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Who fits into the digital workplace? Mapping digital self-efficacy and agility onto psychological traits

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ABSTRACT

Today's rapidly changing and volatile markets demand a novel set of skills from organizations and employees that allows them to agilely adapt to and surmount the ever-evolving challenges posed by the ongoing development of digital technologies and changes in market conditions. Previous research conducted on structured workplaces using traditional industrialist paradigms had established an ideal composition of employee traits. However, today's contrasting fast-paced environments may have made those profiles obsolete, prompting the need to identify a profile of personalities and interests that enables organizations to assemble a workforce high in digital self-efficacy, which fundamentally drives organizations' agility. We proposed and evaluated such a model by conducting two studies at international (Study 1, $N = 309$) and French (Study 2, $N = 1{,}025$) publicly traded organizations. The results indicate the personality dimensions *openness to experience* and *emotional stability* and investigative and realistic vocational interests are predispositions for the development of digital self-efficacy. Furthermore, we found corroborative evidence for digital self-efficacy to facilitate workforce agility. These findings offer novel insights into those individual psychological traits that foster an agile workforce and make it well-equipped to face the challenges of rapidly changing digital business environments today and in the future.

1. Introduction

Long gone are the days when the majority of contemporary added value was created by production workers and driven by advances in basic technologies, such as steam power or electricity (Schwab, 2017). The paradigm shift caused by the Fourth Industrial Revolution has placed highly skilled white-collar employees at the core of today's economies in a world that is characterized by high volatility, uncertainty, complexity, and ambiguity (VUCA; Bennett and Lemoine, 2014). The increasing cadence of novel technological developments and disruptive innovations necessitates and accelerates organizations' implementation of digital transformation processes aimed at maintaining and expanding their competitive advantage, with each one placing greater demands on the workforce (Martínez-Climent et al., 2019; Trost, 2019; Sirirak et al., 2011). Here, employees' mindsets emerge as critical success factors: Each individual employee can regard the challenge of transformation as an opportunity for growth, learning, and achievement or as a threat to their routine, competence, and employment status (Teece et al., 2016; Palmer et al., 2019). Thus, the workforce's trust in their abilities to acquire the knowledge and skills needed to operate the technology (Voogt and Roblin, 2012) may determine whether the organization will succeed not only in its transformation process, but in remaining adaptive ability to an ever-changing environment, and ultimately, in surviving amid more adaptive competitors (Ahmad et al., 2013; Carnevale and Smith, 2013).

Past research had established a personality profile for high-

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performing employees. However, most of this research was conducted within industrialist paradigms when managers mainly used transactional leadership and delegated clearly delineated tasks to their employees. For example, the personality trait of conscientiousness, a constituent of the well-established Big Five model of personality, which describes an individual's dispositions that remain relatively stable over time, distinguishes them from others, and predicts a wide variety of proximal outcomes (e.g., Costa and McCrae, 1992; McCrae and Costa, 1987, 2008), has been shown to be among the strongest predictors of individuals' work performance in a plethora of workplace domains (Wilmot and Ones, 2019). More specifically, considering higher trait conscientiousness in employee selection in addition to unstructured interviews resulted in a 60–62% likelihood of selecting a higher-performing one, a 20–23% increase compared to a selection based on unstructured interviews alone, depending on occupation (Furnham, 2008). These effects go beyond higher work performance and yield compounding returns when extrapolated to the employee's tenure in the organization. However, conscientious employees prefer clearly delineated tasks and orderliness (C.G. DeYoung et al., 2007), but the digital workplace is seldom predictable, giving rise to the question of whether the former profile for high-performing employees has become antiquated. Modern employees work in a more self-organized manner with fewer clear objectives and action planning through a supervisor (Hughes et al., 2018; Islam et al., 2020a, b). Thus, digital workplaces are featuring increasingly higher degrees of uncertainty and freedom accompanied by unstructured challenges that require flexible solutions (Mainemelis et al., 2002). Those situations demand employees who face these challenges from a position of confidence and self-efficacy, who succeed in surmounting them through their own efforts, and who thrive in the process not despite but because of the experienced complexity and ambiguity. Employee selection based on psychological profiles that prefer order and structure may fail to identify the talents needed for the digitized workplace. It may be time to reconsider the applicability of past evidence to present and future issues of research and practice and to overhaul the emphasis in personnel selection if needed.

In this study, we explore how an employee's character shapes their fit for the modern workplace, as indicated by their trust in their ability to utilize digital technologies and tools effectively and their ability to adapt to changing demands. More specifically, we aim to identify which dimensions of personality and vocational interests are linked to employees' digital self-efficacy and agility. We examined two large data samples, the first consisting mainly of employees from various central and western European organizations in the aerospace, food and services, and banking industries (Study 1); the second stemmed from multiple publicly traded companies listed in the French benchmark stock market index CAC 40 (Study 2). Our findings show that an individual's openness and emotional stability advance their digital self-efficacy, and their interests in doing (realistic interest) and thinking (investigative) positively impact this skill even beyond the influence of their personality. Furthermore, we find that these personality dimensions and interests shape individuals' agility in the workplace through heightened digital self-efficacy. Therefore, we decipher a part of the psychological profile that helps employees to develop self-efficacy in the digital workplace, thus paving the way for the formation of an agile workforce.

We contribute to research in a threefold manner: First, we connect modern workplace skills to established models of personality. Traits are stable features and the best-known predictors for individual behavior (Barrick and Mount, 1991; Barrick et al., 2001; Cobb-Clark and Schurer, 2012; Ozer and Benet-Martínez, 2006). Thus, their connection to personal skills is a promising avenue. Second, vocational interests are often neglected, but they have been shown to predict work and life outcomes beyond personality traits (Stoll et al., 2020). Therefore, we highlight how individuals' workplace characteristics predict their possession of workplace-related skills beyond their stable individual dispositions (Bergner, 2020; Costa et al., 1984; Stoll et al., 2017, 2020; Volodina et al., 2015). Third, by connecting personality traits and interests, we describe a comprehensive psychological composition that predicts employees' mastery of new skills in digital workplaces. In doing so, we answer a recent call to acquire a better understanding of those factors that human resource management should emphasize in personnel selection (Su, 2020; Van Iddekinge, Putka, et al., 2011), thereby utilizing the acquired insights to provide guidance for the assembly of a workforce that thrives in digital workplaces and excels through its agility.

2. Theoretical background and hypothesis development

2.1. Digital self-efficacy facilitates workforce agility

Digital competence is widely considered to be one of the critical skills an individual must possess in the knowledge economy of the 21st century (Bouncken and Kraus, 2021). As the application of new technologies is accompanied by technical challenges, individuals must also be willing to engage with the technologies and solve problems as they arise (Ritala et al., 2021). There are a multitude of terms that refer to an individual's ability to utilize information and communication technologies (ICTs; Bawden, 2008). These are typically constructed from the type of technology they refer to (e.g., computer, internet, ICT) and the type of knowledge required for their effective operation (e.g., literacy, skills, competence; Hatlevik et al., 2015). Thus, digital competence involves the utilization of digital technology as a means to acquire and manage information with the aim of solving challenges and creating a body of knowledge collaboratively (Ferrari et al., 2012; Trilling and Fadel, 2009; Vieru, 2015). Being highly proficient in operating only a well-defined and unchanging repertoire of digital technologies and tools to perform one's duties no longer suffices. The ongoing introduction of novel technologies demands employees' mindsets to be characterized by trust in their abilities to acquire the knowledge and skills needed to operate novel and possibly more sophisticated technologies when they emerge in the future (Martin, 2008; Ng, 2012). This trust allows them to respond to novel challenges in an agile manner. If a large proportion of the employees is agile, ultimately, their organization will be as well, allowing it to navigate and adapt to the modern market effectively. In a nutshell, it is not about being a cheese knife that can be used to solve one specific problem, but about being a Swiss Army knife that can be used to solve a wide variety of problems in a multitude of situations.

The most important denominator shaping how an individual approaches the multitude of unfamiliar and difficult challenges is *self-efficacy,* i.e., the belief that one can surmount any problem through one's own effort (Bandura, 1977). It is connected to a wide variety of desirable outcomes, most notably higher performance, but also coping behavior, achievement striving, growth of intrinsic interest, and even physiological stress reactions (Bandura, 1982). A high level of self-efficacy causes individuals to have higher outcome expectations, to be more likely to recognize and utilize opportunities in their environment, and to persevere in overcoming hindrances in their pursuits (Bandura, 2012; Bandura and Locke, 2003). Thus, highly self-efficacious individuals perform better than those who are less self-efficacious, even when controlling for their skill level (Bandura, 1994). It has been shown that self-efficacy serves best as a predictor for outcomes when it is linked to a specific domain (Bandura, 1989). Thus, digital self-efficacy denotes an individual's self-efficacy with regard to the effective and effortless utilization of information technology and the adaptation to updates in hardware and software (e.g., Agarwal et al., 2000). The higher an individual's trust in their digital skills, the less likely they are to feel anxious about using information technology (Bellini et al., 2016), and the more likely they are to be persistent and proficient in doing so (Agarwal et al., 2000; Rohatgi et al., 2016). Yet, the psychological foundation that facilitates the formation of digital self-efficacy beliefs remains unknown. Past research indicates that individuals who are particularly interested in certain types of occupations and activities (e.g., analytical or mechanical ones) are likely to possess relevant domain-specific self-efficacy (e.g., Lent et al., 1989). Further, an individual's personality predicts their level of general self-efficacy (e.g., Larson and Borgen, 2006; Saleem et al., 2011; Thoms et al., 1996); however, domain-specific self-efficacy has greater predictive power than general self-efficacy and should be used in its place if applicable (Bandura, 2006).

