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Peer Influence on the Adoption of Artificial Intelligence Tools in the Workplace

Nicoleta Munteanu

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Intelligence.

Supervised by

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STATEMENT OF INTEGRITY

I declare that I have completed this academic work with honesty and integrity. I assure that no plagiarism, inappropriate use of information, or falsification of results occurred during its preparation. Additionally, I confirm my full adherence to the Rules of Conduct and Code of Honor of NOVA Information Management School.

[Lisbon, 2024]

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ABSTRACT

The rapid advancement of Artificial Intelligence (AI) is revolutionizing numerous industrial sectors, leading to significant enhancements in operational efficiency and productivity. As AI systems become increasingly integrated into workplace processes, they are not only transforming how tasks are performed but also reshaping the dynamics of workplace relations between employees. Despite its potential, the successful implementation of AI tools within organizations depends heavily on employee acceptance and willingness to utilize these technologies.

This paper investigates the intention to use AI tools among employees who observe their colleagues using these tools in their daily tasks. A central issue is understanding how observing coworkers using AI tools influences other employees' intentions to adopt them. It is crucial to determine whether peer influence serves as a motivating factor or poses challenges to the adoption of such tools. This problem is relevant because AI adoption in the workplace can be influenced not only by technological and organizational factors but also by social and psychological dynamics among employees. Studying the power of influence between employees helps to fill an existing gap in the literature.

The research integrates insights from Social Cognitive Theory and Protection Motivation Theory. The data was collected through a survey targeting only working people. Analyzing a sample of 221 employees using SmartPLS, it was found that anxiety significantly influences employees' intentions to adopt AI tools. Employees who feel vulnerable to job displacement and increased competition due to AI integration experience heightened anxiety, which drives them to adopt AI tools as a protective measure.

This thesis contributes to a better understanding of the critical psychological and social factors that impact AI adoption among employees. It is relevant for organizations, as they can enhance the effectiveness of AI integration by fostering a supportive environment, providing necessary training, and addressing employees' anxieties and concerns.

KEYWORDS

Artificial Intelligence; Peer Influence; Social Dynamics; Job Insecurity; Anxiety

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
WEF	World Economic Forum
ATs	Automation Technologies
FARAI	Fear of Autonomous Robots and Artificial Intelligence
SCT	Social Cognitive Theory
PMT	Protection Motivation Theory

1. Introduction

The increasing adoption of AI tools by companies (Albert, 2019; Chen et al., 2021; Guo, 2023), has led to mixed attitudes among employees. Some are enthusiastic about AI, while others express resistance due to anxiety and fear of job displacement (Li & Huang, 2020; Lichtenthaler, 2019; Walsh, 2018).

There is a growing concern that AI will displace jobs, sparking an ongoing debate about the impact of AI on employment (Acemoglu & Restrepo, 2020; Autor, 2015; Frey & Osborne, 2017). Conversely, Kirov and Malamin (2022) believe AI evolution will create more jobs than it eliminates. According to Pentland et al.(2019), knowing how to use AI will be crucial to establishing a competitive advantage in the future. Achieving this requires the symbiotic integration of AI with human work to create cooperative teams (Hamid et al., 2017; Jarrahi, 2018; Wilson & Daugherty, 2018). Several studies have been conducted on the acceptance and use of AI in different industries, such as healthcare (Lambert et al., 2023; Venkatesh, 2022), services (Vitezić & Perić, 2021), agriculture (Mohr & Kuhl, 2021) and psychology (Gado et al., 2022). Additionally, there is substantial research on the fear and anxiety people experience regarding the adoption of AI (Johnson & Verdicchio, 2017; Li & Huang, 2020; Zhan et al., 2023).

Despite extensive research on AI impact, there is a significant gap in the literature regarding adopting AI tools influenced by coworkers. For instance, the study by Wood and Bandura (1989a) focuses on the broader aspects of social learning and self-efficacy related to the intention to use new technology. Compeau and Higgins (1995b) emphasize the role of self-efficacy in technology adoption, suggesting that observing colleagues can enhance one's self-efficacy, which in turn influences the adoption of a technology. Additionally, the study by Sykes et al. (2009) explores how peer support can influence the acceptance of IT systems. However, their research does not directly examine the adoption of AI tools based on peer observation. AI is distinct from previous technologies due to its similarity to human thinking, characterized by flexibility and adaptability (Haugeland, 1993; Russell & Norvig, 2003; Turing, 1950), highlighting the need for further research about this specific area.

To address the gap in the existing literature, this study aims to investigate the intention to use AI tools by individuals who observe their coworkers using these tools to perform their daily tasks. It is particularly interesting to understand how employees' perceptions of their peers using AI might influence their own sense of job security, especially in contexts where AI enhances efficiency and productivity, potentially making some human roles redundant.

This research is relevant because it focuses on a current issue present in different industries where AI is rapidly integrated. It investigates the relationship between individuals observing and comparing each other in the context of AI tool adoption, providing valuable insights into the social and psychological dynamics that influence the intention to use AI tools.

Methodologically, this paper involves empirical research through a quantitative survey. By conducting a questionnaire, we collected 221 valid responses from employees of various organizations. To analyse the survey data, was used SmartPLS 4.1 and was employed structural equation modelling (SEM) to test the hypotheses derived from the theoretical model. By integrating insights from Social Cognitive Theory (Wood & Bandura, 1989a) and Protection Motivation Theory (W. Rogers, 1975), this research provides a holistic understanding of how different factors influence the intention to use AI tools in the workplace. Specifically, the study explores how observing peers successfully using AI tools, observing peer positive performance outcomes, such as increased efficiency and productivity (Brynjolfsson et al., 2023), and perceiving the usefulness of these tools impact an individual's self-efficacy (Compeau & Higgins, 1995). This, in turn, can influence their intention to use AI tools, responding as a coping appraisal. Moreover, this paper investigates how vulnerability, perceived severity of not adopting AI tools and competitive pressure influence anxiety and the intention to use AI tools. The fear of being undervalued compared to coworkers who use AI tools can lead to anxiety, encouraging individuals to adopt these tools as a protective measure against the perceived threat.

The study's findings indicate that feelings of vulnerability and competitive pressure greatly increase employee anxiety, leading them to consider adopting AI tools. This indicates that employees who feel vulnerable to external threats or competitive pressures are more likely to view AI adoption as a necessary response. Interestingly, the perceived severity does not significantly impact anxiety levels. This suggests that while employees may acknowledge the potential seriousness of AI-related changes, these concerns alone are not sufficient to drive anxiety and influence their intention to use AI tools.

This research is essential for helping companies understand the role of social influences in AI tool adoption. By recognizing the impact of peer influence, companies can implement initiatives that promote transparent communication to reduce anxiety and concerns, leveraging the benefits of AI while supporting and empowering their workforce (Nazaretsky et al., 2022). Strategies may include regular workshops, seminars, and peer mentoring programs where employees can observe and discuss the use of AI tools (Kleine et al., 2023). Also, fostering an open dialogue about job security and fair labour practices can further mitigate fears associated with AI integration. This approach facilitates smoother adoption and promotes a positive organizational culture that values and respects employee contributions during technological transitions.

