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Article

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IMPLICATIONS OF ARTIFICIAL INTELLIGENCE ON ORGANIZATIONAL AGILITY: A PLS-SEM AND PLS-POS APPROACH

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Abstract

Artificial intelligence (AI) has radically changed companies' vision of business development, based on its widespread assimilation in key organisational processes. However, in organisational practice, the implementation of AI has generated major challenges, such as those related to the high need for investments in technologies, insufficient level of skill development, and resistance to change of personnel. At the same time, under the conditions in which markets become increasingly dynamic, an increasingly emphasised requirement for companies is to maintain increased organisational agility to quickly adapt to the challenges of the external environment. Therefore, this study aims to analyse the role of AI in capitalising on an organisation's digital capabilities as a means of amplifying organisational agility in order to improve internal and external processes. The research conclusions were based on the application of a questionnaire to employees from various Romanian sectors of activity and for data analysis, structural equation modelling (PLS-SEM) and prediction-oriented segmentation (PLS-POS) were used. The main results indicate that the more digital capabilities organisations have, the more agile they become in relation to internal processes and changes in the external environment. This relationship is facilitated by the use of AI tools. At the same time, prediction-oriented segmentation highlighted two distinct categories of organisations in terms of AI transformation: in those in which this process is more advanced, the mediation effect is stronger. The originality of the study emerges by extending the PLS-SEM results by respondents' segmentation through finite mixture partial least squares (FIMIX-PLS) and PLS-POS, but also by considering AI implications on internal and external organisational agility, which is less addressed in the literature. The study outlines several possible managerial interventions, both on AI-related public policies and on the optimisation of business processes under AI implementation.

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Keywords: artificial intelligence (AI), digital capabilities, organisational agility, structural equation modeling (PLS-SEM), prediction-oriented segmentation (PLS-POS), finite mixture partial least squares (FIMIX-PLS)

JEL classification: O32, M15, L29

Introduction

In the context of the rapid progress of digitisation, artificial intelligence (AI) has generated a technological revolution responsible for the emergence of new industries and professions (Harborth and Kumpers, 2021), which is also a critical factor for boosting the performance of Industry 4.0 specific technologies (Hajipour, Hekmat and Amini, 2023). New digital enterprises have leveraged vertical interactions with customers and suppliers to improve their performance through machine learning and other digital technologies (Guo, Yin and Liu, 2023). Simultaneously, the accelerated progress of AI has created major challenges for companies, involving additional investments in infrastructure, innovation, or talent management to integrate AI into their own processes (Haefner et al., 2023).

The analysis of specialised literature reveals multiple limits and challenges related to the implementation of AI, a large part of which refers to the insufficient preparation of companies, or the low level of development of organisational skills and capabilities regarding AI. Organisational constraints, along with technological issues, lack of key resources, or unrealistic expectations, are among the main factors that have the potential to cause AI projects to fail (Westenberger, Schuler and Schlegel, 2022). Other organisational factors that inhibit, or as the case may be, stimulate the adoption of AI are the level of trust in technological practices, the way data is managed and protected, financial resources and the size of the organisation (Hradecky et al., 2022). Simultaneously, to maximise the benefits of these new technologies, companies must reshape their organisational culture (Bettoni et al., 2021). Corsaro et al. (2022) argue for the low efficiency of some AI projects precisely the issues of adapting the organisational culture to the technological transition. Other challenges include the insufficient integration of existing and new knowledge within the AI-specific learning process (Olan et al., 2022), limits on internal computing and data processing capabilities (Issa, Jabbouri and Palmer, 2022), or lack of investment simultaneously in AI at the ecosystem level (Corsaro et al., 2022). In terms of human resources, the challenges regarding the implementation of AI refer primarily to the insecurity felt by employees (Banciu, Vevera and Popa, 2023), due to both the perception of the risk of job loss (Morandini et al., 2023) and aversion to algorithms, privacy issues, or lack of transparency (Hang and Chen, 2022). In response, companies must use tools to combat resistance to change (Morandini et al., 2023), such as the not-invented-here syndrome (NIHS) (Arias-Pérez and Vélez-Jaramillo, 2021) or techno-skepticism (Leonard and Tyers, 2023). At the same time, organisations should develop specific capabilities for AI implementation (Weber et al., 2022). Therefore, previous research has shown that many of the risks, limitations, and challenges posed by AI are related to digital capabilities.

