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Impact of Artificial Intelligence Awareness on Career Competency and Job Performance

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Abstract

Undoubtedly, artificial intelligence is projected to replace millions of jobs in the near future. Therefore, understanding employees' perceptions of artificial intelligence is crucial, as it can influence the direction of artificial intelligence research and development. Our study utilized online questionnaires to gather responses from employees in Tunisia's industrial sector. We employed explanatory factor analysis, confirmatory factor analysis, path analysis, and bootstrapping. Our results revealed that career competency and job performance are positively correlated. Nevertheless, we found that job performance and artificial intelligence awareness were not statistically correlated. Furthermore, our results showed the absence of a link between artificial intelligence awareness and career competencies. Our study provides insights into employees' perceptions of the potential benefits of artificial intelligence in improving career competencies and job performance. It also gets managers thinking about artificial intelligence's positive and negative impacts. Artificial intelligence employee awareness becomes a double-edged sword for businesses, with the potential to impact both the welfare of employees and the investment made by businesses.

Keywords: career competency, artificial intelligence, job performance, structural equation modeling.

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1 Introduction

The "*father of AI*," John McCarthy, first proposed the concept of artificial intelligence (AI) in 1956 (Benko and Lányi, 2009; Toumia and Zouari, 2024a). Artificial intelligence, which refers to machines that simulate human cognitive processes (Cochran, 2022; Dong et al., 2020), can perform specific tasks much better than humans. Among these applications, we cite medical diagnosis, natural language processing, speech and facial recognition, machine vision, problem-solving, car driving, game playing, and ChatGPT. (Agrawal et al., 2019; Gabbatt, 2011; Kaplan and Haenlein, 2019; Yetgin and Toumia, 2023). AI has the potential to significantly improve the workplace for employees. AI can automate many routine tasks so that employees can focus more on strategic and creative work. By giving employees access to real-time data and insights, AI can assist them in making better decisions and collaborating more effectively by providing employees with shared tools and resources. In this context, understanding employees' artificial intelligence awareness is the basis of this study. Today, the use of AI systems by companies in almost every sector makes it even more important to understand employees' AI awareness. AI is utilized in the healthcare sector for developing new drugs and treatments, diagnosing diseases, and in the finance sector for making investment decisions (Abou Hajal and Meslamani, 2024; Lazo and Ebardo, 2023;

Toumia and Zouari, 2024b; Weber et al., 2023); it is used to automate trading, detect fraud, and provide investment advice (El Hajj and Hammoud, 2023). Javaid et al. (2022) illustrated artificial intelligence applications for Industry 4.0. More precisely, the use of AI in production may optimize production processes, improve quality control, and reduce operating costs; however, in retail, AI is used to personalize suggestions, improve customer service and automate inventory management, provide 24/7 customer service support, answer questions, and solve problems. In many areas of the service industry, artificial intelligence systems continue to develop to improve employees' lives. Therefore, this paper aims to address the following research questions: (1) What is the relationship between career competency and job performance? (2) Does AI awareness act as a mediator in the relationship between job performance and career competency?

The structure of our article is organized as follows: Section two presents the literature review, which encompasses three streams of research related to our study: career competency, job performance, and artificial intelligence. Section three outlines the methodology and sample. Section four describes the findings of our study and its interpretation. Section five concludes our article. In terms of country and sector specificity, the study is limited to the perceptions and evaluations of employees in Tunisia's industrial sector. The subject scope of the study focuses on the relationship between artificial intelligence awareness, career competence, and job performance through an online survey.

2 Literature review

2.1 Career Competency and Artificial Intelligence Awareness

Artificial intelligence is a set of systems designed to endow machines with human abilities, such as recognizing, thinking, analyzing, learning (Al Ka'bi, 2023; Hilker, 1986; Kolbjørnsrud et al., 2017; Kong et al., 2020; Li and Du, 2007; Lu et al., 2019), and ensuring the modification of workers' competencies (Santana and Díaz-Fernández, 2023). Artificial intelligence awareness is the understanding that devices using AI (i.e., robots) may one day take an employee's position and even bring about the extinction of the human race (Brouham and Haar, 2018; Cellan-Jones, 2014). One study estimated that artificial intelligence could potentially replace about 47 percent of jobs in the United States in the future (Frey and Osborne, 2017). Indeed, employee anxiety and insecurity have been proven to decrease occupational self-management and work-related self-efficacy due to AI awareness. (Alisic and Wiese, 2020; Kong et al., 2020). Furthermore, AI can operate effectively and efficiently for many talented people (Makridakis, 2017). However, Kong et al. (2020) found no link between AI awareness and career competencies. This may be attributed to the fact that technological advancements have shortened the cycle of competency development (Gallardo-Gallardo and Collings, 2021; Santana and Díaz-Fernández, 2023; Shamim et al., 2016). Consequently, talents and many new abilities need to be anticipated to suit future employment demands (Gallardo-Gallardo and Collings, 2021). In this context, it was intriguing to investigate the following hypothesis for this study:

