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# Trusting in Generative AI: Catalyst for Employee Performance and Engagement in the Workplace

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## ABSTRACT

This paper investigates the impact of the usage of generative AI (GenAI) and services with integrated GenAI on employee performance, alongside with the role of trusting in these tools and services. Employing a mixed methodology, the research first analyzes data from 251 professionals in Spain using a structural equation modeling (SEM) approach, followed by a qualitative survey of 69 top academics in management sciences. Findings indicate that the adoption and effective use of GenAI services does not directly improve workplace performance. Instead, **an optimal level of trust in these services plays a critical mediating role, enhancing work engagement and thereby performance.** The study draws on the reviewed job demand-resources theory (JD-R) to construct a new theoretical framework of applied in GenAI services, offering insights into how user experience and trust influence engagement and productivity. For managers, these results highlight the importance of building an optimal level of trust in GenAI among employees and users of services with integrated GenAI to boost work engagement and performance.

## KEYWORDS

Generative AI; work engagement; trust; employee performance

## 1. Introduction

Novel technologies raise concerns about potential impacts, ranging from productivity growth to user satisfaction and performance enhancement (Acemoglu et al., 2023). This is exemplified by the emergence of GenAI algorithms in the early 2020s, and particularly the release of Chat GPT 3.0 in November 2022. Subsequent analyses have highlighted its potential influence on productivity and the transformative effect it has had across various industries (Chui et al., 2023; Wijayati et al., 2022).

In this sense, it is worth quoting a study by McKinsey & Company (Chui et al., 2023) which affirms that: “Generative AI has the potential to change the anatomy of work, augmenting the capabilities of individual workers by automating some of their individual activities. Current GenAI and other technologies have the potential to automate work activities that absorb 60%–70% of employees’ time today”. The report also underscores the necessity of support for this transition, stating, “Generative AI can substantially increase labor productivity across the economy, but that will require investments to support workers as they shift work activities or change jobs”.

The potential of GenAI to transform industries envisaged by this report can be analyzed through the behavior of first adopters, when a new technology is in its first step. At this point is when innovators and early adopters players take this technology as a competitive driver (Rogers, 2003). The successful adoption and optimal utilization of

new technology depends significantly on attitudes such as openness and a forward-looking optimism about its potential benefits. Additionally, an innovative spirit in users can significantly enhance their experience, distinguishing between positive and negative outcomes with these technological advancements (Davis, 1989; Parasuraman, 2000; Parasuraman & Colby, 2015).

In the academic field, Noy and Zhang (2023) found that GenAI services significantly enhance productivity, especially of workers with weaker skills, reducing productivity inequalities. Brynjolfsson et al. (2023) come to the same conclusions about the increase of productivity especially of the lower-skilled workers and suggests improvements in worker learning and increases in employee retention levels that occur thanks to the use of GenAI. In this vein, Dwivedi et al. (2023) enhances this discourse by incorporating 43 contributions from specialists spanning diverse fields, including computer science, marketing, information systems, education, policy, hospitality and tourism, management, publishing, and nursing. The contributors recognize the potential of Chat GPT to augment productivity and anticipate substantial benefits in industries such as banking, hospitality and tourism, and information technology. However, they also acknowledge the associated challenges, including limitations, disruptions to established practices, threats to privacy and security, and the potential consequences of biases, misuse, and misinformation.

Furthermore, trust in technology is a critical factor for its effective usage, which, in turn, influences work engagement

(Gkinko & Elbanna, 2023; Llorens et al., 2007). However, there is a hidden point in all this that relay on the nature of the algorithms embedded in AI tools. Usually, these tools are extremely friendly in terms of easy to use, nevertheless, theses algorithms are composed by extensive code that makes it a “black box” for the user. Therefore, although these technologies became easy to use, it does not imply that the results are shown reliable, and the user needs to be cautious accepting the output and taking it as own work output.

Moreover, the use of GenAI is affecting the way how workers get engaged with his or her work when they find the use of these tools as useful resources that enables them to improve their work, or vice versa, they might find these tools unreliable and as a threaten that make more tedious the work and consequently causing burnout (Bakker et al., 2023; Demerouti et al., 2001).

Given the background that shapes the current framework for the use of AI, this study addresses the following issues: (1) Does readiness to utilize GenAI tools facilitate their acceptance and use in the workplace? (2) Does trust in GenAI lead to work engagement and consequently to performance in companies? And (3) Can GenAI engagement facilitate certain tasks and thus increase performance or productivity?

The paper is structured as follows: First, the theoretical foundations are examined in section two. Here, the literature review encompasses the motivators and inhibitors of readiness to use GenAI tools, the conceptualization of trust in these tools, and the facets of work engagement. It leads to our conceptual model. Alongside, embedded in the section we present a set of hypotheses and the research model integrating all previous hypotheses. The methodology is detailed in the third section, while the fourth section discusses the findings. The fifth section shows discussion, whereas the sixth and last section provides conclusions and future research.

## 2. Theoretical framework and hypotheses

Artificial Intelligence (AI) has been conceptualized through various perspectives and is generally recognized as a convergence of technologies, mathematical and statistical models, and extensive datasets. Supported by a growing number of applications, AI aims to emulate human intelligence functions. AI empowers humanity to transcend previous limitations, fostering the creation of innovative products, services, and systems with the potential to significantly enhance the quality of human life and our environment, including engagement in the workplace (Samuel et al., 2022). GenAI refers to a subset of AI that leverages machine learning, especially deep learning, to generate, enhance, summarize, and analyze unstructured data and produce new content, including text, images, music, or video, by identifying patterns in existing data. According to Feuerriegel et al. (2024), the term generative AI refers to computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data.

The definition and conceptualization of work engagement undergone some evolution throughout the last two decades. Originally, it was conceptualized as an antipode to employee burnout. According to Maslach et al. (1997), work engagement was described by energy, involvement, and efficacy. These dimensions are the direct opposites of the three dimensions of burnout. Later, Schaufeli et al. (2002) characterized the construct as a concept distinct to burnout, albeit negatively correlated, categorized by vigor, dedication, and absorption.

Work engagement is often modelled within the Job Demands-Resources (JD-R) theory (Bakker et al., 2023; Mazzetti et al., 2023), which is based on the premise that the job environment can be analyzed in terms of two basic categories: (1) demands; and (2) resources (Bakker et al., 2023). Job demands are aspects of the job that require a significant mental and physical employee contribution, while resources are those features that, on the contrary, reduce the demands and help attaining goals and lead to personal growth and development. Accordingly, both work engagement and burnout result from the interplay of the perceived job demands and resources (Hakanen et al., 2006; Salanova et al., 2005), where burnout originates in health impairments and engagement is driven by motivation and the satisfaction of the basic psychological needs, such as competence, autonomy, and relatedness (Deci & Ryan, 1985). As such, employee engagement has been found to be induced by co-workers' support, leader support, job control, and task variety (Llorens et al., 2007). However, no research has been found regarding the role of GenAI as a colleague or co-worker. Under this perspective, these tools must be considered reliable for the professional and hence the paramount importance of trusting on the results of these tools. This deserves a particular analysis, and the lens of the JD-R theory is adequate for this purpose.

