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Article

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IDENTIFYING SUFFICIENT AND NECESSARY COMPETENCIES IN THE EFFECTIVE USE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES

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Abstract

Recently, there have been significant changes in the labour market and in the lives of employees, as modern society adapts increasingly easily to the implementation of artificial intelligence tools. However, technological changes have also created challenges, including a gap between available and required competencies in the use of artificial intelligence technologies. This study aims to analyse the relationships between employee competencies and effectiveness in the use of artificial intelligence tools, in order to highlight the set of essential competencies in effective interaction with artificial intelligence technology. Therefore, to achieve the purpose of the research, a questionnaire was created and completed by 209 Romanian employees between August and September 2023. For data analysis, two advanced techniques were applied: structural equation modelling (SEM) and necessary conditions analysis (NCA) using the SmartPLS v4 program. The results suggest that employee competencies are significantly associated with the effectiveness of using AI tools, and optimism and innovativeness positively mediate this relationship. The originality of the research stands out through the use of two advanced analysis methods (structural equation modelling and necessary conditions analysis), with the aim of identifying the set of sufficient and necessary skills in the use of artificial intelligence tools. These findings have significant implications for organisations, the educational system, and future research directions on the managerial implications of using artificial intelligence tools.

Keywords: artificial intelligence, competencies, formal education, non-formal education, effectiveness, education

JEL classification: D83, O15, I25

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Introduction

The rapid progress of computer technologies, in general and artificial intelligence (AI) systems, in particular, has led to profound changes in the labour market. Researchers (Pan and Froese, 2022) appreciate that AI has the potential to radically change the future of human resource management in the context of its increasingly emphasised role in the foundation of managerial decisions (Leyer and Schneider, 2021). The World Bank Group (2019) estimates that half of the job growth in Europe between 1999 and 2016 was due to technological changes implemented at the level of repetitive processes. The International Labour Organisation (2023) shows that 24% of office tasks are highly exposed to technological change, while 58% of them are characterised by medium exposure. In the US, for example, approximately 47% of jobs are in the upper risk zone for potential automation (Frey and Osborne, 2017). In Germany, although AI-based robotisation did not have a substantial effect on employment, it did reduce youth employment (World Bank Group, 2019).

At the same time, under the conditions of the challenges launched by the progress of AI-based technologies, a relatively new concept addressed in the specialised literature is that of preparation for AI (AI-Readiness), reflecting the capabilities of an organisation to implement and use AI in a way that generates added value through digital transformation (Holmstrom, 2022). Therefore, companies that succeed in implementing and scaling AI technologies amplify their ability to become competitive and develop AI-based capabilities (Logg et al., 2019). Employee competencies are central to AI training, directly contributing to AI maturity levels defined by Martinez-Plumed et al. (2021) at the level of seven classes: knowledge representation, learning, communication, perception, planning, robotics and collective intelligence. Issa et al. (2022) define an AI training system structured on three components under the influence of AI competencies, respectively: the attitude towards human-machine collaboration, the ability to anticipate the strategic impact of AI, respectively, the technological infrastructure and the capabilities of data management.

On the other hand, research (Qureshi et al., 2021) reveals a gap between available competencies and those needed to meet the demands of AI technologies. Fareri et al. (2020) identify not only the need to integrate existing competencies into professional models, but also the creation of new competencies adapted to Industry 4.0 trends. At the institutional level, the European Commission strongly encourages the Member States (2021) to improve their portfolio of specific competencies for the development and implementation of AI solutions. The OECD (2022) states that governments should collaborate with stakeholders in a way that allows people to use and interact with AI, including developing the necessary competencies. At the same time, UNESCO (2021) proposes the development of mechanisms and tools to anticipate the current and future needs of AI-related competencies in the context of a relevant curriculum for the labour market.

Considering the challenges mentioned above, the purpose of this research is to analyse the relationship between employee competencies and effectiveness in the use of AI tools. In terms of implications of an applied nature, the research aims to contribute to the identification of possible directions of managerial intervention aimed at improving the formal (FE) and non-formal (NFE) education system in order to reduce the gaps between the available skills

and those needed in the workforce market, considering the expansion of AI-based systems. From this perspective, the research objectives show increased relevance in the general context of the field by addressing the current challenges of the lifelong learning system under the influence of the development of AI technologies, thus aligning with the research efforts of other authors (Chatterjee et al., 2012; Fernandez Sanz et al., 2017; Brougham and Haar, 2020; Chowdhury et al., 2022; Da Silva et al., 2022; Varma et al., 2022; Verma and Singh, 2022; Tilibaşa et al., 2023). From the point of view of theoretical contributions, a main element of originality of the paper is the combined use of two advanced analysis methods, namely structural equation modelling (PLS-SEM) and necessary conditions analysis (NCA), in order to define the set of sufficient and necessary skills in the use of AI technologies. Another novelty element is represented by the constructs used to evaluate the preparation for AI at the level of optimism and innovation and, respectively, discomfort and insecurity, as well as highlighting the indirect effects mediated by these constructs in the relationship between employees' skills and their effectiveness.

