that we have highlighted how digital awareness could impact the relationship between motivation to learn and learning behaviors with technologies. Finally, we found an interaction effect of digital awareness which improves the relationship between motivation to learn and the two dimensions of learning behaviors with technologies: media and support.

3.4.1 Theoretical implications

Our results advance the literature of the impact on technological ubiquity on attitudes and behaviors (McFarland & Ployhart, 2015). First, our research has extended the understanding of PTE as learning potential, by demonstrating that increases the motivation to learn. The strength of this finding is that we demonstrate that opportunities offered by technologies foster motivation (Beier, 2019).This supports the assumption that technologies as context can affect the individual’s attitudes (Landers & Marin, 2020). Our findings can fill a gap in the literature on the link between environment and motivation to learn (Noe & Schmitt, 1986). Despite, the self-determination theory which has demonstrated the importance of the environment for motivation (Deci & Ryan, 2002), few studies have considered the link between environment and motivation to learn (Maurer et al., 2003; Colquitt et al., 2000), globally literature has largely neglected the assumptions of the environment as an activator of motivation to learn. The majority of previous studies have essentially focused on the relationship between environment and learning activities (Nikolova et al., 2014; Sung & Choi, 2019; Tracey & Tews, 1995).These results, in addition to providing empirical evidence on the connection between PTE and learning behaviors with technologies, suggest that motivation to learn could be a mechanism by which PTE and learning behaviors are related. In fact, these results are consistent with Nikolova et al. (2014), according to which in order to make learning activities it is necessary to have the perceptions in his environment have sufficient resources to buffer our motivation to realize learning activities.

The lack of a significant relationship between PTE-accessibility and motivation to learn is not surprising because there are factors such as richness, content, diversity, pleasantness and opportunities which play a role in motivation to learn (Klein et al., 2006; Van der Heijde et al., 2019). The accessibility is considered such as a constraint that can be overcome by individuals if they can obtain relevant content for developing their competencies

(Hurtz & Williams, 2009). This result reinforces the importance of opportunities for the learning potential of an environment (Cangialosi et al., 2020; Nikolova et al., 2014). But our findings point to the potential value of accessibility because they can contribute to learning with technologies as this can alleviate certain difficulties without being a reason why individuals activate learning behaviors with technologies.

Second, our study has investigated the role of the views of the impact 4^{th} industrial revolution on work context regarding the learning process (Brougham & Haar, 2017). The results suggest that digital awareness boosts the learning behaviors with technologies and advocates that individuals aware of the changes brought by the 4^{th} industrial revolution have higher involvement in learning with technologies (Brougham & Haar, 2018; Colbert et al., 2016). Thus, individuals would be more likely to adopt behaviors that foster the achievement of their professional objectives by filling requirements of digital work context (Maurer et al., 2003; Cascio & Montaelegre, 2016). This is consistent with the findings of Brougham and Harr (2017; 2018), which highlight that individuals tend to upskill or find a new way in order to stay employable. Our research strives to demonstrate that digital awareness allows individuals to anticipate and cope with the actual requirements by the setting of adequate behaviors.

3.4.2 Practical implications

This research aims chiefly to demonstrate theoretical assumptions but also, to provide some practical implications. First, our findings suggest that universities and organizations should develop and promote the PTE to support learning. Insofar as learning depends on the environment (Nikolova et al., 2014), educators and managers should focus on increasing opportunities to learn, for instance proposing various and different learning methods, allowing some flexibility to give learners the opportunity for self-learning.

Second, our results have emphasized the role of digital awareness to promote learning behaviors with technologies. This paper advises universities or organizations to pay more attention to individuals by providing sufficient knowledge about the challenges of the 4th Industrial Revolution with training, communication, space for reflecting and open discussions (Brougham & Haar, 2017).

3.4.3 Limitations

Although these findings are promising, this research has some limitations. We have gathered data on a voluntary basis, thus leading to a large diversity of participating students with working experience. In this regard, our collection procedure may inflate the heterogeneity of the sample and added to the random nature which can lead to sample selection bias and self-selection bias (Heckman, 1990). The second limitation of our study is the self-reported data which might induce common method bias and inflate the common method variance (Podsakoff et al., 2003). However, it was unlikely that our results are attributable to common method bias because it was tested whether the observed relationships between study variables resulted from common method errors following the statistical recommendations of Podsakoff, et al.. (2012).The third limitation is the nature of the sample. Given the random nature of the sample, we could not examine the role of control variables such as education levels. Education can affect our use and fluency with technologies (He & Zhu, 2017). For instance, STEM education requires more digital skills than that in Human Sciences. The third limit is that our assumptions have been tested in just one university and this limits the possibility to generalize. Therefore, it could be appropriate to replicate this study on other samples, the most suitable being of full time representatives in professional context.

3.4.4 Conclusion

This study supports the assumption that the PTE acts as a learning potential (Nikolova et al., 2014). This opens perspectives for further studies and analysis on this framework. For example, studies focusing on the PTE can successfully promote employability and careers (Strauss et al., 2012), also the role of the PTE on satisfaction (Chen et al., 2011), commitment (Allen & Meyer, 1990), well-being (Deci & Ryan, 2002). In the actual times of change in the professional context, it is likely that the PTE will play the role of facilitator regarding an employee's adaptation to new competencies.

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Chapter 4 : Careers in times of the 4th industrial revolution

4. Theoretical background of career development in 4th industrial revolution

The second contribution of this doctoral dissertation is to understand how the 4th industrial revolution affects career orientation and behaviors. It seems clear that the 4th industrial revolution might thus be one of the most important issue to shape the future nature of career choices, career development, and career counseling (Hirshi, 2018). Nowadays, careers are no longer limited by the boundaries of an only one organization and extend beyond the world of organizations (Arthur & Rousseau, 2001). Careers are now constituted of a series of employment opportunities which involve physical changes in work arrangements (Defillipi & Arthur, 1996). The greatest job growth is in jobs that move beyond the boundary of the firm, in an “organization with a more permeable boundary, where work—and people—move inside and outside more free (Spreitzer et al., 2017). In this context of professional discontinuity, workers are more likely to have multiple professional experiences, multiple employers, and also multiple jobs (Sullivan, 1999). Traditional careers were more dependent on organizations and build a long term relationship whereby good performance and employee loyalty are rewarded with job security, steady salary increases and prospects for hierarchical promotion (Rodrigues et al., 2015). Traditional employment relationships and traditional careers are in decline and are giving way to the rise of alternative work arrangements (Katz & Krueger, 2017; Spreitzer et al., 2017). The transactional model of employment characterized by full-time work and long-term fidelity is undermined by the 4th industrial revolution (Ashford et al., 2018; Hirschi, 2018). In addition, research emphasized that the link between an organization and a worker are increasingly limited to a work contract (Kuron et al., 2016). Employment conditions are volatile and turbulent and create a high level of ambiguity regarding career paths and expectations (Briscoe et al., 2012; Hofstetter & Rosenblatt, 2017). However there is now a widespread view that in the highly uncertain and unpredictable contemporary competitive environment, organizations are no longer in a position to promise a traditional career (Arthur, 1994). To navigate successfully in this changing landscape, employees find themselves disengaging from their organizational identity and becoming owners of their careers by developing the ability to continuously learn and change in order to continue to grow in their careers (Arthur et al., 2005). These changes involve that individuals need to be more self-directed in their career development but also plan their career, assume their skill development and also develop their network in order to stay employable on the market and assume their employment security (Hirschi, 2018).

The major change that the 4th industrial revolution has produced is the advent of a new economy: Gig economy. Digital platforms and ecosystems have disrupted industries by enlisting the work of thousands of dispersed and unorganized workers (Kneese & Rosenblat, 2014). Unlike regular workers, who are covered by relevant employment laws (minimum wage, sick leave, etc.) and taxation codes, platform gig workers are effectively self-employed and thus are responsible for their own economic upkeep and career planning (Farrell & Greig, 2017; Graham et al., 2017; Spreitzer et al., 2017). This new economy has greatly impacted the professional setting and careers inside and outside organizations (Ashford et al., 2018; Graham et al., 2017). The birth of this new economy comes from structural changes where the global competition and the dependence on short term financial results lead to more flexibility of the workforce fitting with the economical fluctuation (Bidwell et al., 2013). In order to stay flexible, organizations offer their employees less full-time jobs and long-term contracts with job security (Davis, 2016). Micro-contracts and mid-term contracts are growing. The increase of this type of contracts is a response to the need for specific skills at a specific time without having the responsibility of the workers in the long term.

Beyond to the macro-economic changes, the technological advancements have allowed many workers to carry out their profession « anywhere and anytime » (Charalampous et al., 2019). For instance, technologies have helped workers to connect to their organizations outside the premises, sharing documents with many other individuals, to program and assist to meetings thanks to technological tools (Cascio & Montaelegre, 2016). Technologies have provided opportunities to form virtual teams, with no interaction face to face and where the teammates share and communicate via technological tools (Handke et al., 2020).

To this statement, career development no longer captures the way to reward efforts and investment in organization by greater job, income improvement etc. (Rodrigues et al., 2015). The most important criteria are no longer fidelity and loyalty towards an employer or organization but having competencies valuable for the organization. Consequently, these are competences allowing having a job, to obtain a better job, have a promotion and evolve in the career (De Vos et al., 2011). These changes explain why learning is becoming so important for individuals, maybe even more than before. But these changes also affect organizations that should be able to attract and retain competences that they need and that are important in order to continue to perform (Collings & Mellahi, 2009).

In sum, these changes capture a major change in the attachment and detachment of individuals to their organizations which is translated by more singular career trajectories. Individuals are freer from their organization both physically (interorganizational mobility) (Arthur, 1994) and psychologically (development of self-directed career) (Hall, 2004). This emancipation (which, however, is not the case for everyone) has changed the way many careers are managed, and shifted from what was a collective responsibility of the organization to an individual responsibility (Hall et al., 2018). This responsibility requires from individuals a higher level of adaptation to become the principal agent of their career with the capacity to define their career success criteria (Hirschi et al., 2017). These changes require employees to manage their careers and develop strategies and competences with the aim to have a career success (King, 2004; Lent & Brown, 2013). The capacity to be proactive has become essential for career development (Strauss et al., 2012). These behaviors are self-starting, change oriented and future focused (Parker et al., 2010). The most important in their new careers is to use their human agency (Bandura, 1986).

In face of these changes in careers, the way of which the research considers and studies careers must evolve. For instance, Akkermans and Kubasch (2017) and Inkson et al., Gunz, Ganesh, & Roper (2012) point out that to understand careers, rather than using a linear perspective, they should be analyzed as a cyclical process, which seems the most appropriate to reflect the infinite variety of forms they can take and in which individuals can engage. Moreover, De Vos, et al. (2020) emphasized three levels of analysis to understand the complexity of new careers. Firstly, analyzing individuals as the main actors in their career, understanding how individuals behave, act and interpret to develop their career and how the actions to develop them affect the individuals themselves. Secondly, careers are affected by multiple contexts in which individuals evolve: the professional context (or sector, occupational sector), the private life context, the market context, and the cultural context. (Andresen et al., 2020). All these have an influence on how individuals can shape and achieve career success. Finally, the consideration of time and time perspective is primordial. Careers are in constantly evolving and understanding how they evolve over time is the core of the study of careers. In this perspective, it is essential to consider the intra-individual changes.

Many researchers have been interested in how individuals can thrive in these new contexts. Hall (2004) considers that specific career orientation seems to be able to help individuals navigate and develop in these contexts in particularly the Protean Career Orientation (PCO). There are different career orientation such as boundaryless career, kaleisdoscopic career (Creed et al., 2011), but it seems that the PCO demonstrates better results for career development (Hirschi & Koen, 2021). This is partly explain owing to the fact that protean concept correspond to an agentic role for the individual. The unique aspect of the protean concept is the internal motivation that is provided by the person's intrinsic values that drive the person's agentic sources. This is the "engine" or motivation for the person's career decisions.

PCO captures the attitude of an individual that leads him to self-define their career independently of an organization. This is expressed through the implementation of actions to achieve subjective criteria for career success (Briscoe et al., 2006). Some authors consider this protean career orientation as a motivational agent for career development (Hermann et al., 2015). The review of Hall et al. (2018) emphasized that a protean career is composed of three elements which are: orientation, mechanism and outcomes. Orientation corresponds to an individual variable that leads individuals to self-define their career and is composed of two dimensions: self-direction and values. Mechanisms (identity, adaptability, and agency) capture attitudinal expression of protean career. Outcomes represent the career success, organizational commitment, career behaviors.

In depth, *self-direction* captures the level to which an individual takes the responsibility of their career in charge (Briscoe et al., 2006; Mirvis & Hall 1994) and refers to a person's independence from external control or influence of an organization (Hall et al., 2018). It is an attitude that represents personal agency for their career decisions and actions (Briscoe et al. 2006, Segers et al. 2008). Self-direction is a critical component of the protean career and represents the agentic aspects of volition and control over one's career (Briscoe et al., 2006, Segers et al., 2008).

In addition to self-direction, values mostly intrinsic and oriented towards autonomy, meaning and growth (Hall et al., 2018), PCO is defined as one where the intrinsic *values* of a person serve as a guide for career decisions (Briscoe & Hall 2006). As Hall (1976) notes, "the criterion of success is internal (psychological success), not external". Where self-direction represents agency and volition in the pursuit of one's career goals, intrinsic values provide meaning to the pursuit.

Protean career mechanisms are composed of three dimensions: *identity awareness, adaptability* and *agency*. They are the processes that explain the relationship between PCO and organizational and career outcomes. Hall (2004) considers these mechanisms such as competences that enable the person to express his PCO and produce outcomes for the career development.

The mechanism of *identity awareness* is based on the role of personal values in career decision making (Hall, 2004). This awareness of one's vocational identity can be seen as a meta-competency for developing a protean career because in times of frequent change and decreasing organizational guidelines for career development, people need a strong internal compass to guide and develop their careers (Hall 1996b).