As mentioned, trust has been studied as one of the antecedents of employee engagement mostly outside the conceptualization of the JD-R model. Mainly, the two foci of trust, namely the leadership trust (and immediate supervisor trust) and co-workers trust, has been modeled as antecedents of engagement (Chughtai & Buckley, 2008). We point out that that trusting in the results of the GenAI can be considered as a job resource, and in this way influence work engagement as proposed by this JD-R framework (Bakker et al., 2023). In other words, trust can represent the motivational resource leading to employee engagement and consequently to increased performance through the so-called “gain cycle” (Bakker et al., 2023). This is a virtuous circle that leads to the development of engagement and results in increased performance. On the other hand, the dark side of trust, an excessive or too small level of trust on these tools can be dysfunctional and can lead to the opposite results, such as low effectiveness (Levine & McCornack, 1991; Skinner et al., 2014; Xavier Molina-Morales et al., 2011).

One of the key evolutions that the JD-R framework has undergone in the recent decade is the “person  $\times$  situational approach” that takes the general concepts of employee burnout and employee engagement to the level of the daily

activities and tasks for a particular person (Bakker et al., 2023). Accordingly, what is different from the original version of the JD-R theory is that personality is proposed to moderate the daily effects of job demands and resources on well-being and outcomes. Accordingly, individuals who lack personal resources for the demands of the job, will suffer most on the days on which they are exposed to a high workload and complex tasks (Debusscher et al., 2016). For example, employees who lack some technical skills and are not optimistic about the technology might feel loss of control in situations where learning new technical skills is required.

Therefore, in this research, we develop a model that links together personal resources and trust in GenAI as antecedents of employee engagement. Our conceptualization involves contrasting the bright side of trust, that leads to the “gain circle” of everyday engagement, with the possible dark side of trust impeding the “gain circle” (Bakker et al., 2023).

The theoretical framework is visualized in Figure 1 delineates the interrelationship among these elements.

The following sections will delve into the development of specific hypotheses and the construction of a research model that integrates these theoretical insights.

### 2.1. Personal resources and daily job resources adoption: The TRI model

In 2014, Parasuraman’s team examined individuals’ propensity to adopt and utilize emerging technologies. This period saw the maturation of revolutionary technologies such as mobile commerce, social media, and cloud computing, which had moved from nascent stages in the early 2000s to become pervasive elements influencing daily life. This led to the development of the Technology Readiness Index (TRI), a comprehensive 36-item scale. The TRI encompasses four distinct dimensions: (1) Optimism, reflecting a positive outlook on technology’s role in enhancing control, flexibility, and efficiency; (2) Innovativeness, denoting a propensity to be a technology pioneer and thought leader; (3) Discomfort, indicating a perceived loss of control and feeling overwhelmed by technology; and (4) Insecurity, stemming from

skepticism and concerns about technology’s reliability and potential adverse effects (Parasuraman & Colby, 2015).

The first two dimensions (optimism and innovativeness) analyses the positive attitude towards a technology. These positive predisposition fosters a favorable view, enriching the user experience. Similarly, the eagerness to pioneer in adopting new technologies also shapes the overall perceived experience, highlighting how both optimism and a pioneering spirit (innovativeness) directly impact on how technology is received and integrated into daily practices (Flavián et al., 2022).

This line of reasoning leads us to formulate the first two hypotheses:

- Hypothesis 1: “Optimism” impacts positively on “User Experience”.
- Hypothesis 2: “Innovativeness” impacts positively on “User Experience”.

### 2.2. Daily job resources and trust: TAM model

Concurrently to the development of the TRI model, Davis (1989) and his team explored the Technology Acceptance Model (TAM), a theoretical framework to understand the acceptance, adoption, and use of new technologies. TAM identifies two critical constructs that encapsulate the user experience with technology: perceived ease of use and perceived usefulness. The integration of TAM and TRI theories has been conceptually developed by Lai and Lee (2020) and shown to be empirically useful (Flavián et al., 2022).

Additionally, trusting in the technology is another key element that is frequently used to complement TAM. The introduction of trust makes a lot of sense in contexts that has implicit uncertainties, such as e-commerce, mobile payment, or self-driven vehicles. We hypothesize that personal resources represented by the readiness to adopt GenAI tools, as framed by the TRI, along with the TAM, play pivotal roles in determining the effective integration of these technologies in the workplace and the creation of an optimal level of trust.

One of the most widespread definitions of trust is the one provided by Mayer et al. (1995) who define trust as “the

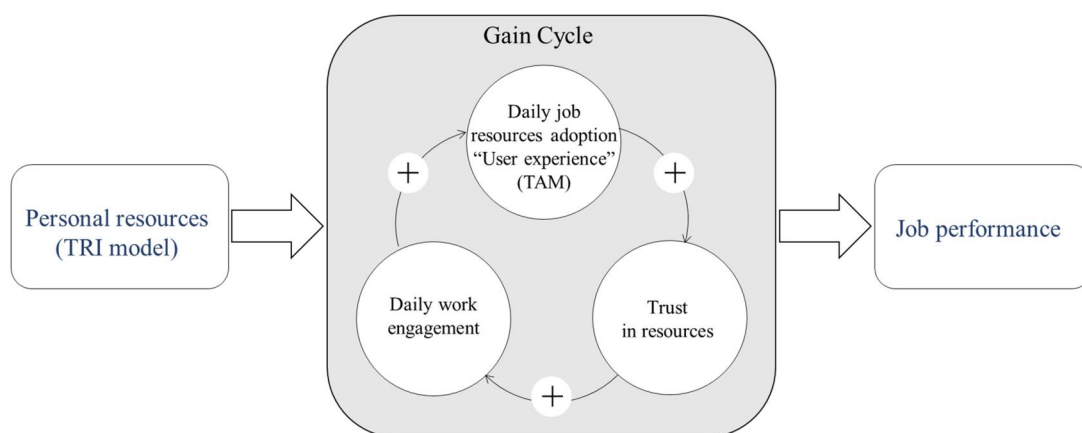


Figure 1. Conceptual framework. Source: Adapted from Bakker et al. (2023); the person  $\times$  situation approach of the job demands–resources model.

willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party". This definition is particularly useful in the setup of this research, as it can be extrapolated to the "human" – "no human" interactions allowing to consider trust on technology, specifically regarding AI. Laato et al. (2021) conduct a literature review focused on AI tools for end users and identify five primary dimensions of muser experience, with the second being Trustworthiness. This pertains to how users perceive the system's honesty and reliability, along with their belief in its effective functioning.

Additional research shows that increasing transparency of the algorithmic decision-making does not necessarily increase workers' trust and propensity to use AI (Bedué & Fritzsche, 2022; Candrian & Scherer, 2022). Additionally, according to (Kelly et al., 2023), perceived usefulness and low effort expectancy significantly and positively predicts attitudes and use behavior of AI across multiple industries. In this sense, Chen et al. (2023) affirm that the successful adoption of AI chatbots in the workplace depends on the trust of its users on the tool. Another specific example is the research by Zhang et al. (2021), which confirmed that both usefulness and ease of use dimensions were significantly and positively related to trust in AI. Furthermore, perceived ease of use is particularly critical for workers to improve their attitudes towards the use of AI and their intention to use it (Chatterjee, Chaudhuri, et al., 2021; Chatterjee, Rana, et al., 2021). User experience (perceived ease-of-use and usefulness) has been demonstrated to have a stronger effect on worker behavior (AI adoption) with the presence of trust (Kashive et al., 2021). And last, Yang and Wibowo (2022) made the reviewing literature about trust in AI, finding that to date there have been multiple applications of TAM to explain the relation between user experience, trust, and adoption of AI. Although previous research was focusing on AI, and not on GenAI, we extrapolate previous finding to propose the following hypothesis.