The main research gaps that the study aims to cover relate to the lack of consensus on the skills required for AI and the role of organisations' preparation for AI in their effective use, aspects that are, however, justified by the novelty of this research field. Thus, by defining sets of essential skills for AI and evaluating their impact on effectiveness, the research provides the premises for identifying some directions of focus of FE and NFE programs for AI, through which to ensure the maximisation of the level of training of organisations for AI and implicitly their effective use.

The paper is structured as follows. In the first section, the theoretical framework of the paper is described based on the analysis of the specialised literature. The second section includes the conceptual model and research hypotheses. The third section presents the materials and methods used, while Section four presents the results of the research. The last section of the paper contains the conclusions.

1. The role of the education system in shaping AI competencies

The issues of AI competencies and the role of education in the development of AI competency models have been addressed in several studies or specialist articles. In traditional approaches, competency models for AI are primarily based on digital competency sets, consisting of knowledge, skills, and attitudes needed to perform tasks, communicate problems, or develop knowledge in the context of IT&C (Fernandez Sanz et al., 2017). Digital competencies provide important competitive advantages even for non-IT occupations (Chen et al., 2022). However, according to some authors (Gupta et al., 2022), technological competencies do not have a significant and positive impact on the intention to adopt AI solutions. According to the Lisbon Council (2022), modern workplaces are significantly based on emotional intelligence and analytical capabilities. Other important cognitive skills in the context of AI are collaborative intelligence (Chowdhury et al., 2022) or critical evaluation (Liaw et al., 2022). On the other hand, concurrently with the development of specific competencies for AI, an ethical issue (Varma et al., 2022) is related to the way of managing the process of diminishing the role of some competencies, such as mainly decision-

making, by replacing these with AI-based algorithms. The specialised literature mainly reveals two major approaches to skills models for AI: (1) the traditional one, based on skills mostly related to the use of technology and (2) the multidisciplinary one, focused on the development of models that integrate complex cognitive skills. The present research aligns with the second type of approach, since three of the five essential competencies for AI integrated in the conceptual model proposed by the authors refer to non-technological competencies, namely leadership, personal, and social competencies. At the same time, although the number of people aged between 25 and 34 with a higher education degree has doubled in the last two decades (Lisbon Council, 2022), there is a skills shortage in the labour market in the scope of using AI systems. In this context, this research aims to examine the role of the lifelong education system in the development of AI skills, simultaneously with the identification of possible directions of managerial intervention aimed at improving this system, at the level of FE and NFE components.

In the FE system plan, Da Silva et al. (2022) emphasise the role of partnerships between universities and the business environment to implement new learning methodologies in the field of AI, based on the use of interactive digital platforms. Moreover, an important aspect of the mission for the society of higher education institutions is the added value regarding the skills needed in the professional activity, developed among the graduates (Marinaş et al., 2021). The benefits of a closer link between universities and industry are exemplified by Eriksson et al. (2020) through the eight AI competence centers created in Italy. The analysis of specialised studies (UNESCO, 2021) also reveals a series of good practices at the educational level on the set of AI skills: in China, the discipline ‘Algorithms and Computational Intelligence’ was introduced as early as 2017 in the ICT curriculum standards for high schools; in Singapore, the SkillsFuture82 initiative is focused on the development of specific skills and digital reskilling; in Finland, Headai was developed, namely an AI solution focused on the development of skills maps to align the university environment with the demands of the labour market. A major initiative at European level (The Lisbon Council, 2022) is the “European Skills, Competences, Qualifications and Occupations” (ESCO) project, launched by the European Commission in 2020, thus outlining the formal regulatory framework for the development of a set of specific skills for AI. The need to standardise the skills development process through ESCO or O*NET nomenclatures is also analysed in other works (Fernandez Sanz et al., 2017; Fareri et al., 2020; European Commission, 2021). Kabashkin et al. (2023) develop the concept of the fifth-generation university based on the review of professional and social skills by applying the results obtained in the field of cognitive sciences. The approaches emphasise the priority role of the public-private partnership, as a tool to integrate the process of developing the skills necessary for AI through EF, with the demands of the labour market.

At the same time, according to the European Commission (2018), the educational system must create models of AI skills that ensure lifelong learning, an approach that involves specific NFE actions. At the organisational level, it is necessary for executive managers to implement appropriate policies in the form of training programs or support centers for the purpose of developing AI skills (Chatterjee et al., 2021). Chowdhury et al. (2022) recommend the implementation of coaching systems in which the leading role in the transition to AI-

based systems is played by employees with relevant experience in the use of these technologies. Also, it is important that AI skills development tools are available at the right time, as research (Verma and Singh, 2022) shows that employees demonstrate more positive behaviour when they are actively supported when learning and using new AI skills. Finally, a specific characteristic of ENF relates to flexibility, in the sense that labor mobility can increase when opportunities arise to develop skills in areas required by the labor market in the context of AI (Brougham and Haar, 2020). Through the specific tools mentioned before, the role of ENF is emphasised especially in the context of the assimilation of new AI solutions, while the need for ENF is increasingly important in the conditions of rapid progress of these technologies. The link between the development of the set of key skills for AI, based on the integrated use of EF and ENF tools and the increase in the level of readiness of organisations for AI with an impact on the effectiveness in using these tools, is the main relationship on which the working hypotheses developed in the framework of the work.