2. Theoretical Background

2.1. Impact of AI on the Job Market

With the continued advancement of machine learning and automation technologies, AI is increasingly capable of performing tasks that require higher-level cognitive abilities. This development points to the possibility of job losses in roles traditionally occupied by highly skilled and well-compensated white-collar workers (Koutroumpis & Lafond, 2018). Georgieff and Hyee (2022) reveal that job roles such as business professionals, managers, chief executives, and engineering professionals are more susceptible to AI due to their high computer usage. Individuals in these occupations must acquire AI skills to remain competitive in the job market. In contrast, roles such as agriculture, forestry, fishery labourers, food preparation assistants, cleaners and helpers are least susceptible to AI impacts.

Existing concerns about digital transformation negatively affecting employment are exaggerated because computers will not outsmart complex knowledge networks (Pettersen, 2019). For example, consultants offer specialized services that are challenging to encapsulate in databases or integrate into AI systems due to their unique expertise and complex nature (Løwendahl, 2005). One of the current challenges in AI research is the ability to transition across different contexts (Elish & Boyd, 2018).

In a study conducted by Zahidi et al. (2020), a total of 803 companies across 27 industries and 45 economies were involved, representing over 11.3 million employees, states that approximately 75% of these companies plan to adopt AI to improve their competitiveness. They anticipate a change in the job market, with 50% expecting job growth and 25% foreseeing job losses.

The literature indicates that AI adoption and innovation increase revenue and add value per employee, reflecting strong productivity effects and greater within-firm wage inequality (Alderucci et al., 2019; Yang, 2022).

McKinsey and Company's study projects that by 2030, artificial intelligence will have created 20 to 50 million new jobs globally in various industries, including manufacturing, healthcare, and finance (Manyika et al., 2017). According to research conducted by WEF, three new types of jobs will surge: trainers, who assist AI systems with learning and information processing tasks; explainers, which provide business leaders with an explanation of how AI systems work; and sustainers, who keep an eye on AI to ensure its responsible, ethical and safe use (Battista et al., 2023).

AI systems can exacerbate social inequalities, particularly affecting vulnerable groups, leading to job losses and economic disparity. Loong et al. (2021) suggest implementing an AI tax to fund social security, retraining programs for displaced workers, and regulations against

arbitrary dismissals. Additionally, Borgesius (2018) examines the current legal safeguards in Europe to address discriminatory AI decisions. The study shows that insufficient regulation and enforcement can increase employees' worries about being unfairly treated by AI systems.

2.2. Required Skills in the Future with the Adoption of AI Tools

In response to the inequalities and challenges of rapid technological advancements, it is crucial to prioritize retraining and upskilling (Andreeva et al., 2019; Shen & Zhang, 2024; Spencer & Slater, 2020). To thrive in this evolving landscape, employees must engage in continuous learning and skill development, while organizations must provide the necessary support and training to facilitate this transition (Morandini et al., 2023; Santana & Díaz-Fernández, 2023).

With the increasing use of artificial intelligence at work, skills such as analytical thinking, technological literacy, self-efficacy (Zahidi et al., 2020), creativity and social skills (Autor, 2015; Guszcza et al., 2017; Wilson & Daugherty, 2018) are crucial.

Additionally, soft skills like communication ability and emotional intelligence are equally important (Tarallo, 2019). However, collaboration stands as a critical human skill that has the potential to significantly enhance the productivity and innovation of AI systems (Kumar, 2023). According to Gibbs (2022), jobs that demand middle-level skills are at a higher risk of automation in comparison to those that require high-level skills.

2.3. Employees Perception of AI Adoption by Companies

Technological advancements can increase job insecurity, which leads to lower job satisfaction and higher stress and anxiety levels (Nam, 2019b; Vieitez et al., 2001). Furthermore, employees working alongside AI often compare their abilities to those of AI, resulting in lower self-esteem (Seeber et al., 2020).

This fear and anxiety arise when people become aware of instances where AI has replaced human labour or when they read news reports about the gradual integration of AI into workplaces (Zhan et al., 2023). These negative feelings are mainly due to a lack of understanding, as suggested by Nam (2019a). People who are informed about automation's effects on the labour market are generally more optimistic and less skeptical. Similarly, Walsh (2018) states that individuals who are not experts in robotics and AI tend to be more pessimistic and often overstate the risk of job automation compared to experts. The study by Liang and Lee (2017) revealed that approximately 40% of the US population, especially women, older individuals, and those with lower incomes and lower education levels, experience a higher level of fear of autonomous robots and AI (FARAI).

For instance, Bulgarian translators' attitudes towards AI show that around 61% view AI and automation as threats to their profession. Many predict that AI will change their profession by causing some tasks to disappear and new ones to emerge, such as AI training and editing automatically translated texts (Kirov & Malamin, 2022).

Brynjolfsson and McAfee (2014), along with Frank et al. (2017), advocate for a positive view of automation technologies (ATs), highlighting their role in freeing individuals from tedious tasks and creating new business opportunities. They argue that advanced technologies like AI will improve human well-being across social, health, and economic areas.

2.4. PEER INFLUENCE IN THE WORKPLACE

Social comparison, where observing more productive colleagues, can lead to feelings of inadequacy, anxiety, and job insecurity, is relevant to my research on how observing colleagues using AI impacts individuals' behaviours. Social comparisons are driven not only by evaluation but also by the desire for self-improvement (learning from others and enhancing their performance) and self-enhancement (preserving or boosting self-esteem) (Taylor et al., 1995; J. et al., 1989).

Evaluating oneself through comparison with others is a common and often healthy practice. According to the social comparison theory initially developed by Festinger (1954), individuals compare themselves to others to evaluate their opinions and abilities. For instance, individuals under threat tend to make explicit self-evaluations against less fortunate targets, known as downward evaluation. Just as individuals under threat can make downward comparisons to enhance self-esteem, employees may compare themselves with less proficient colleagues to feel better about their performance. Conversely, observing colleagues using AI effectively can provide motivation and practical insights into improving their AI skills. As Taylor and Lobel (1989) noted, this offers both motivational benefits and practical learning opportunities for employees.

A leader has the potential to influence our performance. Clear communication and leadership support are crucial in reducing negative effects. Just as doctors need support from their leaders, workers in AI-integrated workplaces also benefit from strong leadership. This support is crucial for reducing anxiety and facilitating a smoother adaptation to AI integration, ultimately enhancing overall job satisfaction and reducing burnout (Dijkstra et al., 2008).

3. Theoretical Model Hypotheses Building

Based on Social Cognitive Theory and Protection Motivation Theory, a conceptual model was developed to analyze the factors that impact the intention to use AI tools. It highlights two main constructs: self-efficacy and anxiety, each impacted by different antecedents. Self-efficacy is hypothesized to be influenced by peer usage perception (H1), peer performance outcomes (H2), and perceived usefulness (H3). Anxiety, on the other hand, is hypothesized to be affected by perceived vulnerability (H5), perceived severity (H6), competitive pressure (H7). Both self-efficacy (H4) and anxiety (H8) can impact the intention to use AI tools.

