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The impact of AI adoption on employee engagement: preparing the workforce for new realities

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Artificial intelligence (AI) adoption is already fundamentally changing the world of work. Main motives for AI adoption include prospects of increased productivity, efficiency of processes and competitive advantage. Employee engagement is considered a key driver of performance and source of sustained competitive advantage. The relationship between AI adoption and employee engagement is understudied, and some findings point to a negative link between the two. This research investigates the mediating role of training provision in the relationship between AI adoption and three dimensions of employee engagement (vigour, dedication, and absorption), considering job complexity as a key factor.

A convenience sample of 211 employees, who considered AI as strategic for their companies, was used to test our model via structural equation modelling. Results are aligned with the previous finding that AI adoption has a negative impact on employee engagement.

Keywords: Artificial Intelligence, Employee Engagement, Training, Work Complexity

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1. Introduction

The path towards economic recovery after the global COVID-19 pandemic requires higher digitalisation levels on side of industry and businesses, and the decision to adopt and effectively use time changing technologies can be crucial to determine their success (Kabalisa & Altmann, 2021). Artificial intelligence (AI) lies at the core technology of current digital transformation processes (Hajishirzi & Costa, 2021; Rettas et al., 2019).

Its broad spectrum of application in nearly every industry, sector, and business function induced scholars to call it a “general purpose” technology (Goldfarb, Taska & Teodoridis, 2021; Crafts, 2021). AI is already, and expected to continue, to fundamentally change the way we work (Lee et al., 2022). Different AI-based applications are already deployed widely in business and production processes and have a high impact on work or daily life activities. Apart from catching up with overall technological developments around AI, motives for AI adoption are expectations of enhanced company performance outcomes such as increased efficiency (Ernst, Merola & Samaan, 2019), productivity and organizational performance (Kabalisa & Altmann, 2021), as well as optimizing strategic and competitive advantages (Wamba-Taguimdje et al., 2020).

Recent research suggests that AI adoption, although diversified across specific AI technologies implemented in work processes, is expected to rise in the future depending on the barriers current businesses face (EC, 2020).

A main internal barrier cited in academic and non-academic literature relates to the lack of skills of the workforce. Academics suggests that companies need a better understanding of the concrete challenges that the implementation of new technologies like AI have with view to the employees working with it, as companies cannot just "*substitute legacy technology by a revolutionary one and hope to marginalize psychological and societal impact* "(Holtel, 2016, p. 172). AI adoption is likely to entail marked implications for skill demands and human resource management within the organisation.

On a general level, it is suggested that all technological skills, both advanced and basic, will see a substantial growth in demand. There is also a clear need for developing competencies related to AI and its applications for employees to stay employable in the future (Jaiswal, Arun & Varma, 2021), which necessitates upskilling efforts and training on side of the workforce. The biggest societal challenge identified by researchers for the future of work is to deal with rising inequalities and to provide sufficient re-training and protection to ensure the well-being of the workforce (Arntz et. al., 2016). As sophisticated AI-technologies are reducing the need for human labour, linking these technologies to the organizational needs requires an in-depth understanding of organizational members` skills and capabilities (Davenport & Kirby, 2016) as well as an understanding of its impact on human motivation.

Previous research has shown that while AI is improving work efficiency (Kabalisa & Altmann, 2021) and productivity (Autor, 2015), it may in fact lead to reduced employee engagement. Employee engagement (often used synonymously for job engagement and considered the opposite of burnout) refers to employee outcomes that enhance organizational success with better financial gains. Investigating the impact of AI-driven technologies on the relations among psychological contract, employee engagement and trust, Braganza et al. (2021) found that AI adoption lowers levels of employee engagement, irrespective of the nature of contract with the employer. As employee engagement is considered a key driver of value creation and a source of sustained competitive advantage (given the strong link between engagement and performance (Kim, Kolb & Kim, 2013)), lower levels of employee engagement is a rather paradoxical finding that needs further exploration: if AI adoption lowers employee engagement, it is contrary to academic research claiming that AI adoption enhances company performance (i.e. Wamba -Taguimdje et al., 2020; Mikalef & Gupta, 2021).

In their meta-analysis, Kim, Kolb & Kim (2013) refer to engagement as ¨a proactive and fundamental approach to organizational performance and sustainability¨ and underline the constructs´ potential to ¨become a strong foundation for sustainability of organizations¨ (p.1). This provides an additional argument to explore the link between AI adoption and employee engagement in organizations that are seeking to enhance sustainability.

As pointed out in the previous paragraphs, the consequences of AI adoption are underexplored and need attention (Jaiswal, Arun & Varma, 2021). This paper responds to calls for more research on the impact of AI adoption on micro-level processes. The aim of the current study is to test the relationship between AI adoption and employee engagement along three dimensions – vigour, dedication and absorption. Furthermore, we test the mediating role of training provision on the AI adoption- engagement relationship, as well the impact of work complexity.

2. Theoretical Framework

AI adoption and the impact on employee engagement

Engagement has been commonly described in the literature as a work-related and positive state of mind with elements of focus and presence, a synergy of persistence, dedication to the task, energy, involvement, enthusiasm, and alertness (Schaufeli et al., 2002). In terms of performance, more engaged employees produce better business outcomes, a finding that holds across industries, company size and nationality (Gallup, 2022).

The most widely used operationalization of engagement in research is the three-dimensional model developed by Schaufeli et al. (2002) where engagement is described in terms of vigour, dedication, and absorption.

Vigour is manifested as high levels of energy and resilience while working, the willingness to invest effort and persist in the face of difficulties at work; dedication manifests as experiencing one´s work as significant, feeling enthusiasm and inspiration while working; and absorption refers to being fully engrossed in one's work, to the point of losing track of time and even being unwilling to detach oneself from work (Schaufeli, 2013). Vigour signifies a physical-energetic component of engagement, dedication- an emotional one, and absorption- a cognitive component (Schaufeli et al., 2002).

Apart from theoretical soundness, the tool for measuring the three engagement dimensions, the Utrecht Work Engagement Scale (UWES), has also shown substantial psychometric validity across cultures and sectors. This operationalization of engagement has gained vast relevance in the organizational psychology literature, largely because of the substantial body of evidence on its relationship with desirable outcomes, specifically performance (Kim, Kolb & Kim, 2013).

In line with this, the current study uses the operationalisation by Schaufeli et al. (2002), firstly, because of its psychometric validity, and secondly, because it offers a chance to expand on the existing knowledge about the AI and engagement link. AI adoption´s impact on employee engagement has been researched predominantly in terms of AI´s use in performance management systems as a potential tool to enhance performance and engagement (i.e. Hughes, Robert, Frady & Arroyos, 2019; Burnett & Lisk, 2019). The relationship has also been explored in terms of engagement with the use of AI technology itself (i.e. Wang, et al., 2021), but little research has been conducted to explore the overall impact of AI adoption on the job engagement of employees.