Adaptability refers to the ability to take the actions necessary to change effectively in response to a disruption in the environment and to cope with the related obstacles (Hall, 2004). Career adaptability is a multidimensional construct that has been conceptualized in different ways (Rottinghaus et al. 2012, Savickas & Porfeli 2012). Super & Knasel (1981) define career adaptability as a person's readiness to cope with changing work and working conditions.

Agency captures how a person is able to use their protean career orientation as a resource for action to pursue his or her most prized values. Agency is the capacity of human beings to make choices and to impose those choices on the world. As Bandura (2001) notes, agency is the ability "to intentionally make things happen by one's actions". And, in fact, there have been many studies that showed positive links between PCO and positive career experiences, such as career self-management behaviors (De Vos & Soens 2008), career growth (Waters et al., 2014), job satisfaction and organization commitment (Supeli & Creed, 2016), as well as subjective career success (De Vos & Soens 2008).

The outcomes of a protean career orientation are diverse and have been found to predict proactive behavior (Creed et al., 2011, Herrmann et al., 2015), career self-management (De Vos & Soens, 2008), and career planning (DiRenzo et al., 2015). In addition, PCO has shown to predict engagement in networking and visibility strategies (De Vos & Soens, 2008). Also, literature found that PCO is associated with proactive career behaviors and performance (Hirschi et al., 2017; Rodrigues et al., 2015), career success and well-being. In addition to being beneficial career development, PCO is also associated with organizational outcomes such as performance, organizational commitment and less turnover (Supeli & Creed, 2016). These results are due to the fact that the protean career, in itself, favors the engagement of individuals in proactive behaviors because it allows them to mobilize, in an autonomous and self-directed manner, the resources and individual strategies to develop knowledge, to train and to direct their careers according to the demands of the context (Briscoe et al., 2012). These behaviors finally appear to be associated with career success and organizational outcomes since they also play a role in the development of the organization and the individual who will be rewarded for them in terms of promotion or salary (Rodrigues et al., 2015).

In a context where career pathways and professional success now depend on the development of critical competences as well as the development of employability (Arthur et al., 2005), one question concerns the strategies and behaviors that can enable employees to develop their careers.

It appears, in light of what has been highlighted previously, namely a world in constant evolution guided by technological development and innovation, that individuals who implement learning behaviors will be the most likely to maintain their skills, expand them, and value them (Major et al., 2005). In this context, individuals must not only react and adapt to change but anticipate and foresee the future professional demands of the world of work (Tornau & Frese, 2013). i.e., become a proactive agent of their career (Strauss et al., 2012).

In the transactional contract, the worker's productivity is rewarded with opportunities to develop their skills and career but also their opportunities to be employed (Mirvis & Hall, 1994). Therefore, it is now up to the individual to be able to identify the needs of the field and the corresponding skills to be acquired (King, 2004). The need to be able to plan one's career and know how to achieve these goals (Claes & Ruiz-Quintanilla, 1998).

To expand one's range of professional opportunities, work indicates the importance of building a professional network, with networking behaviors allowing one to acquire essential resources such as information, influences and friendships (Porter & Woo, 2015). Through these resources, it is likewise a matter of having access to new professional opportunities and of better orienting oneself in strategic choices concerning the competences to be developed that are beneficial to one's career (Volmer et al., 2019).

The literature highlighted early on that these proactive career behaviors were decisive (Claes & Ruiz-Quintanilla, 1998). Some authors have emphasized that these behaviors play a key role in accessing employment (Brown et al., 2006). Others, such as Seibert et al. (2001) for example, have shown that they are significantly related to job promotions or greater career satisfaction. Finally, Smale et al. (2019) establish a robust relationship between proactive career behaviors and career success. In sum, the literature has demonstrated a positive influence of proactive behaviors on career, notably on promotions, career satisfaction and career success (Seibert et al., 2001), but also in the involvement of job search and getting a job (Brown et al., 2006; Saks & Ashforth, 1997).

Based on this statement, we identify that career success is more dependent on individuals and that they need to show high responsibility for one's career plan (King, 2004).

To thrive in a contemporary career, individuals now need to demonstrate a higher level of self-direction and adaptability to handle the uncertainty and inevitable changes inherent in careers (Briscoe et al., 2012).

With the advent of the 4th industrial revolution, the role of technologies in career development is become a central issue (Hirschi, 2018). Thus, technologies can play a key role for facilitate career development and notably foster proactive career behavior. At first, researchers have focused their attention on social networks sites (SNS) as a resource for networking. These technologies have profoundly affected career development and can be defined as web services allowing individuals to create public profiles and connect with other users (Utz & Breuer, 2016). Boyd and Ellison (2007) emphasized that these sites allow seeing and browsing the connections made with other profiles. The aim of these sites is to connect workers more easily and also to show their professional profiles (Utz & Breuer, 2016). The social networks sites increase the visibility of each professional, show their competencies and expertise to a large set of individuals (Treem & Leonardi, 2013). Different studies demonstrate that these sites facilitates interactions between individuals distant geographically or not in the same professional network and can reinforce the link with individuals who can help to career development (Zhang & Leung, 2015). Researchers have emphasized social network sites as a context (McFarland & Ployhart, 2015). Authors such as Johnson and Leo (2020) emphasized that SNS can be agent of proactivity because they foster self-efficacy towards the career behaviors; the literature showed that self-efficacy is an essential mechanism for proactivity (Parker et al., 2010). In addition, Davis et al. (2020) have established that the use of SNS is related to positive results for career development. This study strives to demonstrate that networking behavior with an appropriate use of SNS is related to improvement in career development (promotion, job, higher income). Despite promising work, few research have studied how technologies beyond SNS can help individuals to develop their career.

In the next section, we aim to develop a study showing how individuals develop their in the context of the 4th industrial revolution and how technological ubiquity and technological use can be helpful for individuals to develop their career.

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Chapter 5 Article 3: Who is successful in career development? A person-centered approach to the study of career profile

Abstract

Research on career development has largely considered how Protean career orientation (PCO), motivation to learn and future time perspective predict career outcomes (planning, networking, and skill development). Regarding the protean career orientation, Hall (2002, 2004) stated that a person could exhibit varying levels of self-directed and values, and suggested the existence of different career development profiles. However, the variable centered perspective ignores the possibility of subpopulations of individuals exist and develop their career differently. To address this issue, we conducted a study with a person-centered approach to gain a deeper understanding of how these factors combine to characterize individuals who are more likely to success in career development. Latent profile analysis was conducted among individuals in early career (N=767) to identify different distinct profiles of career development. Four profiles were identified. The first profile called *Idealist*, correspond to people displaying high levels of PCO and low level of motivation to learn. The second profile called *Protean career architect*, corresponded to individuals who more engaged in their career development, as they present higher level of PCO and motivation to learn. The third profile called *Pragmatic*, corresponded to individuals with moderate levels on each indicator. Similarly, the fourth profile called *Non-invested*, corresponded to individuals with low levels on each indicator. Result also show that *Protean career architect* exhibit the highest level of proactive career behaviors, behaviors with aim to improve their career, and learning behaviors with technologies followed by *pragmatic* profile, *idealist* profile and *non-invested* profile. This study is among the first to explore the career development profile and reveal new insights into its nature and how different individuals may develop it.

Key words: protean career orientation, latent profile analysis, career development, learning behaviors, Psycho-motivation to learn, future time perspective, proactive career behaviors

5.1 Introduction

Do we all possess the same aptitudes that allow us to progress and thrive in our career? This question is increasingly important as careers become more and more uncertain and are marked by insecurity (Alisic & Wiese, 2020). To deal with unpredictable and dynamic career environments, individuals need to develop the necessary skills and put in place the necessary behaviors that will allow them to efficiently take charge of their career and adapt to inevitable changes (Briscoe et al., 2012; Hirschi, 2018; King, 2004). To do so, adopting the right attitudes toward one's career is central. Research has shown that the Protean Career Orientation (PCO) enables people to thrive in their career and readily adapt to changing situations (Arthur & Rousseau, 2001; Hall, 2004). Protean career orientation is considered as an agentic orientation toward one's career, in which the person aspires to be self-directed in his or her career choices and guided by personal values (Hall, 2002). The notion of PCO stresses that a career is driven by the person rather than the organization, in response to the actual context which have shifted the responsibility of career development and the success in one's career from organizations to individuals (Hall et al., 2018). Additionally, as career paths are become less prescribed and not drive by organizations, individuals need to demonstrate motivation to learn to ensure their employability through learning (Bertolino et al., 2011) and their representation of the future play a key role to achieve their future goals (Treadway, et al., 2010).

The literature on career development has shown a strong interest in PCO as people who adopt this orientation proactively engage in career behaviors (e.g., networking, planning), which in turn lead to career progress and success (Hirschi & Koen, 2021; Herrmann et al., 2015; Wiernik & Kostal, 2019). Among all proactive career behaviors, Smale et al. (2018) have shown that three behaviors lead to an optimal career development as they entail individuals make a self-assessment of their capabilities and take concrete actions further their career. These three behaviors are networking, career planification, skill development. Moreover, we focus on the learning behaviors with technologies owing to the fact at digital age, these behaviors are become particularly relevant for career progress (Lent, 2018). Some authors have noticed technologies as a mean to develop and assist individuals in their career development (Davis et al., 2020; Beer & Mulder, 2020).

Although it has been posited that PCO should play an important predictor in the adoption of career behaviors (Hirschi, et al., 2017), empirical findings have rather found inconsistent association between PCO and its anticipated outcomes as career behaviors (e.g., networking, career planification, skills development) (Cakmak-Otluoglu, 2018). As PCO is multifaceted in nature, many have argued that people could adopt different combinations of PCO dimensions, which could result in different career success (Rojewski et al., 2017). Indeed, career orientation is not a one size fit all. As people have different orientation, they will engage differently in career development initiatives (Briscoe & Hall, 2006). Therefore, PCO dimensions could not be additive in nature (i.e., the more one displays each element the more success in career) but rather interactive. Thus, different combinations of PCO dimensions, which we will refer to as PCO profiles, would lead to different outcomes.

Additionally, studies typically rely on a single aspect of career development profile rather focusing on a set of variables which can explain how individuals can shape their career (Rojewski, et al., 2017). Cakmak (2018) point out that a focus only on PCO cannot fully explain how individuals develop their career. Consequently, it is needed to integrate motivation to learn and future time perspective insofar these two dimensions are considered as primordial in the understanding of the career success (Lens & Tsuzuki, 2007). The integration of motivation to learn and future time perspective enables us to understand the heterogeneity of career development profiles and provides the opportunities for an in-depth exploration of career development profiles and examine the characteristics of each profile.

Thus, the first aim of this study is to explore and determine empirical career development profiles of PCO, Motivation to learn and Future time perspective. The second aim of this study, is to investigate the link between career development profiles and proactive career behaviors and learning behaviors with technologies. As proposed earlier, this study assesses whether different career development profiles would lead in different levels of engagement in networking, career planification, skills development and learning behaviors with technologies. Through the identification of these profiles, we advocate that certain profiles are well-suited to success in modern career.

To achieve these two objectives, this study used a *person-centered* analytical approach, which allow for the identification of distinct career development profiles based on career orientation dimensions. Specifically, latent profile analysis (LPA), are used to identify profiles of PCO, Motivation to learn and Future time perspective and then explore how these profiles related to networking, career planification, skills development and learning behaviors with technologies.

5.1.1 Protean career orientation

Briscoe et al., (2006) operationalized PCO through two dimensions, *self-direction* and *values*. Self-direction captures the willingness of individuals to adapt to their career environment and the degree to which people assume responsibility for their career (Briscoe & Hall, 2006). *Values* capture the awareness of their identity and more specifically of their needs, motivations, and values, which serve as a guide for career decisions (Briscoe & Hall, 2006). Therefore, people adopting a PCO define their career success based on their own standard and actively manage to achieve their career goals (Hall et al., 2018).

According to the literature, high-PCO individuals have more career success as they thrive in the ambiguity and the uncertainty that characterize the actual career environment (Hall et al., 2018; Hirschi, 2018). In their meta-analysis, Li et al. (2021) showed that PCO is related to a set of relevant career outcomes such as career success (e.g. promotion, organizational status, salary). But, PCO is the dual component of self-direction and values and the interaction of these two dimensions which can explain the inconsistent results noted earlier in the link between PCO and career behaviors (Gubler et al., 2014).

Hall (2002, 2004) stated that a person could exhibit varying levels of self-directed career management and values-driven career orientation (e.g. low self-direction, high values; high self-direction, low values) and emphasized the existence of different career development profiles. In addition, the literature on Protean career seems to indicate that different levels of attitudes, motivation and context can explain discrepancies in terms of results (Baruch, 2014; Supeli & Creed, 2016). In the perspective to deepen our knowledge, a person-centered approach seem to be relevant, allows us to understand how a set of dimensions combine within individuals (Spurk et al., 2020) and allow researchers to understand how variables operate *conjointly and within people* to shape outcomes. To date, Briscoe & Hall (2006), are the first to theoretical hypothesize the presence of several career profiles through which individuals developed their career differently and these authors precise the need to operationalize their purpose by using a latent profile approach. Briscoe and Hall (2006) have developed a classification of different career profiles based on different combinations of PCO and boundaryless careers with high or low levels of self-direction, values, psychological and physical mobility. However, several authors have point out the fact the classification of Briscoe and Hall (2006) considered a narrow spectrum of characteristics for different subpopulations with a focus solely on PCO and boundaryless orientation and can be generated imprecision in the understanding of career development profiles (Cakmak, 2018; Rojewski et al., 2017). This is reason why PCO cannot fully explain engagement in proactive career behaviors and career advancement (Hall et al., 2018). Although researchers has omitted contextual factors as social support or career support, nonetheless research has strongly evidenced the role of motivation in the willingness to learn and future time perspective on developmental activities as career development (Major et al., 2006; Treadway et al., 2010)

5.1.2 Profiles with different combinations of protean career orientation, motivation to learn and future time perspective

As indicated earlier, researchers have long recognized the importance of motivation to learn and future time perspective in career development (Kooij et al., 2018; Major et al., 2006; Battistelli et al., 2007). The interest of future time perspective (FTP) in career literature has grown quickly recently (Kooij et al., 2018) and different views of the future can substantially affect how individuals act in their career (Trasher et al., 2018). Traditionally, FTP has been defined as one's perception of how much time they have left in their future and how they feel about that remaining time (Cate & John, 2007) and as a general concern for corresponding consideration of one's future. Zacher and Frese (2009) extended the concept of FTP to the context of work and career. They consider two dimensions of how individuals feel about their remaining time with a focus on opportunities and a focus on limitations. Focus on opportunities pertains to how many new goals, options, and possibilities people belief they have in their future at work. Focus on limitations pertains to perceptions of time remaining in people's career (Carstensen & Lang 1996; Rudolph et al., 2018). Individuals with a more open focus on opportunities are more likely to be oriented towards resources and seeking on how to further develop their career (Zacher & Rudolph, 2021). Similarly, research on FTP has shown that how much time people feel they have remaining in their career has an impact on outcomes (e.g., career planification, knowledge) (Fasbender et al., 2019).