2.2. Personality

An individual's personality is a complex arrangement of individual dispositions that is relatively stable and shapes their experience of perceiving, evaluating, and interacting with external objects and events as well as internal thoughts, emotions, and sensations (Hogan, 1991). Thus, it can be considered the main determinant that distinguishes one individual from another (McCrae and Costa, 2008). Dimensions of personality reliably shape a wide variety of intra and interindividual processes, preferences, values, attitudes, and behaviors in different domains in which an individual engages. For example, open-minded individuals not only tend to seek novelty in foods, art, and cultures, but they also try more varied approaches in problem-solving and decision-making, dislike rigid structures, and are apt at "connecting the dots" (McCrae and Sutin, 2009). In short, the assessment of personality dimensions allows the prediction of not just a single outcome, but rather a multitude of different behaviors. The most widely used framework to map an individual's personality is the Big Five model (or OCEAN model; see McCrae and Costa, 1987), comprising the dimensions of **o**penness to experience (intellectual, imaginative, curious, and broad-minded), **c**onscientiousness (dependable, responsible, achievement-oriented, and persistent), **e**xtraversion (outgoing, talkative, sociable, and assertive), **a**greeableness (trusting, good-natured, cooperative, and soft-hearted), and **n**euroticism (tense, insecure, worried, and emotionally unstable). The Big Five model was developed inductively and free of theory and has been replicated across cultures. Furthermore, it has garnered widespread acceptance and consensus in personality science. Its far-reaching prevalence extends into organizational research: Apart from cognitive abilities, personality is the best predictor for outcomes like work performance (e.g., Barrick and Mount, 2012; Fang et al., 2015; Furnham, 2008; Mammadov, 2021; Salgado and Táuriz, 2014). The influence of personality on real-world outcomes is particularly pronounced in those situations that are less structured, regulated, and constrained, in other words, where employees can express themselves by making decisions on their own. The predictive power of individual traits also depends on contextual conditions like job demands. For example, extraversion predicts performance best in jobs such as leadership or sales, which require social skills, while agreeableness is less positively related to performance in competitive contexts, such as engineering or management consulting (Judge and Zapata, 2015).

Taken together, a high level of conscientiousness and a low level of neuroticism are the most valid predictors of workplace performance (for extensive meta-analyses, see Barrick and Mount, 1991; Barrick et al., 2001). Further, openness, extraversion, and conscientiousness have been shown to predict creativity (Zare and Flinchbaugh, 2019), which has been linked to firm competitiveness and survival (e.g., Dayan et al., 2013). However, these findings relate to structured and directive workplaces, giving rise to the question of which Big Five traits predict the critical skills necessary for success in the changing workplace of today, in particular the skillful use of information technologies.

Openness reflects an individual's stance toward reality in terms of curiosity, imagination, and esthetic sensitivity (Soto and John, 2017b). Individuals with a higher level of openness tend to seek out novel experiences; they possess a more active imagination, a higher degree of curiosity, and a greater willingness to learn new skills (Costa and McCrae, 1992). Further, they derive feelings of pleasure from thinking through and solving novel and complex challenges (Silvia and Christensen, 2020), and they are more willing to acquire, evaluate, and utilize information that opposes their previously held beliefs (Heinström, 2003). In turn, they are more effective at recognizing and structuring novel solutions (Shane et al., 2010) and at evaluating these novel approaches as being useful and effortless (Svendsen et al., 2013; Uffen et al., 2013). Digital workplaces require the use of novel digital technologies; employees are therefore challenged to face technical issues and to ponder and solve unstructured problems as a consequence of the use of digital technologies. Openness, curiosity, and an active imagination could motivate individuals to approach these problems proactively, to learn how to apply new information technologies flexibly, and finally to cope with more unstructured digital workplaces effectively (D'Zurilla et al., 2011). For example, more open individuals tend to be more apt at programming, which involves the skillful operation of computers to solve complex problems by creating, testing, revising, and combining procedures, typically starting from a blank slate (Gnambs, 2015). Since traits remain stable over long periods of time, highly open individuals build a track record of seeking and mastering unfamiliar challenges. Thus, we expect them to also have built a great amount of trust in their abilities to utilize novel technologies.

Hypothesis 1: Openness is positively related to digital self-efficacy.

Conscientiousness has been linked to dispositions such as a sense of purpose, persistence, and obligation. It entails a structured approach to work, a high degree of discipline and diligence, and the prevalence of a strong work ethic. It has been shown to be one of the most valid predictors of job performance (Dudley et al., 2006; Wilmot and Ones, 2019); however, highly conscientious individuals might struggle in flexible work environments that lack a sense of order. Therefore, despite the important role that conscientiousness plays in predicting job performance, we do not expect a relationship between conscientiousness and digital self-efficacy.

Extraversion is characterized by having an outgoing and social character, being able to hold conversations effortlessly, and having a high sensitivity to experience positive emotions. It can also be a predictor of workplace performance in positions, such as leadership or sales that require communication and interpersonal talents. However, while higher extraversion is associated with more effective leadership, it is unlikely that the facilitation of interpersonal interactions through extraversion aids in the mastery of digital skills and the obtainment of digital self-efficacy.

Agreeableness is characterized by friendliness, politeness, and positive social interactions. It is linked to lower turnover rates and supports collaboration, which is important in agile organizations. However, digital work is typically accompanied by less physical proximity between employees, thus offering fewer opportunities for direct social engagement. In turn, we do not expect agreeableness to be related to digital self-efficacy.

Neuroticism, the opposite of emotional stability, denotes an individual's inability to handle negative psychological states, such as anxiety or sadness, productively. Highly neurotic individuals are unstable and often feel pessimistic, anxious, or offended, making them prone to mental disorders. Further, they fear change and dread having to adapt their behavior to novel circumstances. Once they experience resistance when trying out something new, they tend to get stressed and give up. In contrast, individuals with lower scores in neuroticism tend to be relaxed, emotionally stable, content, unconstrained, and self-assured. In workplace contexts, neuroticism has been linked to low adherence to workplace safety guidelines. Highly neurotic individuals tend to engage in behaviors, such as theft, verbal abuse, or absenteeism that threaten the well-being of the organization or its members (Pletzer et al., 2019). Additionally, their lack of self-confidence to surmount unfamiliar obstacles is transferable to the challenge of applying digital devices and tools in new ways (Costa and McCrae, 1992; Perkins et al., 2015; Pickering et al., 2016). Due to their lack of compliance (Barrick and Mount, 2012), they may refuse to develop or implement novel solutions or even attempt to obstruct the organization from doing so. This deviance, however, is understandable. The implementation of a digital transformation can cause employees to experience stress, especially if they are uncertain about the usefulness of the novel technologies (Zoltners et al., 2021). If the organization manages to reduce their uncertainty, reductions in stress and increases in perceived usefulness ensue, accompanied by wider acceptance and compliance among employees (Guenzi and Nijssen, 2021). However, being less prone to feel stressed amid uncertainty (that is, low in neuroticism or high in emotional stability) should result in a greater likelihood to be more perseverant in solving novel challenges, to be less easily disappointed in the face of change and uncertainty, and to develop a greater trust in their abilities to utilize novel technological solutions. Thus, we expect them to acquire digital self-efficacy more easily.

Hypothesis 2: Emotional stability is positively related to digital self-efficacy.

2.3. Vocational interests

In the past, the fields of vocational psychology and organizational science have seldom crossed paths. Only recently have researchers interested in vocational interests and job performance begun to join forces to elucidate this promising intersection (e.g., Ingerick and Rumsey, 2014). Meta-analytic results suggest that vocational interests predict job performance and call for more extensive studies on the topics (Nye et al., 2012; Van Iddekinge, Roth, et al., 2011). According to the RIASEC model (Holland, 1997), there are six distinct archetypes of vocational interests (**r**ealistic, **i**nvestigative, **a**rtistic, **s**ocial, **e**nterprising, and **c**onventional) arranged in an equilateral hexagon. The greater the distance between the archetypes, the less pronounced they are within an individual (Gurtman and Pincus, 2003). For example, an individual with highly social interests is likely to be less interested in the artistic or enterprising domains, even less so in the investigative and conventional domains, and lowest in the realistic domain. Such a profile of interests can predict performance both at work and school (Nye et al., 2012). Further, vocational interests are not entirely independent from the Big Five personality inventory. Rather, an individual's personality guides them to seek specific learning experiences that shape their interests. Thus, vocational interests are believed to develop in accordance with an individual's personality (Schaub and Tokar, 2005). In fact, some vocational interests can be linked robustly to personality traits: openness is related to artistic, investigative, and social interests; conscientiousness is linked to conventional interests; extraversion is related to enterprising and social interests; and agreeableness is linked to social interests as well (Barrick et al., 2003; Costa et al., 1977; De Fruyt and Mervielde, 1997; Larson et al., 2002).

However, it is important to emphasize that personality traits and vocational interests are not interchangeable constructs. Rather, vocational interests have been shown to explain incremental variance in addition to personality. Research in this avenue was initiated by Costa et al. (1984); 20 years later, the existing body of knowledge was collated in a meta-analysis that compared the relationships and explicitly stated that the two constructs of personality traits and interests should be regarded as complements rather than substitutes (Barrick et al., 2003). More recent studies have investigated both personality and vocational interests in relation to career success (Volodina et al., 2015) and the success of leaders and entrepreneurs beyond cognitive abilities (Bergner, 2020). Further, a longitudinal study spanning 10 years verified the incremental validity of vocational interests above and beyond the Big Five personality traits in relation to life outcomes (Stoll et al., 2017). Therefore, one goal of thisstudy is to examine the predictive value of interests beyond personality traits to highlight their beneficial impact on developing digital self-efficacy and thereby agility.