To our knowledge, the only study that investigates the link between AI adoption and engagement (Braganza et. al, 2021) found a negative relationship between the two. Their study deployed Saks' (2006, p.602) definition of engagement as "a distinct and unique construct that consists of cognitive, emotional and behavioural components that are associated with individual role performance". The current study considers that the three-dimensional model of engagement is more thorough in exploring in-depth the relationship between AI adoption and engagement, since it allows for a nuanced look at each engagement dimension.

Furthermore, the three-dimensional operationalization of engagement is a key element of the Job-Demands-Resources model (JD-R) (Bakker & Demerouti, 2007). The JD-R Model clusters job characteristics in two: job demands and job resources, and they trigger two distinct and parallel processes. Job demands refer to aspects of work that require effort and are associated with a cost to the employee (physical and psychological), while job resources refer to those aspects of the job that allow employees to cope with work demands, foster motivation and stimulate learning and development (Bakker & Demerouti, 2007)

The model proposes an inverse parallelism between engagement and burnout (a response to chronic occupational stress characterized by three dimensions: emotional exhaustion, cynicism, and lack of professional efficacy) (González-Romá et al., 2006). Prolonged exposure to excessive job demands and insufficient job resources may lead to job burnout, while job resources foster employee engagement, and therefore, improved performance and organizational commitment (Taris, 2017). In other words, work engagement is understood as a result of a balance between the demands and resources placed upon employees (Mazzetti, et.al, 2021).

Exploring AI adoption through the prism of the JD-R model is useful as it posits the question of whether it is perceived by employees as an additional demand or a resource, and how this, in turn, affects their engagement levels. Based on the elaboration above, the following hypotheses were stated:

H1: *AI adoption will affect employee engagement and its three dimensions, vigour, dedication, and absorption.*

The mediating role of training

The adoption of AI has marketed implications for skill requirements and demands (Beer & Mulder, 2020) and implies the need for a broad spectrum of different specialists, roles and know-how within a company (Blanka, Krumay & Rueckel, 2022). Training can support the development, transformation and direction of individuals' abilities to carry out specific activities. Training has been defined as the acquisition and development of knowledge, skills and attitudes by employees to perform their work effectively (Goldstein, 1980; Latham, 1988). In prior research, training is widely acknowledged as contributing to improvements in individual and organizational performance (Tharenou, Saks & Moore, 2007). Training has been found to have important consequences for employees such as higher job satisfaction (Chiang et al., 2005), commitment and reduced turnover intention (Newman et al., 2011).

Improvement in these related aspects is likely to increase productivity, flexibility and engagement, thereby lifting individual performance. Several studies have demonstrated a positive relationship between training and employee performance at the individual level (Bartel, 1995; Elnaga & Imran, 2013; Khan, 2012). Training has the potential to raise individual performance through improvements in key workplace attitudes and behaviours (Bartel, 2000; Santos & Stuart, 2003), and enhance their technical capabilities and work motivation (Fletcher, 2016).

The impact of training depends on several factors. Generally, employees must experience a feeling of satisfaction and relevance with the training measures provided (Gagné, 2014) and consider them adequate for continued development in their jobs (Dysvik & Kuvaas, 2008). In response to rapidly changing market demands and new technology, training is an important means of updating employees' mindsets and skills to address new work problems that entail more demanding task assignments (Elnaga & Imran, 2013). Based on this, we posit our second hypothesis:

H2. *The higher the levels of AI adoption in a company, the higher the training quality and quantity.*

The incorporation of technology in different workflows can lead to employees feeling overwhelmed with the mental and psychological effort required for coping with the new complexities (Tarafdar et al., 2011). This cognitive response, comprising feelings of demotivation and depression, has been referred to as technostress (Ragu-Nathan et al., 2008). In this sense, AI adoption would be perceived as a work demand, and as previously stated, the JD-R model posits that resources (such as training to meet new work complexities) provided by the organization must be adequate to the demands.

Training, specifically in the context of AI adoption, can encourage employees' work engagement by enhancing their technical capabilities and improving their work motivation (Fletcher, 2016; Malik et al., 2021). Generally, the success of training depends on two factors – its volume and its quality (Dermol & Cater, 2013). The training offered by an AI adopting business should provide a learning opportunity based on the needs of actual participants and the company to meet new job demands and arising complexities. Training practice may primarily aim to build the requisite skill base for employees to engage in their work but also communicate to the employee that the organization is committed to and prepared to invest in employees (Wright & Kehoe, 2008).

Training is therefore not just a transmission of missing knowledge but also a process of updating, revision and systematisation of employees' knowledge, skills, abilities, and habits. In practice, training may be narrowly focused on learning specific skills or it may be broader, intended to develop understanding of the production process, encourage reflection on the way the job is undertaken in relation to other functions and develop creativity to execute tasks more effectively (Sung & Choi, 2014; Vough et al., 2017). As a kind of managerial and organizational support, training increases employees' job satisfaction and commitment and reduces job-related anxiety, thereby eliciting employees' motivation to engage in their work (Fletcher & Sarkar, 2016). Training, that is high quality and sufficient in quantity is more likely to be perceived as a resource and support from the organization, and thus lead to higher engagement (in line with JDR).

Building on these aruments, the following hypothesis is stated:

H3. *Higher levels of training quality and quantity will lead to higher engagement.*

The role of work complexity

The current study considers the role of work complexity, as a factor that has been shown to contribute to engagement and job satisfaction (Humphrey et al., 2007), as well as a relevant determinant of training perceptions and outcomes. Work complexity here is understood as cognitively challenging work that requires an employee's personal resources to resolve problems and deal with stressors (Sacramento et al., 2013).

In the context of AI adoption, complexity is a key factor of AI skills deployment, training design and learning (Grover, Kar & Dwivedi, 2020), since complex work requires more specific training, both in terms of quantity and quality. The level of work complexity also affects the way training receivers perceive its utility and apply newly acquired competencies in their job. Deploying AI skills through training is likely to benefit those whose jobs entail complex tasks (i.e. decision making, complex problem-solving), and is therefore more likely to be perceived as an opportunity and an additional resource that enables employees to perform their job most efficiently. When the demands of complex jobs are combined with access to quality resources, the latter act as motivators and increase engagement (Bakker, Demerouti & Sanz-Vergel, 2014).

Hence, we argue that employees with higher work complexity will have more positive perceptions of AI adoption and training in AI, translating into higher engagement levels, for several reasons.