- Hypothesis 3: "User Experience" impacts positively on "Trust".

### 2.3. Trust and work engagement

Research indicates that trust plays a key role in the effective utilization of GenAI. Scholars widely agree that behaviors stemming from trust are typically advantageous (Bachmann & Zaheer, 2006) for both individuals and organizations. Trust reduces information-processing costs by minimizing the need for monitoring and surveillance, encourages communication within the organization, and cultivates stronger commitment to the company and work engagement. Consequently, studies suggest that trusting in these technologies and co-working with them, taking them as reliable colleague impact on organizational engagement. At the same time, the use of tools capable of automating administrative and routine tasks impact on employees' motivation and

engagement, since humans can devote their time to more creative and stimulating tasks, trusting that the machine will take the more tedious and repetitive jobs and performing these tasks in a good way (Wijayati et al., 2022). However, trust in GenAI can have varying impacts on workers, revealing its potential 'dark side'. Excessive trust may lead to detrimental effects, potentially fostering misconduct and compromising the quality of information exchange between parties, or inducing passivity among employees (Gargiulo and Ertug, 2006).

Furthermore, Chen et al. (2023) assert that scholars have underscored trust not only facilitates the adoption of AI applications but also influences users' behaviors and interactions, thereby enabling long-term use. Moreover, in the context of AI-based digital assistants, research has shown a positive correlation between satisfaction, productivity, and engagement (Marikyan et al., 2022). Additionally, this study identifies trust as a precursor to satisfaction and consequently to engagement. All in all, we propose the following hypothesis.

- Hypothesis 4: "Trust" impacts positively on "Work Engagement".

### 2.4. Work engagement and employee performance

The JD-R model, developed originally by Demerouti et al. (2001), examines the interplay between job demands and resources. Job demands, such as workload, can lead to stress, while resources, like social support, mitigate stress and enhance well-being. Widely applied in organizational psychology, this model provides insights into managing workplace stress and promoting employee engagement (Hakanen et al., 2008).

Work engagement, in its turn is defined as "a positive, affective-motivational state of fulfillment characterized by high levels of vigor, dedication, and absorption." Vigor entails abundant energy, resilience, a willingness to invest effort in one's job, resistance to fatigue, and persistence in the face of challenges. Dedication involves a profound engagement in one's work, accompanied by feelings of enthusiasm, significance, pride, and inspiration. Absorption describes a delightful state of complete immersion in one's work, where time passes quickly, and detachment from the job becomes challenging (Brodie et al., 2011; Llorens et al., 2007).

Therefore, engaged employees act as active agents in their work environment (Consiglio et al., 2016). They believe in themselves, generate their own positive feedback, and align their values with the organization. While they may occasionally feel tired, their satisfaction with their work allows them to overcome challenges with determination. This engagement is further characterized by secure attachment, job satisfaction, and positive social relations, reflecting a well-being within and beyond the workplace. Hence, the integration of GenAI in the workplace can enhance employee satisfaction by providing advanced tools, allowing them to focus on meaningful, human-centric tasks and delegate repetitive, non-value-added activities. This technological support



contributes to a more fulfilling and productive work environment (Rane, 2024).

While many studies focus on AI adoption (Yang & Wibowo, 2022), there is a lack of research linking AI adoption to organizational outcomes. The AI adoption may affect employee engagement through increasing its autonomy. Again, empirical studies have been focusing on AI and not on GenAI. Still, it could be expected that positive experience with the use of GenAI will lead to increased trust in GenAI, which in turn will positively affect employee work engagement. There is some evidence to support this: Picazo Rodríguez et al. (2024) suggest that company digitalization increases productivity perception and work engagement. Although that in a reverse sense, Chan et al. (2017) advocate that self-efficacy would increase work engagement through cognitive and emotional processes.

Wijayati et al. (2022) clearly show that AI has a significant positive effect on employee performance and work engagement, although there are also other important key points to guaranty employee engagement. Leadership is always a high influential factor in any process in an organization, and it is also key when analysing the use of GenAI. The integration of AI in organizations is extremely challenging, emphasizing the essential role of leaders in ensuring the successful implementation of strategies that enhance employee work engagement. In this way, when leaders encourage the use of GenAI, employees take it as a valuable resource and indirectly it also leads to work engagement. Therefore, we can posit the following hypothesis:

- Hypothesis 5: “User Experience” impacts positively on “Work Engagement”.

Engaged workers are proactive, seizing opportunities and taking the initiative to contribute positively to their work environment (Llorens et al., 2007). Setting higher goals, they cultivate a sense of competence that drives them to excel. Moreover, their experience of positive emotions not only contributes to their well-being but also sharpens their information processing abilities. In essence, engagement serves as a catalyst for superior performance across various dimensions of professional life (Salanova et al., 2006).

On the other hand, secondary effects could emerge from high engagement, because the demanding and competitive nature of online labor markets may increase technostress, impacting worker well-being and productivity (Umair et al., 2023).

Christian and Slaughter (2007) in their meta-analysis review in different settings show how the impact of engagement on performance is proved across industries. This is a phenomenon found consistently in different studies (Chui et al., 2023).

Hence, we propose the following hypothesis:

- Hypothesis 6: “Work Engagement” impacts positively on “Employee Performance”.

All six previous six posted hypotheses all together will end up in the research model. It can be easily visualized the J logic in this research model. The theoretical framework of Figure 1 is spotted and embedded in the research model showed in Figure 2.

### 3. Methodology

The study employs an explanatory sequential mixed-method approach. The first study focuses on a quantitative empirical analysis via a covariance SEM model to address the research questions outlined in the introduction. This phase evaluates the research model depicted in Figure 2. Following this, in a second study based on a survey targeting high ranked academics, specifically full professors in management sciences, will be conducted to better explain the research model's findings, looking for which are the main reasons to explain previous results. The overall intent of this design is to have the qualitative data help explain in more detail the initial quantitative results (Creswell & Poth, 2016). In this section, the first four subsections are devoted to describing the first study, while the last one is devoted to the second study methodology.