Following the RIASEC model, conventional interest ("organize") is characterized by a desire to arrange things or ideas according to a set of rules, which is typical for administrative or governmental professions (Holland, 1997). It might help individuals to structure work effectively and efficiently, but at the same time, it may constrain their modes of thinking and make individuals high in this form interest prefer clear directions that are decreasingly present in digitalized agile workplaces. Further, social interest ("help") involves a high desire to work with other people, typical for the training, educating, or caring professions. It promotes collaboration, which is a central skill in agile workplaces. However, helping others in the workplace also depletes psychological resources that are also needed to overcome technical challenges (Lin et al., 2020). Therefore, we suppose that interest in helping might not predict self-efficacy in using digital technologies. The enterprising interest ("lead") is characterized by a high degree of opportunity-seeking commonly attributed to entrepreneurship, management, or law (Maran et al., 2019). It predicts more self-oriented thinking and an affective motivation to lead; hence, it is more closely related to assertiveness, which might not support the development of or interest in technical knowledge. Similarly, artistic interest ("create") drives individuals to create new things and be innovative, which can be pursued in professions involving arts or crafts, such as painting, carpentry, or music. However, this typically happens in a divergent mode of thinking, while learning to master digital tools requires a more convergent mode of problem-solving (e.g., Webb et al., 2017). Based on these considerations, we do not expect a relationship between digital self-efficacy and the interests to organize, help, lead, or create.

The investigative interest ("think"), however, is characterized by a heightened attraction to think, ruminate, and pursue mental stimulations of a wide variety of novel approaches to solve a given challenge. Individuals high in this interest prefer working with ideas rather than things or people. They possess an internal drive to understand the mechanisms of their surroundings, and they enjoy situations that allow them to assess data to optimize their solutions. Typically, they engage in similar activities in their free time, for example, learning languages, playing chess, or taking courses in topics in which they are interested. Exemplary professions that suit highly investigative individuals particularly well are those that pose complex mental challenges, such as research, programming, or mathematics. Being attracted to such mental stimulation could prove beneficial in coping with the challenges of the digital workplace and in finding new ways to use digital tools. Therefore, we expect this interest to be related to digital self-efficacy.

Hypothesis 3: Investigative interest is positively related to digital self-efficacy beyond the influence of personality.

Individuals high in realistic interest ("do") enjoy tinkering with challenges at hand, trying out different solutions, and learning by doing. In fact, individuals who score high on realistic interest are more interested in things than in people or data. They prefer to solve challenges by implementing a possible solution and adapting it afterward rather than merely stimulating it mentally. This is often accompanied by a high level of persistence. In their free time, they tend to choose physical sports like mountain biking or various types of craft. As opposed to investigative individuals, who derive as much pleasure from solving theoretical or hypothetical problems as they do from solving concrete ones, highly realistic individuals prefer professions that pose concrete tangible problems that require practical solutions. Exemplary professions include engineering, system administration, or architecture. Since individuals high in realistic interest are coined by an iterative and persevering approach to problem-solving, we expect them to utilize useful technologies in their endeavors and to have developed trust in their abilities to solve the challenges they face. In turn, we expect them to benefit from higher digital self-efficacy.

Hypothesis 4: Realistic interest to do is positively related to digital self-efficacy beyond the influence of personality.

2.4. Agility

An employee's agility represents their mindset of tolerance and resilience in the face of changes in the environment and their ability to adapt their behavior by utilizing changes in ways that benefit their organization (Alavi et al., 2014). Change is omnipresent in today's workplace, making agility a vital ability (Sherehiy et al., 2007; Klammer et al., 2017). Therefore, agility should permeate the organization on every level: For an organization to be considered agile, each individual employee must behave in an agile manner. An agile workforce has been shown to benefit from less steep learning curves, generate improved economies of scope, produce better output quality, and provide better customer service (Herzenberg et al., 1998; Hopp and Van Oyen, 2004). Members of an agile workforce are highly responsive to changes in their environment, seek and utilize technology to aid in acquiring and processing information, and share knowledge and power among each other, and they do these things quickly and efficiently (Breu et al., 2002). These behaviors necessitate that employees possess a variety of skills and competencies, such as learning ability, collaboration effectiveness, and responsiveness to changing demands (Breu et al., 2002).

Self-efficacy beliefs are created first and foremost through enactive mastery experiences (Bandura, 1997). Therefore, individuals high in digital competencies typically possess high levels of digital self-efficacy. Further, digital competencies are a main driver of agility within employees, and in turn, within firms (Ravichandran, 2018). Generally, the more technologically advanced a nation or industry is, the more agile its organizations become (Škare and Soriano, 2021). Further, an organization's investment in information technology infrastructure affects its performance through increased agility. The implementation of novel information technology does not have to be at the center of an organization's transformation but can also act as an infrastructural tool that supports strategic adaptation by streamlining processes and administrative work and shortening response times to facilitate organizational agility (Luftman et al., 1993), given that the technology is sufficiently adaptive itself (Mooney and Ganley, 2007). Therefore, employees need to be able to evaluate the appropriateness of prospective technologies and to trust their competencies to select and implement only those that enhance rather than impede the organization's agility (Weill et al., 2002). This is reflected in data showing that those firms that invest largely in information technologies tend to be more innovative and agile (Ravichandran, 2018).

Through digitized business processes, organizations generate information, and thus, can adapt to changes in their environment earlier or even create new offerings based on insights into their customers' needs (Sambamurthy et al., 2003). In turn, we expect employees who have a high level of trust in their digital competencies to also exhibit higher agility.

Hypothesis 5: Digital self-efficacy is positively related to agility.

As stated before, building on our theoretical framework on personality factors and vocational interests, we expect openness and emotional stability as well as the interests to do and to think to be related to digital self-efficacy. Therefore, in the next step, we try to examine the entire path and assume that these traits and interests and the improved use of information technologies enable employees to act more agilely.

Hypothesis 6: Digital self-efficacy mediates the relationship between openness to experience and agility.
Hypothesis 7: Digital self-efficacy mediates the relationship between emotional stability and agility.
Hypothesis 8: Digital self-efficacy mediates the relationship between investigative interest in thinking and agility.
Hypothesis 9: Digital self-efficacy mediates the relationship between realistic interest to do and agility.

These hypothesized relationships between the personality dimensions, vocational interests, and participants' digital self-efficacy and agility are summarized in a conceptual research model (see Fig. 1; Allen et al., 2007). We approached this framework by conducting two separate studies: the first one addresses the direct influence of personality and vocational interests on digital self-efficacy to gather primary evidence for hypotheses 1 to 4, and the second one replicates and extends the former by including workplace agility as a distinct outcome, thus enabling us to examine hypotheses 5 through 9. Following these aims, our initial study collected data from a sample of 309 employees at organizations from central and western Europe that were mostly engaged in the aerospace, food and services, and banking sectors to provide a first general insight into these processes. In our second study, we examined the robustness of our findings and therefore gathered 1,025 employees, thus nearly tripling the sample of our first study. Furthermore, for this second study, we conducted our data analyses exclusively at publicly traded companies listed in the French benchmark stock index CAC 40. Our data collection process thus ensured all participants were working in well-established organizations that had successfully adapted to the changing market environment and were in the process of an ongoing digital transformation. Therefore, as employees for these companies, they would be faced with constant change and the digitization of their work flow.

3. Study 1

3.1. Methods and design

In the first step, to assess the hypothesized interactions between the five factors of personality, vocational interests, and digital self-efficacy, we designed and conducted an international survey study on a diverse sample of employees from various organizations, mostly based in central and western Europe. Data acquisition was conducted by the private research company Praditus, which is recognized by the French Ministry of Research and Education. The company developed a web and mobile application to aid employees in their individual development, and participants are provided feedback on their data (see Clark et al., 2020; Durst et al., 2021). For this study, we collected data via the web app.

3.1.1. Sample

Our sample consisted of 309 (67.1% male, 32.9% female) participants from 33 countries across the globe with a mean age of 39.54 (standard deviation [SD] = 9.20, range 22–61), the majority of whom were employees (52.6%), whereas the remainder were in managing (27.9%) or directorial positions (19.5%). They were mostly working at French (44.3%), German (21.4%), British (7.1%), or Spanish (5.8%) organizations in the aerospace (57.6%), food and services (19.7%), or banking (11.3%) industries, with the biggest share (17.5%) in engineering or architecture, 13.9% in human resources, 9.7% in production or manufacturing, and 9.1% in finance, accounting, or auditing. Participants had predominantly obtained a master's (36.9%), engineering (18.4%), bachelor's (12.9%) or technical degree (12.3%), and 64.1% had acquired at least 10 years, 14.9% had 5–10 years, 11.3% had 1–5 years, and 9.7% had less than one year of work experience. All participants provided informed consent to the further scientific processing of their data.