> *Hypothesis H1:* Career competency is positively correlated with artificial intelligence awareness

2.2 Career Competency and job performance

According to competency theory, job performance may be improved primarily through the development of competencies (McClelland, 1973). Therefore, organizations should invest in career development programs. These programs can improve employee performance, increase managerial development, introduce employees to corporate culture, reinforce core values, help employees in their career advancement, and provide them with privileges (Hoffmann, 1999; Ko, 2012; Yang and Gysbers, 2007). A study conducted in Taiwan showed that career competence positively affects job-related performance and employee satisfaction (Ho, 2001). Furthermore, career competency contributes to the employee's job-related performance (Alshiha, 2023; Beck and Murphy, 1996). Park (2020) demonstrated that the three competencies (i.e., knowing why, knowing how, and knowing whom) positively impacted work performance. As a result, management and human resource development practitioners must pay much attention to allocating resources and developing strategies.

Similarly, Alshiha (2023) examined the relationship between three categories of career competencies (i.e., reflective career competencies, communicative career competencies, and behavioral career competencies) and job performance among Saudi employees in the tourism industry. They found that all three types have a positive influence on job performance. This study emphasizes that comprehensive career development is essential for workers' success in the tourism industry. In this regard, the study's hypothesis was formulated as follows:

Hypothesis H2: Career competency is positively related to work performance

2.3 AI awareness and work performance

Artificial intelligence significantly impacts organizational performance and offers future opportunities (Abrokwah-Larbi and Awuku-Larbi, 2023; Barbosa, 2024). AI-powered tools and technologies can automate tasks, improve decision-making, enable new ways of working, improve supply chain management, and ensure employee efficiency and success (Brau et al., 2024; Ramachandran et al., 2022; Toorajipour et al., 2021). Researchers have predicted that all human employment would be automated within the next 120 years (Grace et al., 2018). Artificial intelligence techniques are widely used in human resource management systems to increase business performance (Lucci and Kopec, 2016). This integration can lead to increased productivity, accuracy, efficiency, as well as new opportunities for innovation and creativity. For instance, fuzzy artificial neural networks were used to predict employees' future job performance and to assign the most suitable employees to appropriate positions and projects (Huang et al., 2004). A prediction model based on artificial intelligence was employed to determine the level of staff competency (Chen et al., 2022). Additionally, a data mining approach was used in an empirical study to investigate the effectiveness of recruiting and retaining high-potential candidates to improve job performance (Chien and Chen, 2007). As a result, the study identified 29 guidelines that can serve as standards for identifying and hiring qualified candidates. In this context, the following hypothesis was established for the study:

Hypothesis 3: Artificial intelligence awareness is positively related to job performance

2.4 Mediating role of artificial intelligence awareness

Artificial intelligence has rapidly changed the world and affected all business functional categories (Budhwar et al., 2023). It included three generations: (1) artificial narrow intelligence is applied for specific tasks, such as Siri and Tesla; (2) artificial general intelligence can independently solve various problems; and (3) artificial superintelligence is expected to have scientific creativity along with social and technical skills (Deepa et al., 2024; Kaplan and Haenlein, 2019; Prentice et al., 2020). Meanwhile, many contributions (Abusalma, 2021; Dignum, 2018; Pillai et al., 2024; Stone et al., 2015) concluded that the implementation of AI may augment human capabilities, positively affect job performance, and improve productivity and employee experience in the workplace. These technologies may improve employee competencies, such as knowledge, skills, and abilities (Stone et al., 2015). For instance, over 25% of corporate training time now occurs online. However, other studies investigated the role of AI as a moderator/mediator (Ergün and Karabulut, 2023; Prentice et al., 2020). For example, Prentice et al. (2020) found that artificial intelligence awareness moderates a positive relationship between emotional intelligence and employee performance. Meanwhile, Ergün and Karabulut (2023) reported the mediator role of AI. Therefore, AI will probably play a significant mediating role in job performance. Hypothesis 4 is proposed:

> *Hypothesis H4:* Artificial intelligence awareness mediates the positive relationship between career competency and job performance

Appendix 1 summarizes several contributions to artificial intelligence awareness, career competency, and job performance. Nevertheless, despite the existing literature, there is a significant gap in research examining the relationship between artificial intelligence awareness, career competency, and job performance.