First, complex work tasks provide more opportunities for applying AI tools as a relief from critically stretched workloads (Aung, Wong, & Ting, 2021). This, in turn makes it more likely to enhance employees´ positive perceptions of AI adoption. For instance, work complexity was shown to enhance the perception of AI adoption as an opportunity (Rodriguez-Bustelo, Batista-Foguet, & Serlavós, 2020). On the other hand, if there is little need or possibility to apply AI in one´s job (more likely in low complexity jobs), AI adoption or training in AI tools would be perceived as a demand, rather than a resource provided by the organization (Tortorella et. al., 2022).

Secondly, AI adoption in an organization usually has either enhancement effects, substitution effects, or both. Other authors refer to these as augmentation and automation (Davenport & Kirby, 2016; Madan & Ashok, 2022). Enhancement (augmentation) refers to the adoption of a new technology allowing employees to perform better while replacement (automation) simply takes over certain tasks from human workers (Davenport & Kirby, 2016; Ivanov, Kuyumdzhiev & Webster, 2020). Yet, enhancement is much more relevant to high- complexity compared to low- complexity jobs. More complex jobs that entail human-in-the-loop collaboration (i.e. in decision-making processes where a software contributes to the process of making decisions), have been found to lead to greater productivity and more positive psychological outcomes (Malik, Tripathi, Kar & Gupta, 2021). On the other hand, when AI adoption is deployed with a replacement function, perceptions are much more likely to gravitate towards fear and distrust of the technology (Arntz, Gregory & Zierahn, 2017; DeCanio, 2016). Rodriguez-Bustelo, Bastida-Foguet & Servalós (2020) discovered that those with higher work complexity experienced less fear of the future and of AI adoption in general.

Furthermore, AI tools contribute in a more direct manner to optimizing performance in jobs with higher cognitive demand (Goldfarb, Gans, & Agrawal, 2019), especially in terms of decision making. More complex jobs are more likely to benefit from the use of AI and specifically AI systems that can improve strategic decision-making and problem solving (Makarius et al., 2020), and AI technology was found to shorten the time of problem solving (Shirado & Christakis, 2017).

Third, work complexity is likely a determinant of training perceptions, as AI application to enhance (complex) work entails more and higher quality training, given that AI requires a substantially different skillset than other IT functions (Grover, Kar & Dwivedi, 2022; Rodriguez-Bustelo, Batista-Foguet, & Serlavós, 2020). More and higher quality of training is thus likely to be perceived much more positively by those in complex jobs. The general inclination is to gravitate towards technologies that are easy to use (Davis, 1989), yet when there is a clear benefit of learning and application of highly complex activities, the engagement in training and learning can be enhanced, because AI technologies that can process high volumes of information to meet desired outcomes in the long run bring more value to jobs with higher complexity (Malik et al., 2021). In contrast, employees with low complex jobs where trained competencies are less applicable, are much more inclined to perceive training as a burden and be overwhelmed by learning that may have little to no direct application in their work tasks. Workers´ perception of AI adoption at their workplace significantly impacts willingness to enhance their own skills to adapt to the new circumstances (Rodriguez-Bustelo, Bastida-Foguet & Servalós, 2020). On top of this, employees with low complex jobs are more likely to experience fear of potential job loss due to automation of tasks.

In addition, training quantity is relevant, since the more training one receives in AI and machine learning technologies, the more it opens up the ¨black box¨, allowing workers to understand the underlying algorithms through which decision or problem-solving options are generated, leading to more trust and practical application of the software (Aung, Wong, & Ting, 2021). Conversely, the less understanding one has of the mechanisms through which AI tools operate, the less trust and application follows, diminishing the utility of the AI tools.

Overall, work complexity and the mental and cognitive challenge it offers correspond to higher needs of fulfilment, learning and growth, as they prompt workers to use advanced skills and dedicate energetic and emotional resources to accomplish work tasks (Nurmi & Hinds, 2016), thus instigating higher engagement. Based on the elaboration above, the following hypothesis is stated:

H4. *The higher the levels of work complexity, the higher the engagement levels of employees.*

The following sections present the methodology and analyses used to test these hypotheses.

3. Methodology

The figure below depicts the conceptual model that combined the hypotheses of the current study.

[Figure 1 about here]

Data collection, sample, and method

The data collection used to meet the objective of the present study was conducted in November 2022. An external specialized company managed the collection process to ensure the reliability of the data, through an online platform that included a structured questionnaire. The study targeted companies in the process of AI adoption, and afterwards screened the initial sample (n=302) to include only those participants who considered that

AI adoption was strategic for their companies, measured via the item ¨AI adoption is strategic for my organization¨ (62,1% of them were working for companies with more than 250 employees). The final sample consisted of 211 employees.

The questionnaire was structured in two sections. The first section included queries related to the profile of the respondent. Table 1 shows the descriptive statistics of the respondents. The second section contained questions related to the respondents' perceptions of the training offered by their companies and to what extent they were engaged with their job. For all the variables, we used a Likert scale with 7-points.

This study applied structural equation modelling (SEM) using the robust maximum likelihood method. The main advantage of SEM is its flexibility to deal not only with a single simple or multiple linear regression but also with several equations simultaneously (Nachtigall et al., 2003).

Operationalisation and measurement

Operationalization of measurement variables reflect validated measures employed in past research with minor modifications and additional measurements developed by the research team.

AI adoption was measured with 4 items based on Braganza et al. (2021) – a sample item is ¨ My work could be completed by a zero-hours contractor/ software / program¨.

Quantity and quality of training were measured using 4 items by Dermol & Cater (2013). A sample item is ¨Training is constantly revised and upgraded to meet the requirements of the changing environment¨.

Engagement and its three dimensions, Vigour, Dedication and Absorption were measured with 11 statements from the UWES Engagement Scale (Schaufeli, Bakker &

Salanova, 2006), and specifically its Spanish version validated by Gómez Garbero et al. (2019). The scale asks participants to evaluate how they feel at work and with what frequency. A sample item from the Vigour dimensions is ¨ At my work, I feel bursting with energy¨; from Dedication it is ¨ I find the work that I do full of meaning and purpose¨, and from Absorption it is ¨ Time flies when I am working¨.

Statements were evaluated on a Likert-type scale from 1(never) to 7- (always/Every day).

Work complexity was measured as a variable following Rodriguez-Bustelo, Bastida-Foguet & Servalós (2020): ¨I am assigned extraordinary and particularly difficult tasks¨.

Reliability and validity indices are presented in the results.

4. Results

This section is organized following the statistical process carried out to validate the proposed model. Firstly, the validity and reliability of the dimensions were assessed and next, we proceeded to the model estimation using SEM.

[Table 1 about here]

Measurement model

In order to check the psychometric validity of our questionnaire and the items related to the dimensions, five independent exploratory factor analyses (EFA) were performed. These determined the set of items for each dimension, presented in Table 2. The reliability of these five dimensions were double checked through Cronbach's alpha and composite reliability. In all cases the values were above the recommended threshold of 0.7. In addition, all dimensions satisfied the criteria for convergent validity as the AVE for each one was greater than 0.5.