3.1.2. Measures

3.1.2.1. Five-factor model of personality. We assessed participants' personality using in-house validated items based on the five-factor model of personality (e.g., Goldberg, 1992; McCrae and Costa, 2008). Participants rated their agreement with a total of 20 items (4 items per factor) regarding their openness ($\alpha = 0.67$; e.g., "I think of myself as open-minded"), conscientiousness ($\alpha = 0.63$; e.g., "I usually work hard"),

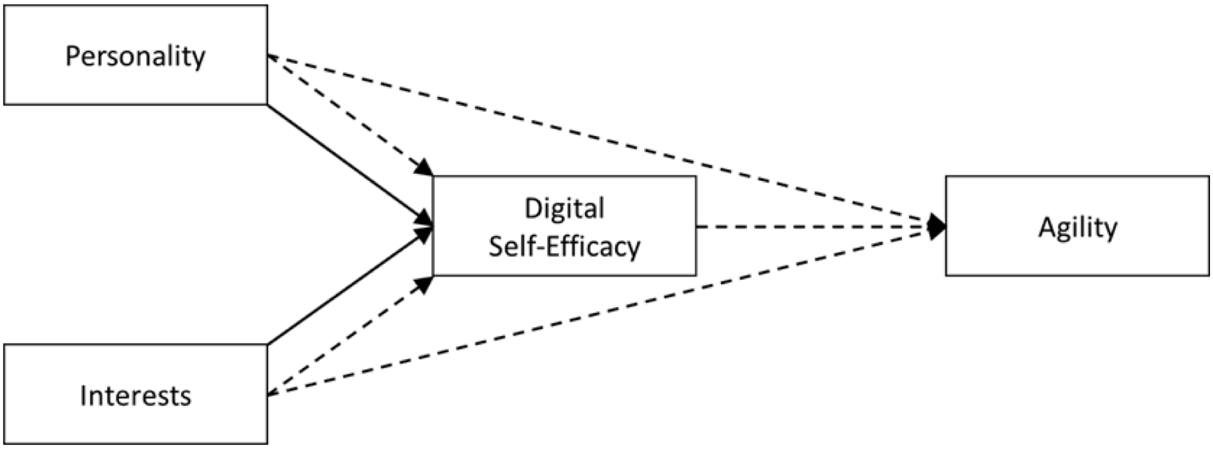

Fig. 1. Proposed conceptual research model for our first study (assessing participants' personality, vocational interests, and digital self-efficacy) and second study (further adding agility as a distinct outcome measure). Continuous lines indicate the research model for Study 1, while broken lines delineate our extended model for Study 2.

extraversion ($\alpha = 0.81$; e.g., "I like going out and meeting people"), agreeableness ($\alpha = 0.48$; e.g., "Helping others gives me a sense of satisfaction"), and emotional stability ($\alpha = 0.77$; e.g., "I am generally calm and relaxed") on a 7-point Likert scale (1 = totally disagree; 7 = totally agree). The calculated reliabilities were within the typical range for extra-short measures of the five factors of personality (e.g., Hahn et al., 2012; Soto and John, 2017a).

3.1.2.2. Vocational interests. Following the vocational interests model by Holland (1959, 1997), we assessed participants' interests to do (*realistic;* $\alpha = 0.86$; e.g., "This kind of activity appeals to me: constructing, assembling, or building machines"), think (*investigative;* $\alpha = 0.69$; e.g., "The kinds of tasks an engineer performs appeal to me"), create (*artistic interest;* $\alpha = 0.73$; e.g., "The kinds of tasks a painter performs appeal to me"), help (*social;* $\alpha = 0.79$; e.g., "The kinds of tasks a nurse performs appeal to me"), lead (*enterprising;* $\alpha = 0.80$; e.g., "The kinds of tasks a CEO performs appeal to me"), and organize (*conventional;* $\alpha = 0.78$; e.g., "This kind of activity appeals to me: computing and verifying statistical and other numerical data"). We captured each aspect with 5 items, and participants had to indicate their agreement with them on a 7-point Likert scale (1 = totally disagree; 7 = totally agree).

3.1.2.3. Digital self-efficacy. We adapted three items from the affinity for technology scale by Edison and Geissler (2003) and added five additional items to capture the construct of digital self-efficacy more thoroughly. Participants indicated their agreement with the eight statements regarding their confidence in interacting with digital technologies ($\alpha = 0.84$; e.g., "I am good at using all the features of word processors") on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

3.2. Data analysis strategy

To gain the first insight into our data, we calculated Pearson product-moment correlation coefficients for all variables in SPSS (Version 26). To test our hypotheses more thoroughly, we then proposed a path analysis, allowing us to model the pathways of the participants' personality and their vocational interests to their digital self-efficacy (Fig. 1). We calculated maximum likelihood estimates in SPSS AMOS (Version 26) and reported standardized coefficients for the structural equation model, as well as $\chi 2$/d.f. (sufficient fit ≤ 3; good fit ≤ 2), RMSEA (sufficient fit ≤ 0.08, good fit ≤ 0.05), and SRMR (sufficient fit ≤ 0.10, good fit ≤ 0.05) as descriptive measures of the overall model fit and the CFI (sufficient fit ≥ 0.95, good fit ≥ 0.97) as a measure of increased model fit compared to the independence model (Browne and Cudeck, 1993; Hu and Bentler, 1999). For the standardized path coefficients, we recognized a β of at least > 0.10 as a small effect and therefore sufficient to be discussed further, while coefficients greater than 0.30 were interpreted as medium effects, and those greater than 0.50 as large effects (Cohen, 1988). Lastly, to reduce the potential influence of heteroskedasticity, we calculated bootstrap estimates of standard errors and 99% percentile confidence intervals (Cis) using 5000 samples (Arbuckle, 2016; Hayes and Scharkow, 2013; Nevitt and Hancock, 2001; Yung and Bentler, 1996).

3.3. Results

3.3.1. Confirmatory factor analysis

To analyze whether our selected scales provide sufficient discriminant validity, we conducted confirmatory factor analyses (CFA; Hu and Bentler, 1999) using SPSS AMOS (Version 26). For more details on the reported measures of model fit, please refer to our data analysis strategy. Additionally, we report the Bayesian information criterion (BIC) and the consistent Akaike information criterion (*CAIC*) as goodness-of-fit measures to allow for a direct comparison between the alternative models (Nylund et al., 2007; Preacher and Merkle, 2012). For both measures, lower values indicated a better fit, and a BIC disparity of at least 10 indicated a significant difference (Rafferty, 1995). When conducting the CFA on our proposed model of five personality dimensions, six interests, and the dependent variable of digital self-efficacy, the model provided a mostly sufficient to good fit ($\chi^2_{(1515)} = 2633.965$, $p < 0.001$, $\chi^2/d.f. = 1.739$; CFI = 0.827; RMSEA = 0.049; SRMR = 0.073; BIC = 3757.700; CAIC = 3953.700. However, the χ^2-statistic indicated possibly skewed estimates (Antonakis, 2017), which might have resulted from high cross-loadings between the employed scales (Crawford and Kelder, 2019; Ropovik, 2015).

To mitigate possible issues caused by employing a single source for our data, we tested for the presence of a common method bias by firstly conducting Harman's one-factor test and secondly establishing a common latent factor model and comparing its fit to our proposed framework (Podsakoff et al., 2003). The exploratory factor analysis with an unrotated solution on a single factor resulted in an explained variance of 12.3%, therefore well below the variance of 50%, at which Harman's test would indicate a single factor, and a variance of 70% at which common method variance would likely cause issues (Fuller et al., 2016). A further CFA model including one common latent factor for all indicators resulted in an overall insufficient model fit ($\chi^2_{(1596)} = 6552.759$, $p < 0.001$, $\chi^2/d.f. = 4.106$; CFI = 0.232; RMSEA = 0.100; SRMR = 0.1320; BIC = 7212.093; CAIC = 7327.093) which was significantly worse compared to our proposed model ($\Delta\chi^2_{(81)}$ = 3918.794, $p < 0.001$; ΔBIC > 10). Therefore, our analyses support that no substantial common method bias affects our data (Podsakoff et al., 2003).

3.3.2. Testing the proposed framework

Correlational analyses revealed the expected accordances between the dependent variable of digital self-efficacy and the five factors of personality (openness: $r = 0.220$, $p < 0.001$; conscientiousness: $r = 0.143$, $p = .012$; agreeableness: $r = 0.192$, $p = 0.001$; and stability: $r = 0.293$, $p < 0.001$) as well as with the vocational interests to do ($r = 0.191$, $p = 0.001$), think ($r = 0.336$, $p < 0.001$), lead ($r = 0.157$, $p = 0.006$), and organize ($r = 0.201$, $p < 0.001$), while it was not related to extraversion ($r = 0.076$, $p = 0.184$) nor the interests to create ($r = -0.049$, $p = 0.388$) and to help ($r = -0.084$, $p = 0.142$).

The five factors of personality were at most moderately correlated with vocational interests (all $rs \leq 0.326$; Table 1). We recognize this finding as further support for the notion that interests and personality are indeed not substitutable (e.g., Barrick et al., 2003; Costa et al., 1984) and thus included both in our further path analyses, as we expect an incremental explanation of variance from doing so (e.g., Stoll et al., 2017, 2020).

Overall, our proposed model (Fig. 2) showed a very good fit with the data ($\chi^2_{(22)} = 27.799$, $p = 0.182$, $\chi^2/d.f. = 1.264$; CFI = 0.992; RMSEA = 0.029; SRMR = 0.036). The participants' openness ($\beta = 0.143$, $p = 0.020$) and stability ($\beta = 0.193$, $p < 0.001$), as well as their vocational interest to think ($\beta = 0.317$, $p < 0.001$) positively and their interests to create ($\beta = -0.123$, $p = 0.036$) and help ($\beta = -0.135$, $p = 0.032$) negatively impacted digital self-efficacy, whereas no other personality dimension or interest reached significance nor a substantial effect size (see Table 2).

To conclude, our initial data analyses provided the first evidence for the five factors of personality and vocational interests to have a distinct impact on employees' digital self-efficacy. In detail, we found an individual's openness (Hypothesis 1) and stability (Hypothesis 2) to positively impact their confidence in their proficiency with digital technologies. Beyond this influence of personality, interest in thinking also predicted digital self-efficacy (Hypothesis 3). However, we did not find support for the anticipated positive relationship between the interest to do and our outcome measure (Hypothesis 4), but instead detected a negative impact of the interests to create and help, which is further investigated in our second study.