#### 3.1. Questionnaire design

The first study investigates the impact of GenAI tool usage on workplace dynamics according to the research model

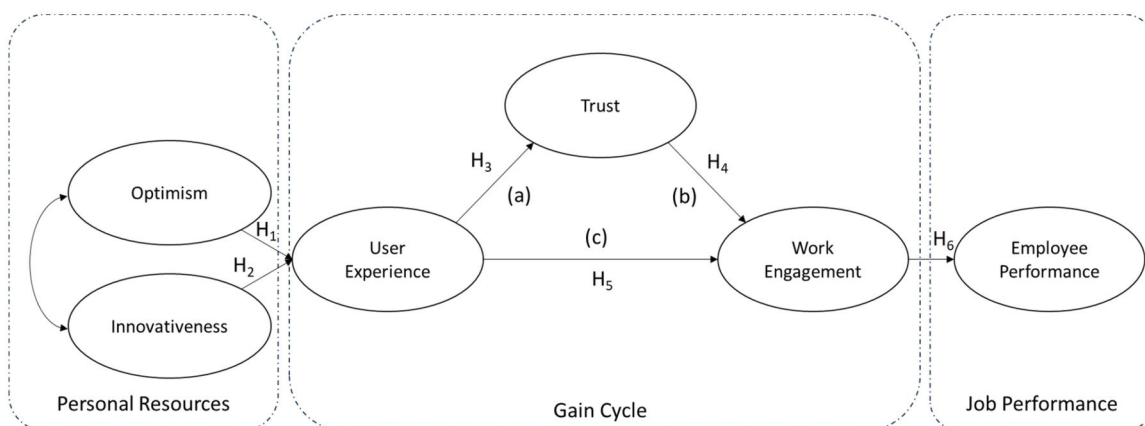


Figure 2. Research model.

**Table 1.** Items proposed for the questionnaire.

	Construct	Code	Item	Adapted from
1	Optimism	OPT1	GenAI tools contribute to a better quality of my life	Parasuraman (2000); Parasuraman and Colby (2015)
2		OPT2	GenAI tools give me more freedom and flexibility	
3		OPT3	GenAI tools give me more control over my work tasks	
4	Innovativeness	INN1	Other people come to me for advice on new GenAI technologies	
5		INN2	In general, I am among the first in my circle of friends to acquire new GenAI technology when it appears	
6		INN3	I can usually figure out new GenAI tools without help from others	
7		INN4	I keep up with the latest GenAI technological developments in my areas of interest	
8	Usefulness	USE1	I find GenAI useful in my job	Davis (1989)
9		USE2	Using GenAI makes it easier to do my job	
10		USE3	Using GenAI in my job would enable me to accomplish tasks more quickly	
11	Easy to Use	EAS1	I think that GenAI is easy to use	
12		EAS2	Learning to use GenAI was easy for me	
13		EAS3	I find it easy to get GenAI to do what I want it to do	
14	Trust	TRU1	In my work, I feel comfortable depending on the information provided by GenAI	Candrian and Scherer (2022); Frank et al. (2023); Glikson and Woolley (2020); Mayer et al. (1995); McKnight et al. (2002)
15		TRU2	I trust that I can rely on GenAI in my work	
16		TRU3	I feel that I can count on the responses of GenAI to help me in my work	
17		TRU4	If I have a challenging problem in my work, I use GenAI	
18		TRU5	I feel assured about data protection on the GenAI-tools	
19		TRU6	I feel adequately protected from problems on the AI-tools used in my company	
20		TRU7	I trust that GenAI-tools used in my company comply with established legal structures	
21	Work Engagement	WEN1	Time flies when I am working	Hakanen et al. (2008); Wijayati et al., (2022); Schaufeli et al. (2002)
22		WEN2	I am enthusiastic about my job	
23		WEN3	When I am working, I forget everything else around me	
24		WEN4	At my work, I always persevere, even when things do not go well	
25		WEN5	My job inspires me	
26		WEN6	At my job, I am very resilient	
27	Employee Performance	EPE1	My tasks are completed as per the specifications and standards	Wijayati et al. (2022)
28		EPE2	The units of output meet organizational expectations	
29		EPE3	My tasks are generally completed on schedule	

(Figure 2), based on a sample of users. The questionnaire was meticulously crafted to cover a range of aspects pertinent to our study. It began with items gauging the respondents' readiness to use new technologies, followed by questions assessing the degree of acceptance and experience used of these technologies, and the level of trust placed in these tools. Additionally, the survey included measures to evaluate the respondents' engagement with their work and their performance in the workplace. To ensure validity and relevance, items for each construct were carefully selected or adapted from existing, validated sources in the field. Table 1 presents a detailed breakdown of the constructs, the specific items included, and the references from which these items were borrowed.

### 3.2. Survey administration and demographics

The data collection process was facilitated by a specialized survey company, ensuring a high standard of reliability and professionalism. The survey was conducted in December 2023, resulting in the collection of 251 complete responses. Respondents were Spanish professionals who had experience using GenAI tools in their workplace.

A thorough analysis of the respondent demographics indicated no significant gender bias within the sample. The demographic breakdown of the respondents is presented in Table 2. Notably, more than half of the participants were under 35 years old, with only 19.5% being senior individuals

(aged 46 years or older). Regarding the frequency of tool usage, 13.9% of respondents reported intensive use of these tools, while 21.1% used them at least once daily, indicating that a substantial portion of the sample was highly familiar with these technologies.

In terms of sector-wise distribution, the 'education' category emerged as the most active in utilizing GenAI tools, accounting for 27.09% of the sample. Interestingly, a significant 51.79% of respondents reported using OpenAI's ChatGPT for text generation, and an additional 8.37% used other chatbots for similar purposes. Combined, these users represented 60% of the sample, underscoring the widespread adoption of chatbot technologies. Following chatbots, the second most prevalent use was for tools related to the generation of images and videos.

### 3.3. Assessment of the research model

The primary objective of this research is to delineate the pathway from the readiness to use generative AI tools in the workplace to employee performance, traversing through intermediate variables such as user experience, trust in these technologies, and work engagement. To achieve this, a two-stage analysis framework was employed.

Initially, five separate Exploratory Factor Analyses (EFA) were conducted using principal component analysis with varimax rotation. The purpose of this step was to identify and refine the items that would best represent each

**Table 2.** Demographic characteristics of the sample.

	Number	%
Gender		
Male	129	51.4
Female	122	48.6
Total	251	100.0
Age		
Between 18 and 20 years	0	0.0
Between 21 and 25 years	78	31.1
Between 26 and 35 years	62	24.7
Between 36 and 45 years	62	24.7
Between 46 and 55 years	49	19.5
>55	0	
Total	251	100.0
Education		
Professional studies	85	33.9
University degree	73	29.1
Master or PhD degree	93	37.1
Total	251	100.0
Professional position		
High Management	15	6.0
Intermediate position	87	34.7
Operational position	71	28.3
Other	78	31.1
Total	251	100.0
Frequency of GenAI Use		
Intensively every day	35	13.9
Once per day	53	21.1
Once per week	71	28.3
In very few occasions	92	36.7
Total	251	100.0
Industry		
Banking/Insurance	14	5.58
High tech	42	16.73
Life- sciences	19	7.57
Entertainment	16	6.37
Education	68	27.09
Manufacturing	17	6.77
Others	75	29.88
Total	251	100.0
Department		
Customer operations	52	20.72
Marketing and sales	30	11.95
Software engineering	37	14.74
R&D	29	11.55
Others	103	41.04
Total	251	100.0
Company size		
Less than 10 employees	37	14.74
Between 11 and 250 employees	103	41.04
More than 250 employees	111	44.22
Total	2151	100.0
Company ownership		
National	190	75.70
International	61	24.30
Total	251	100.0
AI tool used		
Chatbot for text generation (OpenAI ChatGPT)	130	51.79
Chatbot for text generation (Google Bard)	21	8.37
Chatbot for text generation (Microsoft Bing AI)	9	3.59
Text generation (e.g. Jasper, Notion AI, Copy.ai, Writesonic, or others)	5	1.99
Generation of presentations (e.g. SlidesAI, Wepik, Tome, or others)	8	3.19
Image generation (e.g. OpenAI Dall-E, Midjourney, Adobe Firefly, Canva AI, or others)	33	13.15
Video generation (e.g. RunwayML, Canva HeyGen, Pictory, Fliki, or others)	6	2.39
Generative AI assistants in commonly used programs (e.g. Google Duet AI, Microsoft AI copilot, or others)	26	10.36
Another specific tool for department activities	13	5.18
Total	251	100.0

construct in the subsequent research model analysis. This approach ensures that the constructs are both statistically robust and relevant to the research objectives.