3 Methodology and Sample

Our research was conducted using quantitative research methods. To validate our research model, we collected data in 2023 through online questionnaires. In total, 126 Tunisian employees in the industrial sector were surveyed, of which 27% were engineers, 34.1% were logistics specialists, and 38.9% were technicians. Our sample size exceeds 100, making it adequate for analysis (Bagozzi and Yi, 2012; Boomsma, 1982; Jiang et al., 2023). Out of the total respondents, 55.6% were male, 44.4% were female, 56.3% were married, 39.7% were aged between 31 and 40, 83.3% resided in urban areas, 46.8% held a license degree, and 31.7% had experience of over 10 years. In the study, data were obtained using a convenience sampling method. To determine the sample size, the sample calculation formula for quantitative variable research was applied (Gürbüz and Şahin, 2014). Participants who did not return the questionnaires or who provided incorrect responses were excluded from the study. It was observed that n=126 valid questionnaires were collected, which met the compliance value according to the specified sample calculation formula. The validity and reliability of our items were assessed using Explanatory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and path analysis. Furthermore, we employed the bootstrapping technique (see Appendix 2).

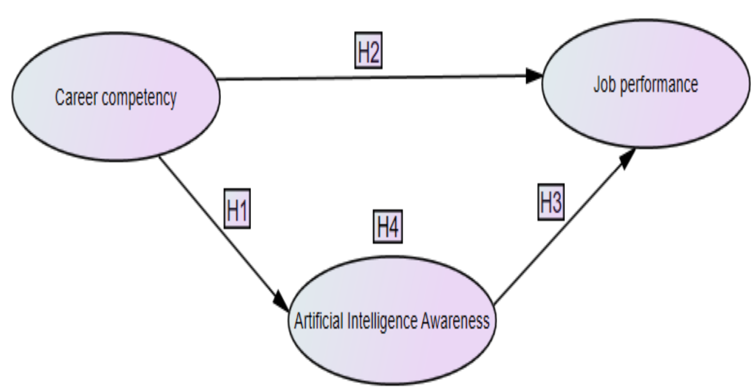

Figure 1. Research model

The survey comprised four blocks. Block 1, "*General Information*," aimed to gather demographic characteristics of the respondents (i.e., gender, age, current situation, region of origin, level of education, and work experience). Block 2, "*Artificial intelligence awareness,*" captured the extent to which Tunisian employees believe that artificial intelligence could replace their jobs. It was measured with a four-item scale (Brougham and Haar, 2018). Block 3, "*Career competency,*" captured the knowledge, skills, and abilities. It was measured with ten items from the contribution of Kong et al. (2021). Block 4, "*Job performance,*" captured the extent to which employees perform their work within the rules set by their institutions. It was measured with an eleven-item scale (Çalışkan and Köroğlu, 2022). To measure all the items, we use a five-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree). Figure 1 presents our research model. To guarantee the validity of the questionnaire, we conducted a pilot study with a small sample of Tunisian employees. We conclude that there were no unclear questions in the questionnaire. In addition, box plots were utilized to examine the response distribution and spot any outliers. Figure 2 shows the distribution of mean scores of AI awareness, career competency, and job performance.

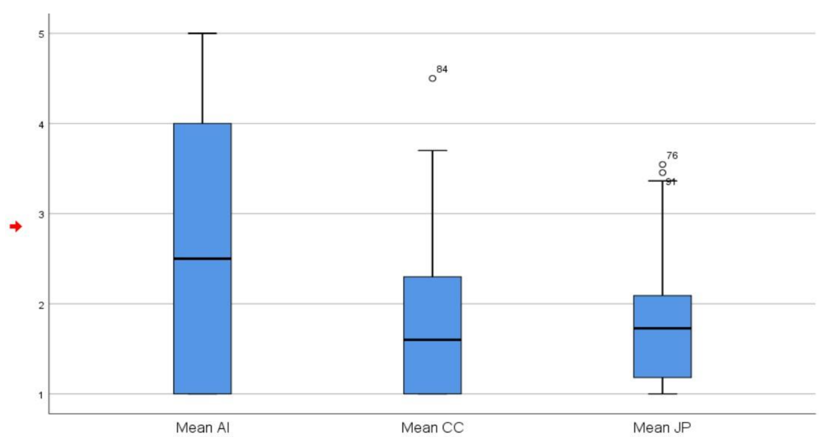

Figure 2. Distribution of mean scores of AI Awareness, Career Competency, and Job Performance