4. Study 2

4.1. Methods and design

In a second step, following up on the promising findings of our initial study, we aimed to replicate and extend our analyses onto employees' agility in the workplace. To achieve this, we collected further data from companies listed in the French benchmark stock market index CAC 40 that were in the process of an ongoing digital transformation. The data acquisition was again conducted by the company Praditus, and we gathered data via their web app.

4.1.1. Sample

This study included 1025 participants (54.1% male, 45.9% female; $M_{age} = 42.06$, $SD = 8.91$, range 22–65), the majority again being employees (54.2%), followed by managers (35.3%) and directors (10.4%) from French companies predominantly from the banking (44.3%), energy (23.5%), automobile (14.4%) and transport (11.1%) sectors. Most participants had obtained a master's (47.2%), engineering (21.8%), technical (13.2%), or bachelor's (9.7%) degree and gathered more than 10 (77.0%), 5–10 (11.9%), 1–5 (9.7%), or less than 1 (1.5%) years of work experience. The most prevalent function was in finance, accounting, or auditing (23.4%), followed by project management (13.8%),

Table 1
Means, standard deviations, reliabilities, and correlation coefficients between digital self-efficacy, participants' reported five factors of their personality, and their vocational interests.

	M	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Digital self-efficacy	2.983	0.630	(0.84)											
2. Openness	4.815	0.712	0.220***	(0.67)										
3. Conscientiousness	4.319	0.875	0.143*	0.126*	(0.63)									
4. Extraversion	3.992	1.148	0.076	0.436***	0.204***	(0.81)								
5. Agreeableness	4.423	0.786	0.192**	0.278***	0.194**	0.345***	(0.48)							
6. Stability	4.091	1.004	0.293***	0.214***	0.277***	0.068	0.320***	(0.77)						
7. Do	3.135	1.334	0.191**	0.062	−0.033	−0.068	−0.055	0.034	(0.86)					
8. Think	3.109	1.100	0.336***	0.107	−0.016	−0.034	−0.006	0.047	0.547***	(0.69)				
9. Create	3.186	1.142	−0.049	0.212***	−0.168**	0.176**	0.158**	0.032	0.196**	0.216***	(0.73)			
10. Help	3.007	1.196	−0.084	0.126*	−0.081	0.088	0.054	−0.050	0.218***	0.222***	0.494***	(0.79)		
11. Lead	3.722	1.207	0.157**	0.308***	0.144*	0.326***	0.197**	0.179**	−0.013	0.127*	0.219***	0.175**	(0.80)	
12. Organize	2.548	1.190	0.201***	−0.120*	0.115*	−0.044	−0.070	0.044	0.299***	0.546***	−0.042	0.114*	0.111	(0.78)

Note. $N = 309$. Reliability coefficients are presented in parentheses along the diagonal.
* $p < .05$, ** $p < .01$, *** $p < .001$.

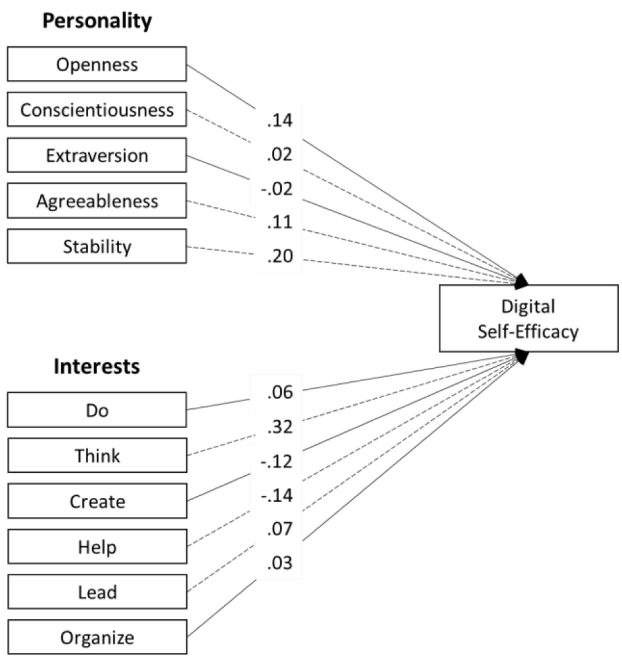

Fig. 2. Path model for Study 1, including the standardized regression weights for each path. Continuous lines indicate significant paths at $p < 0.05$. $N = 309$.

Table 2
Standardized regression weights, bootstrapped standard errors, and p-values for the direct effects of the participants' five factors of personality and vocational interests on their digital self-efficacy.

Direct effects	Digital self-efficacy β	*BootSE*	*p*
Personality			
Openness	0.143	0.061	0.020
Conscientiousness	0.017	0.056	0.744
Extraversion	-0.016	0.056	0.763
Agreeableness	0.114	0.060	0.075
Stability	0.193	0.061	< 0.001
Interests			
Do	0.056	0.060	0.319
Think	0.317	0.074	< 0.001
Create	-0.123	0.060	0.036
Help	-0.135	0.061	0.032
Lead	0.068	0.065	0.249
Organize	0.030	0.066	0.685

Note. $N = 309$. Standard errors were computed at 5000 bootstrapping samples.

information technology or computer science (11.4%), and marketing, public relations, or communication (9.3%). Participants provided informed consent to make their data accessible for further studies.

4.1.2. Measures

We employed the same measures for the five factors of personality (reliabilities for openness: $\alpha = 0.70$, conscientiousness: $\alpha = 0.61$, extraversion: $\alpha = 0.81$, agreeableness: $\alpha = 0.53$, and stability: $\alpha = 0.72$), vocational interests (do: $\alpha = 0.81$, think: $\alpha = 0.66$, create: $\alpha = 0.67$, help: $\alpha = 0.72$, lead: $\alpha = 0.76$, and organize: $\alpha = 0.77$), and digital self-efficacy ($\alpha = 0.79$) as in Study 1 (see 3.1.2. Measures) with the addition of a measure for the participants' workplace agility.

4.1.2.1. Agility. To assess the participants' agility, we selected four items from the workforce agility scale developed by Muduli (2016; based on Breu et al., 2002). We only employed a reduced set of items to avoid any potential overlap with our measure for digital self-efficacy. Participants indicated their agreement with these statements on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). An example item read, "I quickly develop skills, adjust to new environments, and collect information," and Cronbach's alpha for the scale was $\alpha = 0.70$.

4.2. Data analysis strategy

Our data analyses followed the same pattern as reported for Study 1, with the addition of the participants' agility as a dependent variable of digital self-efficacy to the structural equation model. We further proposed direct and indirect effects between the five factors of personality and vocational interests on agility via the mediating pathway of digital self-efficacy. To obtain robust estimates of the indirect paths' significance, we employed 5000 bootstrapping samples and reported standardized total, direct, and indirect effects, including the upper and lower bounds of the 99 percentile confidence intervals for the indirect pathways. Data analyses were again conducted in SPSS (Version 26) and SPSS Amos (Version 26).

4.3. Results

4.3.1. Confirmatory factor analysis

Our proposed factorial structure of five personality dimensions, six interests, and the dependent variables of digital self-efficacy and agility resulted in a mostly sufficient to good fit ($\chi^2_{(1717)} = 4627.287, p < 0.001$, $\chi^2/d.f. = 2.695$; CFI = 0.848; RMSEA = 0.041; SRMR = 0.054; BIC = 6263.345; CAIC = 6499.345), though the significant χ^2-statistic still indicated potentially biased estimates (Antonakis, 2017; Bollen et al., 2007). An alternative model combining the participants' digital self-efficacy and their agility toward a single factor provided a worse fit ($\chi^2_{(1730)} = 4867.965$, $p < .001$, $\chi^2/d.f. = 2.814$; *CFI* = 0.836; RMSEA = 0.042; SRMR = 0.058; BIC = 6413.901; CAIC = 6636.901) for our data ($\Delta\chi^2_{(13)} = 240.678, p < 0.001$; $\Delta_{BIC} > 10$), indicating the measures to be distinct.

To mitigate a possible common method bias, we again conducted Harman's one-factor test, which resulted in an explained variance of 12.1%, thus well below the threshold of 50%, indicating the presence of a single underlying factor. Adapting our confirmatory factor analysis to encompass only a single latent factor for all variables did result in an insufficient model fit ($\chi^2_{(1794)} = 11{,}802.376, p < 0.001$, $\chi^2/d.f. = 6.579$; CFI = 0.478; RMSEA = 0.074; SRMR = 0.099; BIC = 12,904.635; CAIC = 13,063.635) and fit the data notably worse than our proposed model ($\Delta\chi^2_{(77)} = 7175.089$, $p < 0.001$; ΔBIC > 10).