2. Conceptual model and research hypotheses

The concept model proposed in this research is based on an analysis of AI competencies systems presented in the specialised literature, relevant for the purpose of generating increased efficiency in the use of these technologies. Younnis and Adel (2020) define five categories of competencies needed in the context of adopting AI solutions: hard and soft, superior cognitive (problem solving, creativity, judgment, and critical thinking), social and emotional (teamwork, leadership, and communication), technological, and research. The model proposed by Jaiswal et al. (2021) includes five critical competencies (data analysis, digital, complex cognitive, decision making, and continuous learning), with the need for a higher-level development of cognitive and technological competencies being emphasised as a premise for perfecting the human-AI relationship. In terms of managerial competencies, Zhang (2023) defines a model addressed to project managers involved in the integration of AI solutions, structured on 16 competencies such as planning, control regulation, systematic substantiation of decisions, behavioural initiative and, respectively, fairness and impartiality. Other important competencies in the context of AI are collaborative intelligence (Chowdhury et al., 2022) or critical evaluation (Liaw et al., 2022). Frey and Osborne (2017) show that, in the context of advancing technology, employees with low skill levels need to acquire creative and social competencies. Organisational agility is also a factor that facilitates the development of AI competencies necessary for the successful adoption of these technologies (Chatterjee et al., 2021). The proposed conceptual model includes five categories of key AI competencies (technical, digital, leadership, personal and social) and their relationship. Therefore, we propose the following.

Hypothesis 1 (H1): The higher the level of employees' competencies, the more effective they will be in using AI tools.

Previous research suggests a strong relationship between the level of AI competencies and the attitude towards the adoption of these technologies at the employee level, characterised by optimism, enthusiasm, and innovation. In a study looking at the use of AI in the creative industries in the UK, Chowdhury et al. (2022) point out that collaborative intelligence and

innovation can be acquired within organisations through a better understanding of AI systems, but also through a better utilisation of employee competencies obtained through knowledge sharing. A recent OECD study (2023) reveals a higher level of enthusiasm for AI upskilling among AI user groups with specialised competencies, mainly young people under 24 years of age with higher education. At the same time, by automating repetitive activities, AI allows the concentration of professionals in areas focused primarily on innovation, allowing the development of specific competencies such as cognitive, social, planning, or adopting complex decisions (Verma and Singh, 2022). On the other hand, the development of AI competencies allows the enhancement of unrealistic optimism, such as the perception that the implementation of AI would have a superior positive impact within the company in relation to competitors (Weber, 2023). From the above, we formulate the following hypothesis:

Hypothesis 2 (H2): Optimism and innovativeness in the use of AI tools mediates the relationship between employee competencies and their AI effectiveness.

The adoption of AI solutions generates numerous risks and barriers to implementation, such as those related to discomfort and insecurity when using AI tools. The degree of awareness of these risks is correlated with the level of development and influences the effectiveness of the use of AI tools. A study (Brougham and Haar, 2020) conducted on a sample of 1516 employees from the US, Australia, and New Zealand highlights the impact of technological disruption on employee well-being and occupational stress in the context of job insecurity. In research carried out in the US and India, Lingmont and Alexiou (2020) show that the perception of job insecurity is strongly influenced by education and the level of skill development, in the sense that the discomfort felt is higher in the case of employees with lower proficiency levels. Li et al. (2023) show that AI exerts a greater negative impact on workplace learning for employees with lower levels of education, placed in positions with low decision-making autonomy, or with little work experience. According to Brougham and Haar (2020), training is an effective way to manage automation when it threatens job security. Furthermore, the provision of retraining services represents an expectation of employees in the context of their perception of job insecurity (Lingmont and Alexiou, 2020). According to the OECD (2023), fear of job loss is a motivating factor for employees to participate in competence development programs. Finally, Colombo et al. (2019) emphasise the role of social and digital competencies in moderating the negative impact of technology on jobs. Therefore, we formulate the following hypothesis:

Hypothesis 3 (H3): The discomfort and insecurity associated with the use of AI tools mediate the relationship between employee competencies and their AI effectiveness.

Based on the three assumptions mentioned above, the proposed concept model (figure no. 1) integrates the existing correlations between the AI competence system AI readiness and effectiveness in the use of AI, on the one hand, and the challenges launched to the FE and NFE systems, against the background of the continuous development of AI systems and technologies, as well as the increase in the degree of their use, both at the level of the business environment and within the education system.