Considering the above, this research aims to analyse the role of AI in capitalising on digital capabilities, in order to increase organisational agility from the perspective of internal processes and in relation to the challenges of the external environment. In accordance with the proposed goal, the first direction of research addressed in this study is the analysis of the

impact of the organisation's digital capabilities on the implementation of AI tools. By referring to the general context of the field, the research shows increased relevance by analysing the organisational capabilities in the field of AI from a multidisciplinary perspective (human, collaborative, technical, and innovation), thus complementing the ways of approaching the concept in other specialised works (Bettoni et al., 2021; Denicolai, Zuccella and Magnani, 2021; Weber et al., 2022; Werder and Richter, 2022; Westenberger, Schuler and Schlegel, 2022; Banciu, Vevera and Popa, 2023; Lee et al., 2023; Mikalef et al., 2023; Wang and Li, 2023). Moreover, in the context of the topicality of the research subject, the main research gap that the study aims to answer is the lack of a unitary framework for defining digital capabilities for AI, which currently limits the formal regulation of these capabilities for the business environment at the workforce level. The second main component of the proposed model aims at organisational agility, namely, the ability of the enterprise to identify and respond to changes (Werder and Richter, 2022), with a direct impact on organisational performance. Research shows that AI assimilation has a positive impact on organisational agility (Wamba, 2022) and is also considered a predictor (Shafiabady et al., 2023). Therefore, the second research direction of this study is to examine the relationships between digital capabilities and organisational agility, a relationship mediated by the degree of assimilation of AI tools at the level of internal and external processes.

This study highlights the relationships between digital capabilities and organisational agility in the context of using AI tools. Therefore, as a first element of originality, in contrast to most of the analysed works that deal with the connection between AI capabilities and organisational performance as a whole, the impact area in the case of the present research is focused on the level of organisational agility, approached both as a result of the implementation of AI tools and an organisational capability in itself. Another element of originality is the extension of the results offered by PLS-SEM by segmenting the respondents using finite mixture partial least squares (FIMIX-PLS) and prediction-oriented segmentation (PLS-POS). In terms of the contributions in the application plan, the research results provide premises for the formalisation of the key digital skills system, both at the macroeconomic level, in the context of substantiating the policies regarding the review of occupational nomenclature or standards, and at the microeconomic level, in order to calibrate organisational strategies and policies in fields such as IT, human resources, and marketing.

The remainder of this paper is organised as follows. Section one includes the theoretical framework of the work and elaborates on the analysis of the specialised literature. Section two presents the research hypotheses and conceptual model, while Section three outlines the materials and methods used. Section four includes the results obtained, and Section five is reserved for discussion. The final section presents the conclusions of this study.

1. Conceptual framework and research hypotheses

Several studies have addressed the impact of organisational capabilities in the context of AI. Weber et al. (2022) identified four categories of organisational capabilities for AI development: AI project planning, collaborative development, AI project planning, and stakeholder communication. Lee et al. (2023) identify an organisational dimension of AI support capabilities, which includes, among others, the processes of collaboration, continuous development, strategic planning, integration, or cost-benefit analysis, respectively, a technological dimension, based on the design of the system and component

models. Bettoni et al. (2021) structures organisational AI capabilities across five pillars: intelligent organisation, data strategy, human resources, organisational structure, and organisational culture. At the same time, organisational capabilities in the field of AI also include management's ability to identify solutions to generate added value based on AI to experiment with new solutions for the use of AI technologies (Mikalef et al., 2023). In another study (Lada et al., 2023), it was shown that the commitment of top management, doubled by the engagement of resources at a strategic level, significantly influenced the adoption of AI. Decentralisation of decisions is also a factor that encourages digital transformation (Da Silva et al., 2022).

In the context of the AI organisational capabilities system, digital capabilities reflect the ability of organisations to acquire, deploy, correlate, and reconfigure IT resources (Werder and Richter, 2022), which being also necessary to support the implementation of innovation-based business models – Business Model Innovation (BMI) (Van Tinde et al., 2022). Zhu and Li (2023) approach digital capabilities from the perspective of integration within the digital ecosystem based on supply and innovation chains in order to ensure data interoperability, while Westenberger, Schuler and Schlegel (2022) emphasise the need to correlate digital capabilities with the requirements of AI projects, otherwise there is a risk of implementation failures. Finally, organisational capabilities are closely correlated with the level of AI-Readiness, which refers to the level of preparation of organisations regarding the implementation of changes involving AI applications and technologies, thus ensuring support for digital transformation (Denicolai, Zuccella and Magnani, 2021).