Motivation to learn, largely been recognized to be relevant in career development (Maurer et al., 2003), is associated to the participation in training and development activities in order to learn new job skills, extend existing skills, or progress in their careers (Maurer & Lippstreu, 2008; Major et al., 2006). Considering the ever evolving labor market, people constantly engage in periodic cycles of skill learning and ‘‘reskilling’’ in order to reach new positions, jobs, and assignments (Froehlich et al., 2014). Consequently, a high level of motivation to learn is supposedly necessary to get involved in training activities. Motivation to learn encompasses the desire to engage in training and development activities, to learn training content, and to appreciate the training experience (Noe, 1986). Battistelli et al. (2007) point out that motivation to learn is oriented toward three goals, which are the motivation to learn in order to increase knowledge, to increase professionalism, and to career development.

The main goal of this study is to identify potential profiles of career development based on the classification of Briscoe and Hall (2006) and taking into account motivation to learn and future time perspective. We take an exploratory approach by virtue some authors have point out the fact that no theorized profiles can emerge (Cakmak-Otluoglu, 2018; Kuron et al., 2016; Rojewski et al., 2017)

Hypothesis 1: Do distinct profiles of career development (PCO, motivation to learn and FTP) that vary quantitatively (in level) and qualitatively (in shape) exist?

5.1.3 Outcomes of profile membership

In addition to identifying different career development profiles, we sought to explore how different career profiles may lead to different proactive career behaviors and learning behaviors with technologies, which are central to career progression a success (Smale et al., 2018; Venable, 2010). The literature on career development has emphasized the importance of these indicators because they allow people to develop their career despite uncertainty and despite a context where organizations are more disengaged in the career development of their employee. Indeed, studies have showed that these proactive career behaviors and learning activities foster objective and subjective career success (Spurk et al., 2015; De Vos et al., 2009).

First, proactive career behaviors are self-initiated, future-oriented and change inducing (Grant & Ashford, 2008) behaviors aimed at developing one's career (Seibert et al., 2001). This study is specifically interested in three proactive career behaviors, which are skill development, networking and career planning. According to Strauss et al. (2012), these three behaviors are the most relevant for career development and therefore central for people to achieve their career goals and success. Skill development refers to the development of new expertise in terms of knowledge, skills, and experiences (Claes & Ruiz-Catanilla, 1998). Networking refers to behaviors aimed at building, maintaining and using relationship that possesses the potential benefit of career advancements by the exchange of information and resources. This is a proactive way of creating access to social resources and seeking developmental feedback (Wanberg et al., 2020). Career planning refers to the deliberate efforts to outline future career developments, as well as to establish and pursue clear career goals and strategies (Gould, 1979).

Second, as we observe constant advancements in technologies and with the arrival of artificial intelligence, learning through technological means has become an important part of workers training, which includes career development activities (Bazine et al., 2020; Hirschi, 2018; Lent, 2018). Technologies are an important support in the learning process and in career development, as workers increasingly need to use technological tools collaborate, network, and seek feedback from others (Chan et al., 2015; Rashid & Ashghar, 2016).

Studies have shown positive relationships between PCO and proactive career behaviors (Creed et al., 2011; Herrmann et al., 2015), and with learning activities with technologies (Bazine et al., 2020). Additionally, as mentioned in the study of Van Gronendal et al. (2021) motivational profiles can influence the engagement in proactive career behaviors. The level of motivation to learn could shape proactive career behaviors and drive individuals to succeed in their careers. To extent which individuals can success in their career depends on how they regards their future and therefore the representation of future may affect the engagement in proactive career behaviors (Kooij et al., 2018; Strauss et al., 2012).

Further, research has found that career development profiles characterized by high levels of PCO seem to yield higher career behaviors (Cakmak, 2018). However, according to Hall et al. (2018), an interesting intrapersonal dynamic in the PCO is the interaction between self-direction and intrinsic values. Intrinsic values, within a protean orientation, can guide people in actively making meaning through career decisions and transitions, as opposed to a reliance on externally defined sources of meaning. However, a focus on intrinsic values alone, without self-direction, may be maladaptive. As Briscoe & Hall (2006) noted, being values oriented but not self-directed can result in a rigid career orientation and may even inhibit career proactivity. In sum, we stipulate that certain career development profiles can demonstrate different levels of proactive career behaviors.

Thus, it is expected that each different profiles could be demonstrate different levels of proactive career behaviors and learning behaviors with technologies and allow us to determine the profile most suited to thrive in contemporary career.

Hypothesis 2: Career profile membership relate differentially to proactive career behaviors (planning, skill development and networking) and learning behaviors with technologies?

5.2 Method

5.2.1 Sample and Procedure

A sample of 767 French participants was recruited through online platforms using LinkedIn social network and students at the University of Bordeaux. Participation to this study was voluntary, no incentive was offered, and all participants gave their inform consent. Data was collected during the academic year 2019-2020 before the COVID 19 pandemic. To participate in this study, respondents needed to be either at the end of their studies during their transition from university to work and have professional experience in their field of study or to be working in their first job after graduation for no longer than 3 years. The final sample was composed of 352 (45.9%) students with professional experience and 415 (54.1%) young professionals. Among them, 526 (68.5%) identified as women and 241 (31.5%) as men, with an average age of 26.20 years (*SD* = 7.60). Participants came from STEM (71.7%), Human Sciences (19.73%), and Medical Sciences (9.6%). Finally, the participants' education was as follows: 516 had a master's degree (67.23%), 144 had a bachelor's degree (18.8%), and 107 had a doctorate degree (14.0%).

5.2.2 Measures

All measures were originally developed in English, except for motivation to learn and learning behaviors with technologies which were initially created and validated in French. Thus, they were translated to French using the back translation procedure (Brislin, 1980). For all measures, responses were scored using a five-point agreement ranging from 1 (Not at all) to 5 (Totally).

Protean career orientation (PCO) was assessed using Direnzo et al., (2015) 12-item scale. This scale is composed of two dimensions, namely *value (PCO-V)* (6 items; α = .80) and *self-direction (PCO-SD)* (6 items; α = .85). Sample items for the *value* and the *self-direction* dimensions are respectively "My career is guided by opportunity to achieve personally meaningful values" and "I am responsible for expanding my career-related skills and knowledge."

Future time perspective (FTP) was assessed using Zacher and Frese (2011) 4-item scale (α = .85). Sample items for future time perspective include "Many opportunities await me in the future" and "I can achieve anything I want in my professional future."

Motivation to learn (ML) was measured using Battistelli et al. (2007) 10-item scale. This scale is composed of two dimensions, which are *motivation to improve one's career (ML-C)* (6 items; α = .88) and *motivation to improve knowledge and competencies (ML-K)* (4 items; α = .85). Sample items for each dimension respectively include "I desire to improve my professional competencies" and "I hope that this will open up more professional opportunities."

Learning behaviors with technologies (LBT) were measured using Bazine et al. (2020) 11-item scale. This scale comprises two dimensions *media (LBT-M)* (4 items; α = .80) and *support (LBT-S)* (7 items; α = .88). Sample items for *media* and *support* are "I use digital technologies to increase my knowledge in my domain" and "I actively seek new technologies to help with my learning needs."

Proactive career behaviors (PCB) were assessed using 11 items from Strauss et al. (2012) scale. This measure is composed of three dimensions, *planification (PCB-P)* (4 items; α =89), *skill development (PCB-S)* (3 items; α = .82) and *networking (PCB-N)* (4 items; α = .89). Sample items for each dimension include "I am planning what I want to do in the next few years of my career," "I develop skills which may not be needed so much now, but in future positions," "I am building a network of contacts or friendship to provide me with help or advice that will further my work chances."

5.2.3 Analyses

All analyses were conducted on Mplus 8.4 (Muthen and Muthen, 2017) using the maximum likelihood robust estimator (MLR).

5.2.4 Measurement Invariance

To ensure there was no measurement bias between students that were transitioning to their work life and young professionals already working, we first started by conducting multigroup analysis (Millsap, 2011). Multigroup analysis consists in sequence of nested confirmatory factor analysis (CFA) models estimated across groups. Specifically, six different models are estimated, where various model parameters are progressively fixed to be equal across groups in the following order: (i) configural (i.e., same factor structure); (ii) weak (i.e., fixed factor loadings); (iii) strong (i.e., fixed factor loadings and intercepts); (iv) strict (i.e., fixed factor loadings, intercepts, and uniquenesses); (v) partial variance/covariance (fixed factor loadings, intercepts, uniquenesses, and factors variances/covariances); (vi) latent means (fixed factor loadings, intercepts, uniquenesses, factors variances/covariances, and latent means; Millsap, 2011; Morin et al., 2011). Each model was compared using Chen (2001) cut-off criteria for nested model comparisons. More precisely, models differing by less than .010 for CFI and TLI, and less than .015 for RMSEA are considered equivalent. The absence of difference between models up to strict invariance is a mandatory and sufficient condition to support the measurement invariance (i.e., absence of measurement bias) across groups. Latent variance/covariance and latent means are not mandatory, but rather assess the presence of meaningful difference across groups. As we were interested in profiles of likely to success in career development. We conducted a multigroup analysis.

5.2.5 Latent Profile Analysis

LPA was performed using factor scores saved from the most invariant CFA models from the multigroup tests (Morin & Marsh, 2015). In comparison with scale scores, factor scores have the advantage to provide a partial control for measurement error (Morin & Marsh, 2015; Skrondal & Laake, 2001). Factor scores are also estimated in standardized units with a $M = 0$ and $SD = 1$, which simplifies comparisons between profiles.

LPA were estimated on Career development profiles using 3000 sets of random start values, with 100 best sets used for final optimization, and 100 iterations for each random start (Hipp & Bauer, 2006; Morin & Wang, 2016). As recommended by Nylund, et al. (2007), we began by specifying one latent profile and increased the number of latent profiles until the increase in model no longer merited the reduction in parsimony achieved by specifying another latent class. The selection of the optimal number of profiles was first and foremost based on their theoretical adequacy (Foti, et al., 2012; Marsh et al., 2009; Muthén, 2002). Further, as recommended by Gabriel et al. (2018), Nylund et al. (2007), and Tofighi and Enders (2007), the number profiles was determined based on a series of statistical indices: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample-Size-Adjusted BIC (SSA–BIC; recommended by), adjusted Lo Mendell and Rubin's (2001; aLMR), Likelihood Ratio Test (LRT), Bootstrap Likelihood Ratio Test (BLRT). For AIC, BIC, and SSA–BIC lower values should indicate a better fitting model. For aLMR, LRT, and BLRT, a significant p value supports the number of profiles it is associated with compared with a model with one fewer profile. With large sample, these statistical indicators often suggest the addition of profiles as they do not reach a minimum value (Marsh et al., 2009). In these situations, it is recommended that the point at which information criteria (i.e., AIC, BIC, and SSA-BIC) reach a plateau on an elbow plot, can be used to select the optimal solution (Morin & Wang, 2016; Morin et al., 2011). Entropy was also reported as it provides a summary of the accuracy of participants' classification. Specifically, entropy should be larger in comparison to other profile solutions.

Finally, PCO-V, PCO-SD, ML-C, ML-K and FTP were contrasted between profiles using the Mplus DU3STEP command. This function relies on the use of a 3-step method that sets a latent categorical variable to explore relations to distal outcomes and is useful when auxiliary variables have unequal means and variances (Asparouhov & Muthen, 2014).

Table 5.1 *Means, Standard Deviations, Reliability, and Correlations Between Variables in the Present Study*

	Means	SD	1	2	3	4	5	6	7	8	9
1. PCO-SD	3.93	.70									
2. PCO-V	3.81	.74	.49**								
3. LBT-S	2.78	.95	.25**	.27**							
4. ML-K	3.99	.86	.29**	.24**	.45**						
5. ML-C	3.51	1.04	.28**	.28**	.33**	.53**					
6. PCB-P	3.16	1.05	.37**	.38**	.30**	.24**	.30**				
7. PCB-S	3.43	.95	.36**	.31**	.38**	.30**	.28**	.48			
8. PCB-N	3.09	1.06	.32**	.36**	.30**	.25**	.36**	.51**	.45**		
9. FTP	3.64	.91	.20**	.13**	.14**	.15**	.16**	.16**	.20**	.18**	

** $p<.001$

5.2.6 Results

Means, standard deviations and correlations are presented in Table 1. Fit indices from the multigroup analysis are reported in Table 2. The results supported the invariance of up to mean invariance across students and young professionals, as each model presented acceptable fit indices and there was no difference in fit indices exceeding the criteria previously presented. Thus, the generalizability of the solutions across sample is supported. Thus, independent and dependent variables factor scores were pooled together for further analysis.