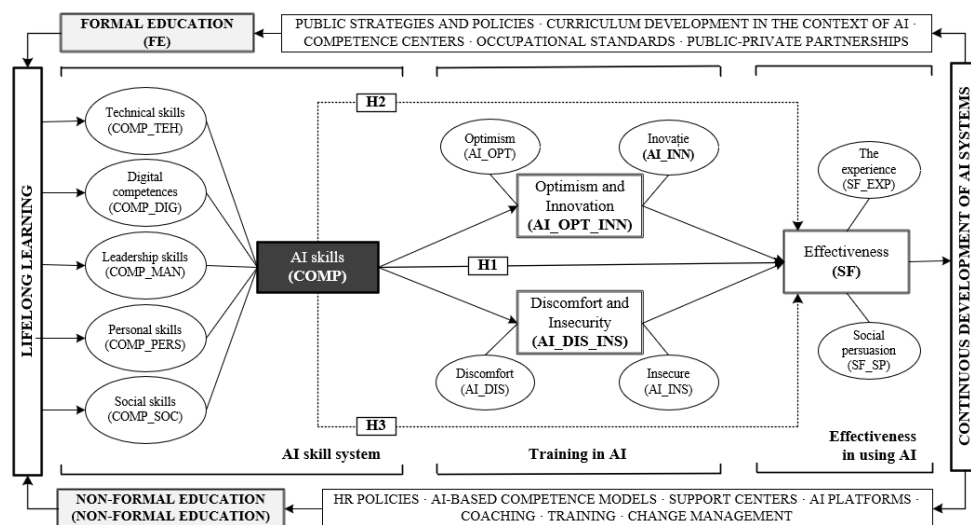


Figure no. 1. Conceptual model on relationships between employee competencies system, AI readiness and AI effectiveness

3. Materials and methods

3.1. Data collection

To achieve the purpose of the research, an online questionnaire was implemented, that was available to fill out between August and September 2023, using the Google Forms platform. The target population for this survey consisted of people who had a job in Romania at the time of the study. The questionnaire was distributed online, reaching a total of 236 participants. However, the number of eligible respondents was adjusted to 208. The sample size was considered sufficient in the context of structural equation modelling (PLS-SEM), both superior to that indicated by the rule suggesting that it should be greater than ten times the number of independent variables of the most complex regression model (30), as well as the one indicated by Hair et al. (2022) for an expected minimum value of statistically significant path coefficients between 0.11 and 0.20 and a significance level of 5% (155).

Regarding the respondents, the majority were women (51%) and had an average tenure of 11 years, mainly in executive positions (68%). Furthermore, most of the respondents came from public sector organisations (55%) and their fields of activity varied, including education, public administration, health and social care, and other services.

3.2. Scales

The questionnaire used for data collection included three scales referring to “AI readiness”, “effectiveness in using AI tools” and “Employee competencies”. Each scale was designed and

evaluated using items measured from 1 to 5. The construction of these scales was guided by an analysis of the specialised literature, and a detailed description of them is presented below.

Competencies (COMP): This scale includes different types of competence, namely, digital competencies (COMP_DIG), technical competencies (COMP_TEHN), managerial competencies (COMP_MAN), personal competencies (COMP_PERS), and social competencies (COMP_SOC). This approach was taken from the work of Kowal et al., (2022) and was adapted to suit the specifics of the research.

AI readiness was analysed through a set of items that measured the level of optimism and innovation (AI_OPT_INN), as well as the level of discomfort and insecurity felt when using AI tools (AI_DIS_INS), developed based on existing scales (Parasuraman, 2000; Parasuraman and Colby, 2015; Chen and Chang, 2023) and adapted in the context of AI use.

Effectiveness in using AI tools (SF): As suggested in the literature (Bandura, 1994; Girasoli and Hannafin, 2006), this scale focuses on assessing the degree of effectiveness reported by employees in the context of using AI technology. This assessment included aspects related to their competencies in solving complex problems and learning and applying these tools (SF_EXP). Also included in the scale were items that investigated how AI users might manage these tools in the future (SF_SP).

3.3. Data analysis

For data analysis, two advanced techniques were used: PLS-SEM and NCA. To perform the two analyses, SmartPLS v4 (Ringle et al., 2022), known for its ability to manage complex models and its flexibility in analysing the relationships between latent and observed variables, was used. The synergistic use of PLS-SEM and NCA provided the opportunity to better support the theoretical foundation, being particularly useful in identifying the set of competencies that contribute to increasing the effectiveness in using AI tools, but also absolutely necessary to obtain a given level of it, in concordance with the sufficiency and necessity logic (Richter et al., 2020).

4. Results

4.1. Evaluation of the model

To support the reliability and validity of the measurement model, we applied the suggestions proposed by Hair et al. (2020) and analysed the model in terms of internal consistency, convergent validity, and discriminant validity. Therefore, analysing the data in Table no. 1, we can see that the Cronbach Alpha coefficient and the composite reliability (ρ_a and ρ_c) are above the recommended value of 0.70 (Hair et al., 2019; Hair et al., 2020). We also analysed convergent validity via average variance extracted (AVE) and external loadings. According to the recommendations of Hair et al. (2020), AVE values exceeded the threshold of 0.50 and external loadings (with one exception) were greater than 0.708.