The technological dimension of organisational capabilities supporting AI based on digitisation has been addressed in several studies. Therefore, in the context of digital capabilities, some authors have appreciated the key role of developing the skills necessary for AI. The incorporation of AI can lead to increased workforce performance (Vorobeva, El Fassi and Mattila, 2022) by developing specific skills, whereas the use of AI-based big data systems leads to improved decision-making skills (Logg, Minsos and Moore, 2019; Dubey et al., 2020; Verma and Singh, 2022). Research has shown that the process of developing AI skills can also integrate specific AI tools in terms of the relationships between AI skills and the functionalities of these solutions. Some authors (Malik et al., 2021; Rozman, Oreski and Tominc, 2022) have shown the role of these technologies in talent management or in the development of an organisational culture conducive to performance. Among the tools used by enterprises to assimilate AI are project-based learning and workshops (Pasko et al., 2022), educational seminars used as a way to overcome negative psychological barriers (Mikalef, Van Der Wetering, and Krogstie, 2021), the exchange of knowledge that ensures the support of an adaptive learning process (Kaasinen et al., 2020), and the development of internal working platforms designed to influence attitudes toward AI and increase their performance (Connelly et al., 2020).

According to some authors (Chatterjee et al., 2021), organisational agility, one of the main components of the proposed conceptual model, represents a capability formed from a set of specific competencies. Other authors (Cegarra-Navarro, Soto-Acosta and Wensley, 2016) consider agility to be a complementary capability that integrates the organisation's resources, such as assets or knowledge. An original element of the proposed model is the differentiated analysis at the level of internal and external organisational processes on the impact of digital

capabilities, mediated by the implementation of AI technologies. This type of approach aligns with the research of Werder and Richter (2022), which differentiates reactive IT capabilities, which provide support for the optimisation of internal work processes, from initiative-taking ones, which support and optimise business strategies and, therefore, external processes. Other authors (Sipola, Saunila, and Ukko, 2023) argue that AI plays a role in ensuring business sustainability, structuring organisational processes at the level of social, ecological, and societal dimensions, and others (Zhao and Gómez Fariñas, 2023) believe that AI is making its way into our daily lives, being used to radically change the nature of and enhance business practices to promote sustainable development. Furthermore, the use of generative AI is considered a technological innovation with limitless potential to revolutionise business and society (Ooi et al., 2023). Starting from the theoretical framework described previously, the proposed concept model approaches digital capabilities in the AI sphere through four classes of capabilities: human, collaborative, technical, and innovative. Considering the relationship between these sets of capabilities and the implementation of AI tools, we propose the following hypothesis:

Hypothesis 1 (H1): The more digital capabilities organisations possess, the more AI tools that will be implemented in organisational processes.

Simultaneously, a series of studies show the close relationship between organisational agility and internal organisational processes under the impact of the implementation of AI technologies. Roblek et al. (2022) showed that organisational agility is an ongoing process aimed at continuous improvement of an organisation's processes and operations (Roblek et al., 2022). Other researchers (Elazhary et al., 2023) believe that to support the relationship between digital capabilities and organisational agility, optimised business models and organisational structures are needed, as well as investments in IT systems, a process that involves costs and challenges specific to the implementation process. Chatterjee et al. (2021) emphasises the role of management in mediating the relationship between digital capabilities and organisational agility at a strategic level, by promoting an organisational culture based on change and dynamism. The implementation of AI tools in organisational practice plays a mediating role in the relationship between digital capabilities and the agility of internal processes. AI allows for the identification of redundancy at the operational process level and the identification of optimal solutions for the use of resources to improve performance (Olan et al., 2022). Simultaneously, through the unique specificity of these technologies, AI triggers fundamental changes that transform organisational processes in new ways (Issa, Jabbouri and Palmer, 2022). Therefore:

Hypothesis 2 (H2): The more organisations possess digital capabilities, the more agile their internal processes become.

Hypothesis 3 (H3): The implementation of AI tools in organisational processes mediates the relationship between digital capabilities and the agility of internal processes.

In relation to the external environment, Tomomitsu and de Oliveira Moraes (2022) show that organisational agility indicates the ability of the organisation to detect events and generate quick responses as a result of an optimised decision-making process. Therefore, according to the same study, organisational agility is structured into three main pillars: sensitivity, decision-making, and responsiveness. Another study (Bouanba, Barakat and Bendou, 2022)

showed that adopting AI techniques is a form of agile innovation that can optimise supply chain performance. Wang, Lin and Shao (2022) emphasise the positive correlation between the use of specific AI tools, particularly chatbots, and companies' agility in relation to external processes. At the same time, digital capabilities in the form of Business Intelligence (BI) infrastructure influence the competitive advantage and performance potential of the organisation (Wang et al., 2022). Another direction (Mikalef et al., 2023) in which AI-based digital capabilities give value to organisations in relation to the external environment is the development of business-to-business capabilities (B2B). Moreover, Denicolai, Zuccella and Magnani (2021) believe that the level of training of organisations in the field of AI positively influences the internationalisation process. Therefore, digitalisation in general and AI assimilation influence the main dimensions of organisational agility, as identified by Roblek et al. (2022), and are related to the external environment in the form of proactivity, change promotion, competitive advantage, or differentiation based on strategic thinking. Therefore:

Hypothesis 4 (H4): The more digital capabilities organisations have, the more agile they become in relation to changes in the external environment.