Table 5.2 *Results From Measurement Invariance Analyses*

Models	χ^2 (*df*)	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$ (Δ*df*)	ΔCFI	ΔTLI	ΔRMSEA
Invariance across Career development Profile									
Configural invariance	1235.860 (578)*	.912	.901	.054	.050; .059	-	-	-	-
Weak invariance	1266.789 (599)*	.911	.903	.054	.050; .058	30.929 (21)	-.001	+.002	.000
Strong invariance	1307.568 (620)*	.908	.904	.054	.050; .058	40.779 (21)*	-.003	+.001	.000
Strict invariance	1351.317 (646)*	.906	.905	.053	.049; .057	43.749 (26)*	-.002	+.001	-.001
Variance – covariance invariance	1429.065 (661)*	.898	.899	.051	.051; .059	77.748 (15)*	-.008	-.006	-.002
Partial variance – covariance invariance	1391.044 (657)*	.902	.903	.054	.050; .058	39.727 (11)*	-.004	-.002	+.001
Mean invariance	1408.012 (662)*	.900	.902	.054	.050; .058	16.968 (5)*	-.002	-.001	.000
Invariance across outcomes									
Configural invariance	746.238 (258)*	.917	.902	.070	.064; .076				
Weak invariance	763.579 (272)*	.917	.906	.069	.063;.074	17.341 (14)	.000	+.004	.001
Strong invariance	817.586 (286)*	.910	.904	.070	.064; .075	54.007 (14)*	-.007	-.002	-.001
Strict invariance	848.961 (304)*	.908	.907	.068	.063; .074	31.375 (18)*	-.002	+.003	.002
Variance – covariance invariance	859.725 (314)*	.908	.910	.067	.062; .073	10.764 (10)	.000	+.003	.001
Mean invariance	870.828 (318)*	.906	.910	.067	.062; .073	11.103 (4)	-.002	.000	000

Note: χ^2 = Chi-square test of exact fit; *df* = Degrees of freedom; CFI = Comparative fit index; TLI = Tucker-Lewis index; RMSEA = Root mean square error of approximation; CI = Confidence interval for the RMSEA; Δ = Change in fit relative to the precedent model.
*p < .05.

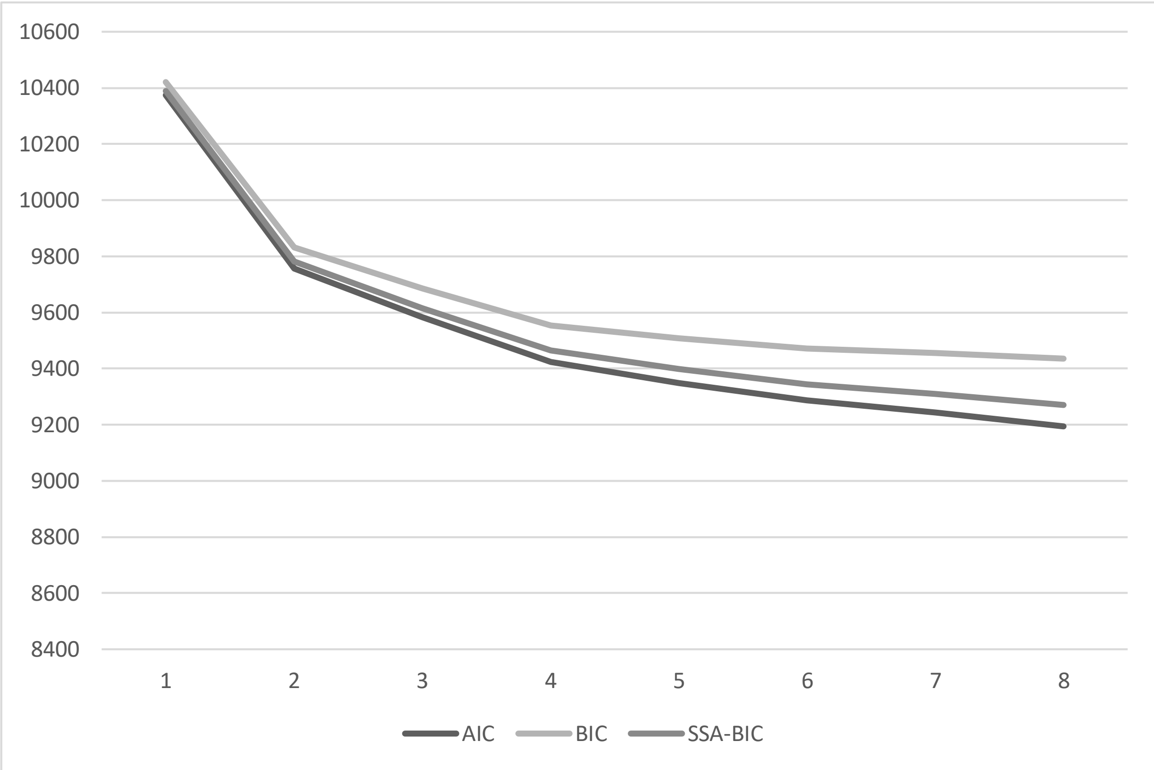
Indices from the LPA analyses including 1 to 8 profiles are reported in Table 3. The aLMR suggested that the retained solution should have a maximum of five profiles. On the contrary, AIC BIC, SSA-BIC, and BLRT failed to reach a minimum value and thus converge on a specific solution as it is often observed in large samples. We thus considered the graphical display of the information criteria (see Figure 1). These indicators appeared to reach a plateau between the 4-profile and 5-profile solutions. Both solutions presented theoretical adequacy. However, as their profiles were similar, the 5-profile solution only added a spurious profile that reflected less than 3% of the sample and no meaningful difference between them. According to Spurk et al. (2020), in LPA a profile with a sample size inferior to 25 cases or inferior to 3 %, should be rejected as it is more hardly generalizable. In our cases, the spurious profile represents 16 cases and 2% of the set of populations. Therefore, the 4-profile solution was retained.

Table 5.3 *Fit statistics for latent profiles structures*

Model	LL	FP	AIC	BIC	SSA-BIC	aLMR	BLRT	Entropy
1 Class	-5177.076	10	10374.152	10420.577	10388.823			
2 Class	-4862.414	16	9756.828	9831.107	9780.30	<.01	<.01	.728
3 Class	-4769.756	22	9583.513	9685.647	9615.787	<.01	<.01	.763
4 Class	**-4684.199**	**28**	**9424.399**	**9554.388**	**9465.476**	**<.01**	**<.01**	**.748**
5 Class	-4640.469	34	9348.937	9506.782	9398.817	<.01	<.01	.787
6 Class	-4603.008	40	9286.017	9471.716	9344.698	.27	<.01	.768
7 Class	-4575.471	46	9242.942	9456.496	9310.426	.13	<.01	.809
8 Class	-4545.002	52	9194.004	**9435.413**	9270.290	.09	<.01	.781

N =767; AIC: Akaïke Information Criteria; BIC: Bayesian Information Criteria; SSA-BIC: Sample-size adjusted BIC; aLMR: Adjusted Lo-Mendell-Rubin Likelihood Ratio Test; BLRT: Bootstrap Likelihood Ratio Test.

Figure 5.1 *Elbow plot of the Bayesian information criterion (BIC), Akaike information criterion (CAIC) and Sample-size adjusted bayesian information criterion in determining profile solution*



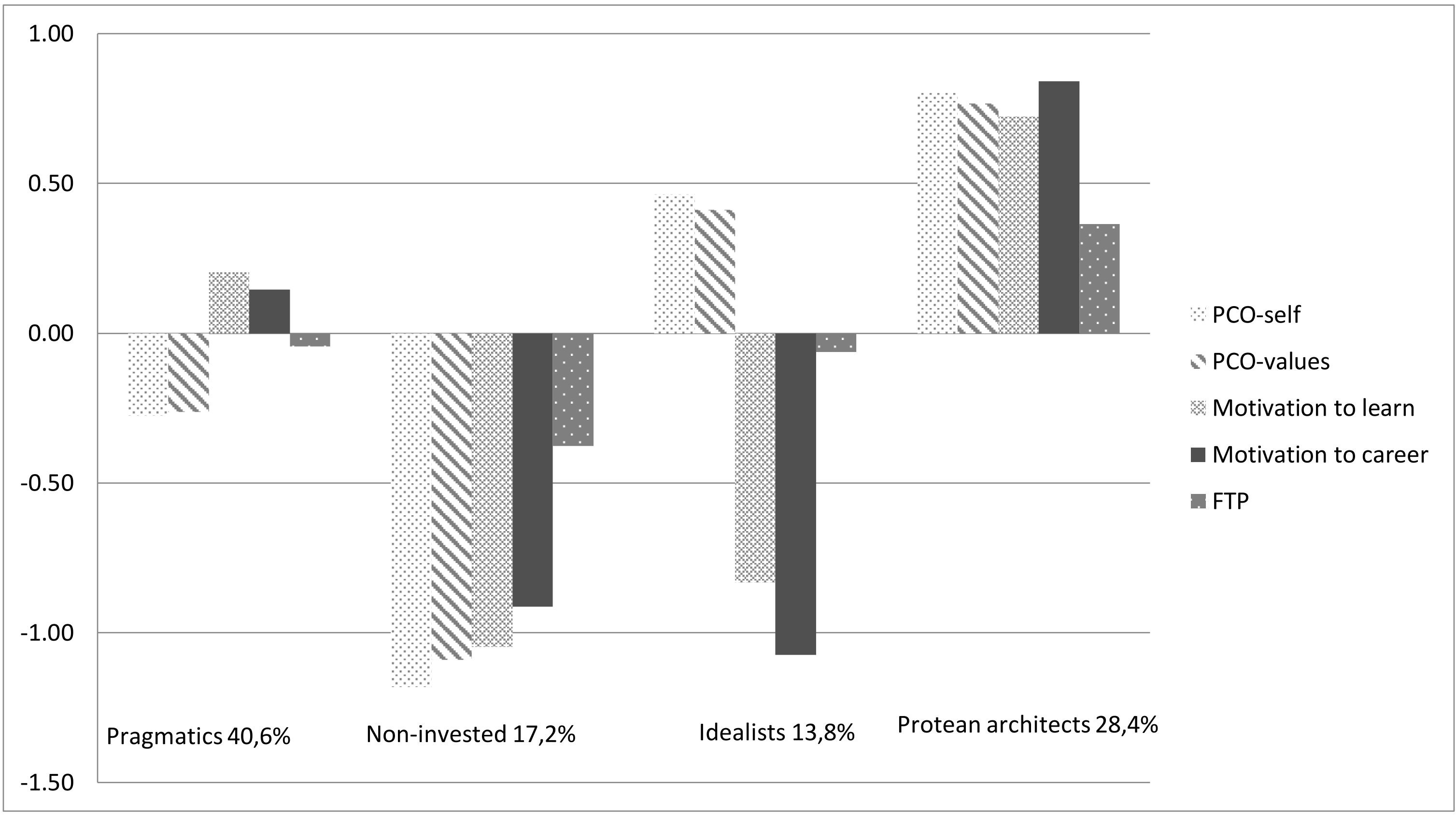
The mean levels of each dimension of career development profiles dimensions are reported in Fig. 2. The first profile, which represented 40.6% of the cases, was characterized by slightly lower than average levels of self-direction and values-driven protean career orientation. It also presented a slightly higher than average levels of motivation to learn towards their career and motivation to learn to improve their knowledge. Finally, a near-average level of future time perspective was observed. We labelled these individuals as *pragmatics*, because they demonstrate some motivation to make more strategies and learning for progress in their career even though their career involvement was slightly lower than average. The second profile, which represented 20.2% of the participants, was characterized by very low levels of values-driven, self-direction, motivation to learn towards their career, motivation to learn to improve their knowledge. It also presented a level of future time perspective that was closer to average compared to the other independent variables. We labelled these individuals as *non-invested* given their very low involvement in their career development. The third profile, with 13.8%, was characterized by high levels of values-driven and self-direction orientations, accompanied with low levels of motivation to learn towards their career and motivation to learn to improve their knowledge, and a near-average level of future time perspective. We labelled these individuals as *idealists* given their willingness to develop their career, couple with low motivation to put in the necessary effort to achieve their goals. The fourth and last profile represented 28.4% of the sample and was characterized by higher than average levels on all variables included in this analysis. We labelled these individuals as *protean career architects*, because they demonstrate a high involvement in career development and a high motivation to attain their objectives.

Table 5.4 *Descriptive Information per Latent Profile*

Profils	% de l'échantillon	PCO auto-direction	PCO valeurs	Motivation à apprendre	Motivation à apprendre carrière	Future time perspective
1	40.6%	-0.275	-0.263	0.203	0.145	-0.044
2	17.0%	-1.182	-1.091	-1.047	-0.912	-0.376
3	13.8%	0.463	0.411	-0.833	-1.074	-0.062
4	28.4%	0.801	0.767	0.724	0.841	0.385

N =767;

Figure 5.2 *Profiles of career development (N=747)*



We then applied the DU3STEP command in Mplus 8.4 by including auxiliary variables for testing the relationship between different profiles and career outcomes. Means and standard deviations of the outcomes in each profile are reported in Table 5. Tests of difference between the four profiles on each of the outcomes are presented in Table 6. Regarding the three career behaviors (i.e., *planification, skill development, and networking*) results showed significant differences among the four profiles. The *protean career architects* profile exhibited the highest levels on all three career behaviors comparatively to other profiles. The *pragmatics* profile and *idealists* profile levels on career behaviors were not statistically different. However, these two profiles showed statistically higher levels on career behaviors than *non-invested*, which presented the lowest levels of on all three career behaviors.

Table 5.5 *Three-step results for outcomes of career profile (DU3STEP)*

	Career behaviors Planification		Career behaviors Skill development		Career behaviors Networking		Learning behaviors with technologies Support	
Latent Profile	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Pragmatic	-0.176	.06	-0.122	.04	-0.161	.06	0.020	.05
Non-invested	-0.876	.07	-0.907	.07	-0.726	.09	-0.771	.07
Idealist	-0.067	.10	-0.057	.09	-0.194	.10	-0.516	.12
Protean career Architect	0.776	.10	0.713	.06	0.699	.07	0.663	.07

Moreover, we found significant differences among the four profiles on learning behaviors with technologies. The *protean career architects* exhibited the highest level of learning behaviors with technologies-support comparatively to other profiles. The *pragmatics* demonstrates a higher level than the *idealists* and *non-invested*. Finally, *idealists* and *non-invested* demonstrate equal level of learning behaviors with technologies, which were also the lowest levels observed.