[Table 2 about here]

Next, a discriminant validity analysis was performed to examine whether the inter-factor correlations were less than the square root of the AVE. Since all the values of the square root of the AVE were over the bivariate correction values, each factor represents a separate dimension, showing satisfactory discriminant validity.

[Table 3 about here]

Structural model

The proposed research model (depicted in Figure 1) was estimated using the software EQS 6.4 (Bentler & Wu, 2002). The fit indices obtained for our model showed good fit. The $\chi 2$ Satorra-Bentler was 250.10 with 155 degrees of freedom and a p-value of 0.000. Since the sample is relatively large, a null p-value was expected. In these cases, it is advisable to use the coefficient between $\chi 2$ and the number of degrees of freedom, which was 1.61, below the recommended value of 5 (Bentler, 1990). The comparative fit index (CFI) was .954, clearly above the general accepted threshold (>.9) according to Hair et al. (2010) and Hu & Bentler (1999). Finally, the root mean square error of approximation (RMSEA) was .027 and its 90% confidence interval was between .047 and .066. Therefore, given that at least three fit indices are over the recommended values, these measures provide sufficient evidence for the explanatory power of the proposed model (Alonso-Almeida et al., 2015).

The standardized solution of the causal model is shown in Figure 2 below.

[Figure 2 about here]

It can be observed that Hypothesis 1 is partially supported, showing a negative effect of AI adoption on one of the engagement dimensions, dedication (- .19; $p < .001$). The other two dimensions were not related significantly to AI adoption. Hypothesis 2 stated that higher levels of AI adoption in a company would be associated with higher training quality and quantity, and it is rejected as we find a non-significant relationship. Hypothesis 3 was supported, as the model shows a significant positive effect of training quality and quantity on engagement, in all three of its dimensions (vigour: .41; $p<.001$; dedication: .44; $p<.01$; absorption: .33; $p< .01$). Hypothesis 4 is partially supported: higher levels of work complexity were associated with higher vigour (.81; $p< .001$) and absorption (.79; $p< .001$) but did not show a significant relationship to the dedication dimension of engagement.

These results are discussed in the following section.

5. Discussion

Artificial Intelligence (AI) is widely considered to have major social and economic impact (Uren & Edwards, 2023). As policy makers and practitioners around the globe emphasize the need for a skilled workforce to meet future job demands in light of AI (World Economic Forum, 2020), academia still falls short in providing an in-depth understanding of the impact of AI adoption on micro-level processes within an organisation to enhance adoption levels. Generally, research suggest that employees need to engage positively with AI technologies to be able to fully exploit its benefits (Braganza et al., 2021). The current study could partially confirm previous research (Braganza et al., 2021) that found AI adoption had a negative relationship with employee engagement.

Concretely, we found a negative impact of AI adoption on dedication using a nuanced engagement scale as developed by Schaufeli et al. (2006).

Dedication, which refers to an employee's experience of work significance, a sense of enthusiasm and inspiration, also encapsulates the emotional component of engagement and previous research has connected AI adoption to negative emotional experiences (Aung, Wong & Ting, 2021). For example, lower levels of employee engagement have been explained with potential uncertainty at work caused by AI technologies (Nam, 2019). The implementation of AI may lead to the creation of new work tasks and the replacement of others, which could lead workers to fear for their work as adversely affected by the implementation of new technologies (Braganza et al., 2021). In addition, research suggests that the implementation process of AI is often carried out without careful consideration of the employees who will be working along with it (Makarius et al., 2020), which can induce negative emotions and perceptions of AI among the employees and hinders the integration of AI based tools and applications (Hah & Goldin, 2021). Other reasons for a negative perception include the fear of replacement, lack of training, or uncertainty (Frey & Osborne, 2017), as well as limited knowledge of how to use it in practice (Raisch & Kraikowski, 2021), all of which can diminish a sense of inspiration and significance at work (dedication).

AI adoption affects the entire workforce of an organization (Von Richthofen, Ogolla & Send, 2021), and comes in various forms. An organization must actively seek the AI solution that optimally fits the organization´s needs (Holmstroem & Haellgren, 2021; Ivanov, Kuyumdzhiev & Webster, 2020). The decision to automate or augment human work through AI technologies (Davenport & Kirby, 2016) has important implications for the workforce (Madan & Ashok, 2022). Implementing either efficiently is conditioned by employee skills and attitudes towards AI, as any actual use of AI in organizations is not only a technological problem, but requires transformation that affects political, organizational, and psychological aspects as well (Holtel, 2016). Employees often feel threatened by AI technologies' potential to replace them (Ivanov, Kuyumdzhiev & Webster, 2020; Loureiro, Guerreiro & Tussyadiah, 2021). Current research suggests that the likelihood of a task being automated depends on how easily it can be performed through coded rules and algorithms, which is generally easier for routine tasks that involve a certain level of predictability (Rodriguez-Bustelo, Bastida-Foguet & Servalós, 2020). Those tasks that involve interacting intelligently, socially, and emotionally with a human counterpart are likely to require predominantly human involvement (Arntz, Gregory & Zierahn, 2017). Rather than replacing human workforce or eliminating entire occupations, AI systems are designed with the intention of augmenting and not replacing, human contributions (Brynjolfson, Rock & Syverson, 2018). AI adoption is likely to transition towards "*human in the loop*" collaborative contexts in which humans focus on value adding activities involving the design, analysis and interpretation of AI outputs and processing (Dwidedi et al., 2021, p.4).

One of the main internal barriers inhibiting wider adoption cited in academic and non-academic literature continues to be a shortage of expertise and skills on side of the workforce, which inhibits businesses from harnessing the full potential of automation and AI (Loureiro, Guerreiro & Tussyadiah, 2021; Jaiswal, Arun & Varma, 2021). Training offered by AI adopting business therefore constitutes a decisive element to reach to ensure that the full potential of AI can be exploited.

Our results showed a non-significant relationship between AI adoption and training quality and quantity. This confirms previous findings that AI adopting organizations need to place higher consideration of the training and resources that will be needed to make sure employees are skilled enough to work alongside new AI tools (Hajishirzi & Costa, 2021; Alekseeva et al., 2021). The incremental increase of tasks that can be performed by AI-based tools may require employees to be flexible and acquire new skills to adapt or perform completely new tasks (Jaiswal, Arun & Varma, 2021). Given the rapid shifts in skill requirements, it is likely that the labour market will be unable to supply sufficient new talent to fill available positions in the short run (Forbes, 2021). The World Economic Forum (2020) found that 50% of all employees will need reskilling by 2025 as adoption of technology increases, which requires individual workers to be highly flexible and engage in lifelong learning if they are to remain not just employable but are to achieve fulfilling and rewarding careers that allow them to maximize their employment opportunities (World Economic Forum, 2020). Recent research suggests, however, that AI adopters overwhelmingly prefer to replace employees with new AI-ready talent rather than retaining and re-training their existing workforce (Hupfer, 2021). Since exponential technological advancements affect current as well as future workers, preparing the current and future workforce to adequately transition into high skilled jobs will be imperative, which requires a focus on flexibility and continuous learning.