Hypothesis 5 (H5): The implementation of AI tools in organisational processes and internal agility mediates the relationship between digital capabilities and agility in relation to changes in the external environment.

Improving agility at the organisational level also results in improved agility in relation to changes in the external environment. In the field of marketing processes, Wang, Lin and Shao (2022) demonstrated the role of internal and external organisational agility in improving customer service performance through the use of AI technologies. Simultaneously, organisational agility facilitates the attraction, retention, and integration of knowledge to develop superior quality products in response to the appearance of new competitors (Cegarra-Navarro, Soto-Acosta and Wensley, 2016). Additionally, the impact of digital capabilities on organisational agility is high when associated with major market turbulence (Elazhary et al., 2023). Wang and Li (2023) show a positive correlation between digital and technological capabilities on the one hand, and digital innovation on the other, while social networks moderate this relationship. Other authors (Guo, Yin and Liu, 2023) show how cooperation positively affects innovation performance, while entrepreneurial agility and adaptive agility are factors that mediate this relationship. In this sense, strategic alliances play a critical role in the direction of continuous innovation and rapid adaptation to market changes (Van Tinde et al., 2022). Considering these aspects, the following hypothesis was formulated:

Hypothesis 6 (H6): The more agile the internal processes, the greater the agility of the organisation in relation to changes in the external environment.

The conceptual model to integrate the research hypotheses and constructs is presented in Figure no. 1.

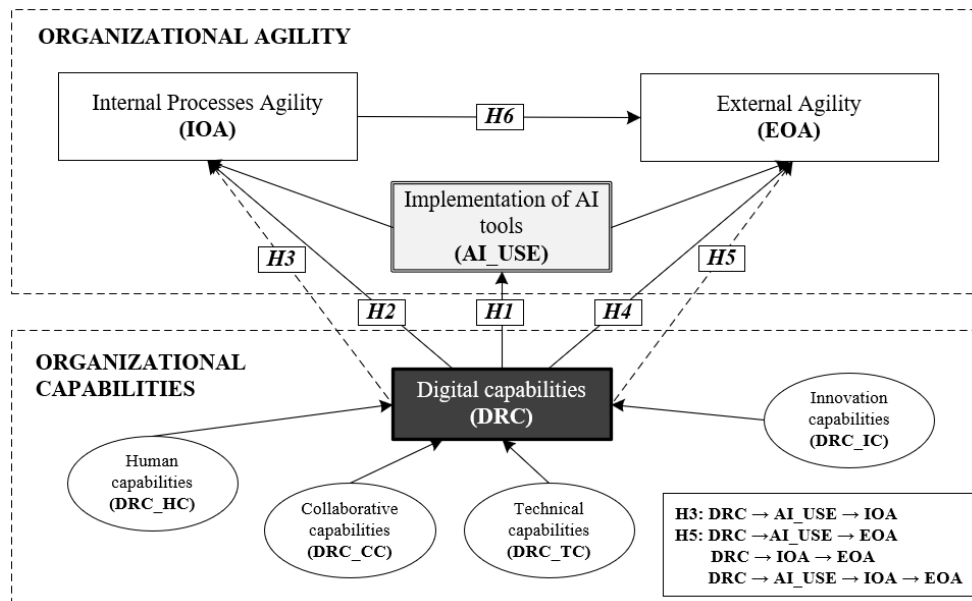


Figure no. 1. Conceptual model of AI implications on organisational agility

2. The methodological framework

The purpose of this research was to analyse the role of AI in leveraging an organisation's digital capabilities and the extent to which AI can amplify organisational agility, such as process agility and external agility, in response to external challenges. To achieve this goal, based on the consultation of specialised literature, a survey that used a questionnaire as a research tool was designed. The questionnaire consisted of questions measured using a 5-point Likert scale and included several scales specific to the variables in this research, as illustrated below.

- Digital capabilities (DRC) (Nasiri et al., 2020a): This scale aimed to analyse the digital capabilities of the analysed organisations and was made up of four subscales that included 13 items specific to the organisations' digital capabilities, human capabilities, capabilities collaboration, technical capabilities, and innovation capabilities.