Table 5.6 *Outcomes and pairwise comparisons between profiles*

	Profile comparisons						Summary of comparisons
	1 vs 2	1 vs 3	1 vs 4	2 vs 3	2 vs 4	3 vs 4	
Planification	-0.701**	-0.109	0.952**	-0.809**	1.652**	0.843**	2<1=3<4
Skill development	-0.785**	-0.065	0.835**	-0.850**	1.620**	0.760**	2<1=3<4
Networking	-0.565**	0.033	0.860**	-0.532**	1.425**	0.893**	2<1=3<4
LBT-support	-0.791**	-0.536**	0.643**	-0.255	1.434**	1.179**	2=3<1<4

* p <0.05 ; ** p < 0.01

5.3 Discussion

This study had two objectives. First, it was to establish if individuals develop their career differently by showing the existence of specific career development profiles. Second, it was to determine the profile the most suited in contemporary careers by the establishment of the link between career development profiles and proactive career behaviors and learning behaviors with technologies (Smale et al., 2018). This research advances the literature owing to the fact, the majority of study on protean career orientation and career development has focused on a variable centered approach. The person-centered analysis of this study adduces a more nuanced examination of the career development allowed us making an overarching contribution to the literature on career. These findings provide an important insight into how individuals develop their career. The major contribution of this study is to demonstrate that individuals develop their career differently and reinforce the purpose of Briscoe and Hall (2006). We also sought to expand our understanding of career development profiles by demonstrating how different career development profiles are related to relevant outcomes to thrive in contemporary careers.

In alignment with Hypothesis 1, our results revealed four profiles which varied in the level and in the shape (Spurk et al., 2020). The results support our first hypothesis by showing that individuals develop their career differently. The profiles extracted fit with our assumption, the integration of motivation to learn and future time perspective has allowing to sharpen our understanding of career development profiles and looking beyond protean career orientation to understand the career profile and the experience of individuals.

In turn, these profiles were associated with different levels of two indicators which lead to career success: proactive career behaviors and learning behaviors with technologies. These findings provide an important contribution to the literature on how career profiles affect career behaviors, within our sample, we are able to characterize individuals as mostly likely to succeed in their career. In addition, the differing outcomes of Profiles 1 and 3 offer a vivid representation of the mixed effects of PCO found in the literature (Hall et al., 2018). As mentioned previously, that those high levels of motivation to learn and FTP may potentially facilitates career development, and emphasized the importance of integration of the two variables for understand the most suited career development profile.

First, *protean career architect* profiles seem to suggest they are individuals which are well-suited to success in modern career by demonstrating the higher level of PCO and motivation to learn and moderate level of future time perspective. This profile is considered as the most suited to thrive in career development inasmuch as they demonstrates a higher level of proactive career behavior and learning behaviors with technologies comparatively to other profiles.

Second, *pragmatic* profile seems to suggest they are individuals who are more seeking opportunities to develop their career than accomplish their inner values. This profile is characterized by moderate level of PCO but with high level of motivation to learn and moderate level of future time perspective. This profile demonstrates a higher level of proactive career behavior and learning behavior with technologies than idealist profile and non-invested profile. This profile seems to be well-adapted to modern career because they demonstrate important level of proactive career behaviors and learning behaviors.

Third, *idealist* profile seems to suggest they are individuals guided by their values with high levels of PCO but demonstrate low levels of motivation to learn and show moderate levels of future time perspective. This profile demonstrates a higher level of proactive career behavior and learning behavior with technologies only than *non-invested* profile. This profile seems to be limited to thrive in modern careers and can struggle to accomplish their values because they demonstrate a moderate low level of career behaviors and learning activities.

Four, *non-invested* profile are individuals which don't take care of their career and depend on luck to obtain a job or grow in their career. The low level in each dimension captures that these individuals are not involved in their career development with the level of proactive career behaviors and learning activities very low.

Another contribution of this study is to gain deeper insights into the ways different career development profiles use technologies for career development. Over the past 10 years, research focused on the relation between career development and technologies have greatly enhanced (Lent, 2018; Davis et al., 2020). However, research is still lacking on how individuals use them. In first, this study shows the disparities between different career profiles in the use of technologies. Our advances our knowledge by showing that individuals use technologies as support differently. The feedback seeking for career development from long-distance learners including knowledge status, advice seeking for improving skills in order to improve their career and sharing relevant content is depending of career profile. In addition, this study reinforces the fact that the use of technologies for career development could be an asset but uniquely if individuals recognize the potential of these technologies and hence are motivated to develop their career.

5.3.1 Practical implications

Our findings also have some practical implications. Our results suggest that organizations or guidance consulting companies should pay more attention to how individuals may manage their career because different career development profiles exist and emphasized the need to personalize the guidance in order to support the career development which fit with the need of different profile (Kraimer et al., 2011). To help workers and graduates to manage their career, a counselor could place more significance in different interventions based on individual characteristics. For instance, for idealist individuals who are in stressful professional situations, the counselor could center these support to increase training and learning for they attain and develop the requirements to apply in jobs which fit with their values (Hall et al., 2018).

5.3.2 Limitations and future directions

Despite the theoretical and practical implications previously displayed, our study has some limitations. The nature of our data which is cross-sectional presents some limitations. Cross-sectional data limits our ability to assume the temporal stability of profiles but also to interpret causality between profile membership and outcomes (Kam et al., 2016). For example, with longitudinal data and through the application of latent transition analysis (Wang & Chan, 2011), it is possible to fill a number of limitations notably the stability of profile in time. In addition, more studies are necessary because the error classification must be taken into account in a person centered approach (Gabriel et al., 2018), consequently the generalizability of our findings should be made with caution. Through the use of multiple different samples, this allow us to verify and confirm the results found (Wang & Hanges, 2011).

To further our understanding of the career profile, future research should focus on extending the person-centered approach to integrate other variables associated with career development such as self-regulation strategies, feedback seeking, etc… Future research should examine the results in time of the career profile and confirm that profile can be associated with career development by focusing on metrics of career development such as career success, salary or again promotion. To do so, for instance by using LTA with the aim to demonstrate the flexibility or stability of profile in time or studying the impact of career development profiles over 2 years on career success.

From a more theoretical perspective, it would be interesting for future studies to gathered a more diverse sample in terms of age, because as demonstrated by the FTP' literature age is greatly associated to the representation of future (Kooij et al., 2018). Our results can highlight only few difference between profiles in terms of future time perspective and we suppose it was due to the relatively young population of our sample.

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Chapter 6 Article 4 : Protean career orientation as a compass for career development in digital age

Abstract

This study aims to make an evidence how technologies can serve to career development. To do so, we explore the relationship between Protean career orientation (PCO) and proactive career behaviors by focusing on the mediating role of Psycho-Technological Environment (PTE) and learning behaviors with technologies. Structural equation models have been conducting to empirically analyze two waves time lagged survey data stemming from students with a professional experience at University of Bordeaux. Our results confirm the mediating role of PTE and learning behaviors with technologies. This study advances our knowledge on career development by demonstrating that learning with technologies can lead career behaviors relevant for career advancement. PCO allows to recognize the opportunities in technological environment and these opportunities lead to learning behaviors with technologies which lead to career behaviors. These findings offer guidance for career counselors that aim to strengthen career development, highlighting how technologies can be benefit for individuals for the de career development.

Key words: Protean career orientation, technology, learning behaviors, Psycho-technological environment, opportunities, proactive career behaviors

6.1 Introduction

Technological developments and digitalization have profoundly changed the workplace and career (Cascio & Montaelegre, 2016). Hirschi (2018) emphasized that the advent of the 4th industrial revolution produced an amount of challenge for the workers and especially for their career development. The changes have fundamentally transform tasks and required skills in most jobs and occupations and will pursue over the coming decades (Arntz et al., 2016). Nowadays, employees must constantly develop new skills, reskilling and up-skilling (World Economic Forum, 2018). In addition, careers are characterized by more frequent transitions and non-linearity (Hall et al., 2018) with professional retraining, changing position, job or organization. It also means that workers need to be able to deal with unpredictable and dynamic career environments which call for more self-directedness in career development (Hirschi & Koen, 2021).

In accordance with the increasingly dynamic career environment and the increasing number of workers in charge of their career, there has been extensive research on career self-management (CSM) (Hirschi & Koen, 2021). King (2004) defines career self-management as the process by which individuals develop, implement and monitor career goals and strategies. Career self-management is expressed by the set-up of a set of behaviors and attitudes (Strauss et al., 2012; Claes & Ruiz-Quintanilla, 1999; Eby et al., 2003). Multiple authors have demonstrating that these career behaviors are the way to attain career success (Spurk et al., 2015). In their review, Hirschi and Koen (2021) demonstrate that career self-management is greatly related to specific career orientations. These authors emphasized that the most studied and the most adapted to thrive in modern career is the protean career orientation (PCO), notably, because this career orientation is the most associated with career behaviors (Wiernik & Kostal, 2019).

The changes bring by the 4th industrial revolution seem to be an asset for individuals and some authors strive to understand how individuals can use technologies for their career development (Hirschi, 2018). However, our knowledge on how individuals can integrate technologies in their career development as well as how these technologies transform the career experience still lacking (Hirschi, 2018). Multiple studies have highlighted that technologies can be a support for career development by facilitating the set-up of specific behaviors (Davis et al., 2020; Krings et al., 2021).

The last great wave of technological innovation is not about one technology. The next one may well feature the emerging general technology paradigm known as technological ubiquity. The technological ubiquity refers to the fact that the technologies have penetrated every part of our lives (work, family and leisure time) especially because the number of technologies has exceeded the number of people and because individuals can no longer perform any activity without technologies (Mohindru, Mondal, & Banka, 2020). The technological ubiquity is not only an aspect of technological evolution but represents a context that has the potential to modify the traditional ways of learning (Landers & Marin, 2021). This new Psycho-Technological Environment (PTE) (Bazine et al., 2020) is derived from the individual's perception of the merging of the physical and digital worlds due to the technological ubiquity (Colbert et al., 2016; McFarland & Ployhart, 2015). PTE is characterized by the interactions between human and technology and is defined by a set of opportunities and constraints affecting behaviors and beliefs (Johns, 2006; McFarland & Ployhart, 2015). Therefore, it is important to examine the antecedents of PTE and the extent to which this perception is related to increased career behaviors by learning behaviors with technologies. Examining these issues will extend our understanding of how technologies can help for career development (Lent, 2018).

In this study, we claim that protean career orientation (PCO) can be an antecedent of PTE and learning activities with technologies because this orientation allows individuals to identify opportunities offered by the environment which lead to career behaviors. The aim of the current study is to examine whether career orientation (PCO), which reflects an agentic orientation toward one's career, in which the person aspires to be self-directed in his or her career choices and guided by intrinsic values (Hall, 2002), can serve as an antecedent of PTE and learning behaviors with technologies (LBT). To further, this research posits a processual model linking of individuals with high protean career orientation using learning potential of PTE as an intermediate for career development.

This research intends to make four contributions to career development. First, the present study is one of first attempts to look at how technologies can be helpful for the process of career development. It extends the current literature on career development by suggesting that PTE and learning behaviors with technologies are related to career behaviors. By examining the joint relationship of PCO, PTE, LBT and career behaviors, this aims at providing further evidence on the relationship between technologies and career development (Venable, 2010). Second, we examine that PCO can be an antecedent of PTE which contribute to the literature of career development and technologies by demonstrating that the individuals' perceptions of PTE can be shaping by individual differences (Barrick & Mount, 1993; Hall et al., 2018). Third, we advance the literature of career development by demonstrating that LBT can activate career behaviors. And furthering away in how technologies usage can be benefit for career development. Finally, we contribute to the career literature by emphasizing the importance of technologies for career development. We introduce PTE and LBT as sequential mechanisms through which protean career orientation relates to career behaviors. This helps to clarify how individuals can use the resource of technological ubiquity for their career development.

6.1.1 Protean career orientation as antecedent of Psycho-technological environment

Hall (1976) was the first to describe the protean career orientation (PCO) which refers to an agentic orientation toward one's career where the person is self-directed in his career choices that are guided by intrinsic values. Briscoe et al. (2006) identifies two dimensions of PCO: *self-direction* and *values*. *Self-direction* captures the willingness of individuals to adapt to their career environment and the degree to which people assume responsibility for their career (Briscoe & Hall, 2006). *Values* capture the awareness of their identity and more specifically of their needs, motivations, and values, which serve as a guide for career decisions (Briscoe & Hall, 2006). Therefore, contrary to a situation where one's career depends on his/her organization, people adopting a PCO define their career success based on their own standard and actively manage to achieve their career goals (Hall et al., 2018).

As noted previously, the antecedents of PTE are not well understood. Building on the notion that personal experience or personal characteristic shape the perception of an environment (Kozlowski & Farr, 1988; Schneider et al., 2000; Kraimer et al., 2011), we propose that individual's level of PCO contribute to the perception of PTE. This assumption is based on this specific orientation which allows individuals to recognize and seek opportunities in their environment for developing their career (Redondo et al., 2021). Protean individuals strive in an agentic way to find and identify possibilities or actions in order to improve their career and knowledge (Waters et al., 2014). And as noted previously, technological ubiquity can be important resource that individuals with high protean orientation can use for growth. Despite studies showing that the combination of two dimensions demonstrate greater variance in positive outcomes (Briscoe et al., 2010), the focus here is only the engine of agentic way of protean individuals to the perception of PTE, consequently we not consider values because values represent direction and not the fuel for actions.