Table no. 1. Fidelity and validity of the measurement model

Constructs	Loadings	Cronbach alpha	rho_a	rho_c	AVE
COMP*	0.853 – 0.908	0.972	0.974	0.974	0.569
COMP_DIG	0.634 – 0.878	0.917	0.926	0.933	0.636
COMP_MAN	0.892 – 0.925	0.928	0.930	0.949	0.823
COMP_PERS	0.699 – 0.906	0.932	0.935	0.946	0.715
COMP_SOC	0.895 – 0.915	0.924	0.925	0.946	0.813
COMP_TEH	0.850 – 0.907	0.936	0.937	0.949	0.757
AI_OPT_INN*	0.922 – 0.934	0.920	0.925	0.935	0.646
AI_INN	0.741 – 0.893	0.866	0.881	0.909	0.715
AI_OPT	0.870 – 0.910	0.909	0.910	0.936	0.786
AI_DIS_INS*	0.826 – 0.906	0.836	0.839	0.877	0.507
AI_DIS	0.750 – 0.834	0.823	0.825	0.883	0.654
AI_INS	0.798 – 0.874	0.776	0.782	0.870	0.690
SF*	0.946 – 0.970	0.958	0.959	0.963	0.687
SF_EXP	0.879 – 0.898	0.909	0.910	0.936	0.785
SF_SP	0.741 – 0.901	0.936	0.938	0.949	0.726

Note: * – second-order construct; rho_c – composite reliability; rho_a – adjusted composite reliability; AVE – average variance extracted.

The discriminant validity was assessed through the Fornell Larker criterion and the Heterotrait-Monotrait ratio (HTMT) (Table no. 2). With two exceptions, these criteria indicate the discriminant validity of the measurement model, as evidenced by HTMT values lower than 0.9 (Hair Jr, Howard. and Nitzl, 2020; Henseler, Ringle and Sarstedt, 2015) and correlations between constructs lower than the square root of AVE. However, the two constructs were retained in the model, as they represent concepts with similar meanings (Hair et al., 2022).

Table no. 2. Discriminant validity

Constructs	1	2	3	4	5	6	7	8	9	10	11
AI_DIS	0.809	0.417	0.626	0.178	0.200	0.126	0.171	0.239	0.148	0.184	0.199
AI_INN	0.340	0.846	0.099	0.799	0.638	0.496	0.514	0.467	0.598	0.711	0.658
AI_INS	0.509	0.027	0.831	0.131	0.076	0.070	0.190	0.244	0.070	0.123	0.108
AI_OPT	0.139	0.724	-0.065	0.886	0.515	0.410	0.421	0.391	0.490	0.742	0.695
COMP_DIG	0.132	0.557	0.026	0.466	0.798	0.715	0.698	0.650	0.892	0.630	0.634
COMP_MAN	0.106	0.438	0.011	0.376	0.671	0.907	0.871	0.792	0.791	0.576	0.541
COMP_PERS	0.141	0.451	0.148	0.387	0.659	0.813	0.846	0.928	0.738	0.606	0.566
COMP_SOC	0.205	0.410	0.200	0.360	0.616	0.735	0.861	0.902	0.673	0.547	0.532
COMP_TECH	0.105	0.536	-0.037	0.453	0.827	0.740	0.690	0.629	0.870	0.598	0.609
SF_EXP	0.147	0.637	-0.035	0.676	0.573	0.527	0.557	0.503	0.552	0.886	0.915
SF_SP	0.169	0.600	-0.026	0.643	0.585	0.504	0.528	0.496	0.571	0.845	0.852

Note: bottom left – Fornell-Larcker criterion; top right – HTMT report.

As suggested by Hair Jr, Howard and Nitzl (2020), the structural model was evaluated from the perspective of collinearity, statistical relationships between constructs and coefficients of determination. Therefore, according to the determination coefficient $R^2 = 0.599$, approximately 59.90% of variance in effectiveness in the use of AI tools can be explained by optimism and innovation, discomfort and insecurity and the competencies of the employees. Furthermore, variance inflation factor (VIF) values below 3 for all predictors in the structural model indicate that multicollinearity is not a concern in this case.

4.2. Assessment of research hypotheses

To evaluate the three research hypotheses, both direct effects between competencies and effectiveness in using AI tools and indirect effects mediated by AI optimism and innovation and AI discomfort and insecurity were analysed (Table no. 3).

Table no. 3. Direct and indirect effects

Hypotheses	Relations	Beta	SE	T statistic	BCCI	f ²
H1	COMP → SF	0.360***	0.065	5.491	0.251; 0.467	0.224
H2	COMP→AI_OPT_INN	0.549***	0.058	9.476	0.441; 0.632	0.431
	AI_OPT_INN→SF	0.522***	0.061	8.486	0.414; 0.617	0.470
	COMP→AI_OPT_INN→SF	0.286***	0.046	6.275	0.216; 0.367	-
H3	COMP→AI_DIS_INS	0.138*	0.077	1.795	0.013; 0.264	0.020
	AI_DIS_INS→SF	-0.037	0.048	0.775	-0.115; 0 -.042	0.003
	COMP→AI_DIS_INS→SF	-0.005	0.008	0.664	-0.024; 0.003	-

Note: BCCI - bootstrap confidence interval; f² - effect size.; * - p < 0.05; *** - p < 0.001.