- The implementation of AI tools (AI_USE) (Nasiri et al., 2020b; Wang, Lin and Shao, 2022; Ly, 2023) was assessed using 11 items constructed to determine both the extent to which AI is used in organisations and how organisations can transform under the influence of the use of AI tools (e.g., how the organisation uses AI to improve the quality of products/services, create a stronger network between different processes, improve its activities, etc.).

- Internal Process Agility (IOA) and External Organisational Agility (EOA) (Wendler, 2014; Cegarra-Navarro, Soto-Acosta and Wensley, 2016; Wang, Lin and Shao, 2022; Ly, 2023) were evaluated based on 14 and, respectively. Nine items aimed at assessing the measure in that an organisation has the ability to respond quickly to customer needs, adapt its products/services according to demand, has information technologies appropriate to its

needs, has employees capable of adapting to changes in the business environment, and how organisations adapt to external environmental challenges.

The scales were part of larger research (Popa et al., 2024), and the questionnaire was distributed through Google Forms between August and September 2023, addressing people employed in private or public sector organisations in Romania. A total of 232 responses were collected, of which 24 were removed because they were from people who were not employed or who did not agree to participate in the research. The final research sample included 208 respondents, 54.80% of whom were employed in a public sector organisation. Most of the respondents were women (51.10%), came from organisations with more than 250 employees (59.10%), and held executive positions within the organisation (67.30%).

Structural equation modelling was used to represent the relationships proposed through the conceptual model and to evaluate the research hypotheses. This approach allows us to explain the variance in internal and external organisational agility by maximising the coefficients of determination and minimising error terms, as well as quantifying the contribution of digital capabilities and AI tools. On the other hand, it can be assumed that various characteristics of organisations, AI users, and several external environmental factors could constitute sources of heterogeneity in the dataset (observed heterogeneity). However, other sources of heterogeneity can even come from the way the structural relationships between the constructs are specified; they cannot be identified a priori, but only after estimating the model (unobserved heterogeneity) (Khatri et al., 2023).

Therefore, to highlight whether the relationships between digital capabilities, the use of AI tools, and organisational agility can be considered homogeneous or whether groups can be identified for which these relationships manifest differently, a sequence of two available procedures is available in the PLS-SEM application (FIMIX-PLS and PLS-POS). Therefore, the five stages proposed by Hair et al. (2023) were followed: (1) running the FIMIX-PLS procedure to determine whether the dataset is homogeneous and (if not) (2) what is the number of segments (homogeneous groups) to retain; (3) running PLS-POS to improve the solution provided by FIMIX-PLS and maximise the variance explained by the segmentation solution; (4) explaining the latent structure of the segments by means of variables with managerial implications (ex-post analysis) and (5) analysis of the resulting patterns for each segment, including significant differences between their parameters, by means of multigroup analysis (MGA).

3. Results

3.1. Model evaluation and research hypothesis testing

To represent the relationships proposed in the conceptual model and evaluate the research hypotheses, a PLS-SEM model was built. As recommended (Hair Jr. et al., 2017), the measurement model was assessed for reliability, convergent validity, and discriminant validity. More specifically, the reliability (Table no. 1) was analysed using the Cronbach Alpha coefficients, ρ_a and ρ_c , obtaining values above the recommended limit of 0.70 (Hair Jr. et al., 2017). Convergent validity was evaluated through outer loads and AVE, with values greater than 0.708 and 0.50, respectively (Hair Jr. et al., 2017; Hair et al., 2019).

Table no. 1. Assessing the fidelity and validity of the measurement model

Construct	External loads	Cronbach Alpha	Rho_a	Rho_C	AVE
DRC_HC	0.908 - 0.938	0.909	0.911	0.943	0.846
DRC_CC	0.877 - 0.923	0.895	0.896	0.935	0.827
DRC_TC	0.910 - 0.944	0.943	0.943	0.959	0.855
DRC_IC	0.905 - 0.934	0.915	0.919	0.947	0.855
DRC	0.873 - 0.931	0.964	0.964	0.968	0.697
AI_USE	0.775 - 0.940	0.978	0.978	0.980	0.820
IOA	0.855 - 0.907	0.976	0.976	0.978	0.764
EOA	0.893 - 0.933	0.975	0.976	0.978	0.835

Notes: rho_c: coefficient of internal consistency; rho_a: adjusted internal consistency coefficient; AVE: average variance extracted.

Furthermore, discriminant validity was analysed using the Fornell–Larcker criterion (Table no. 2), showing that the “square root” of the AVE of each latent variable was greater than the correlations between the latent variables (Hair et al., 2019). Based on these results, it can be concluded that the final measurement model was reliable and valid.