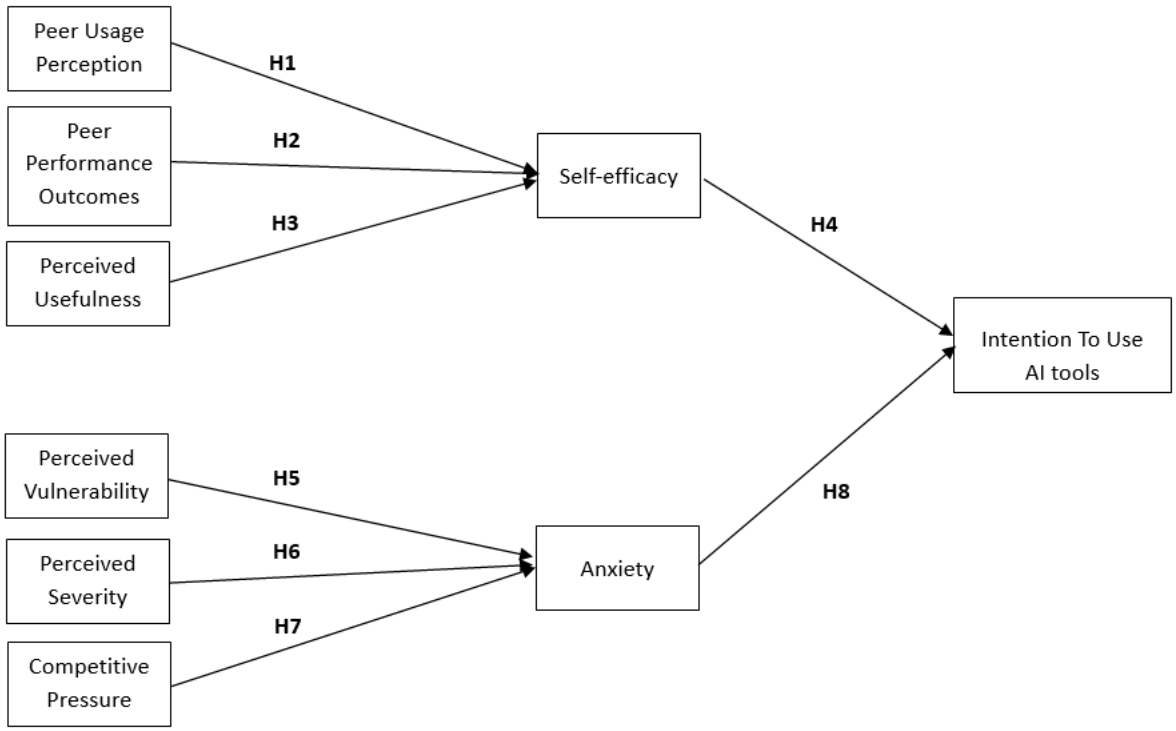

Figure 1 - Research model and hypotheses

3.1. SOCIAL COGNITIVE THEORY

Social cognitive theory, as described by Wood and Bandura (1989b), provides a comprehensive explanation of how individuals learn and perform behaviours by observing others. The theory emphasizes the significance of observational learning, imitation, and modelling in acquiring behaviour.

According to Boh and Wong (2015), employees are likely to observe and copy the actions of their peers. This behaviour modelling process is also evident in training programs,

where observing others can improve an individual's self-efficacy, performance outcomes and can significantly impact workplace dynamics.

In the workplace, employees tend to see their coworkers and immediate supervisors as role models for ethical behaviour rather than distant executives. Suggesting that the behaviours and attitudes exhibited by those nearby have a more significant influence. When employees observe their peers demonstrating positive behaviours, such as cooperation, integrity, and diligence, they are likelier to adopt similar behaviours. This peer influence is crucial in promoting a productive and ethical work environment (Weaver et al., 2005). Social learning is highly effective within workgroups due to the collaborative environment and regular member interactions, which generate abundant learning opportunities (Robinson & O'Leary-Kelly, 1998).

Peer Usage Perception

Observing peers using AI tools can significantly boost an individual's self-efficacy. According to social cognitive theory, individuals enhance their belief in their capabilities by observing others (Bandura, 1988). When they see peers successfully using AI tools, they are more likely to believe they can achieve similar success.

Vicarious learning, or social modelling, positively affects self-efficacy (Compeau & Higgins, 1995) and reinforces self-beliefs through social comparison (Mccormick & Martinko, 2004). For instance, Almory et al. (2023) found that peer interactions and observing peers' successful use of AI tools positively influenced students' self-efficacy and intention to use them. Additionally, Soler (2019) examined the impact of vicarious learning in translation classrooms on students' self-efficacy beliefs. The study concluded that observing professional translators and peers positively impacted students' self-efficacy through role modelling.

H1: The greater an individual's exposure to others using AI tools, the greater the individual's AI self-efficacy.

Peer Performance Outcomes

Observing the outcomes of coworkers using AI tools can significantly impact an individual's self-efficacy. According to R. Wood and Bandura (1989a), witnessing others succeed through sustained effort boosts one's belief in one's capabilities. This is especially relevant in organizational contexts, where employees who see their coworkers effectively using new technologies will likely gain confidence in their ability to use them (Compeau & Higgins, 1995).

Davis et al. (1989) states that individuals will use computer technology if they believe it will result in positive outcomes. However, SCT (R. Wood & Bandura, 1989) claims that beliefs

about outcomes may not influence behaviour if individuals doubt their capabilities to successfully undertake behaviours.

According to Luo et al. (2018), self-efficacy is positively linked to job satisfaction and task performance, partly due to its influence on social status. When individuals witness their colleagues achieving high social status through successful use of AI tools, they are inspired to believe in their own abilities to achieve similar success. Additionally, Iroegbu (2015) explains that individuals with high self-efficacy demonstrate greater performance due to their confidence in their capabilities. This confidence is further reinforced when individuals believe that their actions will result in desired outcomes, further enhancing their self-efficacy.

H2: The more individuals observe their coworkers achieving positive outcomes using AI tools, the higher their AI self-efficacy.

Perceive Usefulness

Perceived usefulness is the belief that using a particular technology will improve job performance (Davis, 1989). This construct significantly influences an individual's intention to use and self-efficacy regarding new technologies (Davis et al., 1989). When individuals believe that AI tools are useful and can increase efficiency or improve performance, they are more likely to develop confidence in their ability to use them effectively. According to Venkatesh et al. (2003), perceived usefulness strongly predicts technology adoption and related self-efficacy. Similarly, Halim et al. (2023) discovered that perceived usefulness and self-efficacy significantly influenced AI tool adoption.

H3: The higher the perceived usefulness of AI tools, the higher the individual's AI self-efficacy.

Self-efficacy

Self-efficacy acts as a bridge connecting the Social Cognitive Theory (SCT) (Bandura, 1994) and the Protection Motivation Theory (PMT) (R. W. Rogers, 1975).

In our model, self-efficacy is influenced by various factors related to SCT, such as peer usage perception, peer performance outcomes and perceived usefulness. According to SCT, self-efficacy refers to individuals' beliefs in their ability to achieve specific performance levels, influencing the outcomes that impact their lives (R. Wood & Bandura, 1989). It can be developed through direct experience, observing others, social persuasion, and managing physical and emotional states. Direct experience is the most effective way to develop a strong sense of efficacy. This means that the individual's lived experiences, particularly their successes, contribute to building a strong belief in their abilities. On the other hand, experiences of failure can undermine this belief, especially if they happen before a sense of efficacy is firmly established (Bandura, 1994).

Within the PMT framework, self-efficacy is a component of coping appraisal, where individuals assess their ability to adopt protective behaviours and their effectiveness in mitigating perceived threats (R. W. Rogers, 1975). According to Floyd et al. (2000), self-efficacy will increase the probability of selecting the adaptive response. By strengthening self-efficacy through peer observations and performance outcomes, employees are more likely to develop a positive coping appraisal, leading to an intention to use AI tools.

H4: Higher levels of self-efficacy will significantly influence the intention to use AI tools.