We found that the mean score for AI (Artificial Intelligence) is typically greater among employees than the mean score for CC (Career Competency), and the mean score for JP (Job Performance). This finding suggests greater variability in responses. More precisely, most employees showed higher levels of AI awareness. Indeed, we noticed that there is a similarity between career competency and job performance scores. Therefore, we may conclude that employees with better career competency scores are more likely to have higher job performance scores. To verify the reliability of the latent variables, Cronbach's alpha was employed. We found that the scales with Cronbach's alpha are larger than the threshold: $\alpha_{\text{overall}} = 0.895$, $\alpha_{\text{AI-awareness}} = 0.925$, $\alpha_{\text{career competency}} = 0.871$, $\alpha_{\text{job performance}} = 0.895 > 0.7$ (Hair et al., 2013; Taber, 2018). Therefore, all items are deemed reliable and valid for measuring the three components.

4 Results and Discussion

4.1 Explanatory Factor Analysis, Confirmatory Factor Analysis, and Path Analysis

We used both exploratory factor analysis and confirmatory factor analysis to ascertain the optimal factor structure that represents the relationship between career competency and job performance. This method was used by many contributions, such as Toumia and Zouari (2024a, 2024c) and Zouari and Toumia (2024d). To test the suitability of factor analysis, we used the Kaiser-Meyer-Olkin index. We found that the index is equal to 0.880. Therefore, the EFA is acceptable. Kaiser (1974) ascertained that values > 0.5 are considered acceptable. More specifically, values between 0.5-0.7 are described as mediocre, 0.7-0.8 as good, 0.8-0.9 as great, and > 0.9 as superb. In our analysis, the alpha coefficient revealed a high level of internal consistency. Additionally, we noticed a statistically significant correlation among the items, allowing us to proceed with the analysis (i.e., Barlett's test of sphericity was significant: p-value $= 0.000 < 0.05$). Furthermore, we found that the factor loadings can be deemed "*good*" (> 0.55, see Comrey and Lee (1992)). We utilized the Kaiser-Guttman criterion to determine the number of factors to keep (see Toumia and Zouari, 2024a). We determine that five factors should be kept. (i.e., they explained 73.298% ($> 50\%$) of the variance). For the rotation method, we chose to run the varimax rotation, and we decided to retain items with factors loading more than 0.70 (Hair et al., 2010). We performed CFA for each of the latent variables used in our research model. To achieve unidimensionality, we followed the contributions of Awang (2015) and Hair et al. (2010). Therefore, we removed items with a factor loading below 0.6. Figure 3 illustrates the measurement model using IBMSPSS AMOS.21. As depicted in Figure 3, the factor loadings ranged from 0.72 to 0.96.