4.3.2. Testing our proposed framework

Correlational analyses reiterated the previously found positive relations between digital self-efficacy and four of the five factors of personality (openness: $r = 0.294, p < 0.001$; conscientiousness: $r = 0.139$, $p < .001$; agreeableness: $r = 0.157$, $p < 0.001$; stability: $r = 0.254$, $p < 0.001$) and the vocational interests to do ($r = 0.253, p < 0.001$), think ($r = 0.278$, $p < 0.001$), lead ($r = 0.170$, $p < 0.001$), and organize ($r = 0.158, p < 0.001$) with the interests to create ($r = 0.015, p = 0.643$) and to help ($r = -0.023, p = 0.463$) showing no relation and extraversion not reaching a substantial effect size ($r = 0.094$, $p = 0.003$). Further, participants' agility was positively linked to the five factors of personality (openness: $r = 0.464, p < 0.001$; conscientiousness: $r = 0.174, p < 0.001$; extraversion: $r = 0.286$, $p < 0.001$; agreeableness: $r = 0.288, p < 0.001$; stability: $r = 0.254, p < 0.001$) and the interests to think ($r = 0.139, p < 0.001$), create ($r = 0.103$, $p = 0.001$), and lead ($r = 0.242$, $p < 0.001$). The interests to do ($r = 0.092, p = 0.003$), help ($r = 0.013, p = 0.674$), and organize ($r = -0.062$, $p = 0.046$), however, did not show a substantial or significant effect on agility. Lastly, digital self-efficacy was strongly related to agility ($r = 0.515, p < 0.001$).

Again, correlations between the participants' personality and their vocational interests reached moderate levels at most (all $rs \leq 0.367$; Table 3), indicating the constructs are not substitutable and therefore

Table 3
Means, standard deviations, reliabilities, and correlation coefficients between digital self-efficacy, agility, participants' reported personality, and their vocational interests.

	M	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Digital self-efficacy	3.034	0.542	(0.79)												
2. Agility	3.356	0.467	0.515***	(0.70)											
3. Openness	4.888	0.674	0.294***	0.464***	(0.70)										
4. Conscientiousness	4.163	0.891	0.139***	0.174***	0.145***	(0.61)									
5. Extraversion	3.997	1.104	0.094**	0.286***	0.388***	0.242***	(0.81)								
6. Agreeableness	4.390	0.794	0.157***	0.288***	0.331***	0.249***	0.429***	(0.53)							
7. Stability	3.960	0.943	0.254***	0.254***	0.239***	2.460***	0.216***	0.327***	(0.72)						
8. Do	2.989	1.200	0.253***	0.092**	0.027	0.013	−0.009	0.007	0.048	(0.81)					
9. Think	3.271	1.055	0.278***	0.139***	0.127***	0.000	0.026	0.043	0.090**	0.515***	(0.66)				
10. Create	3.498	1.064	0.015	0.103**	0.232***	−0.073*	0.141***	0.162***	0.049	0.190***	0.163***	(0.67)			
11. Help	3.188	1.074	−0.023	0.013	0.116***	0.056	0.156***	0.195***	0.022	0.138***	0.204***	0.323***	(0.72)		
12. Lead	3.884	1.079	0.170***	0.242***	0.284***	0.164***	0.367***	0.099**	0.240***	0.067*	0.163***	0.137***	0.106**	(0.76)	
13. Organize	2.349	1.147	0.158***	−0.062*	−0.145***	0.120***	−0.075*	−0.111***	−0.004	0.418***	0.496***	−0.068*	0.059	0.059	(0.77)

Note. $N = 1025$. Reliability coefficients are presented in parentheses along the diagonal. .
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

both suitable for inclusion in our path analyses (Fig. 3).

The addition of agility to our previously proposed model provided a very good model fit ($\chi^2_{(14)} = 17.868$, $p = 0.213$, $\chi^2/d.f. = 1.276$; CFI = 0.999; RMSEA = 0.016; SRMR = 0.019). We replicated the pathways of the participants' openness ($\beta = 0.254$, $p < 0.001$), stability ($\beta = 0.146$, $p < 0.001$), and their interest to think ($\beta = 0.145$, $p < 0.001$) detected in Study 1, while the negative effects of the interests to create ($\beta = -0.078$, $p = .008$) and help ($\beta = -0.098$, $p = 0.002$) did not reach a substantial level. Additionally, we detected a positive influence of the interest to do ($\beta = 0.168$, $p < 0.001$), as anticipated by Hypothesis 4. All other pathways on digital self-efficacy did not reach sufficient effect sizes or significance (Fig. 3; Table 4).

Digital self-efficacy itself was positively related to agility ($\beta = 0.406$, $p < .001$) and mediated the effects of the participants' openness (total effect: $\beta = 0.347$, $p < .001$; direct effect: $\beta = 0.244$, $p < .001$; indirect effect: $\gamma = 0.103$, 99% CI = 0.068 to 0.144) and stability (total: $\beta = 0.080$, $p = 0.008$; direct: $\beta = 0.021$, $p = 0.437$; indirect: $\gamma = 0.059$, 99% CI = 0.029 to 0.092; see Table 4), as well as the interests to do (total: $\beta = 0.075$, $p = .022$; direct: $\beta = 0.007$, $p = 0.802$; indirect: $\gamma = 0.068$, 99% CI = 0.030 to 0.109), think (total: $\beta = 0.085$, $p = 0.013$; direct: $\beta = 0.031$, $p = 0.357$; indirect: $\gamma = 0.059$, 99% CI = 0.021 to 0.100), create (total effect: $\beta = -0.019$, $p = 0.525$; direct effect: $\beta = 0.013$, $p = 0.637$; indirect effect: $\gamma = -0.032$, 99% CI = −0.066 to −0.001), and help (total: $\beta = -0.088$, $p = 0.004$; direct: $\beta = -0.049$, $p = 0.074$; indirect: $\gamma = -0.040$, 99% CI = −0.075 to −0.007) on agility.

The indirect effects of the remaining personality factors (conscientiousness, extraversion, and agreeableness) and interests (lead and organize) did not reach significance, and only the direct pathway of the interest to organize ($\beta = -0.100$, $p = 0.002$) barely reached a substantial effect size (Table 4).

To summarize, we were able to replicate the distinct relations of an individuals' openness (Hypothesis 1) and their stability (Hypothesis 2) on their digital self-efficacy with their interest to think being a valid predictor beyond the five factors of personality (Hypothesis 3). Additionally, we now detected the anticipated relation between the interest to do and digital self-efficacy (Hypothesis 4). These constructs further indirectly shape agility (Hypotheses 6–9), with digital self-efficacy directly increasing agility (Hypothesis 5). Furthermore, we found openness to both directly and indirectly affect the workplace agility of our participants.

The limiting effect on digital self-efficacy by the interests to create and help, on the other hand, did not reach a substantial level in this second study. However, they did indirectly hamper the participants' agility, though still at a rather low potency, while the interest in organizing directly and negatively affected agility.

5. Discussion

The world has been changing, and there is no end in sight for this change (Kraus et al., 2021). Workplaces used to be based on rigid processes, transactional leadership, and monotonous repetitive duties. Most research on traits and skills suitable for workplace environments was conducted decades ago within paradigms that have since been transformed. Nowadays, employees work on a wide variety of tasks that demand their abilities to organize seamlessly, to innovate creatively, and to allocate their time between the tasks effectively (Covin et al., 2020; Kraus et al., 2019). Modern professions bear different challenges, prompting the revision of long-held principles. Today's high-performing employees need to be versatile enough to utilize novel technological solutions confidently and effortlessly. However, how can organizations select the most suitable one from an array of candidates? Which features, skills, or traits should a human resources manager consider to guide their selection? Over the course of two studies, we examined the relationship between an individual's stable personality traits, vocational interests, digital self-efficacy, and agility. Interestingly, we found openness and emotional stability to outperform conscientiousness as

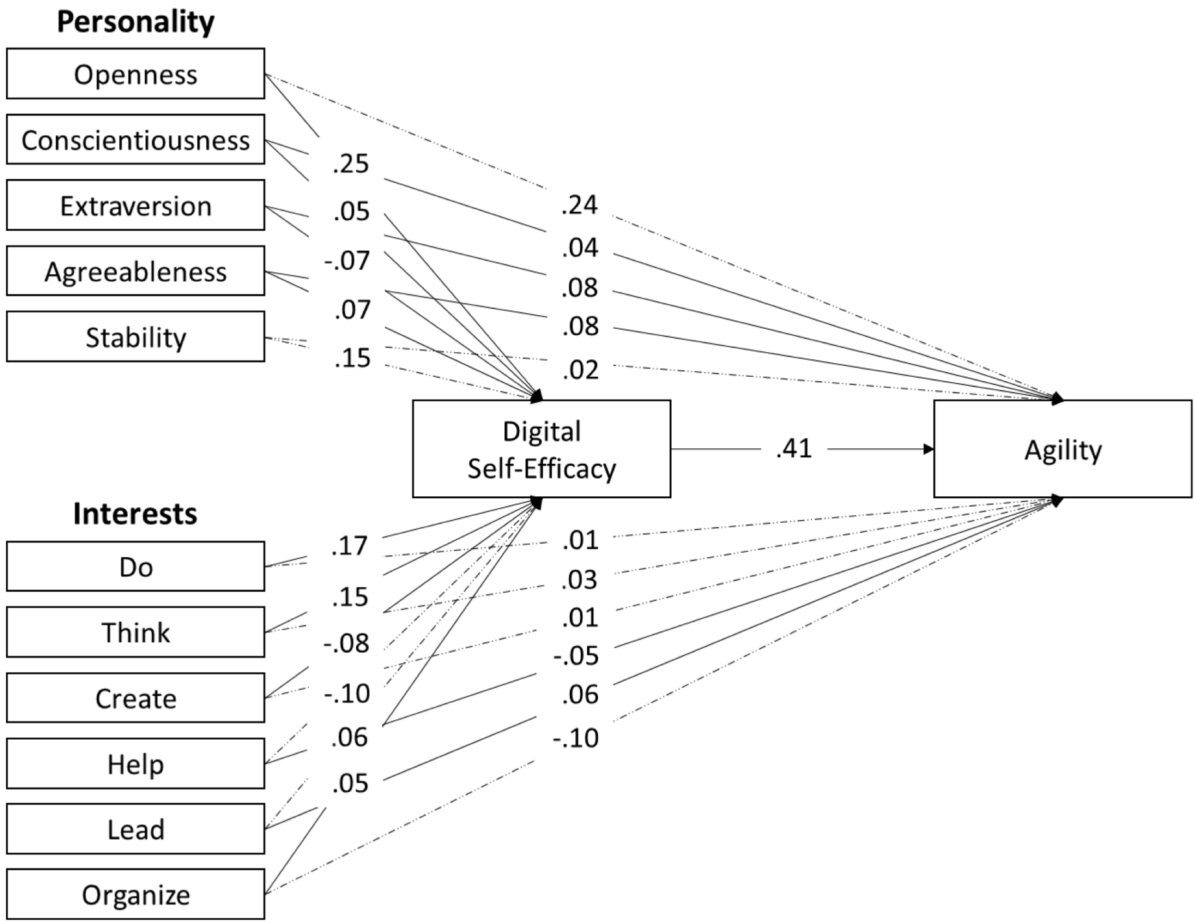

Fig. 3. Path model for Study 2, including the standardized regression weights for each path. Continuous lines indicate significant paths at $p < 0.05$. $N = 1025$.