3.2. PROTECTION MOTIVATION THEORY

Rogers (1975) introduced protection motivation theory (PMT) to explain how individuals are motivated to protect themselves from perceived threats. According to the theory, individuals' perceptions of coping mechanisms and threats significantly influence their behavioural intentions. Specifically, threat appraisal involves evaluating the potential harm a threat may cause and the likelihood of exposure to the threat (E. M. Rogers, 1983). Meanwhile, coping appraisal assesses the effectiveness of the protective behaviour in mitigating the threat.

Observing colleagues successfully using AI tools in the workplace can significantly influence an individual's coping appraisal. This observation can alleviate fears about the complexity or inefficacy of AI tools. Consequently, observing colleagues' successful use of AI tools can reduce anxiety and highlight the benefits, enhancing self-efficacy and response efficacy (Y. Lee, 2011).

Moreover, threat perceptions related to job insecurity due to technological advancements can drive employees to adopt AI tools as a protective measure against job displacement. The perception of job insecurity is a significant motivator for adopting AI technologies, as it underscores the necessity of staying competitive in an evolving job market (Xu et al., 2003). Higher levels of fear arousal are more persuasive in motivating protective behaviours, as they increase perceived severity, vulnerability, and the importance of the avoidance response (Floyd et al., 2000).

In this study, PMT is applied to understand how threat perceptions (such as job loss due to automation) and coping mechanisms (such as perceived self-efficacy) influence the adoption of AI tools.

Vulnerability

Vulnerability refers to how personally susceptible an individual feels to the communicated threat (R. W. Rogers, 1975). Employees may feel vulnerable after witnessing coworkers using AI tools. The perception of job insecurity can lead to increased anxiety in individuals, motivating them to develop technology-related skills (Probst et al., 2018).

This vulnerability is further exacerbated by the combination of ageing and technological advancements, as highlighted by Alcover et al. (2021). Moreover, integrating AI can intensify psychosocial risks, such as stress and anxiety, due to increased surveillance and changes in working conditions (Dodel & Mesch, 2020; Moore, 2019). Furthermore, when employees perceive a high level of vulnerability and severity of threat, coupled with low self-efficacy and response efficacy, their anxiety levels tend to increase. This heightened anxiety can lead to resistance or cautious adoption of AI technologies, as explained by Floyd et al., (2000). For instance, employees who feel incapable of adapting to new AI tools may resist their implementation, fearing negative consequences on their job security and performance.

H5: High levels of perceived vulnerability after observing coworkers using AI tools lead to increased anxiety.

Severity

Perceived severity refers to an individual's belief in the potential severe consequences of a threat. According to Rogers (1975), when people perceive a threat as severe and personally relevant, they are more likely to respond adaptively. When individuals perceive a threat as severe, they experience heightened concern and anxiety, which can drive them to adopt protective behaviours aimed at reducing the perceived threat. Recognizing potentially serious consequences elicits a strong emotional response, motivating individuals to take action to lower the risk or impact of the threat (Milne et al., 2000; So et al., 2016).

H6: The greater the perceived severity after observing coworkers using AI tools, the higher the anxiety levels.

Competitive Pressure

Competitive pressure refers to the peer pressure of adopting new technology (Zhu et al., 2006), which can lead to anxiety. Salvador (2005) conducted a study examining how competitive situations influence anxiety responses. Cognitive appraisal activates coping responses, which can vary based on factors such as the importance of the competition, individual involvement, and perceived control. Individual factors significantly determine anxiety levels under competitive pressure.

Moreover, Hanton et al. (2008) and Cooke et al. (2011) reviewed how competitive pressure affects athletes and expert performers. They noted an increase in anxiety levels, which affects performance and well-being. Similarly, Lee (2020) investigated how competitive pressure within organizations affects employees, revealing that anxiety arises from task interdependence, competition-oriented personalities, and performance appraisal systems based on relative evaluation. These factors collectively contribute to heightened anxiety among employees who feel inadequately prepared to meet the demands of new technological implementations.

According to Ryckman et al. (1990), employee competitiveness can be attributed to their personality traits. Those with strong competitive traits typically enjoy competing and winning, and they tend to experience lower anxiety in competitive situations due to reduced negative expectations about their success. Such individual tendencies result from one's social value orientation shaped by interpersonal experiences from childhood to young adulthood (Van Lange et al., 1997).

H7: Competitive pressure is positively correlated with anxiety.

Anxiety

According to Protection Motivation Theory, emotions are linked to the events that trigger them and the responses they generate. There is a notable connection between emotional states and muscular activity. When emotional disturbances occur in the viscera, they enhance muscular responses, aiding the organism in defending itself against harmful environmental stimuli (Darwin, 1872; Mccormick & Martinko, 2004). When an individual perceives a threat, emotional responses trigger physical actions that help mitigate or avoid the danger, highlighting the interplay between psychological and physiological responses in protective behaviour (R. W. Rogers, 1975).

Spielberger (2013) recognizes anxiety as an unpleasant emotional state. It is characterized by feelings of apprehension, tension, or dread and is temporary and may vary in intensity. This emotional state is often triggered by perceiving a situation as threatening, which involves evaluating the potential negative consequences of the situation.

Observing coworkers effectively using AI tools can create anxiety about one's own competencies. This anxiety can motivate employees to learn and improve skills to keep up with peers, enhancing their proficiency with AI tools (Wang & Wang, 2022). Additionally, anxiety about falling behind can increase readiness to adopt AI tools, as employees become more open to training and new technologies (Suseno et al., 2022).

Furthermore, seeing peers successfully navigate AI tools creates social pressure, leveraging anxiety to drive engagement and adoption (Jain et al., 2022). Anxiety can also trigger cognitive appraisals that lead to better preparation and a proactive approach towards AI tools (Xu et al., 2023). Moreover, it can foster increased collaboration as employees seek peer support to overcome challenges, enhancing overall AI adoption (Kleine et al., 2023).

H9: The higher the anxiety experienced by employees due to observing coworkers using AI tools, the greater their intention to use AI tools.

4. Methodology

4.1. Data Collection-Measures and Samples Results

The objective is to understand what accelerates AI adoption after observing co-workers using these tools daily. To achieve this, we gathered data from working individuals over the age of 18. Data was collected using an electronic questionnaire developed on the Qualtrics platform and active from April 20th to May 24th, 2024. The questionnaire was written in Portuguese and reviewed by my thesis coordinator. It was distributed through online platforms such as WhatsApp, Instagram, Facebook, and email.

At the beginning of the questionnaire, the respondents were presented with an explanatory introduction outlining the purpose of the survey. To prevent sampling bias, respondents were informed that their data would be treated with complete confidentiality and used only for scientific purposes. The questionnaire design and data collection strictly followed the ethical procedures required by the University NOVA of Lisbon, demonstrating full compliance with all standards.

We adjusted all measurement items based on relevant literature to ensure they were suitable for our research context. The items were measured using multiple-type close-ended questions on a seven-point Likert scale from 1 (totally disagree) to 7 (totally agree). We collected a total of 296 responses, and after cleaning the data, we considered 221 responses to be valid. Most of the participants are females (60.6%), and the majority of the respondents are between the ages of 23 and 27 (47.5%). Additionally, most employees questioned have a bachelor's degree (48.4%). Furthermore, about 57.9% of respondents have an income between 801€ and 1500€. See Table 1. for the demographic profile of the respondents.

The evaluation of the research models is conducted using partial least squares structural equation modelling (PLS-SEM), as (Hair Jr. et al., 2021a) recommended. PLS-SEM is particularly suitable when the analysis aims to test a theoretical framework from a predictive perspective, especially with complex structural models involving numerous constructs and indicators. It enables researchers to test and refine theories by exploring complex relationships.