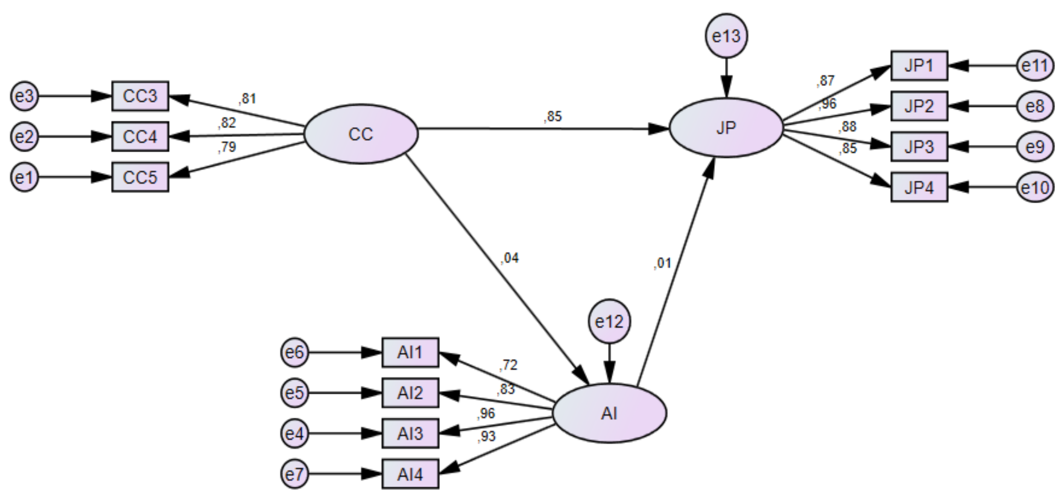

Figure 3. Measurement model

Three categories of model fit are considered when evaluating the model's fit: absolute fit, incremental fit, and parsimonious fit (Hu and Bentler, 1999; Iqbal, 2023). Our research revealed that all fitness indicators had been attained and were deemed to be sufficiently error-free. More precisely, the Parsimonious fit included Chi-square divided by degrees of freedom (Chisq/df) $=$ 2.076 <3, Parsimony Normed Fit Index (PNFI) $= 0.694 > 0.05$ (Bagozzi and Yi, 1988; Kline, 1998; Marsh and Hocevar, 1985; Toumia and Zouari, 2024a; Yetgin and Toumia, 2023); incremental fit included Comparative Fit Index (CFI) $= 0.962 > 0.90$, Tucker-Lewis Index (TLI) $= 0.949 > 0.90$, IFI$= 0.963 > 0.90$, Normed Fit Index (NFI) $= 0.930 > 0.80$, Adjusted Goodness of Fit Index

(AGFI) = 0.827 > 0.80 (Bentler and Bonnet, 1980; Bollen, 1990; Hair et al., 2010; Jöreskog and Sörbom, 1993; Toumia and Zouari, 2024a; West et al., 2012; Yetgin and Toumia, 2023; Zouari and Toumia, 2024d); and absolute fit category included Goodness of Fitness Index (GFI) = 0.892 > 0.80, Root Mean Square Error of Approximation (RMSEA) = 0.093 < 0.1 (Awang, 2015; Hashmi et al., 2020; MacCallum et al., 1996; Toumia and Zouari, 2024a; Yetgin and Toumia, 2023).

To conduct a path analysis, we used structural equation modeling (Toumia and Zouari, 2024c). We found that career competency significantly influences job performance ($\beta = 0.681$; p = 0.000 < 0.05). However, career competency does not affect AI awareness ($\beta = 0.083$; p = 0.659 > 0.05). Indeed, AI awareness does not impact job performance ($\beta = 0.006$; p = 0.825 > 0.05).

4.2 Bootstrapping

We used the maximum likelihood estimator to perform a bootstrap[1] on 5,000 samples. In addition, three different bootstrap confidence levels (i.e., 80%, 90%, and 95%) were tested,

and we discovered that the findings were consistent across all confidence levels. Therefore, the 95% level is employed. Our model fits better in 4552 bootstrap samples. The P-value of the Bollen-Stine bootstrap = 0.090 >0.05; therefore, our model is correct.

Table 1. Hypothesis testing

Hypotheses	Path Description	β (p-value)	Confidence Intervals	Conclusion
Direct effect				
H1	CC → AI	0.044 -0.661	[-0.171; 0.251]	Not supported
H2	CC → JP	0.855 0	[0.738; 0.951]	Supported
H3	AI → JP	0.014 -0.796	[-0.105; 0.142]	Not supported
Indirect effect				
H4	CC → AI → JP	0.001 -0.649	[-0.010; 0.024]	Not supported

Table 1 presents the test results of our theoretical model. Hypothesis H1, which posited a positive relationship between career competency and artificial intelligence awareness, was not supported (H1: $\beta = 0.044$; p = 0.661 > 0.05). This finding aligns with the conclusions reached by Kong et al. (2021), in which they concluded that there is no substantial direct association between career competencies and AI awareness. Furthermore, following the contribution of Sartika et al. (2022), we found a strong positive correlation between career competency and employee performance (hypothesis H2 was supported: $\beta = 0.855$; p = 0.000 < 0.05). More specifically, career competencies may promote engagement at work by allowing employees to take the initiative in identifying opportunities and establishing objectives (Akkermans et al., 2013). Surprisingly, we conclude the absence of a link between artificial intelligence and job performance (hypothesis H3 was not supported: $\beta = 0.014$; p = 0.796 > 0.05). This contradicts the results of Abusalma (2021). Our findings could be explained because individuals are not sufficiently aware of the role

1. This technique was first introduced through the pioneering work of Efron (1979, 1982).

of artificial intelligence in their job performance. Finally, the indirect effect of career competencies on job performance via the mediating channel of artificial intelligence awareness was not supported (H4: $\beta = 0.001$; p = $0.649 > 0.05$).