According to the results, there is a statistically significant and positive relationship ($\beta = 0.360$; $p < 0.001$) between competence and the effectiveness of the use of AI tools, supporting hypothesis H1. The results also support H2 and show that optimism and innovation in the use of AI tools significantly and positively mediate the relationship between employee competencies and their effectiveness in the use of these tools ($\beta = 0.286$; $p < 0.001$). In other words, employee competencies positively influence optimism and innovation in the use of AI, which in turn contributes to a significant increase in effectiveness. At the same time, the results do not support H3, as discomfort and insecurity in using AI tools do not mediate the relationship between employee competencies and AI effectiveness ($\beta = -0.005$; ns). Consequently, the results indicate that as employee competencies evolve, the level of discomfort and insecurity in using AI tools increases, resulting in a decrease in the effectiveness of using AI tools.

4.3. The “should have” and “must have” competencies in the interaction with AI tools

The analysis was extended to identify the set of competencies sufficient and necessary for employees to use AI tools. Therefore, two perspectives were considered. The first perspective had in mind the identification of those skills that are able to lead to an increase the employees’ readiness in using AI tools, thus applying the “*should have*” (sufficiency) logic (Table no. 4), and the second considered the absolutely necessary level of each category of competencies, applying the “*must have*” (necessity) logic (Table no. 5). The sets of “*should have*” and “*must have*” competencies were identified for three target constructs: (1) Discomfort and insecurity, (2) Innovativeness and optimism and (3) Effectiveness in using AI tools.

Table no. 4. “Should have” competencies in AI context

Independent variables	Discomfort and insecurity		Innovativeness and optimism		Effectiveness in using AI tools	
	Beta	t	Beta	t	Beta	t
Constant	0.000	7.786	0.000	3.687	0.000	1.916
AI_DIS					0.028	0.491
AI_INN					0.130*	1.739
AI_INS					-0.054	0.977

Independent variables	Discomfort and insecurity		Innovativeness and optimism		Effectiveness in using AI tools	
	Beta	t	Beta	t	Beta	t
AI_OPT					0.400***	6.058
COMP_DIG	0.093	0.751	0.317**	3.003	0.157*	1.877
COMP_MAN	-0.172	1.342	-0.026	0.240	0.016	0.184
COMP_PERS	0.027	0.169	0.107	0.792	0.147	1.399
COMP_SOC	0.378**	2.814	0.019	0.169	0.063	0.695
COMP_TECH	-0.153	1.141	0.203*	1.770	0.047	0.527
R ²		0.081		0.327		0.608
F		3.577		19.608		34.158

Note: regression coefficients (Beta) with significant values are highlighted in gray. * - p < 0.05; ** - p < 0.01; *** - p < 0.001.

The results show a significant and positive relationship between social competencies and the level of discomfort and insecurity ($\beta = 0.378$; $t = 2.814$; $p < 0.01$). This fact indicates that the implementation of AI in a work environment can change the way employees communicate, make decisions and work as a team. These changes can create a sense of uncertainty and discomfort among employees, especially if they have not developed the social competencies to adapt to these changes.

Furthermore, there is a significant and positive relationship between digital competencies ($\beta = 0.317$; $t = 3.003$; $p < 0.01$) and technological competencies ($\beta = 0.203$; $t = 1.770$; $p < 0.05$) and the level of innovation and optimism. In other words, when employees have more developed digital and technological competencies, this is associated with a significant and positive increase in their level of innovation and optimism in the use of AI tools.

Last but not least, there is a positive and significant relationship between optimism and employee innovation in the effective use of AI tools ($\beta = 0.400$; $t = 6.058$; $p < 0.001$; $\beta = 0.130$; $t = 1.739$; $p < 0.05$). There is also a positive and significant effect of digital competencies ($\beta = 0.157$; $t = 1.877$; $p < 0.05$). Therefore, employees with well-developed digital competencies can have a deeper understanding of how to use these tools and have more confidence in their abilities, which can lead to greater effectiveness in using AI tools.

Next, to identify and highlight the set of necessary conditions for each type of competence, two distinct thresholds were used: 50% and 100% and for each, an evaluation scale from 1 to 5 (Table no. 5).

Table no. 5. “Must have” competencies in AI context

Independent variables	Discomfort and insecurity		Innovativeness and optimism		Effectiveness in using AI tools	
	50%	100%	50%	100%	50%	100%
AI_DIS					NN	1.514
AI_INN					NN	1.679
AI_INS					NN	NN
AI_OPT					NN	2.525
COMP_DIG	NN	3.243	NN	2.419	NN	2.862
COMP_MAN	NN	2.766	NN	2.064	NN	2.064
COMP_PERS	NN	3.561	2.252	3.548	2.143	3.932
COMP_SOC	NN	4.733	2.249	4.058	2.249	4.058
COMP_TECH	NN	3.142	NN	3.179	NN	2.862

Note: *NN = not necessary. Necessary conditions with significant effect size (d) are marked in gray.