Following the EFA, the research model, as depicted in [Figure 2](#), was subjected to Structural Equation Modeling (SEM). This analysis utilized the robust maximum likelihood

method based on the asymptotic variance-covariance matrix, with the assistance of the EQS software. The psychometric properties of each construct were thoroughly examined, including assessments of reliability (via Cronbach's alpha and composite reliability (CR) and convergent validity (measured through average variance extracted (AVE)).



Additionally, a discriminant analysis was conducted to evaluate the distinctiveness of the dimensions within the scale by comparing the square of its AVE with its correlations with other dimensions.

The model's overall fit was then evaluated using several metrics, including the Bentler-Satorra chi-square, its coefficient and degrees of freedom, and other fit indices such as the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA). Upon confirming the model's fitness, the standardized coefficients were analyzed and interpreted to understand the relationships between the constructs.

### 3.4. Mediation role of "trust"

A critical aspect of this study, as illustrated in Figure 2, is the mediation role of "Trust" in the relationship between user experience and work engagement. This section is dedicated to an in-depth analysis of this mediation effect, which represents the secondary objective of the paper.

The methodology for assessing the mediation role of trust was inspired by the seminal works of (Baron & Kenny, 1986; Hayes, 2009; Zhao et al., 2010). These foundational studies provide a framework for understanding the mechanisms through which trust influences the transition from technology acceptance to engagement in the workplace. The analysis delves into how trust functions as an intermediary construct, potentially altering or facilitating the impact of user experience on employee engagement. This nuanced exploration aims to offer a deeper understanding of the dynamics at play in the adoption and effective utilization of GenAI tools in professional settings.

This section of the methodology provides a comprehensive overview of the analytical approaches used to assess both the overall research model and the specific mediation role of trust, setting the stage for a detailed exploration of these dynamics in the subsequent sections of the paper.

### 3.5. Survey to academics on business management

Following the analysis of the research model, a survey conducted by a panel of distinguished academics, all of whom are full professors, will critique the initial findings. This is the second study, aiming to deepen the understanding of the results obtained from the quantitative analysis (first study) by incorporating expert insights and perspectives.

Driven from the conclusions from the first study, the authors posit three of questions to a panel of 69 professors of management from European universities, mostly from Spain (58.0% of professors), since the empirical sample of the first study was collected in Spain. Other origin countries are Croatia, Germany, Indonesia, Italy, Pakistan, Poland, Portugal, and the United Kingdom. Women constitute 31.9% of the group, while men make up the remaining 68.1%. A significant proportion, 31.9%, hold tenured full professorships in management, attesting to a high level of expertise. The mean age of participants is 48 years, with a standard deviation of 7.5 years. The distribution of ages is

evenly split, with one-third of the individuals being under 46 years old, another third ranging from 46 to 51 years, and the final third being over 51 years of age. 29 respondents, which represents 46.4% use these tools every day, intensively. Only 31.8% uses it "in very few occasions".

The three questions presented to this panel are derived from the research questions outlined in the introduction section. These questions have been rephrased to enhance clarity for the expert panel and to elicit focused and concise responses.

- To what extent does a predisposition to try new technologies and optimism about their capabilities influence your future experiences with these technologies?
- How crucial is it for you that the outcomes of these tools are reliable, consistent, and can be confidently used in your work?
- To what degree do you agree that using these tools enhances productivity?

## 4. Results

In the same way that in the previous section, the first subsection is centered on the first study, which consists of the empirical analysis using the sample of 251 users of Gen AI, and the second subsection will provide results from the second study, conducted through a survey to 69 high ranked academics on management science.

### 4.1. First study. Quantitative analysis

Before starting the analysis, we conducted Harman's Single-Factor Test to ensure that the data did not have common method bias (CMB) issues. An Exploratory Factor Analysis using all 46 items revealed eight factors with an eigenvalue greater than one, with the first factor explaining only 36.0% of the total variance. This result indicates that CMB is not a significant issue in our study.

The quantitative analysis initiated with a set of five EFAs. The first one, focusing on items from the TRI scale's optimism and innovativeness dimensions, affirmed the distinction of these original dimensions. Subsequent EFAs for other constructs yielded a single dimension for each, adhering to the criteria outlined by Ladhari (2012) and Wolfenbarger and Gilly (2003). Thus, the criteria were that the items (i) loaded at 0.7 or more on a factor, (ii) did not load at more than 0.50 on two factors, and (iii) had an item-to-total correlation of more than 0.50. Table 3 shows the results of these EFAs, discriminating items that remain from those who were dropped. Notable exceptions were EAS3 (with a load of 0.698) and WEN1 (with a load of 0.696), which, despite slightly lower loadings, were retained for their informational value.

Once the items that would be used in the whole model (Figure 2), the model was conducted using SEM (based on covariances). Table 4 summarizes the reliability analysis of the six constructs. The internal consistency of the constructs was verified through Cronbach's alpha coefficient and

**Table 3.** Matrixes of the components extracted using principal components analyses and varimax rotation.

TRI										
Innovativeness		Optimism	User experience		Trust		Work engagement		Employee performance	
INN1	0.782	0.261	USE2	0.779	TRU2	0.777	WEN2	0.765	EPE2	0.803
INN2	0.780	0.175	USE1	0.770	TRU6	0.768	WEN5	0.748	EPE1	0.776
INN4	0.764	0.276	USE3	0.743	TRU3	0.741	WEN4	0.715	EPE3	0.773
INN3	0.708	0.268	EAS1	0.740	TRU1	0.727	WEN6	0.703		
OPT3	0.246	0.790	EAS2	0.706	TRU7	0.720	WEN1	0.696		
OPT2	0.280	0.784	EAS3	0.698	TRU5	0.702	WEN3	0.671		
OPT1	0.222	0.783			TRU4	0.623				

In grey loads under 0.7. Although EAS3 and WEN1 does not match the criterion, are in back because they were retained for the analysis of the complete research model.