Table no. 2. Evaluation of discriminant validity – Fornell-Larcker criterion

Construct	AI_USE	DRC_CC	DRC_HC	DRC_IC	DRC_TC	EOA	IOA
AI_USE	0.905						
DRC_CC	0.584	0.910					
DRC_HC	0.620	0.856	0.920				
DRC_IC	0.577	0.727	0.651	0.925			
DRC_TC	0.555	0.769	0.690	0.870	0.924		
EOA	0.549	0.679	0.719	0.574	0.595	0.914	
IOA	0.547	0.660	0.727	0.586	0.629	0.902	0.874

The structural model was evaluated with respect to collinearity, coefficient of determination of endogenous constructs (R^2) and significance of the path coefficients (Hair et al., 2019). Therefore, collinearity was analysed using variance inflation factor (VIF) values below the recommended value of 3 (Hair et al., 2019). Regarding R^2 , DRC can explain 41.10% of AI_USE variance ($R^2 = 0.411$), DRC and AI_USE together can explain 52.50% of IOA variance ($R^2 = 0.525$), and all together 82.20% of the EOA variance ($R^2 = 0.822$). At the same time, with one exception, all path coefficients were statistically significant, while an SRMR value of 0.067 indicated a good model fit.

Regarding direct effects (table no. 3), it can be seen that DRC positively influences AI_USE ($\beta = 0.641$; $p < 0.001$; $f^2 = 0.699$), IOA ($\beta = 0.620$; $p < 0.001$; $f^2 = 0.476$) and EOA ($\beta = 0.096$; $p < 0.05$; $f^2 = 0.021$), providing support for hypothesis H1, H2 and H4. At the same time, IOA positively influences EOA ($\beta = 0.810$; $p < 0.001$; $f^2 = 1.731$), the hypothesis H6 being supported. The indirect effects indicate that AI_USE complementarily mediates the relationship between DRC and IOA, supporting H3. At the same time, AI_USE and IOA determine the existence of a multiple (Cepeda-Carrion, Nitzl and Roldán, 2018) and positive mediation in the relationship between DRC and EOA, supporting H5.

Table no. 3. Testing the research hypotheses

Hypotheses	Relations	Beta	SE	T statistic	BCCI	f ²
H1	DRC → AI USE	0.641***	0.045	14.403	0.560-0.707	0.699
H2	DRC → IOA	0.620***	0.059	10.478	0.516-0.711	0.476
H3	DRC → AI USE → IOA ^a	0.096*	0.048	2.008	0.020-0.176	-
H4	DRC → EOA	0.096*	0.052	1.864	0.019-0.189	0.021
H5	DRC → AI USE → EOA ^a	0.028	0.022	1.242	-0.011-0.064	-
	DRC → IOA → EOA ^a	0.502***	0.056	9.012	0.411-0.593	-
	DRC → AI USE → IOA → EOA ^a	0.078*	0.038	2.033	0.016-0.141	-
	DRC → EOA ^b	0.607***	0.049	12.476	0.527-0.686	-
H6	IOA → EOA	0.810***	0.044	18.515	0.731-0.876	1.731

Notes: ^a – specific indirect effects; ^b – total indirect effects; *** - $p < 0.001$; * - $p < 0.05$; BCCI – Bias Corrected Confidence Interval; f²- Effect size.

3.2. Highlighting the unobserved heterogeneity

The FIMIX-PLS procedure was performed in the first step to identify and characterise specific segments. The decision on the number of segments to be retained was based on an examination of the fit indices and the size of the resulting segments for partitions that included one to four segments. The partition range was narrowed by retaining those with two and three segments, which were greater than the number indicated by the MDL and less than the BIC (Hair et al., 2023). However, considering that the three-segment solution also included one that represented less than 10% of the cases, it was decided to retain the two-segment solution in the next stage. The final partition resulting from FIMIX-PLS was adopted as input to PLS-POS with the aim of identifying segments that are sufficiently distinct in terms of the relationships between the latent constructs and for which the weighted sum of R^2 was maximised. The obtained result presented for all constructs weighted sums of the weighted R^2 superior to the single-segment solution, which supports the unobserved heterogeneity regarding the implications of the use of AI tools in Romanian firms (AI_USE: 0.479 compared to 0.411, IOA: 0.730 compared to 0.525 and 0.830 compared to 0.822 for EOA).

The final partition, resulting from PLS-POS, includes two segments, whose relevant characteristics are presented in Table no. 4. Although there are minimal differences in terms of DRC, IOA, and EOA, the only significant difference between latent construct scores was identified for AIS_USE ($t = 3.489$, $p < 0.001$), suggesting that Segment 1 includes respondents who make greater use of AI tools. Regarding the demographic variables, the two segments differ only with respect to seniority in the organisation, the respondents included in the first segment having more work experience ($t = 2.450$, $p < 0.05$).