5 Implications

5.1 Theoretical Implications

The results of the study show that the relationship between career competence and job performance is strong as predicted by social learning theory (Bandura, 1977). This finding supports that employees learn by observing and imitating AI skills. When the scale items of career competence and the explanations requested in line with these items are examined; it is seen that the explanations support the Human Capital Theory (Blaug, 1976), Skill-Based Theory (Katz, 2009), and Social Cognitive Career Theory (Lent et al., 1994). It is seen that the knowledge, skills, and abilities of employees operating in Tunisia are a kind of capital and that this capital significantly affects business performance. When it is observed that employees can contribute to human capital by improving their knowledge and skills by having artificial intelligence awareness, it is evident that these findings obtained can be explained by associating with the Human Capital Theory. Since it is evaluated that employees' competencies in the field of artificial intelligence and their awareness in this field can increase the competitiveness of businesses operating in intelligence sectors compared to the fields that do not use artificial intelligence, it has been seen that the study can be associated with the Skill-Based Theory, and some inferential explanations are possible. Social Cognitive Career Theory explains individuals' career development by interacting with personal characteristics, environmental factors, and learning experiences. Since the AI awareness of employees in Tunisia is considered to enrich their learning experiences and contribute to their career development, this may have positive effects on business performance. Some aspects of job performance in the study can be explained by Job Design Theory (Oldham and Fried, 2016). In the study, it was observed that how jobs are designed can have a significant impact on the motivation and performance of employees in Tunisian sectors, and in this context, it was understood that performance can be improved by enriching jobs, empowering employees, and giving meaning to their work.

5.2 Practical Implications

In terms of practical implications, the results of the study emphasize the importance of businesses providing AI training to their employees. Such trainings will enable employees to learn more about AI, reduce their anxiety, and acquire new skills. Managers should implement strategies to increase employees' awareness of artificial intelligence; in this context, it is foreseen that employees' participation in training programs and artificial intelligence projects is essential. It is recommended that employees develop their AI skills to improve their careers, online courses, seminars, and certification programs will contribute to this development. Sectors or supervisory and authority institutions in Tunisia need to create more effective policies regarding the use of artificial intelligence. In this context, it would be useful to address the employees' concerns about artificial intelligence and to establish ethical principles.

6 Conclusion

Thanks to the quick advancement of artificial intelligence, we are now at the beginning of another industrial revolution (i.e., Industry 4.0) (Santana and Díaz-Fernández, 2023). Thus, it is crucial to evaluate the employee's understanding of AI and how their career competencies and job performance will change to fit this new environment. It is known that employees with career competencies have a higher chance of being successful in their jobs and reaching their career goals. Benešová and Tupa (2017) added that competencies will be critical in knowledge-intensive fields (i.e., computing, data analysis, and self-study). A strong relationship was found between career competencies and job performance. According to the findings, it was understood that career competencies positively affect employees' job performance.

On the one hand, employees can prepare themselves for the future of work by developing the skills and competencies needed to work with AI. They can be more productive, efficient, and creative by using AI to their advantage. They can also use artificial intelligence to help them solve problems and make better decisions. On the other hand, companies may lack the necessary skills to survive in the new competitive reality. Therefore, they must improve their ability to adapt to changing situations (Eisenhardt and Martin, 2000). For instance, organizations may invest in skills development (Gallardo-Gallardo and Collings, 2021) by developing training programs in companies and educational institutions (i.e., data visualization, decision-making models, machine learning, etc.), encouraging talent mobility, and attracting and developing digital talent (Alharthi et al., 2017; Khilji et al., 2015; Malik et al., 2020; Miller, 2014) to lessen the disparity in competency (Alharthi et al., 2017). Moreover, they have to develop strategies to evaluate, design, and redesign AI-enabled jobs to improve the innovative work behavior of employees (Verma et al., 2021). Thus, managers must find solutions to the various obstacles, such as IT infrastructures, AI's complexity, the absence of essential competencies among employees, and organizational cultures (Alharthi et al., 2017). In this context, Deepa et al. (2024) identified competencies needed to adopt AI in HRM, such as technical expertise, aptitude for leadership, organizational structure, adaptability, and aptitude for job design. Indeed, Reese (2005) stated that employees might observe high performers to pick up new skills and knowledge relating to their jobs. However, despite all these, no statistically significant relationship was found between the awareness of artificial intelligence and the career competencies of the employees in the study.