**Table 4.** Loads of the six constructs and statistics for their reliability analyses.

	1 Optimism		2 Innovativeness		3 User experience		4 Work engagement		5 Trust		6 Employee performance	
	OPT1	0.801	INN1	0.839	USE1	0.838	WEN1	0.674	TRU1	0.731	EPE1	0.466
	OPT2	0.856	INN2	0.791	USE2	0.802	WEN2	0.760	TRU2	0.786	EPE2	0.382
	OPT3	0.838	INN3	0.736	USE3	0.763	WEN4	0.744	TRU3	0.776	EPE3	0.398
			INN4	0.811	EAS1	0.650	WEN5	0.733	TRU5	0.664		
					EAS2	0.627	WEN6	0.929	TRU6	0.763		
					EAS3	0.670			TRU7	0.736		
Alpha Cronbach		0.869		0.870		0.878		0.849		0.880		0.825
Composite Reliability		0.968		0.873		0.871		0.880		0.881		0.828
Average Variance Extracted		0.692		0.632		0.532		0.597		0.553		0.617

**Table 5.** Correlation matrix of latent factors.

	1	2	3	4	5	6
1 Optimism	0.832					
2 Innovativeness	0.505	0.795				
3 User Experience	0.647	0.524	0.729			
4 Work Engagement	0.378	0.336	0.392	0.773		
5 Trust	0.668	0.607	0.728	0.444	0.744	
6 Employee Performance	0.249	0.280	0.407	0.596	0.374	0.786

In the main diagonal the square of AVE.

composite reliability (CR), whose values exceeded the recommended threshold of 0.7 (Hair et al., 2010). The average variance extracted (AVE) also surpassed the cut-off point of 0.5 (Nunnally & Bernstein, 1994), confirming convergent validity.

Table 5 provides the results of the discriminant validity analysis, which was conducted using linear correlations or standardized covariances between latent factors by examining whether the inter-factor correlations were less than the square root of the AVE (Fornell & Larcker, 1981). Table 5 shows that the square roots of each AVE were greater than the off-diagonal elements, vouching for discriminant validity.

Additionally, the Heterotrait-Monotrait ratio (HTMT) test was conducted to assess discriminant validity. According to Henseler et al. (2015), all HTMT values between the constructs were below the recommended threshold of 0.85. The HTMT values ranged from 0.287 (between Optimism and Employee Performance) to 0.798 (between User Experience and Trust). The mean HTMT value across the 15 pairs of constructs in the model was 0.546, with a standard deviation of 0.165.

The fit indices obtained in the model estimation showed that the variables converged towards the factors established in the research model. The Satorra-Bentler  $\chi^2$  was 577.75,

with 317 degrees of freedom and a  $p$ -value of 0.000;  $\chi^2/df$  was 1.82, which was below the acceptable limit of 5. The root mean-square error of approximation (RMSEA) was 0.057 and the comparative fit index (CFI) was 0.913. Taking the significance of the robust  $\chi^2$  statistic with caution and noting the global indicators, the global fit was acceptable (Hair et al., 2010).

Figure 3 shows the research model with the standardized coefficients and its  $t$ -values associated on brackets. All coefficients are significant (at significance of 0.05) expecting the path between “User Experience” and “Work Engagement”. Therefore, the six hypotheses are accepted, excepting the fifth, which is refused. We recall that hypothesis 5 was “User Experience” impacts positively on “Work Engagement”. It is not accepted. This finding is particularly important and will need a detailed analysis. It is not proved that “User Experience” impacts directly on “Work Engagement”.

In the first place, it is showed that “Optimism” impacts on “User Experience” twice than “Innovativeness”. What really matters to get a good experience in the use of these techniques is an optimistic mood. This predisposition and willingness are key. However, the tendency to be a technology pioneer is not negligible at all. This finding is aligned with (Wang et al., 2023), that using the TAM examines how AI can improve effectiveness and profitability in an e-commerce setting. Therefore, our first research question is satisfied. We affirm that readiness to adopt GenAI influences a positive user experience.

Due to the importance of “Trust” in our research, Table 6 is inserted to show the decomposition of the effect of “User Experience” on “Work Engagement”. It is in the core of the research model. The finding is that the direct effect is not significant, whereas the indirect path through

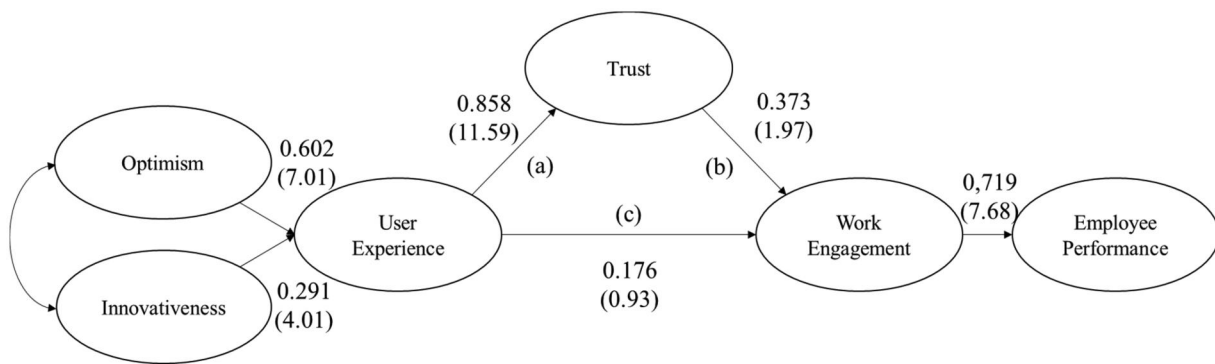


Figure 3. Research model with standardized coefficients. Standardized coefficient and t-values associated in brackets.

Table 6. Decomposition of the mediation analysis of “trust” between “user experience” and “work engagement”.

	Direct effect		Indirect effect		Total effect	
	standardized coefficient	t-value	standardized coefficient	t-value	standardized coefficient	t-value
User Experience → Trust	0.86 (a)*	11.59	–	–	0.86*	11.59
Trust → Work Engagement	0.37 (b)*	1.97	–	–	0.37*	1.97
User Experience → Work Engagement	0.18 (c)	0.93	0.32 (a*b)*	2.08	0.50*	5.58

\*Significant value at significance 0.05.

The letters a, b and c correspond to the notation in Figure 2.

“Trust” is significant. As anticipated when the fifth hypothesis was rejected, it brings an important finding pointing strategic role of trust in this model. Consequently, following Zhao et al. (2010) classification, this is a full mediation. In other words: without “Trust” in the GenAI output, there is no way to get engagement and, in its turn, no way for improving employee performance. Utilizing GenAI tools to foster workplace engagement is not a quick fix; it is absolutely required trust in these tools. Consequently, our second research question is also answered. We affirm that trusting in GenAI is crucial to increase employee productivity.

This provides another important finding. The gain cycle proposed by Bakker et al. (2023) is broken in the link from “user experience” to “engagement”. There is not cycling, but a linear flow instead, in which trust is in the middle of the chain of constructs that link from the predisposition to adopt GenAI to the employee performance. It is consistent with the role of trust in other contexts, such as in the context service recovery process, where trust has also taken an important role as a mediator (DeWitt et al., 2008).

The sixth and last hypothesis is confirmed, and engagement is impacting significantly on employee performance. This is the right hand of the research model. There is no doubt on the significance of these last link. This last hypothesis responds for our last research question, confirming that work engagement is in the path to employee performance.