The advantage of using PLS-SEM is that both reflective and formative measurement models are handled effectively and perform well with relatively small sample sizes, such as the 221 observations in this study. Furthermore, it addresses distribution issues like lack of normality, making it suitable for real-world data. By maximizing the explained variance of endogenous latent variables, PLS-SEM ensures robust and reliable results, providing latent variable scores essential for subsequent analyses (Hair Jr. et al., 2021b).

The analysis and interpretation of a statistical model using PLS-SEM require a two-stage approach: Measurement model analysis and Structural model analysis. Measurement model analysis assesses the reliability and validity of the constructs, while structural model analysis evaluates the relationships between variables through path calculations.

The software SmartPLS version 4.1 was chosen for this study because it can combine both assessments within the same model, providing a comprehensive analysis framework.

Table 1 - Sample demographic characteristics

Characteristics (n=221)	Frequency	Percentage (%)
Gender		
Feminine	134	60.63
Masculine	86	38.91
Other	1	0.46
Age groups (years)		
23-27	105	47.51
18-22	35	15.84
48 or more	23	10.41
28-32	21	9.50
43-47	17	7.69
33-37	15	6.79
38-42	5	2.26
Education		
Banchelor	107	48.42
Master degree	54	24.43
High school	37	16.74
Post-graduation	17	7.69
Doctorate	6	2.71
Income		
801-1500	128	57.92
1501-2200	42	19
Less than 800	27	12.22
2201-2900	14	6.34
3600 ou mais	7	2.71
2901-3600	5	1.81

5. Results

5.1. Measurement Model Assessment

5.1.1. Reliability and Validity

This model includes reflective indicators. According to Hair Jr. et al. (2021a) approach for assessing model quality, reflective measurement models are evaluated based on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

In the first step, we examine how much of each indicator's variance is explained by its construct, which indicates its reliability (outer loadings). A commonly accepted threshold for outer loadings is 0.708. This value is derived because squaring it gives approximately 0.50, indicating that the construct explains at least 50% of the variance in the indicator

In our model, the outer loadings are well above the threshold value of 0.708, which suggests sufficient levels of indicator reliability. The indicator Ppo_3 (outer loading: 0.729) has the smallest indicator reliability with a value of 0.532 (0.729^2). The construct explains 53.18% of the variance in the indicator. This suggests that the indicator has acceptable reliability, although it is slightly above the 0.50 threshold, indicating moderate reliability. While the indicator Pu_1 (outer loading: 0.931) has the highest indicator reliability, with a value of 0.867 (0.931^2), it means that the construct explains 86.6% of the variance in the indicator. This indicates high reliability, as the indicator explains a substantial portion of its variance through the construct. A high outer loading means that the indicator is a good representation of the construct (Leguina, 2015). See the results for the outer loadings in annexes Table 9.

The second step involves examining internal consistency reliability, measured by Cronbach's alpha (CA) and composite reliability (CR). Values above 0.7 indicate satisfactory internal consistency across all constructs. A higher Cronbach's alpha value suggests better internal consistency, while composite reliability (CR) accounts for the different loadings of items that measure the construct, offering potentially more accurate reliability estimates (Hair Jr. et al., 2021a).

In our model, Cronbach’s alpha values are all above 0.746. This indicates that the items within this construct have good internal consistency, which means that they are well-correlated and measure the same underlying construct. The items included in this construct are too diverse, capturing different aspects that do not cohere well into a single construct. Composite reliability has values above 0.843, showing that the measuring tools successfully capture the constructs they are designed to assess.

The third step is to evaluate the convergent validity, which measures how well the construct explains the variance of its indicators. To measure this, we used the average variance extracted (AVE), a common threshold for an acceptable AVE of 0.5 or higher. In this

study, all indicators exceeded this threshold with a minimum AVE of 0.582, this means that the construct explains more than 50% of the variance of its items.

Table 2 - Internal consistency, Indicator reliability and Convergent validity

	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Anxiety	0.854	0.910	0.772
Competitive Pressure	0.832	0.899	0.748
Peer Performance Outcomes	0.764	0.848	0.582
Intention to Use	0.855	0.902	0.698
Peer Usage Perception	0.870	0.919	0.792
Perceived Usefulness	0.833	0.923	0.857
Self-Efficacy	0.748	0.843	0.641
Severity	0.753	0.844	0.644
Vulnerability	0.873	0.922	0.797

This paper evaluated discriminant validity using three criteria (Sarstedt et al., 2021):

(i) Cross loadings: Each indicator must be higher than all cross-loadings to ensure that each indicator has a stronger relationship with the intended construct than any other construct. The difference in explaining the intended construct versus another should be greater than 0.10. A larger difference indicates better discriminant validity for each item.

Table 3 – Cross loadings

	Anxiety	Competitive Pressure	Intention to Use	Peer Performance Outcomes	Peer Usage Perception	Perceived Usefulness	Self Efficacy	Severity	Vulnerability
Anx_1	**0.901**	0.559	0.643	0.177	0.338	0.237	0.242	0.164	0.518
Anx_2	**0.837**	0.411	0.522	0.289	0.229	0.157	0.232	0.382	0.547
Anx_3	**0.897**	0.614	0.741	0.231	0.394	0.326	0.275	0.258	0.663
Cp_1	0.469	**0.880**	0.582	0.297	0.553	0.577	0.408	0.134	0.502
Cp_2	0.568	**0.845**	0.579	0.084	0.313	0.278	0.148	0.082	0.459
Cp_3	0.536	**0.870**	0.708	0.316	0.626	0.630	0.472	0.159	0.491
Int_1	0.609	0.577	**0.833**	0.097	0.342	0.360	0.211	0.086	0.571
Int_2	0.541	0.545	**0.771**	0.238	0.361	0.377	0.268	0.172	0.494
Int_3	0.544	0.656	**0.828**	0.179	0.512	0.551	0.349	0.162	0.519
Int_4	0.732	0.638	**0.905**	0.246	0.525	0.440	0.386	0.217	0.687
Ppo_1	0.211	0.211	0.097	**0.760**	0.328	0.257	0.379	0.511	0.263
Ppo_2	0.180	0.233	0.202	**0.796**	0.340	0.359	0.426	0.320	0.271
Ppo_3	0.229	0.199	0.221	**0.729**	0.386	0.375	0.322	0.319	0.250
Ppo_4	0.176	0.130	0.191	**0.764**	0.209	0.165	0.248	0.342	0.243
Use_1	0.387	0.516	0.515	0.378	**0.928**	0.627	0.746	0.156	0.404
Use_2	0.288	0.496	0.436	0.404	**0.921**	0.717	0.649	0.084	0.360
Use_3	0.317	0.518	0.450	0.350	**0.818**	0.505	0.486	0.087	0.311
Pu_1	0.268	0.538	0.482	0.364	0.658	**0.931**	0.525	0.179	0.400
Pu_2	0.253	0.506	0.471	0.362	0.635	**0.921**	0.492	0.159	0.382
Sef_1	0.146	0.163	0.126	0.450	0.347	0.333	**0.757**	0.299	0.179
Sef_2	0.148	0.258	0.245	0.254	0.445	0.445	**0.811**	0.098	0.175
Sef_3	0.323	0.423	0.413	0.414	0.779	0.500	**0.833**	0.167	0.348
Sev_1	0.327	0.189	0.248	0.490	0.177	0.236	0.249	**0.876**	0.504
Sev_2	0.171	0.025	0.031	0.319	0.019	0.046	0.080	**0.772**	0.188
Sev_3	0.148	0.067	0.111	0.311	0.040	0.081	0.148	**0.755**	0.263
Vul_1	0.595	0.528	0.621	0.219	0.390	0.377	0.253	0.292	**0.910**
Vul_2	0.542	0.366	0.489	0.444	0.277	0.310	0.321	0.584	**0.858**
Vul_3	0.628	0.587	0.715	0.260	0.413	0.437	0.288	0.338	**0.910**

(ii) According to Fornell and Larcker (1981), a construct is considered sufficiently different if the square root of its Average Variance Extracted (AVE) is greater than its correlation with any other construct and higher than the correlations between the other constructs (values below the diagonal). In this model, the AVE square root (in bold Table 4) is greater than all correlations with other constructs, indicating good discriminant validity.