Table no. 4. Characterisation of segments

Construct	Segment 1 (N = 154)		Segment 2 (N = 54)		t-statistic
	Mean	Std. Dev.	Mean	Std. Dev.	
AI_USE	3.181	1.152	2.550	1.106	3.489***
DRC	3.733	0.968	3.756	0.965	-0.149
EOA	3.600	1.080	3.507	0.986	0.290
IOA	3.587	1.063	3.559	0.852	0.177
Seniority in the organisation	12.071	10.621	8.111	8.958	2.450*
Age	40.799	12.452	37.741	12.220	1.560

Notes: *** - $p < 0.001$; * - $p < 0.05$

To characterise the two segments resulting from PLS-POS in terms of the relationships between the latent constructs, a multigroup analysis (PLS-MGA) was conducted, and the results are presented in table no. 5. As can be seen, the path coefficients are significantly higher for the cases assigned to segment I, both in terms of the direct relationships involving AI_USE (DRC → AI_USE and AI_USE → IOA) and the indirect ones.

Table no. 5. Multigroup Analysis

	Relations	Segment 1	Segment 2	$\Delta\beta_{(S1-S2)}$
Direct effects	DRC → AI_USE	0.789***	0.269*	0.519***
	DRC → IOA	0.376***	0.565***	-0.189
	DRC → EOA	0.019	0.167*	-0.148
	AI_USE → EOA	0.128*	0.112	0.017
	AI_USE → IOA	0.556***	-0.693***	1.249***
	IOA → EOA	0.790***	0.860***	-0.071
Indirect effects	DRC → AI_USE → EOA	0.101*	0.030	0.071
	DRC → AI_USE → IOA	0.438***	-0.187	0.625***
	DRC → AI_USE → IOA → EOA	0.346***	-0.161	0.507***
	DRC → IOA → EOA	0.297***	0.486***	-0.189
	AI_USE → IOA → EOA	0.439***	-0.597***	1.036***

Notes: *** - $p < 0.001$; * - $p < 0.05$

4. Discussions

The aim of this study was to highlight the role of AI technologies in capitalising on the digital capabilities of organisations so that they become more agile from the perspective of internal processes and in relation to the challenges of the external environment.

The results highlight that the more organisations have digital capabilities related to human capabilities, collaboration capabilities, technical capabilities, and innovation capabilities, the more they use AI to transform the organisation to improve the activities and processes of the organisation, in order to improve the quality of products and/or services and customer relations, and in the development of new applications to support the performance of activities. Moreover, the results also show that the existence of digital capabilities at the level of organisations also leads to the improvement of the internal agility of the organisation, to the increase in its ability to adapt to the needs of customers, fluctuations in demand, to implement information technologies appropriate to its needs, etc., but also to its external agility (i.e., improving the organisation's ability to respond quickly to changes in the market). Previous research has shown that organisational agility is also correlated with the level of trust, attitude, and behavioural intention to adopt AI (Chatterjee et al., 2021). Cegarra-Navarro, Soto-Acosta and Wensley (2016) consider that organisational performance depends on preexisting organisational agility, while Elazhary et al. (2023) argue that the relationship between IT governance and organisational agility is mediated by IT and innovation capabilities. Based on the direct effects obtained, it is important to underline that the agility of the internal processes of organisations positively and significantly influences the external agility of organisations. Therefore, the more agile an organisation is in terms of organisational processes, the more agile it will become in relation to changes in the external environment.

However, the results of empirical research also indicated that the use of AI tools at the level of an organisation, and AI transformation, mediates the relationships between digital

capabilities and the agility of internal processes within the organisation, while the use of AI tools together with the agility of internal processes positively mediates the relationship between digital capabilities and the organisation's agility in relation to changes in the external environment. Other research has shown the positive correlation, direct or indirect, between IT capabilities and organisational agility (Tomomitsu and Moraes, 2021), but also the fact that organisational agility is a permanent process aimed at the continuous improvement of an organisation's processes and operations (Roblek et al., 2022). At the same time, the intention to adopt AI is based on a number of significant predictors specific to the external environment, such as market dynamics or competitive pressure (Gupta et al., 2022).