An additional multi-group analysis of the research model was conducted, dividing the sample into two subgroups: men (129 cases) and women (122 cases). Equality constraints were imposed on the regression parameters between constructs in the model. For all six constraints, the  $p$ -value associated with the univariate  $\chi^2$  increment exceeded 0.05. Therefore, in all cases, the regression values between constructs are not significantly different. The model behaves similarly for both groups. In other words, the research model (Figure 2) operates equivalently for both samples

(men and women). The standardized coefficients presented in Figure 3 do not exhibit significant differences between the two samples. Both genders demonstrate similar behavior in the context of the model.

#### 4.2. Second study. Survey of academics

The academics showed high agreement in their answers to the three questions. The first question was: “To what extent does a predisposition to try new technologies and optimism about their capabilities influence your future experiences with these technologies? (Rate from 1 to 5)”. It was a consensus on the first question, that was ranked 4.2 in a Likert scale between 1 and 5, and a standard deviation of 0.7 This reinforces previous answer to our first research question. See below some representative answers:

- “In general I am very open to new technologies, especially if they have high capabilities and they are not very complicated to work with. This latter point can discourage the use of technology; hence I think the trade-off between capabilities and costs of adoption is crucial.”
- “I can share the fact that since I do not have a strong predisposition to try new technologies, I do not feel compelled to experiment them.”
- “I only agree with predisposition to try new tech, but not with optimism (...) my predisposition makes me more willing to try new techs, but I can also say I stop trying it when I see the new tech does not provide what it promises”.

The comments highlight a general optimism and openness towards new technologies, emphasizing that a positive predisposition encourages experimentation, forgiveness of flaws, and adoption. Positive predisposition often leads to

early adoption and a higher tolerance for initial setbacks, fostering a virtuous cycle of engagement and exploration.

Additional lessons drawn from this enquire is that optimistic employers on new technologies will try GenAI, use it intensively, and therefore will learn what they can expect and what not from GenAI, guaranteeing a good use of it and thus getting good and reliable results. This will encourage exploring new utilities fostering good experience and trusting more and more on it.

However, there are notable drawbacks mentioned. Some respondents pointed out that without a certain level of initial optimism, the experience could be less satisfactory, affecting future willingness to engage with new technologies. There were also criticisms regarding the effectiveness of some AI tools like ChatGPT, especially in contexts where clear sourcing and up-to-date information are crucial, like in research.

Again, it was also absolute consensus in the second question: "How crucial is it for you that the outcomes of these tools are reliable, consistent, and can be confidently used in your work? (Rate from 1 to 5)". The average rate was 4.4, with a standard deviation of 0.8. Interesting note some of the commentaries:

- "Reliability is important for sure. However sometimes having a rough result is better than nothing."
- "I will trust on it if I get good results. I will trust when according to my experience it works and I can take advantage for my job."
- "Initially, I utilized ChatGPT without hesitation. However, after recognizing several errors in the technology, I now carefully analyze the results before incorporating them, using them merely as a guide."
- "For me this is very important, that is why I always check the outcomes before I use them. If reliability and/or consistency are low, then I will not be very keen to use the technology."
- "The main problem of these generative AI tools is the black box they are. The outcome requires review. However, if used wisely, the total time used for interaction plus revision is lower than the time required to do that thing without it."

An employee checks the output of these tools, and according to his or her knowledge and expertise on it, the user assesses the Gen AI results. This judgment will affect the trusting for future experiences. In short, this second question of this survey reinforces the positive answer that was anticipated in the first study. This reveals something hidden in the first quantitative study conducted through SEM, based on a sample of 251 employees. The employee assesses the quality and consistency of the GenAI work and takes it as reliable or not based on his or her expertise. The AI is taken as a productive assistant and excellent colleague, but it is the employee who takes control of his or her work. Trusting on the GenAI is key. In this sense, when the employee finds inconsistent quality and inaccuracies in the outputs of the GenAI, such as mathematical errors or

incorrect information, the trust is damaged. On the other hand, when the results of the GenAI are blindly taken by the employee without any criticism, perhaps due to the lack of expertise of the employee, it might lead to unreliable outcomes and poor-quality work.

The answers to the third question ("To what degree do you agree that using these tools enhances productivity? (Rate from 1 to 5)") were rated also with 4.3 (standard deviation of 0.8), showing how enthusiastic are the academics on this. Attached some commentaries that provides insight on it.

- "According to my experience, I get an incredible better results using this tool. The more I use it, the more I learn what I can get from it. I perform work of better quality, in terms of content and of 'format'."
- "Repetitive work requiring an extensive knowledge base can be speeded up considerably."
- "Anyone who has taken a deep look at this technology knows that this tool is not only the future, but also that boost your productivity and your creativity in many ways."
- "As you can get quickly a first draft, productivity increases a lot."

It is confirmed that GenAI can take some repetitive tasks in a very efficient way, giving extra time to the employee for more creative and higher added value tasks. The main positive points highlight that these tools significantly boost productivity by providing first drafts, summarizing large volumes of information, improving content quality and format, and assisting with tasks like translation and email writing. Many respondents noted that these tools save time and enhance creativity, making routine tasks quicker and easier, which allows more focus on higher-level creative or critical tasks. In this way, the GenAI increases productivity, and additionally influences positively on satisfaction in the job position. Some experts drawn attention to the fact that this increase in productivity is temporal, only considered until the new productivity standard is set as the regular. However, the effectiveness of these tools was seen to vary significantly depending on the task and the user's familiarity with the technology. Overall, while there is enthusiasm for the potential productivity gains offered by AI, there is also caution advised about over-reliance without sufficient understanding and scrutiny.

Other considerations were risen from the survey that were not the direct aim of the questions. One respondent claims that the GenAI give him a plus of security and autonomy in his job because he knows that can rely on these tools when he needs some information. He is more autonomous because he interacts in a quicker way than with a colleague or expert. Moreover, these tools are always available. There are also some psychological issues: "When the job goes wrong, you feel guilty, worse than if you had done it yourself."

As aforementioned, the three questions of this survey are highly connected with the three research questions posted in

the introduction section, shedding light for a better understanding of the quantitative study results, and providing additional findings that the first study did not provide.

## 5. Discussion

### 5.1. Discussion about the three research questions

The comprehensive analysis conducted in this research offers valuable insights into the dynamics of GenAI adoption and utilization in the workplace. Through a methodical examination of various constructs, including technology readiness, user experience, trust, and work engagement, this study sheds light on the complex interplay of factors influencing employee performance in the context of GenAI technologies.

All this can be summarized in three points. The first one enhances the importance of Optimism as a first trigger for a good experience in the use of these tools that will end up in professional results. The optimistic attitude towards technology plays a more influential role in shaping user experience compared to the tendency to be a technology pioneer. It is consistent with the scale designed to gauge attitudes toward the acceptance of AI, known as the General Attitudes towards Artificial Intelligence Scale (GAAIS) (Schepman & Rodway, 2023). The findings revealed that the positive GAAIS subscale correlated strongly with the TRI's positive aspects (Innovativeness and Optimism). This outcome suggests that fostering a positive outlook towards technological advancements is crucial for enhancing user engagement with GenAI tools. On the other hand, the most optimistic are those who adopt first, and consequently it allows them to take an advantageous position with respect to those who enter later.