The results of this research show a significant positive effect of training quality and quantity on engagement, in all three of its dimensions, aligning with previous studies that provide evidence that on-the-job training and skill development leads to higher engagement (Azeem & Paracha, 2013; Felstead at.al., 2010;). Training in the use of AI technology is particularly useful for employee engagement and involvement, as quality training would ensure an understanding of how the software/machine/algorithm functions, fostering transferable knowledge and skills that contribute to employability and are applicable to a large variety of job positions. This transferability of skills is a direct contributor to engagement according to human capital theory (Felstead et.al., 2010).

Furthermore, our results show that work complexity had a positive impact on two of the three engagement dimensions: absorption and vigour. In terms of absorption, this finding goes in line with more complex tasks being generally linked to higher absorption levels, and even more specifically, cognitive complexity due to technology uses has been linked to higher levels of absorption and flow (Agarwal & Karahanna, 2000). AI adoption and the provision of adequate training in AI allows workers in complex jobs to deal with the challenging and cognitively demanding parts of the job, which require and elicit focus and concentration, ultimately leading to higher absorption in one´s work. In terms of vigour, more complex and demanding tasks would require more energy and effort, and employees with complex work are less likely to experience boredom (Bai, Tian & Liu, 2021). In the context of AI adoption and training, the element of novelty can be a reason for elevated energy and interest at work, especially if training is perceived as a resource provided by the organization. Overall, our results align with previous studies that have found a positive effect of complexity on engagement (Bai, Tian & Liu, 2021), with the exception of the dedication dimension. Dedication, representing the emotional component of engagement may be more dependent upon the general experience of one´s work, and to a lesser extent by complexity of tasks or the perception of AI adoption and training.

6. Conclusions, Limitations and Future Research

This study corroborates previous findings that AI adoption may be negatively linked to employee engagement, and particularly to its emotional component. It also points to work complexity as a factor that deserves to be studied further in order to determine the most cost-effective training designs aligned with employees´ work complexity levels in the context of AI adoption and training. Most importantly, the current study shows that in the process of AI adoption, the quality and quantity of training offered to employees may not be adequate, raising the practical question of whether businesses that apply AI are implementing the insufficient upskilling, thus contributing further to the existing skills shortage of the workforce.

As any study, it has its limitations, the first one being a cross-sectional design, that does not allow for causal conclusions to be drawn. A second limitation has to do with the data relying on self-report only, which poses the risk of common method variance. However, the fit indices show that our model is robust, and the psychometric qualities of the questionnaire used are adequate, as shown in the results.

Furthermore, the study adds value as the constructs in our model have not been studied enough in the context of AI adoption and our findings align with previous studies (e.g. Braganza et. al., 2021). Future work should explore further the AI adoption-engagement relationship and gather longitudinal data on its effects on employee engagement. A negative relationship between the two may imply that AI adoption, as it is currently applied, may be a short-term winning strategy in terms of efficiency but one that overlooks human factors, and particularly employee engagement, a key element of sustainable performance and wellbeing.

References:

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS quarterly*, 665-694.

Alekseeva, L., Azar, J., Giné, M., Samila, S., Taska, B. (2021). The demand for AI skills in the labor market. Labour Economics, Volume 71, 102002, ISSN 0927-5371, DOI: https://doi.org/10.1016/j.labeco.2021.102002.

Alonso-Almeida, M.M., Bremser, K. & Llach, J. (2015). Proactive and reactive strategies deployed by restaurants in times of crisis. *International Journal of Contemporary Hospitality Management*, 27(7), 1641 – 1661. DOI: https://doi.org/10.1108/IJCHM-03-2014-0117

Arntz, M., et al. (2016) The Risk of Automation for Jobs in OECD Countries. OECD Social, Employment and Migration Working Papers, OECD Publishing, Paris.

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters.* 159, 157-160

Aung, Y. Y., Wong, D. C., & Ting, D. S. (2021). The promise of artificial intelligence: a review of the opportunities and challenges of artificial intelligence in healthcare. *British medical bulletin*, 139(1), 4-15.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *J. Econ. Perspect.* 29, 3–30. DOI: 10.1257/jep.29.3.3.

Azeem, M. F, & Paracha, A.T. (2013). Connecting training and development with employee engagement: how does it matter? World Applied Sciences Journal, 28(5), 696-703.

Bai, J. Y., Tian, Q., & Liu, X. (2021). Examining job complexity on job crafting within conservation of resources theory: a dual-path mediation model. Frontiers in psychology, 4482.

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. I. (2014). Burnout and work engagement: The JD–R approach. *Annual review of organizational psychology and organizational behavior*, 1(1), 389-411.

Bakker, A.B.; Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology*. 22 (3): 309–328. DOI:10.1108/02683940710733115.

Bartel, A. P. (1995). Training, wage growth, and job performance: Evidence from a company database. *Journal of labor Economics*, 13(3), 401-425.

Bartel, A. P. (2000). Measuring the employer's return on investments in training: Evidence from the literature. *Industrial relations: a journal of economy and society*, 39(3), 502-524.

Beer, P., & Mulder, R. H. (2020). The effects of technological developments on work and their implications for continuous vocational education and training: A systematic review. *Frontiers in Psychology*, 11, 918.

Bentler, P. M. & Wu, E. J. C. (2002). EQS 6 for Windows User's Guide. Encino, CA: Multivariate Software, Inc. ISBN 1-885898-04-5.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2), 238–246. DOI: https://doi.org/10.1037/0033-2909.107.2.238

Blanka, C., Krumay, B., Rueckel, D. (2022). The interplay of digital transformation and employee competency: A design science approach. *Technological Forecasting and Social Change*, Volume 178, 2022, 121575, ISSN 0040-1625, DOI: https://doi.org/10.1016/j.techfore.2022.121575.

Braganza, A., Chen, W., Canhoto, A., Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of Business Research*, Volume 131, pp. 485-494, DOI: https://doi.org/10.1016/j.jbusres.2020.08.018.

Brynjolfsson, E., Rock, D., Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics." In The economics of artificial intelligence: An agenda, pp. 23-57. University of Chicago Press.