The results show that to feel a degree of discomfort and insecurity of 50% when using AI tools, there is no need for competencies, while to feel a degree of discomfort of 100%, there is a need for social competencies of 4.733 on a rating scale from 1 to 5. Additionally, to achieve a 50% level of innovation and optimism in the use of AI tools, two types of competencies are both necessary: personal competencies (2.252) and social competencies (2.249). However, to achieve a 100% level of innovation and optimism in the use of AI tools, personal competencies (3.548) and social competencies (4.058) were identified as necessary. Regarding the need for employees to be effective in using AI tools, for the 50% level, there were two types of necessary competencies, namely personal competencies (2.143) and social competencies (2.249). However, to achieve a 100% effectiveness level, all types of competencies were identified as cumulatively required, as well as a level of optimism on the part of employees regarding the use of AI tools.

5. Discussions

Through this research, the aim was to analyse the relationship between employees' competencies and effectiveness in the use of AI tools to identify possible directions of managerial intervention aimed at improving the EF and ENF systems in order to reduce the gaps between competencies available and needed in the labour market amid the expansion of AI-based systems.

Therefore, the results of empirical research highlighted the fact that there is a significant relationship between competence and the effectiveness of the use of AI tools, which supports hypothesis H1. Specifically, employee competencies, including their digital, technical, managerial, personal, and social competencies, have been associated with significantly improved effectiveness in the use of AI tools. Previous research has discussed the importance of employee competencies in using advanced technologies, including AI tools (Younis and Adel, 2020; Jaiswal et al., 2021). This research has shown that individual competencies and competencies have a significant impact on the adoption and effectiveness of technologies within organisations. This fact is supported by studies by He et al. (2007) and Zaman et al. (2019) that investigated, for example, the impact of technical competencies on performance in the use of complex software or the impact of social competencies on collaboration in technological projects. In addition, in the context of rapid changes in the technological landscape, employees' competencies not only influence how they can use and benefit from technologies such as AI but also play a significant role in organisations' ability to quickly adapt to technological changes. Employees with developed digital, technical, and social competencies are more likely to adopt and integrate new technologies into their work processes, thus contributing to increased organisational efficiency and innovation (Jaiswal et al., 2021).

Furthermore, the empirical results of the study show that optimism and innovation in the use of AI tools significantly and positively mediate the relationship between competencies and their effectiveness in the use of these IT tools, thus supporting hypothesis H2. Previous research, such as that of Verma and Singh (2022), shows that AI improves decision-making skills among employees, enhancing their creativity and innovation ability. The involvement of employees in innovative activities increases the level of trust (Cheng et al., 2023) thus favouring not only the increase in effectiveness in the use of AI tools but also the generation

of positive results at the organisational level in the era of AI technologies (Braganza et al., 2020). Moreover, technological skills can facilitate communication and collaboration between departments and organisational teams. The effective use of AI tools can lead to faster and more efficient information sharing, creating a synergistic work environment, and fostering collaborative innovation (Olan et al., 2022).

Furthermore, the results of the study indicated that discomfort and insecurity in using AI tools do not significantly mediate the relationship between employee competencies and effectiveness, rejecting the last hypothesis (H3) of the investigation. Although there may be some initial discomfort or insecurity in using AI tools, these feelings have not been found to significantly impact employee effectiveness in implementing and using these technologies. Organisations that implement AI can provide resources, support and training programs to help employees overcome initial uncertainty or discomfort (Zhu et al., 2020).

The synergistic use of PLS-SEM and NCA facilitated a significant expansion of the discussion of various types of competencies essential and necessary to ensure effective use of AI tools. Thus, based on the results, we can highlight the following aspects.

Digital competencies play a key role in the use of AI tools, so typically AI models are based mainly on digital competencies, as suggested by Fernandez Sanz et al. (2017). The results of the present study show that there is a positive relationship between digital competencies and the level of innovation and optimism. Furthermore, to achieve a 100% effectiveness level in the use of AI tools, digital competencies have been identified as necessary. Consequently, amid the rapid evolution of AI technology, characterised by the constant emergence of new techniques and tools, digital competencies have become an essential tool for employees, allowing them to stay abreast of these developments and integrate them into their work activities. day by day (Van Laar et al., 2017). Several studies (Kispeter, 2018; Anisimova et al., 2021) show that digital competencies are increasingly important for professional success and active participation in modern society. The ability to work with AI tools can have a significant impact on employment and personal development opportunities (European Commission, 2021).

Managerial skills were evaluated as those at the individual level, so the empirical results of the study show that there is no significant relationship between this type of skill and the effective use of AI tools. However, following the NCA analysis, these competencies were identified as necessary to achieve a level of 100% effectiveness in the use of AI tools. Although individual managerial competencies may seem less relevant to the technical use of AI tools, they can play a key role in coordinating and motivating teams working with this technology (Sousa and Rocha, 2019). Research by Cortellazzo et al., (2019) showed that leadership and communication competencies can influence how a team approaches and uses technology.