Table 4 - Fornell-Lacker Criterion (square root of AVE in bold)

	1	2	3	4	5	6	7	8	9
1. Anxiety	**0.879**								
2. Competitive Pressure	0.611	**0.865**							
3. Intention to Use	0.734	0.722	**0.835**						
4. Peer Performance Outcomes	0.261	0.262	0.229	**0.763**					
5. Peer Usage Perception	0.373	0.568	0.525	0.423	**0.890**				
6. Perceived Usefulness	0.282	0.564	0.514	0.392	0.698	**0.926**			
7. Self-Efficacy	0.286	0.389	0.368	0.466	0.719	0.550	**0.801**		
8. Severity	0.298	0.143	0.194	0.492	0.126	0.183	0.221	**0.803**	
9. Vulnerability	0.661	0.559	0.687	0.339	0.407	0.423	0.320	0.445	**0.893**

(iii) Heterotrait-Monotrait Ratio (HTMT): Henseler et al. (2015) states that values less than 0.9 indicate strong discriminant validity. In Table 5, all the HTMT criterion results are clearly below the conservative threshold of 0.90. The proposed model exhibits discriminant validity, indicating that the constructs are different from each other.

Table 5 - Heterotrait-Monotrait Ratio

	1	2	3	4	5	6	7	8	9
1. Anxiety									
2. Competitive Pressure	0.707								
3. Intention to Use	0.837	0.855							
4. Peer Performance Outcomes	0.326	0.324	0.306						
5. Peer Usage Perception	0.421	0.680	0.603	0.507					
6. Perceived Usefulness	0.323	0.687	0.613	0.473	0.812				
7. Self-Efficacy	0.314	0.459	0.397	0.581	0.779	0.661			
8. Severity	0.338	0.150	0.207	0.595	0.124	0.186	0.272		
9. Vulnerability	0.758	0.650	0.781	0.419	0.458	0.492	0.358	0.490	

5.2. STRUCTURAL MODEL ASSESSMENT

After analysing the measurement model and ensuring its quality, this assessment aims to determine its ability to predict one or more target constructs, following the approach outlined by Sarstedt, Ringle and Hair (2021). Four key components must be evaluated for this assessment: path coefficients (β-values), the coefficient of determination (R^2 value) and predictive significance (Q^2 values).

Firstly, we begin to analyse the path coefficient's significance and relevance to determine if they support the hypothesized relationships between the constructs. Were used the bootstrapping technique to evaluate 8 hypotheses with 5000 subsamples. When assuming a 5% significance level, a t-value above 1.96 (for a two-tailed test) indicates that the indicator weight is statistically significant. A positive path coefficient indicates a positive relationship, while a negative coefficient indicates an inverse relationship. If the p-value is less than the chosen significance level of 5%, it suggests that the path coefficient is statistically significant.

Hypotheses H1 and H8 are the most impactful in the study. The relationship between peer usage perception and self-efficacy (H1) is positive and significant ($\beta = 0.599$, $p < 0.01$). This indicates that the more individuals observe their peers using AI tools, the higher their self-efficacy becomes.

In addition, Hypothesis H8, which examines the relationship between anxiety and intention to use AI tools, also reveals a strong positive relationship ($\beta = 0.685$, $p < 0.01$). This finding provides strong evidence against the null hypothesis, suggesting that as anxiety increases, the intention to use AI tools also significantly increases.

The statistical significance of these hypotheses is further supported by their t-values. Specifically, the t-value for H1 is 8.057, and for H8, it is 16.192. Both values are well above the critical value of 1.96, indicating a high level of statistical significance. Moreover, hypotheses H2, H4, H5, and H7 are also positive and significant in explaining the intention to use AI tools. This further corroborates the robustness of the study's findings. However, hypotheses H3 and H6 are not significant, suggesting that the relationships they describe are not strong enough to be conclusive.

Table 6 - Structural measurement: significance and relevance

	Path Coefficient (β-value)	t-value	p-value
H1: Peer Usage Perception -> Self-Efficacy	0.599	8.057	0.000
H2: Peer Performance Outcomes -> Self-Efficacy	0.190	2.605	0.009
H3: Perceived Usefulness -> Self-Efficacy	0.057	0.806	0.420
H4: Self-Efficacy -> Intention to Use	0.172	3.525	0.000
H5: Vulnerability -> Anxiety	0.437	5.502	0.000
H6: Severity -> Anxiety	0.052	1.013	0.311
H7: Competitive Pressure -> Anxiety	0.359	5.270	0.000
H8: Anxiety -> Intention to Use	0.685	16.192	0.000

In Table 7, there is a summary of the hypotheses that are supported and those that are not.

The proposed hypotheses underscore the significance of peer influences and the perceived usefulness of AI tools on self-efficacy. This, in turn, influences an individual's intention to use them. Additionally, vulnerability and competitive pressure play a significant role in influencing anxiety levels, which impacts the intention to use AI tools.

Table 7 - Summary of hypotheses testing

	Supported?
H1: Peer Usage Perception -> Self-Efficacy	Yes
H2: Peer Performance Outcomes -> Self-Efficacy	Yes
H3: Perceived Usefulness -> Self-Efficacy	No
H4: Self-Efficacy -> Intention to Use	Yes
H5: Vulnerability -> Anxiety	Yes
H6: Severity -> Anxiety	No
H7: Competitive Pressure -> Anxiety	Yes
H8: Anxiety -> Intention to use	Yes

5.3. PREDICTIVE POWER AND RELEVANCE

Secondly, to measure the model's predictive power, we use R^2 (Raithel et al. 2012). As a rough rule of thumb, R^2 values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak, respectively. In this study, the model demonstrated moderate predictive power. Specifically, the R^2 values indicate that the model explains 52.3% of the variance in anxiety, 56.5% of the variance in intention to use and 55.1% of the variance in self-efficacy. These values suggest that the constructs included in the model account for a significant portion of the variability in these key outcomes, providing moderate support for the model's ability to predict these constructs effectively. This level of predictive power is sufficient to draw meaningful conclusions about the relationships between constructs in the model, although there is still room for improvement in explaining the remaining variance (Hair Jr. et al., 2021a).

Next, we used the blindfolding procedure with an omission distance set to 7 to obtain the Q^2 cross-validation redundancy values, demonstrating the model's predictive relevance. Values greater than zero indicate that the model has good predictive power, reinforcing the validity of the exogenous constructs in predicting the endogenous constructs. This high level of predictive relevance indicates that the model can effectively predict the outcomes for the endogenous constructs based on the exogenous constructs included in the analysis. The Q^2 values for this model are 0.504 for anxiety, 0.574 for intention to use, and 0.521 for self-efficacy.