PTE is composed by two dimensions, *opportunities* and *accessibility*. *Opportunities* refer to the perception that the environment offers different technological resources and facilitations for learning (Bazine et al., 2020; Dunn & Kennedy 2019; He & Li 2019). The diverse technologies offer innovative learning methods (cooperation, gamification, MOOC, etc.) and richness of contents that has never been seen before (Warschauer, 2007). Thus, these various technologies create a specific environment perceived as being more flexible, rich and favorable for self-learning experience (Brown et al., 2016). Sung, Chang and Liu (2016) in their meta-analysis highlighted that learning is stimulating in an environment where several technologies are integrated with multiple uses. This integration allows individuals to improve their learning by using technologies that can compensate for the shortcomings of each different learning method (Motsching-Pitrik & Standl, 2013).

Accessibility captures the perception that technologies are more accessible, easy to use and can alleviate several constraints such as access to resources, the place where you learn and the possibility to share content (Beier 2019; Maurer et al., 2003). Individuals who perceive that situational constraints exist in their environment, develop weak positive attitudes toward learning that result in lower levels in learning activity (Noe & Wilk, 1993).

In sum, we make the assumption that PCO-self-direction contribute to the perception PTE as learning potential and allows individuals to recognize and identifies opportunities providing by technologies in their environment, for learning and development

Hypothesis 1: Protean career orientation-self-direction is positively related to psycho-technological environment opportunities

Learning behaviors with technologies refer to a large panel of actions that contribute to the acquisition of skills through the use of technologies such as mobile, computers, etc. (He & Li, 2019). The specificity of learning behaviors with technologies is the ability to broaden learning possibilities (Shen & Ho, 2020). For instance, technologies allow receiving feedback from long-distance learners including knowledge status, advice on how to improve skills, sharing relevant content (Beier, 2019). Also, individuals can manage the learning process at their pace, needs and goals thanks to a larger repertoire of contents (Brown et al., 2016; Bell & Kozlowski, 2008). Consequently, individuals can use technologies in different ways: as a *media* (tool) or *support* (integrator) (Bazine et al., 2020). The first dimension, *media,* refers to the technologies allowing to acquire knowledge and to develop skills (He & Zhu, 2017; Noe et al., 2014). Technologies act as a tool/media because they can allow individuals to have access to information, content and generally to resources for learning (Bell & Kozlowski, 2009). The second dimension, *support,* captures the fact that technologies could be a support for the learning process, for example the learner can use technologies to seek feedback from others and adopt the collaboration approach (Chan et al., 2015; Rashid & Ashghar, 2016). The flexibility and the variety of possibilities offered by technologies have the advantage of better answer to the individual's needs (Dyson et al., 2015).

According to the literature on learning potential (Nikolova et al., 2014), an environment which provides opportunities to learn is associated with learning behaviors. If individuals have access to sufficient opportunities to learn and have the possibility to experiment new ways of learning, they can activate more behaviors for improving knowledge and skills (Kozlowski & Hults, 1987; Noe & Wilk, 1993). Moreover, Farr and Middlebrooks (1990) underline the importance of individual perception of having sufficient resources for developing relevant skills. Several studies have postulated that insufficient resources can be considered as situational constraints because they develop the perception that efforts to engage in developmental activities would be less beneficial (Nikolova et al., 2016). We propose a research model that draws on the learning climate literature and recent studies (Nikolova et al., 2014; Sung & Choi, 2014) to hypothesize that an environment with many resources to learn triggers more learning behaviors. Consequently, we make the assumption that the PTE-opportunities may enhance learning behaviors

Hypothesis 2: Psycho-technological environment-opportunities is positively related to learning behavior with technologies-support

According to the literature on Protean career, high protean individuals demonstrate more behaviors oriented to the development of knowledge and skills (Smale et al., 2018). But it's not enough investigated about the relationship between PCO and learning activities with technologies. Drawing on the study of Bazine et al. (2020), learning activities with technologies depend on the perception that the environment provides sufficient resources in terms of multiple technologies which allow to facilitate their knowledge and skills development. Although, research has demonstrated PTE motivates individuals to participate in learning behaviors with technologies (Bazine et al., 2020), we believe that PTE mediates the relationship between PCO and learning behaviors with technologies. In other words, a protean individual strives to find resources for develop their careers and is more likely to recognize the opportunities offered by PTE and consequently develop their perception of the learning potential of PTE. Individuals who have these perceptions will be more likely to participate in developmental activity with technologies.

Consequently, we make the assumption that PTE plays a mediating role in the relationship between PCO and LBT-support.

Hypothesis 3: Protean career orientation is positively related to learning behavior with technologies-support through psycho-technological environment-opportunities

6.1.2 The relationship between protean career orientation and proactive career behaviors

Most research has demonstrated the role of PCO such as an antecedent of proactive career behaviors (Hirschi et al., 2017; De Vos & Soen, 2008). These behaviors are particularly important because they allow individuals to respond to the needs of modern career self-management (King, 2004; Strauss et al., 2012). Proactivity is conceived as a process that can be applied to any set of actions through anticipating, planning, and striving to have an impact on workplace or career (Grant & Ashford, 2008). Proactive behavior refers to the attempts to create a future outcome that can have an impact on the self or environment (Grant & Ashford, 2008; Parker et al., 2006) and concerns also the behaviors that individuals undertake to actively develop their careers (Hirschi et al., 2014; Spurk et al., 2020).

Technologies have been recognized such as tools providing support to accomplish many specific behaviors as career behaviors (McFarland & Ployhart, 2015). In this line, many scholars strive to understand this (Davis et al., 2020; Bala et al., 2019) and some authors suggest that the specific utilization of technology facilitates proactive career behaviors (Ogbuanya & Chukwuedo, 2017). In this study, we focus on three specific behaviors: planning, skill development and networking. These behaviors were chosen because the literature has showed they are the most relevant for career success (Claes & Ruiz-Quintanilla, 1998; Strauss et al., 2012; Smale et al., 2018).

Learning through technologies can facilitate proactive career planning. The seeking of support via technologies to develop knowledge and skills is associated to the improvement of the capacity to anticipate, plan and bring information, knowledge and advices. Learning from other allows individuals to clarify the objectives by self-reflection on why the development of this specific skill is relevant (Chen et al., 2017). This self-reflection leads set to clearly defined career objectives and be equipped to identify suitable development pathways to achieve their career goals (Jackson, 2017). In addition, the collaboration and sharing with others information and knowledge are facilitate through technologies and, the consequent learning behaviors represent a central mechanism for proactivity and networking activity (Yu et al., 2010). Learning through different practices also promotes personal development and skills development. Moreover, LBT-support allows to enhancing employees' ability to solve problems, to think in other ways, through the feedback seeking, collaboration, connection with others (Bazine et al., 2020).

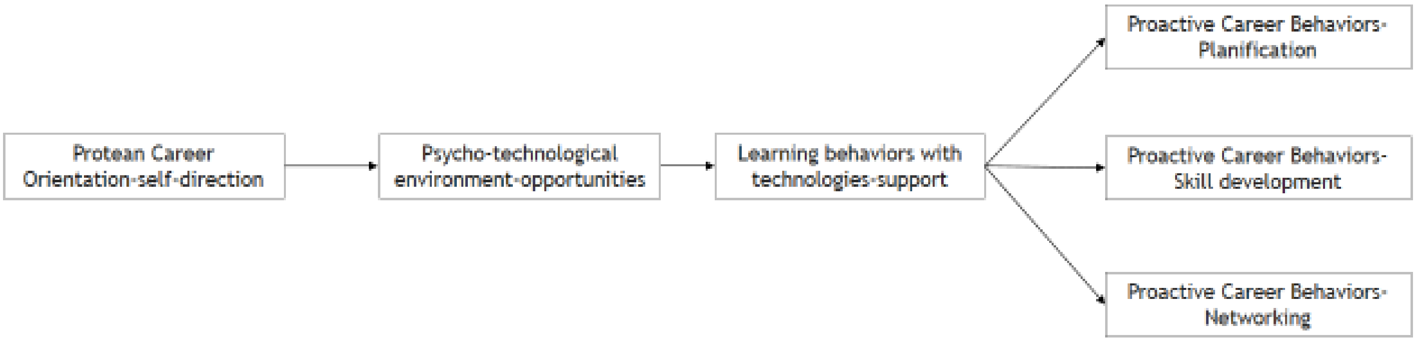
On this basis, learning behaviors with technologies-support is associated with proactive career behaviors (planification, skill development and networking).

Hypothesis 4: Learning behaviors with technologies-support is positively related to (a) planification, (b) skill development, (c) networking

In sum, at digital age, most researchers agreed that career development and technologies is complex process (Hirschi, 2018). To achieve their career development goals, individuals engage in multiple ways. In this study, we focus on the fact that individuals use the opportunities given by technological ubiquity to attain their aims. Consequently, we make the assumption that the relationship between protean career orientation and proactive career behaviors would be mediated by PTE-opportunities and learning behaviors with technology. As emphasized previously, individuals with high PCO-self-direction can perceive more opportunities to in their environment thanks to technological ubiquity which lead to engage in learning behaviors with technologies and linked to proactive career behavior.

Hypothesis 5: PTE-opportunities and Learning behaviors with technologies-support sequentially mediate the positive relationship between PCO-self-direction and proactive career behavior (a) planification, (b) skill development, (c) networking

Figure 6.1 *Hypothesized model*



6.2 Method

6.2.1 Sample and procedure

This study is based on two wave survey data. The data was gathered from students at University of Bordeaux by sending emails with the invitation to answer a survey and explain the main objectives of the study. Data was collected during the academic year 2019-2020 and 2020-2021. Participants come from STEM (25%), from Human Sciences (42.64%) and from Medical Sciences (32.36%). Finally, the participants' education is as follows: 138 master's degree (67.27%), 45 bachelor's degree (18.78%), 21 doctorate's degree (13.95%). Participants who engaged in this study have professional experience between Time 1 and Time 2. Time lag was 7 month between Time 1 and Time 2. We opted for this time lag because there is necessary time for student to seek and find an internship. The initial sample size at time 1 was 647 and the sample size at time 2 was 204. A significant level of dropout was observed, the sample decreased by 68,37% between Time 1 and time 2. The percentage of respond 159 (77,9%) of the participants were women and men were 45 (23,1%) with an average age of 26.84 (SD= 8.55).

6.2.2 Measures

All measures were originally developed in English, except learning behaviors with technologies and Psycho-technological environment which were validated in French. All remaining scales were translated to French using the back translation procedure (Brislin, 1980).

At time 1, *Protean Career Orientation-self-direction* (PCO-SD) was measured with 6 item (Direnzo et al., 2015) using Likert type scale ranging from 1 (Not at all) to 5 (Totally). Sample item includes “I am responsible for expanding my career-related skills and knowledge”.

At time 1, he perception of the *Psycho-Technological Environment-Opportunities* (PTE-O) is assessed with 7-items from Bazine et al. (2020) Likert type scale ranging from 1 (Not at all) to 5 (Totally). Sample items for PTE-O are: “I have the perception that the use of digital technologies is a real benefit for the development of knowledge and skills; I have the perception that digital technologies offer me a more attractive way for learning “

At time 2, *Learning behaviors with technologies-support* (LBT-S) were measured with 7-item from Bazine et al. (2020), developed in French on the basis of the study of He and Zhu (2017) using Likert type scale ranging from 1 (Not at all) to 5 (Totally). Sample item is: “ I actively seek new technologies to help with my learning needs”.

At time 2, *Proactive Career Behaviors* (PCB) was measured with the 11 items from Strauss et al. (2012) using Likert type scale ranging from 1 (Not at all) to 5 (Totally). This measure is composed by three dimensions: *planification*, *skill development* and *networking*. Sample item for each dimensions respectively includes: “ I am planning what I want to do in the next few years of my career “, “ I develop skills which may not be need so much now, but in future positions “, I am building a network of contacts or friendship to provide me with help or advice that will further my work chances”.

6.2.3 Results

The means, standard deviations, and correlations among variables are indicated in Table 1. To estimate internal consistencies, we analyzed and reported in Table 1 Cronbach’s alphas and McDonald’s omegas (Dunn et al., 2014). Before examining our model, we verify significant statistical differences for demographic variables (age, sex, formation and education) considering our interest variables. We perform an analysis of variance (ANOVA) and our results confirm that demographic variables demonstrated any significant statistical difference among our results (all $p>.05$).

Table 6.1 *Means, Standard Deviations, Coefficient Alphas and Coefficient Omegas, and Correlations Between Variables*

Variables	Mean	SD	ω	1	2	3	4	5	6
1.PCO-selfdirection T1	3.56	.64	.86	(.85)					
2.PTE-opportunitites T1	3.00	.82	.81	.25**	(.82)				
3.LBT-support T2	3.89	.64	.87	.25**	.62**	(.87)			
4.PCB-Planification T2	3.29	.80	.87	.21**	.08	.26**	(.87)		
5.PCB-Skill development T2	3.96	.64	.84	.25**	.06	.30**	.48**	(.84)	
6.PCB-Networking T2	3.64	.65	.86	.34**	.06	.15*	.52**	.55**	(.89)

Note: N=204, ***p*<.001; The alpha score corresponds to the number in brackets;

Confirmatory factor analysis (CFA) through Mplus 8.4 (Muthen & Muthen, 2017) and the MLM estimator was used to examine the theorized 6 factor structure. This analysis indicated that all items loaded significantly on their corresponding latent variables ($p<.001$)

and the latent variables loaded significantly on their corresponding second order variables latent variables. Following Hu and Bentler (1998), the fit indices are good with an RMSEA of .05 a value lower than .06, the minimum threshold to be considered a good fit and an SRMR of .06. The CFI and TLI indices show good fits, with acceptable fit superior to .90, generally the rule is to accept a value greater than .90 for an acceptable fit (Brown, 2015). The CFA model yielded a good fit to the data: χ 2/df= 1.58, RMSEA=.05, CFI=.91, TLI=.90 and SRMR=.06.