predictors of digital self-efficacy in the modern workplace. Further, we found that an individual's vocational interests predict their digital self-efficacy beyond the effects of their personality. Our findings establish a composition of personality traits and interests that an organization might screen their applicants for to be better equip organizations to deal with the challenges of digital transformation processes and the resulting uncertainty and complexity.

First, our studies consistently revealed an individual's openness to experience to be the most prevalent predictor of their digital self-efficacy. The measure of openness showed a substantial direct effect on digital self-efficacy across both studies (Hypothesis 1). Furthermore, openness directly and indirectly shaped agility, thus confirming Hypothesis 6 and indicating openness to increase workforce agility above and beyond the observed direct influence of digital self-efficacy (Hypothesis 5). As openness is related to flexibility and a willingness to develop new skills (Costa and McCrae, 1992), this comes as no surprise. Openness is related to complexity and curiosity and also cognitive ability (DeYoung et al., 2007). In turn, more open individuals are better able to and derive greater enjoyment from solving novel challenges compared to their less open counterparts. In fact, they do not only enjoy novel experiences, but they also even go so far as to actively seek them out (McCrae and Costa, 1997). Interestingly, prior research found openness to be linked with artistic interest (Šverko and Babarović, 2016), which is not reflected in the results of our study. This discrepancy highlights the difference between personality and interest: Openness is related to an appreciation for aesthetics and creativity, but even more so for cognitive stimulation, complexity, and most importantly, curiosity (Silvia and Christensen, 2020). The mastery of novel technology necessitates an intuitive and iterative approach to learning by doing (Sobkow et al., 2018). More open individuals obtain a broader array of information in their problem-solving endeavors, and they are better able to utilize acquired knowledge to find appropriate solutions (Heinström, 2003). In turn, they are more likely to evaluate their outcomes positively (Svendsen et al., 2013; Uffen et al., 2013). Therefore, our findings emphasize the relevance of this trait for the modern workplace. Increasing both digital self-efficacy and agility implicates open employees play an important role in enabling their organization to be agile, that is, to be able to quickly react to changes in their VUCA environment.

Second, we proposed another dimension of personality to directly impact digital self-efficacy. Emotional stability, or a low level of neuroticism, safeguards individuals from developing an aversion to change and consistently strengthens participants' confidence in engaging with digital technologies (Hypothesis 2). Furthermore, following digital self-efficacy, stability is indirectly associated with a higher level of agility (Hypothesis 7). Together with conscientiousness, a low level of neuroticism (or a high level of emotional stability) has been identified as a key predictor of employee performance in traditional workplaces (e.g., Wilmot and Ones, 2019 Barrick and Mount, 1991; Barrick et al., 2001). Highly neurotic individuals are emotionally unstable and often pessimistic or anxious. Their negative expectations of the future make them avoid changes in behavior. When faced with complex demands, high levels of neuroticism can overly quickly lead to frustration and stress (Ormel et al., 2013), making neurotic individuals less likely to persevere in implementing novel technologies if they experience setbacks (Perkins et al., 2015; Pickering et al., 2016). Subsequently, more neurotic individuals are more likely to engage in destructive coping mechanisms, such as escapism, denial, and blaming oneself or others (Lee-Baggley et al., 2005; Suls and Martin, 2005), further hampering digital transformation. These findings emphasize the importance of having an emotionally stable, relaxed, content,

Table 4
Standardized regression weights, bootstrapped standard errors, and p-values for the direct effects of the participants' five factors of personality and vocational interests on their digital self-efficacy as well as for the direct, total, and indirect effects (including their 99% confidence interval) of these predictors on the participants' agility.

	Direct effects					
	Digital self-efficacy			Agility		
	β	*BootSE*	*p*	β	*BootSE*	*p*
Personality						
Openness	0.254	0.032	< 0.001	0.244	0.029	< 0.001
Conscientiousness	0.050	0.030	0.095	0.043	0.026	0.092
Extraversion	-0.071	0.035	0.048	0.080	0.029	0.005
Agreeableness	0.068	0.034	0.049	0.081	0.030	0.011
Stability	0.146	0.028	< 0.001	0.021	0.029	0.437
Interests						
Do	0.168	0.035	< 0.001	0.007	0.030	0.802
Think	0.145	0.036	< 0.001	0.031	0.033	0.357
Create	-0.078	0.029	0.008	0.013	0.028	0.637
Help	-0.098	0.030	0.002	-0.049	0.027	0.074
Lead	0.058	0.031	0.068	0.058	0.027	0.034
Organize	0.047	0.034	0.172	-0.100	0.031	0.002
Digital self-efficacy				0.406	0.030	< 0.001
	Total effects on agility			Indirect effects on agility		
	β	*BootSE*	*p*	γ	*BootSE*	[LLCI, ULCI]
Personality						
Openness	0.347	0.031	< 0.001	0.103	0.015	[0.068, 0.144]
Conscientiousness	0.064	0.029	0.027	0.020	0.012	[-0.012, 0.051]
Extraversion	0.052	0.033	0.103	-0.029	0.014	[-0.065, 0.010]
Agreeableness	0.109	0.033	0.002	0.027	0.014	[-0.008, 0.063]
Stability	0.080	0.030	0.008	0.059	0.012	[0.029, 0.092]
Interests						
Do	0.075	0.035	0.022	0.068	0.015	[0.030, 0.109]
Think	0.090	0.036	0.013	0.059	0.015	[0.021, 0.100]
Create	-0.019	0.029	0.525	-0.032	0.012	[-0.066, -0.001]
Help	-0.088	0.030	0.004	-0.040	0.013	[-0.075, -0.007]
Lead	0.081	0.031	0.005	0.023	0.013	[-0.010, 0.057]
Organize	-0.081	0.034	0.016	0.019	0.014	[-0.016, 0.056]

Note. $N = 1025$. LLCI = Lower limit of the 99% confidence interval; ULCI = Upper limit of the 99% confidence interval; Standard errors were computed at 5000 percentile bootstrapping samples.

unconstrained, and self-assured workforce, and especially so in the modern digitized workspace.

Third, participants' interests predicted digital self-efficacy even beyond the five factors of personality, thus reiterating that these constructs should not be seen as substitutable (e.g., Barrick et al., 2003; Costa et al., 1984). We predicted that the interest to think is of special relevance for organizations that are in the process of adopting novel technologies, as it is characterized by an increased willingness to engage in mental stimulations and problem-solving. Highly investigative individuals prefer pondering ideas and assessing data rather than maneuvering physical objects or people. We hypothesized that their internal drive to understand and optimize the implications of the way they interact with their surroundings makes them possess a high degree of digital self-efficacy (Hypothesis 3), a proposition that both of our studies support. Further, the interest to do is coined by a preference to work with things other than data or individuals to solve concrete and tangible challenges. Highly realistic individuals approach tasks by iteratively implementing and improving upon solutions. Through their preference for learning by doing and their high degree of perseverance in doing so, we expected them to be particularly suitable for modern organizations through their possession of higher digital self-efficacy (Hypothesis 4). Our second and more robust study provided compelling evidence in support of this notion. Again, both interests indirectly influenced the workplace agility of our participants, matching the expectations proposed in Hypotheses 8 and 9. Interestingly, and extending beyond our expectations, our initial study provided evidence for vocational interests to help and hamper digital self-efficacy. In fact, individuals with such interests are more likely to choose professions that deal with ideas rather than things or data. These are professions like novel writing, music, or religious roles (Shivy et al., 1999). As these direct pathways and the indirect effects on agility did not reach substantial effect sizes in our second study, we concluded that they do not seem impactful enough for further consideration, as effect sizes usually tend to approach their true effects in larger samples.

Lastly, the interest in organizing only had a negative direct impact on workplace agility, an effect we did not consider when proposing our hypotheses, but which might be due to employees possessing a conventional vocational interest being more prone to steadily optimize workflows. This behavior may in direct consequence limit their readiness to adapt to a changing environment. To summarize, we were able to detect initial evidence of the relationship between an individuals' emotional stability and their openness with their digital self-efficacy in our first study. The participants' interests in thinking, helping, and creating explained incremental variance beyond these dimensions of personality. We were able to replicate our findings for stability, openness, and the interest to think in our second study, which we conducted with a nearly tripled sample acquired from some of the most valuable publicly traded French companies. However, the negative influence of the interests to help and create did not reach significant levels. Instead, we found the interest to do to increase digital self-efficacy beyond the previously detected pathways. Additionally, stability, openness, and the interest to do and think indirectly shaped the agility exhibited in the workplace by strengthening digital self-efficacy. The interests to create, do, and organize, however, might not support agility. These findings reveal that the personality of an individual plays a critical role in their suitability for jobs that require digital self-efficacy and agility. More importantly, we extend this suggestion by emphasizing the importance of vocational interests as a distinct factor to consider.