Since AI is still early, employees might need help to comprehend how it is used. Employers must thus provide suitable training and tools, such as proactive career planning (Brougham and Haar, 2018), or identify tasks that can be accomplished by AI (Prentice et al., 2023). Similarly, no statistically significant correlation was discovered between AI awareness and job performance. This finding aligns with Toumia and Zouari's contribution (2024a). In their conclusions, they enumerated three reasons to explain their results: (1) AI cannot replace both human judgment and creativity, (2) AI cannot replace interpersonal interactions, and (3) AI can displace jobs rather than assess job performance. The fact that the meeting of artificial intelligence with the sectors has a recent history makes the study important in understanding the employees' perceptions. Reaching a more comprehensive range of employees in different sectors will significantly expand the quality of the research on the subject.

Our article has some limitations. First, the purpose of our study was to precisely examine the perceptions of Tunisian employees. Therefore, our findings might be unique to the cultural setting of Tunisia (i.e., attitudes towards technology, religion, education, etc.) and may not be generalized. For example, different societies may adopt and employ new technologies differently. Future research may involve a larger and more diverse sample of employees from many nations with diverse economic histories. Second, our sample is limited to the industrial sector. Comparing our findings with analyses conducted in other sectors (i.e., agriculture, service) would provide more general findings. Third, our study may be constrained by the particular characteristics of our sample. As a result, researchers may explore the impact of demographic factors (gender, education, experience, etc.) on the relationships between career competency, job performance, and

AI awareness. For instance, compared to older generations, younger employees may be more willing to adopt new technologies. Fourth, it may use other methodologies (i.e., a longitudinal study) to comprehend the direction of the effects and the causal relationships between our variables and to monitor changes over time (Akkermans et al., 2013) or use qualitative research (i.e., interviews) to offer more in-depth understandings of the perceptions of employees. Finally, AI may create jobs or help others, depending on the nature of the jobs. For instance, Wirtz et al. (2018) ascertained that AI is only capable of replacing low-level human jobs. Thus, it is important to investigate how AI affects various job types differently.

The results of this study provide important insights into the relationship between AI awareness and job performance. However, this field is still new, and more research is needed. In line with the expansion of the research area, examining the awareness and effects of AI in different sectors such as the service sector, health, and education can provide a broader perspective and analyze the impact of cross-cultural differences on the perception of AI by making comparisons with employees in different countries. Separately examining the effect of various types of AI on employees, such as narrow AI, general AI, etc., can provide a more in-depth understanding. From a methodological perspective, qualitative methods such as recommendations, in-depth interviews, and focus group studies can be used to understand better employees' thoughts, feelings, and experiences about AI. Using big data analysis techniques, more comprehensive results can be obtained by analyzing various data such as employees' social media interactions and performance data. Theoretically, extensible studies can be conducted, in which theories from social sciences (psychology, sociology) (e.g., learning theories, motivation theories) can be used to develop theoretical models that can better explain AI awareness and its effects.

It is suggested that theoretical-based studies should be carried out to associate some theoretical approaches, such as Rogers's Diffusion of Innovation (DOI) Theory (Rogers et al., 2014), developed in 1962, with the development of artificial intelligence in the social sciences.

The rapid development of artificial intelligence in management, production, service, and marketing from a sectoral perspective also questions the future of human-employee value, which is the most valuable resource for a sector. The question of what kind of working environment the human factor will encounter regarding career and work performance will be one of the most curious questions. Narrow field studies on the human-employee-oriented effects of artificial intelligence will enable the subject to be explained in a broad sense.