To assume the robustness of our model, we proceed to a comparison analysis with the use of the Satorra-Bentler method (Pavlov et al., 2020; Satorra & Bentler, 2001). The results of CFA comparisons analyses were reported in Table 2. The six factor solution outperformed simpler models that are obtained by merging two or more factors. These results confirm that the six-factor model is a better solution.

The data collection at two time points for analyzing the effect across time of our hypothesized model reduces the potential for common method variance (Podsakoff, et al., 2003). Nevertheless, we examine if our data have affected by common method variance. Model fit and correlation between latent factors remained unchanged with add an orthogonal latent factor named CMV encompassing all the variables items. The CMV factor accounted for 21.8% of the total variance, suggesting that although common method bias was partly present in this study, it is unlikely to affect the validity of the research results (Williams et al., 1989). The probability of common method bias was low.

6.2.4 Hypothesis testing

The hypothesized structural model based on our hypotheses was examined with Mplus 8.4 (Muthen & Muthen, 2017). Standardized path coefficients associated with the overall hypothesis model are reported in Figure 1. Our results supported Hypothesis 1 which stated that the PCO-SD is positively related to PTE-O (β=.25, p<.001). In addition, Hypothesis 2 was confirmed with PTE-opportunities being positively related to learning behaviors with technologies-support (β=.37, *p*<.001). Hypothesis 3 predicted the existence of a positive indirect path between PCO-SD and LBT-S through PTE-O. The indirect effect of PCO-SD on LBT-S through PTE-O was estimated (estimate =.12, 95% CI=.05-.20). A closer examination of our results indicated that PTE-O partially mediated the association between PCO-SD and LBT-S because an association was founded (direct effect β =.26, p<.001).

Table 6.3 *Results of sequential mediation path models*

	Direct effect									
Variables	PTE-opportunities		LBT-support		PCB-Planification		PCB-Skill development		PCB-Networking	
	B	SE	B	SE	B	SE	B	SE	B	SE
PCO-self-direction	.25**	.08	-.04	.08	22**	.08	.28**	.08	.40**	.07
PTE-opportunities			.37**	.09	-.06	.10	-.15	.10	-.29*	.10
LBT-support					.24**	.08	.40**	.08*	.37**	.10
R^2		.06**		.13**		.10**		.21**		.26**

Note. *N* = 204; **p* < .05, ***p* < .01;

Table 6.2 *Model Measurement Fit Indices for Assessed the Differences between the Variables*

Model	Model Description	χ^2	*df*	RMSEA	CFI	TLI	SRMR	AIC	BIC	$\Delta\ \chi^2$
Measurement model (MLM)										
M1	6-model factor	616.889	390	.05	.91	.90	.06	16313.938	16662.340	
M2	5-model factor (combining factor PCO and PTE)	959.303	395	.08	.77	.74	.11	16678.482	17010.294	$\chi^2(5)=398.78^{**}$
M3	4-model factor (combining Factor Career behaviors)	886.698	399	.07	.80	.78	.08	16423.626	16742.165	$\chi^2(9)=265.66^{**}$
M4	3-model factor (combining career behaviors and LBT)	1316.358	402	.10	.61	.58	.13	16891.950	17200.648	$\chi^2(12)=744.13^{**}$
M5	2-model factor (combining PCO and PTE and Career behaviors and LBT)	1600.716	404	.12	.50	.46	.14	17199.110	17501.059	$\chi^2(14)=1101.41^{**}$
M6	1-model factor	1995.592	405	.14	.35	.31	.15	17638.228	17936.859	$\chi^2(15)=1461.11^{**}$

Note: N = 204. ** *p* < .01. RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR: standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion; PTE = psycho-technological environment; LBT = learning behaviours with technologies; PCO=protean career orientation

Hypothesis 4 that LBT-S will be related to PCB received full support. LBT-S was significantly and positively related to planification β =.24, p<.001, to skill development β =.40, p<.001 and to networking β =.37, p<.001.

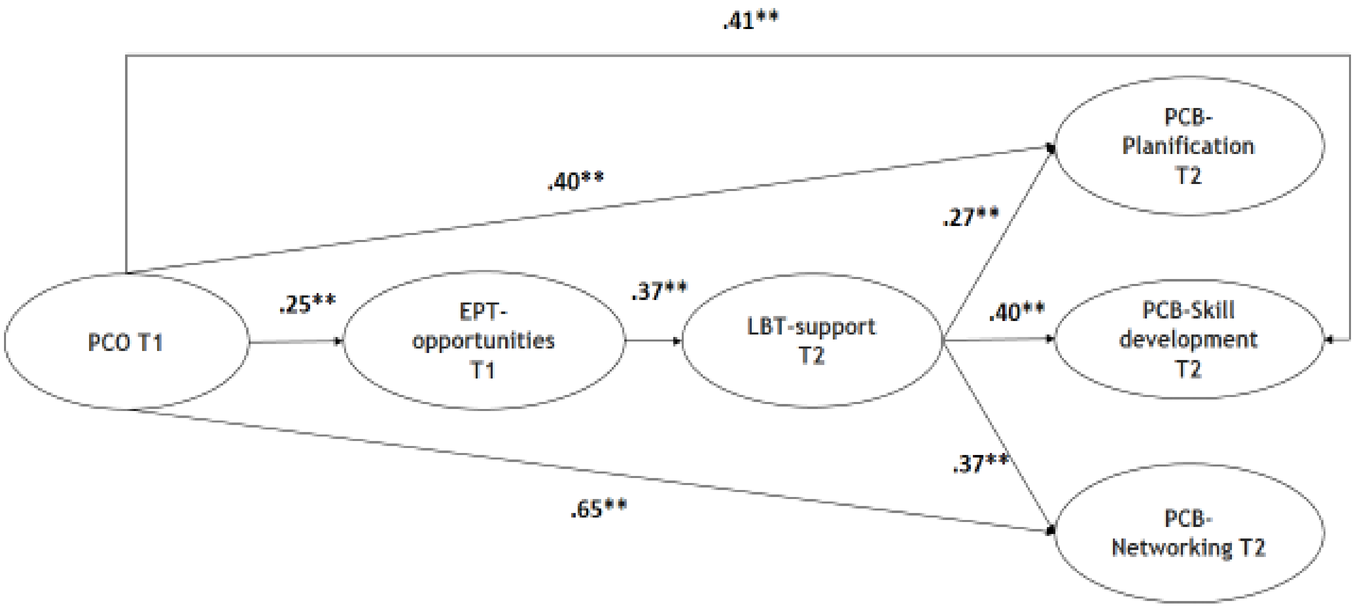
Hypothesis 5a, 5b and 5c posited sequential indirect effects of PCO-SD on career behaviors through PTE-O and LBT-S. We have tested the indirect relationship between PCO-SD and PCB-planification through PTE-O and LBT-S. Hypothesis 5a was found with an indirect sequential effect (estimate =.04, 95% CI=.01-.08). This sequential mediation was partial because an association was found between PCO-SD and planification (direct effect β =.40, p<.001). Hypothesis 4b was confirmed with an indirect sequential effect of PCO-SD and PCB-skill development through PTE-O and LBT-S (estimate =.06, 95% CI=.02-.10). This sequential mediation was partial because an association was found between PCO-SD and skill development (direct effect β =.41, p<.001). And the hypothesis 4C was tested and confirmed the sequential indirect relationship between PCO-SD and networking through PTE-O and LBT-S (estimate =.02, 95% CI=.01-.06). This sequential mediation was partial because an association was found between PCO-SD and skill development (direct effect β =.42, p<.001).

Table 6.4 *Results of sequential mediation path models*

Variables		
Indirect effects	Estimate	95% CI
PCO-self-direction to LBT through PTE-opportunities	.12**	[.05-.20]
PCO-self-direction to Planification through PTE-opportunities and LBT-support	.04**	[.01-.08]
PCO-self-direction to Skill development through PTE-opportunities and LBT-support	.06**	[.02-.10]
PCO-self-direction to Networking through PTE-opportunities and LBT-support	.06**	[.00-.11]

Note. *N* = 204; **p* < .05, ***p* < .01; 95% CI: 95% confidence interval.

Figure 6.2 *Standardized path coefficients associated with the final model (N = 204)*



6.3 Discussion

6.3.1 Theoretical implication

This study offers some important insights into the career development literature by the enactment of technological focus. The general aim of this research was to explore how individuals can use the resources of the technological ubiquity in order to develop their career. Based on the model of PTE which stipulate that the perception of opportunities to learn lead to learning behaviors with technologies, we investigated that the facilitative role of protean career orientation for the identification of technological opportunities in the environment leading to proactive career behaviors. The presented findings depict a relationship between Protean Career Orientation (PCO) and career behaviors by the sequential relation of Psycho-Technological Environment (PTE) and Learning Behaviors with Technologies-Support (LBT-S). Our findings reaffirm the central role that technologies play in career development. As mentioned by Venable (2010), technologies can help individuals for career development but it is not sufficient. Davis et al. (2020) highlight that for an optimal use of opportunities offered by technologies, specific aptitudes or skills are required. In the same vein, Hirschi (2018) have postulated that PCO may be an antecedent in the use of technologies for career development. Our findings seem to support this statement by showing that the relationship between PCO self-direction and career behaviors was mediated by PTE-opportunities and LBT-support. From the perspective of the learning potential of PTE, this result hints at the fact that technological ubiquity is a real strength for career development.

Another key contribution of this study, is related to the results which revealed that PCO, the dimension of self-direction, was directly associated with PTE-opportunities. These findings stress the role of PCO-self-direction in recognizing the opportunities given by the technological ubiquity. These results are in line with prior studies underlining the fact that self-direction represents a person taking responsibility to develop their career by searching resources to grow (Li et al., 2020; Gubler et al., 2014). Therefore, these confirm that personal orientations and prior experience affect the perception of the environment (Kraimer et al., 2011). Beyond contributing to the PCO literature, our findings may also inform why Protean individuals succeed. A growing body of research attest to the fact that PCO is a robust predictor of career success (Hall et al., 2018) but the strength of this study is to show in a technological environment individuals use technologies for their career development. To date, researchers largely have focused on demonstrating the link between PCO and career success and only recently has interested shifted towards investigating how PCO allow to recognizing and use opportunities offered by technologies for career development (Hirschi, 2018). Our study contributes to the growing body of technologies and career (Lent, 2018), and extend it, by suggesting that higher PCO-SD recognize and use all opportunities for progress in career.

As our findings suggest, protean individuals can recognize more opportunities and may have more career options available. Researchers who have examined the

In addition, our results are consistent with prior studies which emphasized that individuals with high perception of PTE generated more learning behaviors with technologies (Bazine et al., 2020). In accordance with the learning potential literature (Nikolova et al., 2014), the perception of PTE exert learning behaviors because they are depending on the perceptions that the environment provides sufficient opportunities for learning. These results are important, it is reinforce the statement that the perception of opportunities to learn provided by technologies served as a fuel for learning behaviors with technologies and highlight that accessibility or easy to use technologies are not considered as important for learning with technologies.

Finally, the present outcomes highlight that learning behaviors with technologies-support activate proactive career behaviors. The findings reinforce the statement that learning with technologies can widen the learning experiences and facilitate actions to obtain support, maintain motivation or also develop strategies (He & Zhu, 2017; Heflin et al., 2017). Therefore, this study offers further evidence that learning with technologies has a key role for activating career behaviors. Our results provide some evidence to the literature assuming that actions with technologies matter beyond to develop knowledge as a mean to personalize career development and as an aid to finding content allow individuals to achieve their aims. Moreover, the strength of this study is to fine-grained our understanding of which type of behaviors activates career behaviors by demonstrating that LBT-support which activate proactive career behaviors.

6.3.2 Practical implications

The present study provides some insights for managers and practitioners. First, it informs organizations and career counselors that technologies play a crucial role in the career process. It would thus be very helpful for career counselors and organizations, especially the vocational education institution or program of career advancement to integrate technologies functions in any training that involves career development.

These findings also advise organizations and career counselors what behaviors with technologies are associated with career behaviors. In the focus to offer guidance for individuals, career counselors should pay more attention to developing programs fostering the integration of the use of technologies for career development.

6.3.3 Limitations

Despite these findings present some theoretical and practical implications; this study also suffers some limitations. The collection data procedure may inflate the heterogeneity of the sample and add to the random nature which can lead to sample selection bias and self-selection bias (Heckman, 1990). The second limitation of our study is the self-reported data which might induce common method bias and inflate the common method variance (Podsakoff et al., 2003). However, it was unlikely that our results are attributable to common method bias because it was tested whether the observed relationships between study variables resulted from common method errors following the statistical recommendations of Podsakoff, et al. (2012).The third limitation is the nature of the sample. Given the random nature of the sample, we could not examine the role of control variables such as education levels. Education can affect our use and fluency with technologies (He & Zhu, 2017). For instance, STEM education requires more digital skills than that in Human Sciences. The third limit is that our assumptions have been tested in just one university and this limits the possibility to generalize. Therefore, it could be appropriate to replicate this study on other samples, the most suitable being full time representatives in a professional context. A third limitation of this study is the dropout of participants at different times of measure. More than 50% of participants does not respond between time 1 and time 2. This important loss of participants can limit the generalizability of our findings.

This current study opens perspectives for further studies on this framework. For instance, understanding how individuals can set-up proactive career behaviors via technologies tool and not only focus on learning behaviors with technologies. This study reinforces the need to investigate the antecedents and process which allow to technologies to be benefit for individual and an asset for career development.