The second important remark is the analysis of the full mediation of trust from user experience to engagement at work. The lack of a direct significant effect of user experience on work engagement, coupled with the significant indirect effect through trust, establishes trust as a full mediator in this relationship. This implies that trust in GenAI is a critical factor that bridges the gap between user experience and engagement in the workplace. There is no shortcut to get engagement at the workplace using GenAI tools. Trust on these tools is a "must". **Without a foundation of trust, the potential benefits of these technologies in terms of enhancing work engagement and, consequently, employee performance, cannot be fully realized.** It means that it is not enough to have access and full usage of GenAI tools, although it is a requirement to boost employee performance. As analyzed, what really matters is the trusting of the employees on these techs. Employees need to rely on these techs, on the veracity, reliability and validity of the results provided by these GenAI tools. In its turn, it will contribute to engage employees in their workplace and will end up boosting performance.

Additionally, it is also important taking into account that traditional views on trust considers it a rational, decision-making process. However, trust can also stem from emotions, characterized by an optimistic affective attitude

towards another's goodwill and competence, based on emotional bonds rather than calculated reasoning (Gkinko & Elbanna, 2023).

The third and last point regards to the impact on Employee Performance. The study confirms that work engagement significantly influences employee performance, validating the last hypothesis. This relationship highlights the importance of engagement as a catalyst for improved performance in the context of using generative AI tools. This point is also stated in the recent literature (Babina et al., 2024; Bankins et al., 2023; Czarnitzki et al., 2023; Kellogg et al., 2020; Marikyan et al., 2022).

These three points are directly linked with the initial research questions. Now we extend our conclusions with some implications, first for managers and second for academics.

### 5.2. Managerial implications

We extend the analysis with managerial implications that derive from this frame. There are several actions to strengthen trust in the outputs provided with the assistance of GenAI. These actions might be classified attending to different criteria. The first set of actions aims to cultivating and strengthen trust on GenAI. Organizations can provide opportunities for employees to familiarize themselves with these tools (training, brainstorming, benchmark activities with other users and with external stakeholders or other organizations, etc...). Trust is also strengthened through the knowledge of how these tools works. This understanding helps set expectations regarding the quality and nature of the outcomes.

The second set of actions should be interesting for the providers of these GenAI tools. Trust is built on the historical interactions, behaviors, and experiences within the trustee-trustor relationship. According to Gkinko and Elbanna (2023) research, trust has multiple dimensions that offer practical ways to enhance it. "Closeness" is one such dimension, characterized by feelings of being heard, supported, and understood. GenAI should act in a way that the user feels that is understood and that the GenAI will work to benefit the best interest of the user. The interaction human – GenAI should be performed in a way that the human knows that his or her requirements and demands are well known by the GenAI. The GenAI should provide feedback letting the employee know that has been listened and understood. Another critical dimension is "transparency," which is achieved when the sources of information are clear and open. When the sources used by the GenAI are shown and considered reliable, the trust on the GenAI increases. Another point is the "black box" effect: a tool that shows its internal logic lowers the effect "black box", improving the feeling of control. An additional point that might increase transparency is regulation from a reputational institution that guaranties the right and ethical use of the algorithms embedded. To enhance the trust that users place in Generative AI, it is essential to adhere to the foundational principles outlined by Mayer et al. (1995) in their



seminal definition of trust. According to this framework, trust is built when users can confidently believe that the Generative AI system operates with their best interests as its primary focus. This means that the system should function as a reliable assistant, dedicated to supporting the user's needs and objectives without being influenced by the interests of other stakeholders, such as the developers or providers of the technology. In practice, this requires transparent operation of the AI, where users are not misled or presented with biased information, ensuring that the Generative AI remains a neutral and supportive tool in their decision-making processes. By consistently demonstrating that it acts solely in the user's interest, the Generative AI can foster a strong sense of trust, which is critical for its effective utilization and acceptance.

There is still a third set of actions that might be conducted by official institutions or governmental agencies, such as fostering a positive technology culture. It can be achieved encouraging a culture that values optimism and openness towards new technologies, enhancing user experience and engagement with GenAI tools. Some actions that might be taken to promote this positive culture on tech are such as awareness campaigns to address misconceptions or fears related to these tools, user education providing clear information with emphasis on positive impacts, transparent communication through open dialogues, providing awards and actions for recognition of achievements, etc.

### 5.3. Theoretical contribution

From the academic point of view the paper contributes to three main points. First, it is conceptualized a framework in which the TAM and TRI models are considered to explain the impact of new GenAI tools on productivity. We termed this framework as "Trusting in trust as an enhancer from experience to work engagement and performance (TTEEWEPE)". It is used twice the word "trust" on purpose to highlight how key is trust in the model. In the research model analyzed, trust takes the central position.

Second, it is probed that trust is key in the research model. Its mediation role between user experience and work engagement proves that the gain cycle proposed by Bakker et al. (2023) according to the JD-R theory, is broken. User experience does not directly lead the work engagement.

Third and last, the whole research model shows that the connection among user experience, trust, work engagement and employee performance follow a particular pattern, in which trust plays a mediation role of paramount importance.

## 6. Conclusions and future research

It is confirmed that the positive gain cycle that starts with user experience using GenAI works partially. A good experience enhances the trust of the professional towards the results of the GenAI. Consequently, trusting on the output and collaboration of the GenAI leads to engagement in the work. An employee that uses GenAI in a confident way,

taking GenAI as a reliable and expert colleague, becomes him or her more engaged. This worker devotes more energies on his/her work, is more enthusiastic on it and experiences high absorption working. This is part of the gain cycle proposed by Bakker et al. (2023), founded in the JD-R theory. It is proved that "Trust" has a significant role, thorough its mediation between user experience and work engagement. This construct enables that a good experience ends up in work engagement. This is part of Bakker's gain cycle, with the key difference that in our setting, the loop remains open, due to the no significant correlation between user experience and engagement.

Finally, the study opens avenues for future research to explore these relationships in different cultural and organizational contexts. The JD-R model also encompasses a "losing cycle," which introduces constructs such as "job demands," capturing the various efforts and demands of a job, and "exhaustion," addressing the psychological state of an overloaded employee. These aspects warrant further exploration in future research. Additionally, longitudinal studies could provide insights into how these relationships evolve over time as GenAI tools become more ingrained in workplace practices. The field is still in its first steps. More explorative studies are required to assess how the constructs of our model are affected by other close constructs such job satisfaction, life satisfaction, well-being, etc., which will enable to better understand the theoretical framework. An alternative venue are explorations of the use of GenAI for different purposes, such as for providing brainstorming for a creative project or just as a proof-reading service, or for utilitarian services versus for entertainment (Barrett et al., 2024).

Lastly, the group analysis across the subsamples for men and women reveals similar behaviors for both groups. However, future research should explore how certain factors might differently impact each group.

The article started with a quotation from Acemoglu, setting the stage for a comprehensive exploration of the intricate relationship between new technologies and their effects on diverse stakeholders. The intersection of new technologies and their impact on various stakeholders forms a complex tapestry that has been the subject of extensive academic inquiry. Acemoglu et al. (2023) investigates how advancements in technology initially boost productivity but observes that the resultant benefits are not uniformly distributed among all stakeholders. This disparity often arises from the perspectives and power dynamics of different parties involved, influencing who reaps the greatest advantage. Empirical studies like this one will shed light on all this.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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