Burnett, J.R., Lisk, T. C. (2019). The Future of Employee Engagement: Real-Time Monitoring and Digital Tools for Engaging a Workforce. International Studies of Management & Organization, 49(1), 108-119, DOI: 10.1080/00208825.2019.1565097

Chiang, C. F., Back, K. J., & Canter, D. D. (2005). The impact of employee training on job satisfaction and intention to stay in the hotel industry. *Journal of Human Resources in Hospitality & Tourism*, 4(2), 99-118.

Crafts, N. (2021). Artificial intelligence as a general-purpose technology: an historical perspective. *Oxford Review of Economic Policy*, 37(3).

Davenport, T. H., & Kirby, J. (2016). Just how smart are smart machines? *MIT Sloan Management Review*, 57(3), 21–25.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.

DeCanio, S. J. (2016). Robots and humans–complements or substitutes? Journal of *Macroeconomics*, 49, 280-291.

Dermol, V., Cater, T. (2013). The influence of training and training transfer factors on organizational learning and performance. Personnel review. Vol. 42 No. 3, pp. 324-348. DOI: https://doi.org/10.1108/00483481311320435.

DOI: https://doi.org/10.1016/j.obhdp.2013.01.008.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 10199.

Dysvik, A., & Kuvaas, B. (2008). The relationship between perceived training opportunities, work motivation and employee outcomes. *International Journal of Training and development*, 12(3), 138-157.

Elnaga, A., & Imran, A. (2013). The effect of training on employee performance. *European journal of Business and Management*, 5(4), 137-147.

Ernst, E., Merola, R. & Samaan, D. (2019). Economics of Artificial Intelligence: Implications for the Future of Work. *IZA Journal of Labor Policy*, 9(1), DOI: https://doi.org/10.2478/izajolp-2019-0004

European Commission (2020). European enterprise survey on the use of technologies based on artificial intelligence. Final Report. Contract number: LC-01136848.

Felstead, A., Gallie, D., Green, F., & Zhou, Y. (2010). Employee involvement, the quality of training and the learning environment: an individual level analysis. *The International Journal of Human Resource Management*, 21(10), 1667-1688.

Fletcher, D., & Sarkar, M. (2016). Mental fortitude training: An evidence-based approach to developing psychological resilience for sustained success. Journal of Sport Psychology in Action, 7(3), 135-157.

Fletcher, L. (2016). Training perceptions, engagement, and performance: comparing work engagement and personal role engagement. *Human Resource Development International*, 19(1), 4-26.

Forbes (2021). The changing labour force: what's driving it, and what to prepare for in the near future. Via [The Changing Labor Force: What's Driving It, And What To Prepare For In The Near Future (forbes.com)](), last accessed 28/12/2022.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change*, 114, 254-280.

Gagné, M. (2014). The Oxford Handbook of Work Engagement, Motivation, and Self-Determination Theory. Oxford University Press. New York.

Gallup (2022). What is employee engagement and how do you improve it? Via [How to Improve Employee Engagement in the Workplace - Gallup](), last accessed 28/12/2022.

Goldfarb, A., Gans, J., & Agrawal, A. (2019). The Economics of Artificial Intelligence: An Agenda. University of Chicago Press.

Goldfarb, A., Taska, B., & Teodoridis, F. (2023). Could machine learning be a general-purpose technology? A comparison of emerging technologies using data from online job postings. *Research Policy*, 52(1), 104653.

Goldstein, I.L. (1980). Training in work organizations. Annual Review of Psychology. 31, pp. 229, ISSN: 0066-4308.

González-Romá, V., Schaufeli, W. B., Bakker, A. B., & Lloret, S. (2006). Burnout and work engagement: Independent factors or opposite poles? *Journal of vocational behavior*, 68 (1), 165-174.

Grover, P., Kar, A.K. & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Ann Oper Res* 308, 177–213. DOI: https://doi.org/10.1007/s10479-020-03683-9

Hah, H., & Goldin, D. S. (2021). How Clinicians Perceive Artificial Intelligence–Assisted Technologies in Diagnostic Decision Making: Mixed Methods Approach. *Journal of Medical Internet Research*, 23(12), e33540.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Prentice Hall.

Hajishirzi, R., & Costa, C. (2021). Artificial Intelligence as the core technology for the Digital Transformation process. 2021 16th Iberian Conference on Information Systems and Technologies (CISTI), 1-6.

Hamm, P., & Klesel, M. (2021). Success Factors for the Adoption of Artificial Intelligence in Organizations: A Literature Review. In AMCIS.

Holmström, J., & Hällgren, M. (2022). AI management beyond the hype: exploring the co-constitution of AI and organizational context. *AI & SOCIETY*, 37(4), 1575-1585.

Holtel, S. (2016). Artificial intelligence creates a wicked problem for the enterprise. *Procedia computer science*, 99, 171-180.

Hu, L. T. & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6 (1), 1–55. DOI: https://doi.org/10.1080/10705519909540118

Hughes, C., Robert, L., Frady, K. and Arroyos, A. (2019). Artificial Intelligence, Employee Engagement, Fairness, and Job Outcomes. Managing Technology and Middle- and Low-skilled Employees (The Changing Context of Managing People). Emerald Publishing Limited, Bingley, pp. 61-68. DOI: https://doi.org/10.1108/978-1-78973-077-720191005

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: a meta-analytic summary and theoretical extension of the work design literature. *Journal of applied psychology*, 92(5), 1332.

Hupfer, S. (2021). Talent and workforce effects in the age of AI. Insights from Deloitte's State of AI in the Enterprise, 2nd Survey. Via AI adoption in the workforce | Deloitte Insights, last accessed 28/12/2022

ISSN 0378-7206, DOI: https://doi.org/10.1016/j.im.2021.103434.

Ivanov, S., Kuyumdzhiev, M., & Webster, C. (2020). Automation fears: drivers and solutions. Technology in Society, 63, 101431.

Jaiswal, A. C., Arun J., Varma, A. (2021): Rebooting employees: upskilling for artificial intelligence in multinational corporations, *The International Journal of Human Resource Management*, DOI: 10.1080/09585192.2021.1891114.

Kabalisa, R., Altmann, J. (2021). AI technologies and motives for AI adoption by countries and firms: a systematic literature review. In: K. Tserpes et al. (Eds.): GECON 2021, LNCS 13072, pp. 39–51, 2021.

Kim, W.; Kolb, J.A.; Kim, T. The Relationship between Work Engagement and Performance: A Review of Empirical Literature and a Proposed Research Agenda. *Hum. Resour. Dev. Rev.*12, pp. 248–276.

Latham, G.P. (1988). Human Resource Training and Development. Annual Review of Psychology. Vol 39, pp. 545-582. DOI: https://doi.org/10.1146/annurev.ps.39.020188.002553.