Personal competencies in the use of AI refer to the set of competencies, knowledge and personal traits needed to interact effectively with AI technologies and to take advantage of their full potential. These competencies are not technical in nature, but focus more on behavioural, cognitive and relational aspects (Arun and Carma, 2021). The study results revealed that to reach a level of 50% in terms of innovation and optimism in the use of AI tools, personal competencies must reach an average value of 2.252 on a rating scale of 1 to 5. Furthermore, it was found that to achieve 100% innovation and optimism in the use of AI

tools, personal competencies were identified as absolutely necessary. This can be supported by previous research (Chowdhury et al., 2022; Verma and Singh, 2022), which has shown that behavioural and psychological factors such as trust in technology and adaptive competencies can significantly influence technology performance and adoption. Last but not least, both to reach a 50% effectiveness level and to reach a maximum level of 100% in the use of AI tools, personal competencies are required. Consequently, personal competencies such as critical thinking, adaptability and ethics can contribute to a more efficient and responsible use of AI tools, a fact supported by other specialist studies (Younis and Adel, 2020). These competencies can influence how people understand, use and manage AI technology in different contexts.

Social competence in the use of AI refers to the personal competencies and traits that enable people to interact and work effectively in different social and collaborative settings. The results of the present study showed that there is a significant and positive relationship between this type of competence and the level of discomfort and insecurity felt by employees when using AI tools. This fact indicates that the implementation of AI in a work environment can change the way employees communicate, make decisions, and work as a team. It was also found that to feel a 100% degree of discomfort when using AI tools, a social competence of 4.733 was recorded as necessary on a rating scale of 1 to 5. This can be justified by the fact that the use of AI technologies can lead to a decrease in human interactions, including communication and collaboration with colleagues, in an environment where AI is present. However, social competencies were identified as necessary both to reach a level of 50% and 100 in the case of innovation and optimism in the context of AI and to use these IT tools.

Technological competence plays an important role in the use of technologies, as demonstrated by numerous studies (Younnis and Adel, 2020; Jaiswal et al., 2021). The results of this research revealed a positive relationship between technological competencies and the level of innovation and optimism felt by employees in the context of the use of AI tools. Additionally, technological competencies were identified as absolutely necessary to achieve a 100% level of effectiveness in the use of these tools. Therefore, as employees gain a deeper understanding of how AI works, they develop a more pronounced sense of optimism about its capabilities (Chowdhury et al., 2022). With strong technological competencies, employees can contribute to the development and implementation of innovative solutions that use AI to tackle complex problems or make significant improvements in various fields (Verma and Singh, 2022).

Conclusions

This research focused on examining the role that different types of competencies play in the effective use of AI technologies in a context characterised by the rapid evolution of the work environment in the digital age. The research successfully achieved its purpose by revealing significant relationships between employees' competencies and their effectiveness in using AI tools. The obtained results provide a clearer understanding of how digital, technical, managerial, personal and social skills influence employees' performance with AI tools, identifying potential interventions in both FE and NFE.

Regarding the research hypotheses, H1 and H2 were confirmed, while H3 was rejected. Furthermore, the NCA analysis highlighted the necessary and sufficient conditions for each type of competency required by employees to use AI tools.

Theoretical contributions. This paper introduces novel theoretical contributions to the specialised literature in the field of AI implications. The integration of two advanced analysis techniques, namely PLS-SEM and NCA, adds significant value to understanding the intricate relationships between employees' competence and the effectiveness of using AI tools. Through the combined application of these methods, the paper identifies two types of competence—categorised as “should have” and “must have”—which emerge as essential in the context of utilising these technological tools. Consequently, this work offers substantial implications for the existing specialised literature on the adaptation of organisations and employees to AI, as well as for FE and NFE.

Managerial contributions. The research results delineate potential courses of action for public authorities and the business environment to adapt the Lifelong Learning (LLL) system to the demands and challenges posed by AI. Based on best practices, public strategies and policies should prioritise the implementation of strategic options to improve the Education and Training Framework (EF) system. These options include tailor-made AI curriculum development, the establishment of AI competence centers, the promotion of public-private partnerships, and the development of occupational standards. Simultaneously, the research findings, particularly in understanding the relationship between employee competence and effectiveness in using AI tools, offer valuable insights for enhancing human resources policies within the Employment and National Framework (ENF) system. This involves creating AI-based competence models, establishing support centers, implementing specific training and coaching programs and introducing change management initiatives to mitigate uncertainty and discomfort among employees.

Limits and future research directions. As AI continues to play an increasingly prominent role in society, future research could focus on two crucial issues: the ethical considerations surrounding AI use and its broader impact on organisations. Furthermore, to achieve more generalisable results, future studies may involve a larger number of respondents, thereby addressing the limitations of our current research.

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