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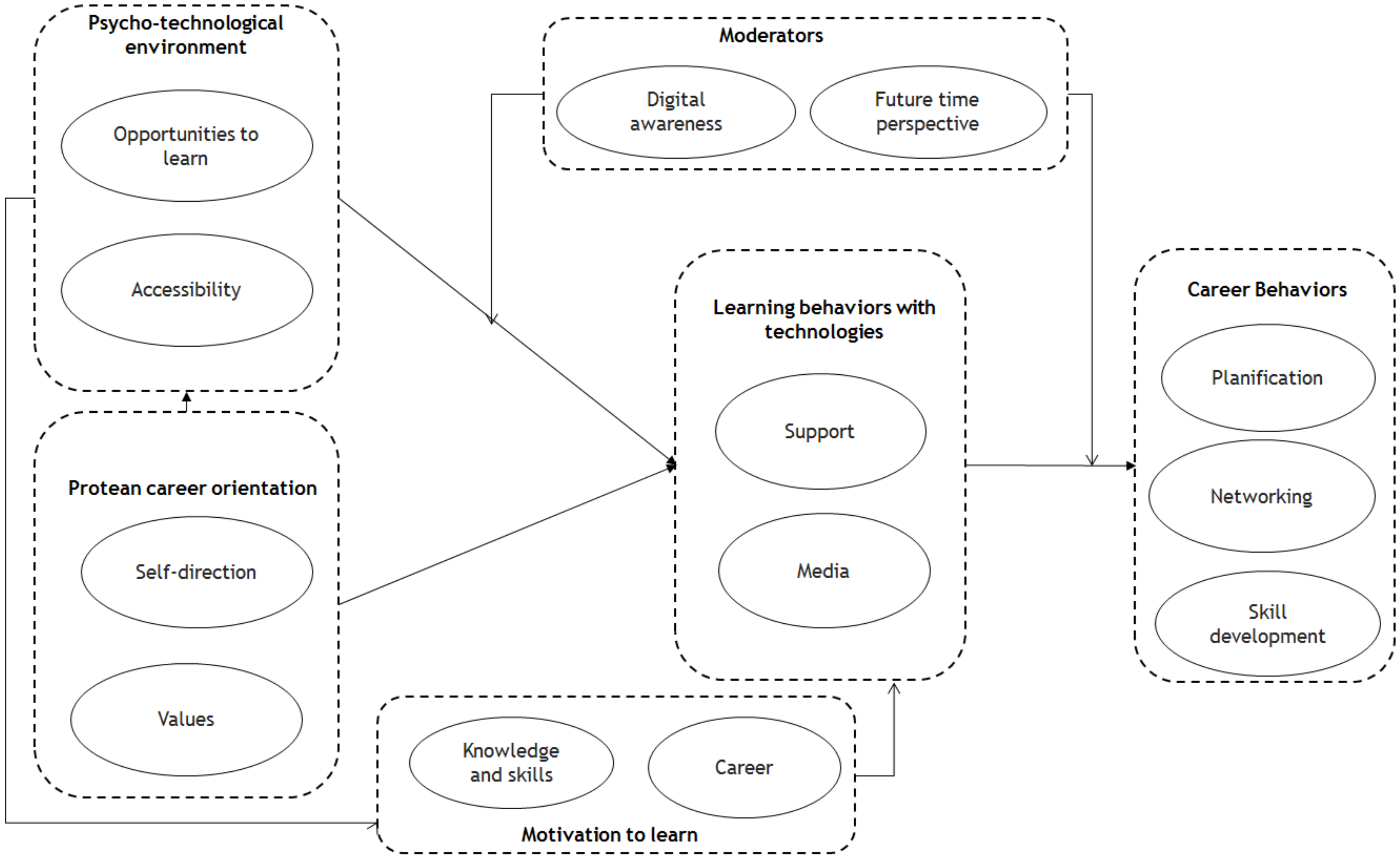
General discussion

The aim of this doctoral dissertation was to investigate, from a theoretical and empirical perspective, the changes produced by the 4th Industrial Revolution on the professional and career development of individuals. The premise that the technological ubiquity, as one of the most important characteristics of this new context, can represent a resource for fostering the development of knowledge and skills and promoting professional career building is the basis of the theoretical analysis and empirical studies carried out. While the impacts of the 4th industrial revolution on individuals (e.g., employment, skills, career development) and on organizations (e.g., flexibility, HRM, training and development) represent a growing scientific and applied interest, there is scarce evidence and knowledge on how and what they are producing on the individual (Hirschi, 2018). Apart from providing some theoretical and empirical advances to these issues, this doctoral dissertation strives to give some practical implications in order to present some advice and guidance to individuals, psychologists, organizations and career counselors and to help workers and students thrive in this new context. With the figure 7, we schematically summarize the general research model tested through the various empirical studies.

As mentioned by Cascio and Montaelegre (2016), the critical stake is to develop a theoretical framework to explore how technologies and more specifically technological ubiquity can be a resource for career and learning. To do so, we develop a conceptual framework of a largely neglected aspect of the 4th industrial revolution which is technological ubiquity based on the postulate that it provides more learning opportunities and greater accessibility for learning. As explained in the introduction, rather than referring to a specific technology, this concept reflects the merging of computer sensors (such as radio frequency identification tags, wearable technology, smart watches) and other equipment (tablets, mobile

Figure 7. General Research Model



devices) with various objects, people, information, and computers thus producing the fusion of physical and digital environments

In Chapters 2 and 3, we contribute to the career and learning literature with the development of two measures that capture the emergence of a new psycho-technological environment (PTE) which is characterized by more opportunities to learn and more accessible technologies. PTE is conducive to learning and career building. These chapters map out how the technological ubiquity affects individuals but also how individuals in this context use technologies for their learning. More specifically, in the Chapter 3 we lend evidence that the individuals perceive a PTE which offers some opportunities to learn and that PTE can be considered as motivational agent for learning. This is consistent with the theoretical model proposed by Chung et al. (2021). Environmental favorability or perceptions of the favorability of the environment influence the motivation to learn (Noe, 1986). Among the factors that prompt motivation to learn, beliefs regarding opportunities to learn, practicing skills, the use of acquired knowledge in learning activities or receiving reinforcement and feedback from others are of particular importance. This reinforces the fact that PTE and technological ubiquity are relevant for fostering learning, skill building and knowledge development. These two studies have responded to the overarching goal by providing evidence that technological ubiquity and more specifically PTE can be valuable assets for individuals: on the one hand by providing some opportunities to learn which motivate individuals to learn, and on the other hand by highlighting that technologies facilitate some learning behaviors such as feedback seeking, collaboration, information and knowledge sharing. As reported by Eraut et al. (2001), opportunities to have interactional learning are also associated with motivation to learn. Diversity in learning does not encompass only having many relevant contents but also having the possibility to learn with others (e.g., peers, tutors, professors). These results emphasized that technological ubiquity has widen social environment of individuals. Thanks to the technologies, individuals can connect to a greater number of persons. They allow individuals to easily connect, share, and communicate with people from different organizations, countries and backgrounds with which they would probably not have been connected otherwise. Therefore, individuals have more opportunities of interactional learning. Our findings have also shown no relation between accessibility of technologies and motivation to learn as well as low correlation with learning behaviors. One explanation of this result is that the measure used here to assess motivation to learn stem from the theoretical background of Noe (1986) and captures the pleasure or the desire to learn. Yet, accessibility is less likely to stimulate desire and pleasure to learn. Based on the social cognitive theory (Bandura, 1989), accessibility can motivate individuals by fostering their self-efficacy to develop learning by the use of technologies. Consequently, individuals can be more confident in using technologies to learn but are not necessarily eager to learn. Since PTE has been found to relate to professional development and skill development, we carried out a study for showing that PTE and learning with technologies are important for career development. In the last study, we demonstrate that some types of learning behaviors with technologies (e.g., knowledge sharing, feedback seeking from others) facilitate the set-up of career behaviors. This study reinforces our claim that learning with technologies can widen our possibilities of collaboration, sharing and feedback which in turn facilitate career behaviors.

In the third study, we test our hypothesis that certain profiles are suitable to succeed in modern careers which is evaluated through the identification of different profiles. An analysis of different career development profiles allows us to clarify the requirements of a modern career. This study responds to the general aim by providing some theoretical advances, notably by underlining the attitudes and capacities needed to thrive in the career context and by pointing out the personal aspect needed to maximize the use of technologies. In addition, this study advances the literature on career profiles and learning activities with the aim of demonstrating that depending on career profiles, individuals act differently with technologies and in particular with learning. This step is essential to gain knowledge to determine how we can help learners make decisions and choices about their careers. Consequently, it highlights the diversity and differences in the needs of students and employees.

Implications

This PhD thesis raises new questions and theoretical implications on the study of the 4th industrial revolution, learning and careers. First, we develop the conceptual underpinnings of the PTE construct, a new psychological construct that advances the literature on learning in the digital age and highlights how technology can be a resource for individuals. In the literature, different conceptualization of resource exists such as Conservation Resource Theory (COR) or Job Design enrichment. Technological ubiquity is a resource for individuals because this environment acts as an activator which is supposed to have a direct influence on motivation to learn and learning activities and fits with the social cognitive theory (Bandura, 1986). The social cognitive theory (Bandura, 1986) is a theoretical framework which can help us to understand the effects of technological ubiquity on individuals. This theory postulates that a behavior is the result of triadic relation between environment, personal attributes and precedents behaviors (Wood & Bandura, 1989). Our results can be seen through a triadic relation as personal attributes (PCO) and personal beliefs (PTE) play a key role on the effect of technological ubiquity on behaviors. This interaction explains why opportunities offered by technological ubiquity are transformed into learning behaviors. Our doctoral dissertation strives to integrate a theoretical framework that helps us to understand the effects of technological ubiquity. Cascio & Montaelegre (2016) have underlined that the role of technologies has not been sufficiently addressed in the psychological literature. In addition, this PhD thesis provides a theoretical framework that proposes and shows off that PTE can be considered as an activator of behavior. The opportunities and resources offered by technological ubiquity allows to implement learning activities. Furthermore, this doctoral dissertation provides some theoretical implications about human agency with technologies. Our findings emphasized that actions with technologies is not limited to autonomous actions or depend only of environmental determinism. The behaviors with technologies are dependent of the environment but are also shaped by individuals' actions.

Regarding the implementation of changes in the organization to facilitate learning, our findings help to emphasize the importance of developing and promoting the PTE to support learning. To the extent that learning depends on the environment (Nikolova et al., 2014), educators and managers should focus on increasing opportunities to learn, for example by proposing various and different learning methods, allowing some flexibility to foster the possibility of self-learning. Cahill and Martland (1995) noted that "each technology has strengths and weaknesses and the choice depends on the task, the availability of equipment, and the cost". This doctoral dissertation calls attention to the importance of technological ubiquity as a research subject which is a largely overlooked aspect. Cascio and Montaelegre (2016) call for further research to explore the importance of its impact. Although, these advancements are promising, scholars need to deepen their knowledge on how to manage this impact and foster implementation of technological environments in organizations. Multiple studies have shown that, like any organizational change, the implementation of technologies in organizations requires different requirements to be beneficial for employees and organizations (Sitzmann & Weinhardt, 2018; Derouin et al., 2005; Weick & Quinn, 1999). In sum, our first result seems relevant to provide knowledge and advice for psychologists to help individuals to cope the multiple challenges brought by the 4th industrial revolution.

Another implication was to explore the relationship between technologies and career development. In chapter 5 and 6, we proved the importance of technologies for career development in the digital age. Indeed, as specified by Venable (2010), the technologies offer flexible services to meet students and workers' career development needs. Our results are promising for future research on career development and technologies.

From a development perspective, providing help or advice to individuals concerning the assessment needs may reduce mistakes or fails in the support for career development. The study 3 demonstrates that individuals have not the same needs for developing their careers. If individuals do not understand why and how their strengths and weaknesses were diagnosed or doubt the accuracy of the information, they likely will be resistant to the help for their career development. Career counselors may provide employees with a clearer picture regarding their career paths and the prerequisite skills for their career evolution.

Limits

The main limit of our study, which has been presented in every chapter, is related to the nature of the different samples studied. Despite that recruitment of participants in all studies was carried out using specific selection criteria, most of our studies are based on volunteering. In this regard, our data collection procedure may inflate the heterogeneity of the sample and add to its random nature which may lead to sample selection bias and self-selection bias (Heckman, 1990).

The second limitation of this doctoral dissertation is that university students represent the majority of our sample. Despite this limitation, we focused on students with professional experience. Future research is needed to replicate these studies in other samples, for instance on a sample of employees which allows to ensure the validity of our results without sample-related bias.

Another limitation that has been extensively discussed in our three articles is related to the use of self-report measures that could induce common method bias and inflate the common method variance (Podsakoff et al., 2003). This is a methodological and statistical issue, but as indicated on most articles, our choice of self-report questionnaires was justified.

Furthermore, our results are unlikely to be attributable to common method bias because in each study we tested whether the observed relationships between study variables resulted from common method errors following the statistical recommendations of Podsakoff, et al. (2012).

The last limitation is a methodological and statistical one. Although we theorized technological ubiquity as a contextual variable, we did not use multilevel analysis for this measure. For further clarification, future research is needed to show that the perception of PTE represents a context which influences the engagement in learning behaviors and that PTE is not only about technological literacy which prompts learning behaviors with technologies. The literature on digital literacy has demonstrated the importance of this antecedent of literacy on learning with technologies (Anthonysamy et al., 2020).

As pointed out above, a multilevel analysis needs to be applied. One neglected aspect in this doctoral dissertation is the specific skill requirements to use some technologies (Peña-Jimenez et al., 2021). Technological literacy can affect how we use them and the benefit of learning with them (Oberlander et al., 2020). Additionally, future research should examine outcomes over time of the career profile and confirm that a specific profile can be associated with career development by focusing on metrics of career development such as career success, salary or promotion. This can be done by using LTA whose aim is to demonstrate the flexibility or stability of the profile over time or by studying the impact of career development profiles on career success over 2 years.

Although, researchers in different fields are conducting much research on the 4th industrial revolution, our understanding is still lacking and this research field is always open for new research. As noticed in the future perspective section, many studies still need to be developed. In the future, a better integration of the relationship between individuals, teams, organizations and technologies is essential. Future research needed because in this work, we focus only a positive side and not consider the potential negative effects of technological ubiquity on individuals. Thus, this doctoral dissertation represents an important step in the understanding of how 4th industrial revolution and more specifically technological ubiquity can become an asset for individuals.

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