Lee, Y.S., Kim, T., Choi, S., Kim,W. (2022). When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy, *Technovation*, Volume 118, 2022, 102590, ISSN 0166-4972, DOI: https://doi.org/10.1016/j.technovation.2022.102590.

Llorens, S., Bakker, A. B., Schaufeli, W., & Salanova, M. (2006). Testing the robustness of the job demands-resources model. *International Journal of stress management*, 13(3), 378.

Madan, R., Ashok, M. (2022). AI adoption and diffusion in public administration: A systematic literature review and future research agenda, *Government Information Quarterly*, 2022, DOI: https://doi.org/10.1016/j.giq.2022.101774

Makarius, E., Mukherjee, D., & Fox, J., Fox, A. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*. 120. 262-273. 10.1016/j.jbusres.2020.07.045.

Malik, N., Tripathi, S.N., Kar, A.K. and Gupta, S. (2022). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower*, Vol. 43 No. 2, pp. 334-354. https://doi.org/10.1108/IJM-03-2021-0173

Mazzetti, G., Robledo, E., Vignoli, M., Topa, G., Guglielmi, D., & Schaufeli, W. B. (2021). Work engagement: A meta-analysis using the job demands-resources model. *Psychological Reports*, 00332941211051988.

Mikalef, P, Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, Volume 58, Issue 3, 2021, 103434, Nachtigall, C., Kroehne, U., Funke, F., & Steyer, R. (2003). (Why) Should we use SEM?- Pros and cons of Structural Equation Modelling. *Methods of Psychological Research*, 1–22.

Nam, T. (2019). Technology usage, expected job sustainability, and perceived job insecurity. *Technological Forecasting and Social Change*, 138 (2019), pp. 155-165, DOI: 10.1016/j.techfore.2018.08.017

Newman, A., Thanacoody, R., Hui, W. (2011). The impact of employee perceptions of training on organizational commitment and turnover intentions: A study of multinationals in the Chinese service sector. *The International Journal of Human Resource Management*, 22, pp.1765-1787. DOI: 10.1080/09585192.2011.565667.

Nurmi, N., & Hinds, P. J. (2016). Job complexity and learning opportunities: A silver lining in the design of global virtual work. *Journal of International Business Studies*, 47(6), 631-654.

Ragu-Nathan, T.S., Tarafdar, M., Ragu-Nathan, B.S., Tu, Q. (2008). The consequences of technostress for end users in organizations: conceptual development and empirical validation. *Information Systems Research*, Vol. 19 No. 4, pp. 417-433, DOI: 10.1287/isre.1070.0165.

Raisch, S. Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review*. 46. 192-210. 10.5465/amr.2018.0072.

Rettas, D., Lerner, S.,White, B. (2019). The Evolution of Artificial Intelligence. *Enterprise Digitalization*, pp. 3-8.

Richthofen, G.V., Ogolla, S., & Send, H. (2022). Adopting AI in the Context of Knowledge Work: Empirical Insights from German Organizations. *Inf.,* 13, 199.

Rodriguez-Bustelo, C., Batista-Foguet, J. M., & Serlavós, R. (2020). Debating the future of work: the perception and reaction of the Spanish workforce to digitization and automation technologies. *Frontiers in psychology*, 11, 1965.

Sacramento, C.A., Fay, D., West, M.A. (2013). Workplace duties or opportunities? Challenge stressors, regulatory focus, and creativity. *Organizational Behavior and Human Decision Processes*, 121 (2), pp. 141-157, ISSN 0749-5978,

Saks, A.M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology*, Vol. 21 No. 7, pp. 600-619. https://doi.org/10.1108/02683940610690169

Santos, A., Stuart, M. (2003). Employee perceptions and their influence on training effectiveness. Human Resource Management Journal, 13 (1), pp. 27-45.

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. Educational and psychological measurement, 66(4), 701-716.

Schaufeli, W.B. (2013). What is engagement? In C. Truss, K. Alfes, R. Delbridge, A. Shantz, & E. Soane (Eds.), Employee Engagement in Theory and Practice. London: Routledge.

Schaufeli, W.B., Salanova, M., González-romá, V. et al. (2002). The Measurement of Engagement and Burnout: A Two Sample Confirmatory Factor Analytic Approach. *Journal of Happiness Studies*, 3, 71–92 (2002). https://doi.org/10.1023/A:1015630930326

Shirado, H., Christakis, N. Locally noisy autonomous agents improve global human coordination in network experiments. *Nature* 545, 370–374 (2017). DOI: https://doi.org/10.1038/nature22332

Sung, S. Y., & Choi, J. N. (2014). Multiple dimensions of human resource development and organizational performance. *Journal of Organizational Behavior*, 35(6), 851- 870. https://doi.org/10.1002/job.1933.

Tarafdar, M., Tu, Q., Ragu-Nathan, T.S., Ragu-Nathan, B.S. (2011). Crossing to the dark side: examining creators, outcomes, and inhibitors of technostress. *Communications of the ACM*, Vol. 54 No. 9, pp. 113-120, doi: 10.1145/1995376.1995403.

Taris, T.W., Leisink, P.L.M., Schaufeli, W.B. (2017). Applying Occupational Health Theories to Educator Stress: Contribution of the Job Demands-Resources Model. In: McIntyre, T., McIntyre, S., Francis, D. (eds) *Educator Stress. Aligning Perspectives on Health, Safety and Well-Being*. Springer, Cham. https://doi.org/10.1007/978-3-319-53053-6_11.

Tharenou, P., Saks, A.M., Moore, C. (2007). A review and critique of research on training and organizational-level outcomes. *Human Resource Management Review*, Volume 17, Issue 3, 2007, pp. 251-273, ISSN 1053-4822, DOI: https://doi.org/10.1016/j.hrmr.2007.07.004

Tortorella, G. L., Prashar, A., Saurin, T. A., Fogliatto, F. S., Antony, J., & Junior, G. C. (2022). Impact of Industry 4.0 adoption on workload demands in contact centers. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 32(5), 406-418.

Uren, V., Edwards, J.S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, Volume 68, 2023, 102588, ISSN 0268-4012, DOI:https://doi.org/10.1016/j.ijinfomgt.2022.102588

Vough, H. C., Bindl, U. K., & Parker, S. K. (2017). Proactivity routines: The role of social processes in how employees self-initiate change. *Human Relations*, 70(10), 1191–1216. https://doi.org/10.1177/0018726716686819.

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J.R.,Tchatchouang Wanko, C.E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal*, Vol. 26 No. 7, pp. 1893-1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wang, W., Chen, L., Xiong, M. et al. (2021). Accelerating AI Adoption with Responsible AI Signals and Employee Engagement Mechanisms in Health Care. *Inf Syst Front* DOI: https://doi.org/10.1007/s10796-021-10154-4

World Economic Forum (2020). The Future of Jobs Report. Via The Future of Jobs Report 2020 | World Economic Forum (weforum.org), last accessed 28/12/2022

Wright, P. M., & Kehoe, R. R. (2008). Human resource practices and organizational commitment: A deeper examination: Journal of the institue of personnel management australia. *Asia Pacific Journal of Human Resources*, 46(1), 6.