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Appendix 1: Literature review summary

Study	Method & Sample Summary results
Santana and Díaz-Fernández (2023)	Bibliometric analysis that examined 421 papers published between 1992 and 2020. AI competencies are prominent issues.
Alshiha (2023)	Data were obtained from hotels in the Riyadh and Makkah regions between February and June 2022, and partial least squares structural equation modeling was used to analyze the data. Individual job performance is significantly predicted by all three career competencies.
Abusalma (2021)	They used a descriptive approach to analyze data from a sample of 319 managers. The existence of a statistically significant effect of AI on job performance via genetic algorithms and intelligent agents.
Brau et al. (2024)	They conducted interviews with 25 executives and used grounded theory to analyze the data. AI should be applied in judgments, decisions, and opportunities.
Prentice et al. (2020)	They send questionnaires to employees in 60 different types of hotels in Portugal. Indeed, they demonstrated the moderator role of AI in employee performance.
Ergün and Karabulut (2023)	They applied structural equation modeling for a sample composed of 569 employees. The existence of the mediator role of artificial intelligence on the relationship between corporate and competitive strategies on company performance.
Abou Hajal and Al Meslamani, (2024)	Artificial intelligence is used to develop new drugs and treatments in the health sector, to diagnose diseases, and to make investment decisions in the finance sector.
Abrokwah-Larbi and Awuku-Larbi (2023)	It was pointed out that AI has a significant impact on the performance of organizations and offers opportunities for the future.
Agrawal et al. (2019)	Artificial intelligence such as medical diagnosis, natural language processing, speech and face recognition, machine vision, problem solving, car driving, game playing, ChatGPT, etc. are covered extensively.
Akkermans et al. (2013)	Career competencies can promote engagement by enabling employees to take initiative in identifying opportunities and setting goals.
Al Ka'bi, A. (2023)	Artificial intelligence is a set of systems that aim to give machines human abilities such as recognition, thinking, analysis, learning, etc., and detailed explanations are given in this context.
Alisic and Wiese (2020)	One of the important findings of the study is that employee anxiety and insecurity have been proven to reduce professional self-management and work-related self-efficacy due to AI awareness.

Study	Method & Sample Summary results
Alharthi et al. (2017)	It has been suggested that organizations can invest in skills development by developing training programs in companies and educational institutions (e.g., data visualization, decision-making models, machine learning, etc.), promoting talent mobility, and attracting and developing digital talent.
Beck and Murphy (1996)	It is concluded that career competence contributes to the job-related performance of the employee.
Cellan-Jones, R. (2014)	AI awareness is the understanding that devices using artificial intelligence (i.e., robots) could one day take the position of an employee and even cause the extinction of the human race.
Deepa et al. (2024)	According to the study, it identified competencies such as technical expertise, leadership ability, organizational structure, adaptability, and job design ability that are necessary for the adoption of AI in human resource management.
Dong et al. (2020)	Artificial intelligence is defined as machines that simulate human cognitive processes.
El Hajj and Hammoud (2023)	The areas where artificial intelligence is used in a sectoral sense have been discussed.
Frey and Osborne (2017)	It was mentioned that artificial intelligence could replace about 47 percent of jobs in the US in the future.
Gallardo-Gallardo and Collings (2021)	It did not find a link between AI awareness and career competencies, which could be explained by the fact that technological advances have shortened the competency cycle.
Hoffmann (1999)	It was mentioned that organizations should invest in career development programs, which can improve employee performance, enhance managerial development, introduce employees to the corporate culture, and reinforce core values.
Khilji et al. (2015)	Organizations can invest in skills development by developing training programs in companies (e.g., data visualization, decision-making models, machine learning, etc.), promoting talent mobility, and attracting and developing digital talent.
Lu et al. (2019)	Artificial intelligence is explained in detail.
Malik et al. (2020)	The importance of artificial intelligence for companies has been described.
Park (2020)	Career competence is found to contribute to the employee's job-related performance.
Sartika et al. (2022)	A strong positive correlation was found between career competence and employee performance.

Study	Method & Sample Summary results
Stone et al. (2015)	It is concluded that the application of AI can augment human capabilities, positively impact job performance and improve productivity and employee experience in the workplace.
Weber et al. (2023)	Sectoral impacts of artificial intelligence are discussed.

Appendix 2: Method used in analysis

Method	Reason for use
Exploratory Factor Analysis (EFA)	It allows the identification of the common factors that explain the structure and order among measured variables (Watkins, 2018).
Confirmatory Factor Analysis (CFA)	It confirms the number of dimensions conceptualized and the unidimensionality of the scales (Churchill, 1979; Siu et al., 2001).
Path Analysis	It computes the indirect effects independently of the direct effects (Güneri et al., (2017).
Bootstrapping	It analyzes the degree of significance for the loadings, weights, and path coefficients (Hair et al., 2016).

Biographies

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