Table 8 - Structural measurement: predictive power(R^2), predictive relevance(Q^2)

	R^2	Q^2
Anxiety	0.523	0.504
Intention to Use	0.565	0.574
Self-Efficacy	0.551	0.521

6. Discussion

Based on Social Cognitive Theory and Protection Motivation Theory, this research aimed to understand which factors influence the intention to use AI tools in the workplace through the observation of coworkers using them.

The model shows a significant positive relationship between peer usage perception and self-efficacy (β=0.599 ; p< 0.000). This significant and strong positive relationship indicates that when employees perceive their peers as effectively using AI tools, their self-efficacy is significantly boosted. This result supports H1 and aligns with Social Cognitive Theory, which emphasizes the role of vicarious learning or social modelling in enhancing self-efficacy. Observing peers successfully using AI tools provides individuals with practical examples and benchmarks, reinforcing their belief in their own capabilities to use these tools effectively. Studies by Bandura (1988), Compeau and Higgins (1995), Soler (2019) and Almory et al.(2023) underscore the importance of social comparison and role modelling in boosting self-efficacy. The significant impact of peer usage perception confirms that social influences are crucial in building confidence in AI tool adoption.

The model indicates a significant positive relationship between peer performance outcomes and self-efficacy (β=0.190; p=0.009). This finding supports H2, suggesting that witnessing coworkers' success using AI tools enhances an individual's belief in their ability to achieve similar results. According to R. Wood and Bandura (1989) and Davis (1989), observing positive outcomes can strengthen self-efficacy by demonstrating the practical benefits of AI tools. Luo et al. (2018) and Iroegbu (2015) also highlight how positive performance outcomes and the associated social status can inspire confidence and motivate others to adopt similar behaviours. This result reinforces the notion that practical, observable success stories within the workplace are vital in increasing employees' self-efficacy.

The relationship between perceived usefulness and self-efficacy is not significant (β=0.057, p=0.420). Contrary to H3 (not supported), the study found that perceived usefulness does not significantly impact self-efficacy. This suggests that while employees might recognize the potential benefits of AI tools, this recognition alone is insufficient to enhance their confidence in using these tools. This finding diverges from studies by Davis (1989), Venkatesh et al. (2003) and Halim et al. (2023), which emphasize perceived usefulness as a strong predictor of technology adoption and related self-efficacy. It implies that practical experiences and social influences (e.g., peer usage and performance outcomes) are more critical in building self-efficacy than perceptions of utility.

The model demonstrates a significant positive relationship between self-efficacy and the intention to use AI tools (β=0.172, p < 0.000). This result supports H4, highlighting the crucial role of self-efficacy in driving the intention to adopt AI tools. According to SCT

(Bandura, 1994), employees with higher self-efficacy are more likely to engage in adaptive responses and adopt new technologies. The significant influence of self-efficacy on the intention to use AI tools confirms that building employees' confidence through positive experiences, peer observations, and observed performance outcomes is essential for fostering AI tools adoption.

Regarding the Protection Motivation Theory, the study found that anxiety was the most significant and strongest predictor of the intention to use AI tools. This finding is consistent with earlier research by Rogers (1975), Spielberger (2013) and Wang (2022). These studies suggest that after individuals observe their coworkers using AI tools, their anxiety increases, making them more willing to adopt these tools as protective measure. Interestingly, self-efficacy did not emerge as a strong predictor of the intention to use AI tools.

According to PMT, vulnerability is a critical factor influencing individuals' emotional and behavioural responses to perceived threats. This study findings support this notion, revealing a significant positive relationship between vulnerability and anxiety. Suggesting that employees who perceive themselves as vulnerable to the impacts of AI tools are likely to experience heightened anxiety. Consequently, this anxiety serves as a motivational force, driving them to engage in protective behaviours to mitigate perceived threats.

Moreover, this study found a significant and positive relationship between competitive pressure and anxiety ($\beta = 0.359$, $p < 0.000$). This implies that as competitive pressure increases, so does anxiety. This finding aligns with Salvador (2005) research about competitive situations, highlighting how cognitive appraisal activates coping responses. These responses vary based on factors such as the importance of the competition, individual involvement, and perceived control. Individual factors significantly determine anxiety levels under competitive pressure, corroborating the current study findings.

Interestingly, the study revealed that there is no significant relationship between perceived severity and anxiety ($\beta = 0.052$, $p = 0.311$). This suggests that while employees may recognise the serious consequences of AI integration, this perception alone does not drive their anxiety levels. This finding diverges from the theoretical expectations of PMT and previous research by Milne et al. (2000) and So et al. (2016).

In my opinion, to justify the previously insignificant relationship between the constructs, employees' familiarity with AI may lead to desensitization, where continuous exposure to discussions about AI diminishes the immediate emotional response. Furthermore, a sense of control or self-efficacy regarding their ability to adapt to AI technologies can make the potential consequences less intimidating, reducing anxiety. Additionally, employees may prioritize immediate, tangible concerns over abstract, long-term consequences, focusing on day-to-day tasks and short-term goals rather than the severity of AI integration. Strong support systems and positive organizational culture can also buffer the impact of perceived

severity, while individual differences in personality and resilience play a significant role. The combination of familiarity, perceived control, focus on immediate concerns, support systems, and individual differences collectively suggests that the perceived severity of AI integration does not translate into heightened anxiety.

7. Conclusion

In conclusion, the model reveals that perceived vulnerability and competitive pressure significantly increase anxiety, which in turn drives the intention to use AI tools. However, perceived severity does not significantly impact anxiety, suggesting that familiarity with AI, perceived control, and organizational support play key roles in mitigating these effects.

These insights suggest that addressing employees' perceived vulnerability may be key to managing anxiety and facilitating using AI tools in the workplace. Companies can better support their employees during technological transitions by reducing perceived vulnerability and managing competitive pressures. Organizations must foster an environment where employees can observe and learn from each other. Encouraging peer modelling and sharing successful AI use cases can significantly boost self-efficacy. Moreover, it is important to provide opportunities for hands-on experiences with AI tools, like training programs and workshops, that can help employees build familiarity and reduce anxiety. Clear communication about job security, transparent AI implementation plans, and assurances about the supportive role of AI can help alleviate anxiety.

Furthermore, this study highlights the importance of vicarious learning and social modelling in the adoption of AI tools. Observing coworkers effectively using AI tools and achieving positive outcomes with them has a significant and positive impact on employees' self-efficacy, and their confidence in their own ability to use these tools increases.

Organizations should create supportive environments where employees can observe and learn from each other, enhance their confidence through positive experiences, and address perceived vulnerabilities, competitive pressures and anxiety to promote effective AI adoption. emphasizing the importance of addressing social and psychological factors.

8. Limitations and Future Research

One limitation of this study is the sample size and diversity. While the sample may provide valuable insights, it might not fully represent the broader population of employees across different industries and regions. A more diverse and larger sample could offer a more comprehensive understanding of the factors influencing AI tool adoption in various workplace contexts and industries.

The reliance on self-reported data can introduce biases such as social desirability and self-perception bias. Employees might overestimate their self-efficacy or underreport their anxiety due to the desire to present themselves in a favourable light or a lack of accurate self-awareness. Social desirability bias occurs when respondents answer questions in a manner that others will view favourably, leading to overreporting positive behaviours or attitudes and underreporting of negative ones. On the other hand, self-perception bias may arise from employees' difficulty in accurately assessing and reporting their internal states and behaviours. These biases can distort the data, leading to skewed results that do not accurately reflect the accurate levels of self-efficacy or anxiety among employees.