5.1. Practical implications

Openness and its direct effects on digital self-efficacy and agility might experience a rise to prominence when it comes to the personality predispositions most relevant for the modern workplace. Conscientiousness had evolved to be the most potent explanatory variable for work performance (e.g., Wilmot and Ones, 2019). This may be due to the fact that up until the widespread use of information technology from the turn of the millennium onward, changes in an organization's environment mostly occurred in a gradual manner. Their slow pace allowed sufficient time for conscientious employees to monitor their environment and to make the required iterative adaptations. Today, the tables have turned: disruptive digital business models created by open and creative individuals can overturn entire industries seemingly overnight. Thus, it no longer suffices to conscientiously optimize; organizations must also remain open and creative to recognize the need to pivot in their business models (Christensen, 1997). The acceleration of environmental changes further affects organizations' cultures. Digitized processes allow flatter hierarchies and more organic structures. Some organizations have even discarded their hierarchies altogether and now assign temporary leadership roles based on competence (Robertson, 2015). Even with hierarchies intact, many companies utilize temporary teams that form and disband rapidly when needed (Bakker et al., 2013) and typically organize themselves with the help of collaborative agile project management and information management software (Romano et al., 2002).

In summary, organizations, especially those in the process of a digital transformation, might want to consider shifting their focus to hire open employees. In fact, based on the binomial effect size display (Rosenthal and Rubin, 1982), our data indicate employers who select more open individuals have a 62.7% likelihood of hiring an employee with higher digital self-efficacy (or 58.4% for a selection based on a more pronounced realistic interest; or 57.3% for either a selection based on higher emotional stability or one based on a more pronounced investigative interest). Furthermore, our data suggest emotional stability further increases employees' proficiency with digital technologies, thus again increasing their agility in the workplace. However, employers should not solely focus on the personality traits of their employees; our findings showed that employees' interests play a critical role in their development of digital self-efficacy and agility. Their realistic interest in doing, and especially their investigative interest in thinking, both strengthened their digital self-efficacy. Employees high in digital self-efficacy constitute an agile workforce, which enables the organization itself to become more agile, raising their ability to succeed in today's complex and rapidly changing market environment.

5.2. Limitations and future research directions

Though our studies present important practical implications, there remain some limitations that future research might be able to overcome. First, in our studies, we focused on the five factors of personality (e.g., McCrae and Costa, 2008) and the vocational interests model (Holland, 1997) as predictors for digital self-efficacy and workplace agility. Our aim was to identify general predispositions that facilitate employees to adapt to the (technological) challenges of the modern digitized workplace better and more quickly, irrespective of the particular sector or occupation in which an individual is currently engaged. When it comes to the predictive validity of vocational interests on job performance, however, meta-analytic evidence suggests the congruence of interests and environmental requirements posed by the respective job to be the pivotal predictor (Nye et al., 2012, 2017). This might extend to the outcomes of digital self-efficacy and agility. Thus, future researchers could consider incorporating measures for interest fit when building on our findings.

Second, the congruence of individual attributes and environmental requirements is particularly decisive in unstructured situations. While modern workplaces are noticeably less structured than industrial ones, workplaces of any kind are still reasonably structured environments. Therefore, the organizational culture, leadership, and specific tasks constituting the job may determine the degree to which an individual develops self-efficacy beliefs. However, while our second study included fewer organizations, it comprised employees within a specific sector. The second study replicated the findings of the first one. Therefore, while the consideration of contextual differences is important, it may account for only a small proportion of variance. A further contextual factor to consider is the organization's age. Early-stage companies are typically a lot more creative and dynamic. As they grow, they become more efficient, but also more formalized, rigid, and slower to respond to change. This aging process emphasizes the need to deliberately implement measures to increase workforce agility for older organizations.

Third, personality traits and interests were shown to be related to one another (e.g., Barrick et al., 2003), giving rise to the question of whether assessing an individuals' interests would be redundant and substitutable by assessing their personality. However, many researchers have engaged with this question, and their findings encouraged us to consider both personality and interests as related factors that distinctly influence individuals' behavior (Bergner, 2020; Costa et al., 1984; Stoll et al., 2017, 2020; Volodina et al., 2015). Our findings support this notion, as correlations between the constructs were moderate at most, and our path analyses revealed a consistent incremental validity of including vocational interests as predictors in our models.

Fourth, though we employed robust statistical precautions, our approach necessitated us to collect data based on self-reported questionnaires, as self-ratings would be the only valid source for the data, and we therefore could not completely rule out the possibility of common method and endogeneity (i.e., neglected variable) bias (e.g., Antonakis et al., 2014). Related to this limitation, though founded in theory, our chosen methodology also could not guarantee the assumption that personality and interests causally shape digital self-efficacy and agility, which underlies our mediation analyses. Future research may extend on our set foundations by capturing predictor and outcome variables from distinct sources or points in time and by employing experimental, objective, comprehensive, and highly controlled measures to mitigate these issues.

Further, we found the reliability for some of the Big Five subscales to be limited, thus indicating these subscales to be questionable measures for the intended construct. This, however, only affected those personality factors that were not the primary focus of our study (mainly agreeableness and conscientiousness), while the ones of particular interest (stability, openness, and interests to do and think) provided sufficient reliability. Still, this might have resulted in our data not adequately representing the connection between the affected subscales and both digital self-efficacy and workplace agility. Future research should be able to overcome this issue by employing extended measures of personality, such as the NEO-FFI (McCrae and Costa, 2010) or BFI-2 (Soto and John, 2017b). The latter would further allow more detailed insights into the distinct impact of the 15 personality facets captured by this measure. Nevertheless, Likert-type measures share the issue of not being deception proof. However, participants had no vested interest in manipulating their personality assessment because the data were collected anonymously, thwarting the possibility of drawing inferences about individual subjects; notably, personality assessments conducted in personnel selection processes could incentivize deception. To counteract this, alternative "fake-proof" ways of measuring the Big Five have been proposed, including relative measures requiring participants to choose between statements assessing different dimensions of personality (Hirsh & Peterson, 2007), as well as a rapid response measure requiring quick and thus hard-to-manipulate decisions (Meade et al., 2020). While not necessarily essential for research, employing these measures instead of traditional ones might prove beneficial for practice.

In a similar vein, though the Big Five conceptualizations of personality are ubiquitous in research (Meade et al., 2020) and one of the best predictors of behavioral outcomes in organizations (e.g., Barrick and Mount, 1991; Barrick et al., 2001; Cobb-Clark and Schurer, 2012; Ozer and Benet-Martínez, 2006), distinct dimensionalities of personality have been proposed (e.g., Zuckerman et al., 1993) that might enable further insights into the psychological traits indicating optimal employee fit. For example, the HEXACO model, adding the dimension of honesty-humility to the Big Five factors of emotionality (inverse of emotional stability), extraversion, agreeableness, conscientiousness, and openness to experience (Ashton et al., 2004; Ashton and Lee, 2007) gained acclaim in personality research and can be considered the most prominent and valid alternative to the Big Five. Though we would not expect the honesty-humility dimension to relate to digital self-efficacy or agility, future research might want to investigate the value of this trait for the modern workforce. Furthermore, other characteristics beyond personality might prove as being suitable predictors for our selected outcomes beyond personality. These factors of consideration include cognitive abilities, especially intelligence, which fundamentally shape our behavior at work (e.g., Drasgow, 2013; Furnham, 2008; Schmidt and Hunter, 2004) and potentially our adaptability to novel technologies (e.g., Czaja et al., 2006; Martin, 2008; Ng, 2012), thus providing a promising avenue for future research. Further conceptualizations relevant for employee selection that have been brought up in the past include narcissism and grit. However, the Big Five model was shown to fully encompass both narcissism, which constitutes the inverse of agreeableness (Zajenkowski and Szymaniak, 2021), and grit, which is largely engulfed by conscientiousness (Credé et al., 2017; Ponnock et al., 2020; Schmidt et al., 2018).

Lastly, the method of data acquisition through a computer-based questionnaire survey presents an inherent technological hurdle that individuals who lack digital skills may not be able to overcome. Thus, participants in this study might possess an above-average tech savviness compared to the broader public. To assess a distribution of digital self-efficacy that is representative of the population, future research could conduct studies with even more accessible means of data acquisition.

6. Conclusion

We conducted two studies with the aim of offering insights into the new requirements the modern VUCA world poses on employees. In more detail, we aimed to gather insights into the personality traits and vocational interests most beneficial for excelling in this agile environment by aiding individuals in developing their digital self-efficacy and agility in the workplace. Our findings from two large samples of various central and western European companies and publicly traded organizations from the French CAC 40 stock market index, which are in the process of digital transformation, consistently revealed that the traits of openness and emotional stability as well as the investigative and realistic vocational interests to be direct drivers for individuals' trust in their abilities to utilize digital tools effectively. Based on our sample, when faced with the decision to select an employee to hire, selecting the one with a higher level of openness yielded a 62.7% likelihood that the chosen one also possesses greater digital self-efficacy, a 12.7% increase compared to selecting one lower in openness or a 25.4% increase compared to selecting based on chance. In addition, mediated by digital self-efficacy, they indirectly shape employees' agility in their workplace. Therefore, we provide insights into those characteristics that modern organizations need to consider when trying to survive and thrive in today's complex and volatile markets.

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Supplementary materials

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