The use of PLS-SEM together with PLS-POS analysis allowed the discussion to expand on the implementation of AI tools for organisational transformation and their use across organisations. Therefore, the results highlighted the existence of two segments. Segment I, which is characterised by a greater use of AI tools at the organisation level and the existence of respondents with greater work experience. Moreover, it is relevant to emphasise that the values of the path coefficients obtained for Segment 1 were significantly higher than those of Segment 2, both in terms of the direct relationships involving the implementation of AI tools, but also the indirect ones. Specifically, direct effects show that organisations that are characterised by a higher use of AI tools and by staff with a longer tenure, the existence of digital capabilities positively and significantly influences the implementation of AI tools and internal agility. The influence of employees' experience in using AI tools, on the development of digital capabilities, is also highlighted by a series of previous research. Knowledge sharing within AI environments facilitates increased job satisfaction and employee engagement (Malik et al., 2021), while stimulating the acquisition of new AI skills and increasing confidence in these technologies (Chowdhury et al., 2022). Wang and Li (2023) define digital capabilities as the ability of businesses to understand, apply, and use new generations of digital technologies based on AI, cloud computing, or big data. At the same time, the implementation of AI tools directly influences the internal and external agility of organisations and positively mediates the relationship between digital capabilities and organisational agility, both internal and external.

On the other hand, for Segment 2, characterised in particular by a lower use of AI tools within organisations, it is observed that the existence of digital capabilities positively and significantly influences the internal and external agility of organisations. However, the use of AI tools has negative and significant effects on the agility of internal processes of organisations, and negatively and significantly influences, through internal agility, the organisation's agility in relation to changes in the external environment.

Based on the multigroup analysis, it is also observed that there are statistically significant differences between the two segments. These significant differences are related to the direct relationships between digital capabilities and the implementation of AI tools, and between the implementation of AI tools and the agility of internal processes, but also to the indirect relationships related to the implementation of AI tools.

Conclusions

This research aimed to highlight the role of the implementation of AI tools, which determines the transformation of the organisation, in leveraging the digital capabilities of organisations, so that they become more agile from the perspective of internal processes and in relation to

the challenges of the external environment. The main results showed that the digital capabilities of organisations positively influence both the implementation of AI tools and the internal and external agility of organisations. Moreover, the results also illustrated the fact that the implementation of AI tools and, respectively, the transformation of the organisation under the influence of AI mediated the relationships between the organisation's digital capabilities and the agility of internal processes, but also between these capabilities and the organisation's agility in relation to changes in the external environment.

The theoretical contributions of the research result from the fact that a conceptual model is proposed that links organisations' digital capabilities and the implementation of AI tools with their internal and external agility, providing empirical evidence on the direct and indirect relationships between these variables. Research also brings more knowledge on niche concepts, such as AI capabilities, AI transformation and organisational agility, less addressed in the specialised literature as an area of impact of AI technologies. Methodological contributions can be highlighted by the simultaneous use of PLS-SEM and PLS-POS analysis, which allowed the discussion to expand on the implementation of AI tools for organisational transformation and their use at the organisational level.

The managerial contributions of the research include possible directions of intervention, outlined both in the sphere of the regulatory system and public policies, as well as at the level of companies. Therefore, in macroeconomic terms, the structuring of the AI capabilities system through the human, collaborative, technical and innovation components, as well as the analysis of the capabilities revealed to increase the degree assimilation of AI tools, constitute relevant information for decision-makers in order to substantiate public policies aimed at this field of activity. Public policies in areas such as the regulation of occupational standards for professional categories that currently use AI solutions, the financing of the research and development sector to emphasise the innovation component at the enterprise level, or the development of the education system by integrating AI-related skills can be included here (Popa et al., 2024). At the level of the business environment, the managerial contributions of the paper aim at two levels. First of all, the study of correlations between digital capabilities and internal processes, under the influence of the use of AI technologies, allows the calibration of process organisation elements, the optimisation of business processes by integrating AI tools and the improvement of process agility, resulting in faster adaptation to the challenges of the external environment. Second, by modeling the relationship between digital capabilities and external processes, practical solutions are provided to improve the relationship between the organisation and stakeholders using AI tools. Increasing the degree of use of AI technologies at the level of marketing or customer relations processes, for example, allows a much deeper understanding of the market but also a more realistic anticipation of external developments, thus ensuring the increase in the accuracy of company strategies and policies.

The novelty of the analysed field generates a series of research limits. The lack of a formalised regulatory framework for relevant AI skills and capabilities at the level of different economic sectors or professional categories limited the possibility to focus on a more relevant research population. Furthermore, considering the still early stage of assimilation of AI technologies at the organisation level, the responses provided after the application of the questionnaire may be affected by the possible lower familiarity of respondents with the AI issue as a result of the lack of experience with it. In view of a higher accuracy of managerial contributions, future research directions could focus on analysing the impact of AI use on organisational

performance in terms of specific process classes, such as marketing, supply chain management, or customer relations. Equally, investigating behavioural and attitudinal aspects of human-AI interaction could highlight new managerial implications.

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