The study focuses primarily on self-efficacy, peer usage perception, peer performance outcomes, perceived usefulness, vulnerability, competitive pressure and anxiety. However, other factors such as organizational culture, management support, and individual personality traits might also play significant roles in AI tool adoption.

Additionally, the role of leadership and management in supporting and promoting AI tools is crucial. When managers actively endorse and facilitate the use of AI, employees are more likely to feel confident and supported in their efforts to learn and integrate these tools. Management can provide necessary resources, training, and incentives that enhance self-efficacy and reduce anxiety. Future research should explore the impact of other variables, such as organizational culture, leadership styles, and individual differences (e.g., personality traits and prior experience with technology) on AI adoption.

Furthermore, personality traits such as openness to experience, conscientiousness, and risk tolerance can affect how employees perceive and adopt new technologies. For instance, individuals who are more open to new experiences may be more willing to experiment with AI tools, while those who are highly conscientious may be motivated by the potential for improved performance and efficiency. Additionally, integrating physiological measures, such as stress biomarkers, could be used to assess anxiety levels objectively.

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10. Annexes

Table 9 - Outer Loadings

	Anxiety	Competitive Pressure	Peer Performance Outcomes	Intention to Use	Peer Usage Perception	Perceived Usefulness	Self Efficacy	Severity	Vulnerability
Anx_1	0.901								
Anx_2	0.837								
Anx_3	0.897								
Cp_1		0.880							
Cp_2		0.845							
Cp_3		0.870							
Ppo_1			0.760						
Ppo_2			0.796						
Ppo_3			0.729						
Ppo_4			0.764						
Int_1				0.833					
Int_2				0.771					
Int_3				0.828					
Int_4				0.905					
Use_1					0.928				
Use_2					0.921				
Use_3					0.818				
Pu_1						0.931			
Pu_2						0.921			
Sef_1							0.757		
Sef_2							0.811		
Sef_3							0.833		
Sev_1								0.876	
Sev_2								0.772	
Sev_3								0.755	
Vul_1									0.910
Vul_2									0.858
Vul_3									0.910

Figure 2 - Introduction of the survey

Caro(a) participante, este questionário insere-se no âmbito do Mestrado em Data-driven Marketing com especialização em Marketing Intelligence da NOVA IMS.

Pretendo estudar o comportamento de um indivíduo ao observar os seus colegas de trabalho a usarem IA, podendo isso colocar em risco a segurança do seu próprio trabalho.

O preenchimento do questionário leva aproximadamente 5 minutos e as respostas são confidenciais.
Declaro que tenho 18 anos ou mais e trabalho. Estou ciente que a minha participação é opcional e entendo que todos os dados coletados serão tratados de forma confidencial.

○ Concordo em participar neste estudo

○ Não concordo em participar neste estudo

Figure 3 - Demographic questions

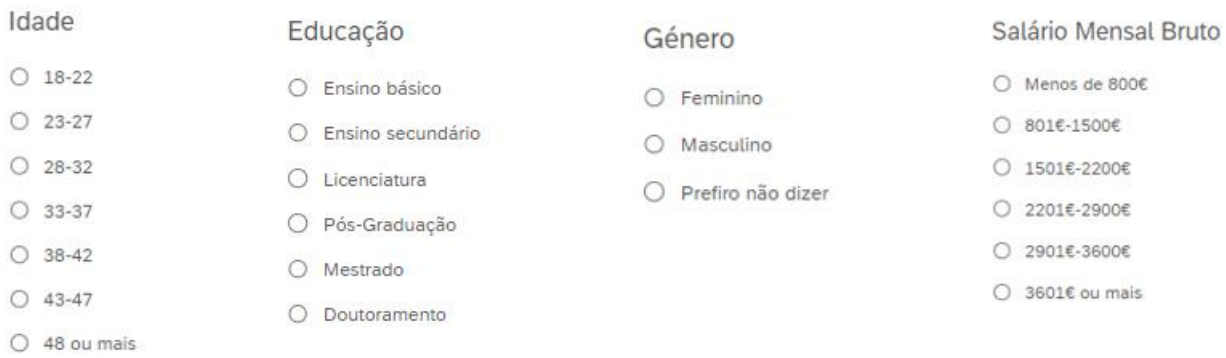

Figure 4 – Survey with all questions asked to the employees

Peer Usage Perception

De uma escala de 1 a 7, em que
1= Discordo Totalmente e 7=Concordo Totalmente, indique o seu nível de concordância com as seguintes afirmações sobre Inteligência Artificial (IA):

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
Eu vejo os meus colegas de trabalho a usarem IA em todas as tarefas diárias	○	○	○	○	○	○	○
Eu vejo os meus colegas de trabalho mais produtivos a usarem IA	○	○	○	○	○	○	○
Eu vejo o meu chefe a usar IA no desempenho das suas funções de gestão	○	○	○	○	○	○	○

Peer Performance Outcomes

Os meus colegas de trabalho que usam IA no trabalho:

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
São mais produtivos	○	○	○	○	○	○	○
Passam menos tempo a fazer tarefas rotineiras	○	○	○	○	○	○	○
Entregam um trabalho de maior qualidade	○	○	○	○	○	○	○
Alcançam mais resultados positivos	○	○	○	○	○	○	○

Perceived Usefulness

Ao usar IA no trabalho:

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
Vou aumentar a minha produtividade	○	○	○	○	○	○	○
Vou melhorar o meu desempenho	○	○	○	○	○	○	○
IA é útil para fazer as minha tarefas diárias	○	○	○	○	○	○	○

Vulnerability, Severity

Com o aumento da utilização das ferramentas de IA pelos meus colegas de trabalho:

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
Estou preocupado em ser substituído	○	○	○	○	○	○	○
Estou preocupado em ser visto como menos valioso	○	○	○	○	○	○	○
Estou preocupado em ficar para trás na minha carreira	○	○	○	○	○	○	○
É grave para mim ser visto como menos competente	○	○	○	○	○	○	○
Para efeitos de qualidade, clica no 7	○	○	○	○	○	○	○
É grave para mim estar insatisfeito no trabalho	○	○	○	○	○	○	○
É grave para mim saber que posso ser despedido	○	○	○	○	○	○	○

Self-Efficacy

Eu poderia adotar IA nas minhas tarefas:

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
Se tivesse visto alguém a usar antes de eu tentar sozinho	○	○	○	○	○	○	○
Se tivesse alguém para me dar instruções passo a passo	○	○	○	○	○	○	○
Mesmo que não houvesse ninguém por perto para me orientar	○	○	○	○	○	○	○

Competitive Pressure

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
Eu sinto-me pressionado em adotar IA para me manter competitivo	○	○	○	○	○	○	○
A pressão competitiva que eu sinto em usar IA faz-me sentir com ansiedade	○	○	○	○	○	○	○
A pressão competitiva que eu sinto motiva-me a usar IA	○	○	○	○	○	○	○

Anxiety

Quando vejo os meus colegas a usarem IA no trabalho:

	1-Discordo Totalmente	2	3	4-Neutro	5	6	7-Concordo Totalmente
Sinto ansiedade	○	○	○	○	○	○	○
Sinto-me intimidado	○	○	○	○	○	○	○
Assusta-me que a produtividade deles possa fazer com que eu seja despedido	○	○	○	○	○	○	○