Tables and figures

Figure 1. Conceptual model.

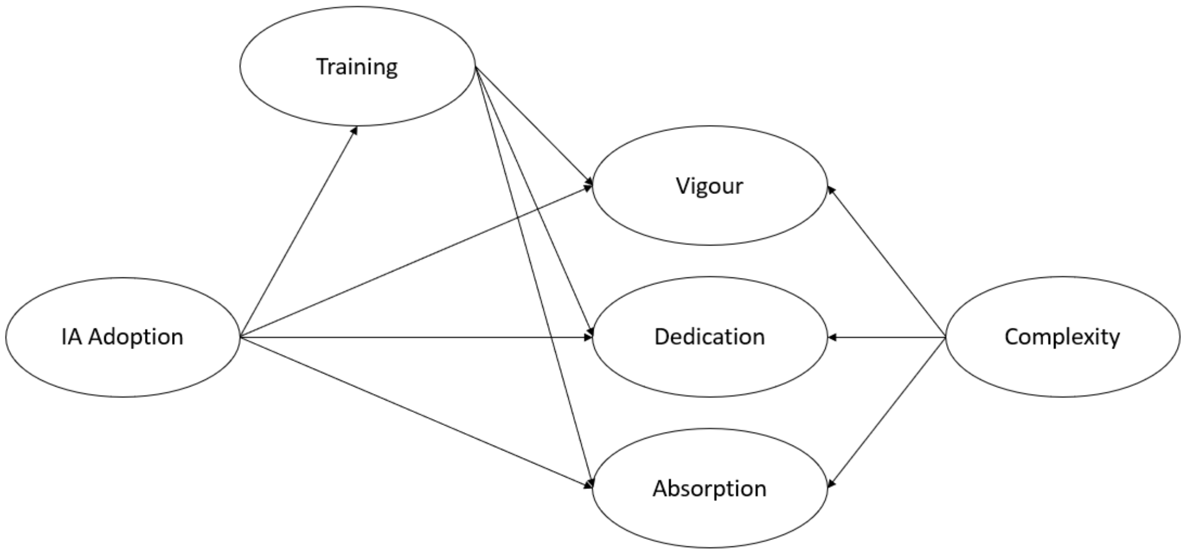
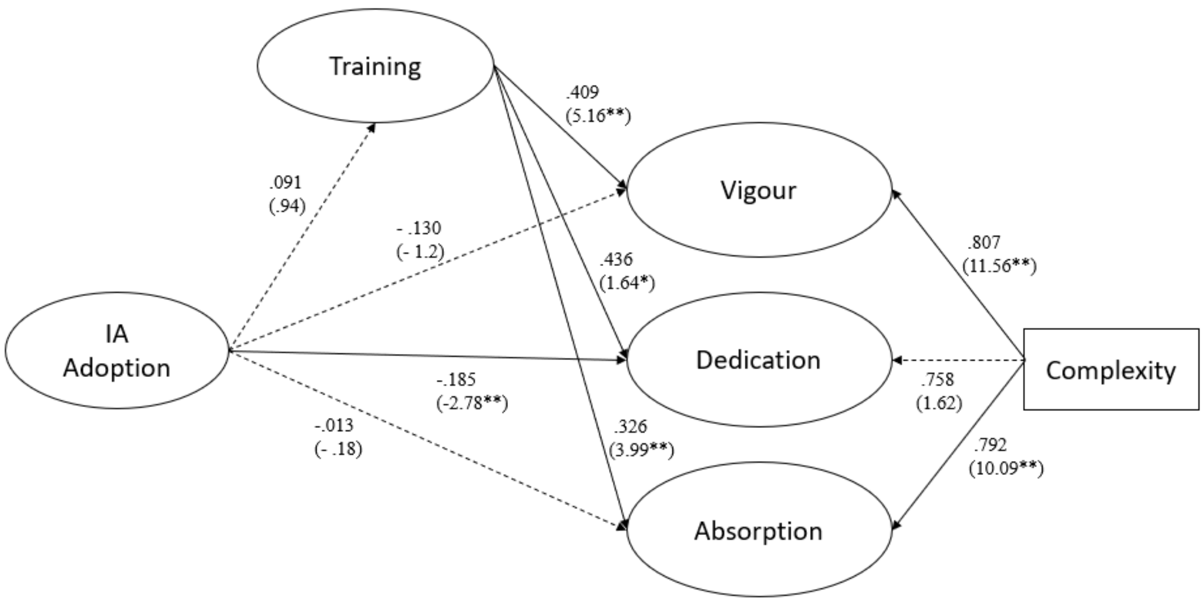


Figure 2. Standardized solution of the causal model



Note: Dashed arrows refer to insignificant relationships.
** p< .05; **p< .001*

Table 1. Descriptive statistics of the respondents

Gender	n	%	Education level	n	%	Position	n	%	Size of the firm	n	%
Male	109	51.7	Less than Grade	90	42.7	Low Responsibility	82	38.9	<10 employees	27	12.8
Female	100	47.4	Grade	87	41.2	Medium responsibility	107	50.7	10 - 49 employees	22	10.4
I prefer not to answer	2	0.9	Master or PhD	33	15.6	High Responsibility	22	10.4	50 - 249 employees	31	14.7
			N/A	1	0.5				>250 employees	131	62.1
Total	211	100%		211	100%		211	100%		211	100%

Table 2. Item loadings, Reliability indices and Convergent Validity

	AI adoption (AI)		Vigour (VG)		Dedication (DD)		Absorption (AB)		Training (TR)	
	item	loading	item	loading	item	loading	item	loading	item	loading
	AI1	.772	VG1	.924	DD1	.889	AB1	.843	TR1	.922
	AI2	.760	VG2	.906	DD2	.923	AB2	.795	TR2	.923
	AI3	.775	VG3	.863	DD3	.922	AB3	.804	TR3	.929
	AI4	.790			DD4	.854	AB4	.706	TR4	.918
α	.775		.871		.919		.795		.942	
CR	.856		.925		.881		.867		.958	
AVE	.599		.806		.650		.622		.852	

α: *Cronbach's alpha*
CR: composite reliability
AVE: average variance extracted

Table 3. Correlation matrix and discriminant validity

	1	2	3	4	5
AI adoption	*.773**				
Vigour	-.030	*.897*			
Dedication	-.092	.719	*.806*		
Absorption	.058	.645	.580	*.788*	
Training	.085	.376	.407	*.316*	*.923*

**square root of AVE in the diagonal*