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ORGANISATIONAL AND INDIVIDUAL DETERMINANTS OF HUMAN-AI COLLABORATION

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ABSTRACT

The article examines organisational and individual factors influencing employees' openness to collaborating with artificial intelligence (AI). The adopted understanding of "collaboration" refers to current practices in this field, where distinctions between human persons and AI are blurring. The study concerns the determinants of readiness to work within a hybrid, biological-silicon cooperation network.

The theoretical framework draws on socio-technical systems theory, the socio-cognitive model of trust (SCMT), task-technology fit theory (TTF), and self-determination theory (SDT), which enabled a multidimensional analysis of attitudes towards AI. The research data consisted of survey results covering organisational practices, respondents' personal attitudes and beliefs regarding digitalisation and work organisation, and their digital competencies. Three complementary methods were applied: exploratory factor analysis, cluster analysis, and linear regression, analysing responses from 614 respondents.

The results revealed a difference between the strength of influence on openness to AI of individual factors - personal attitudes, beliefs, and digital competencies - and organisational factors. The bidirectional influence of formalisation on openness to AI was also confirmed.

For the presented research, an original concept of "openness to AI collaboration" was developed, encompassing readiness to accept AI in a relatively broad range of organisational roles. In this regard, the study offers new insight into the conditions for an effective human-AI relationship.

Based on the findings, recommendations were formulated for business practitioners interested in the effective implementation of AI.

KEY WORDS

organisational culture, digitalisation, artificial intelligence, digital competencies, formalisation

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INTRODUCTION

Applications of artificial intelligence (AI) in business are not new. The first experiments with advisory systems using knowledge representation in the form of conditional "if-then" statements date back to the

1950s. In the 1980s and 1990s, solutions based on machine learning and neural networks began to appear (Diao, 2024). However, the rapid development of AI occurred after 2000, driven by key technologies such as big data, cloud computing, machine learning, and deep learning, as well as the spread of the internet amid rapid increases in hardware availability and

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computing power. AI, on the one hand, is part of the business digitalisation process; on the other, it defines the next phase of this process (Bharadiya et al., 2023). The potential to generate value for companies is considered a breakthrough for businesses worldwide and across various sectors (Enholm et al., 2022). According to research conducted by MIT Sloan Management Journal and The Boston Consulting Group among managers and board members, nearly 85% of them were convinced that AI would allow their companies to gain or maintain a competitive advantage, and 75% stated that AI would allow them to start activities in a new area of operation. At the same time, fewer than 39% of companies had an AI strategy, and only 5% considered their AI use practices intensive (Kane et al., 2016).

While AI offers potential for business development that managers appreciate, its practical use encounters several barriers. AI capabilities go beyond simply automating activities. The generative potential of AI enables the development of innovative products, the individualisation of consumer experiences, and the improvement of decision-making processes. However, we still have incomplete knowledge of the potential of these capabilities (Edilia & Larasati, 2023). Moreover, the biggest problem is not the technical complexity of AI but the resistance and lack of trust among employees towards the implementation of complex cognitive functions by machines (Yap et al., 2024; Łapińska et al., 2021).

This study aims to examine the conditions conducive to the acceptance of AI not as a tool but as a partner in the work process. Identifying such factors can improve the effectiveness of AI applications in organisational practice by explaining the conditions for building employee trust in AI. This understanding is essential for shaping employees' readiness to collaborate with an intelligent, eloquent nonhuman participant in communication and decision-making processes.

The remainder of the article is structured as follows. Section 1 presents the literature review and theoretical background of human-AI collaboration, with particular attention to the architecture of human-AI relationships and the concept of openness to AI collaboration. Section 2 describes the research method, including the research design, sample characteristics, measurement approach, and analytical procedures. Section 3 presents the empirical results obtained through exploratory factor analysis, cluster analysis, and linear regression. Section 4 discusses the findings in relation to the theoretical framework and

previous studies, highlighting the role of organisational and individual determinants of openness to AI collaboration. The final section provides conclusions, practical recommendations, limitations of the study, and suggestions for future research.

1. LITERATURE REVIEW

1.1. HUMAN-AI COLLABORATION

The cognitive capabilities of AI make its implementation in organisational practice a special aspect of digitalisation (Schildt, 2022). Research on human-AI collaboration has been grounded in Technology Acceptance Models (TAM) and their extensions (TAM2, TAM3, UTAUT, UTAUT2) (Jain et al., 2022). However, the anthropomorphism, sophistication, and potential of AI lead employees to develop a specific bond with products of this kind, which is clearly more emotionally charged than with other IT solutions. Therefore, studying human-AI collaboration required a more complex model than technology acceptance models (Xu et al., 2025). The following theoretical foundations of the conducted research can be identified:

1. Socio-technical systems theory. This theory provided a theoretical basis for examining the roles of knowledge-sharing practices, AI-related skills, and organisational role definitions in the effectiveness of AI collaboration.

2. Socio-Cognitive Model of Trust (SCMT). A fundamental factor influencing the decision to delegate tasks to AI is trust in this technology. The systemic model of mutual trust building in human teams offered by the SCMT explains trust development as a process encompassing trust attitudes, trust decisions, and trust acts (Wen et al., 2025). Extending the applications of this model to the domain of human-AI collaboration allows for the analysis of perceived credibility, cognitive trust, affective trust, and trust-related behaviours in such relationships (Georganta & Ulfert, 2024).

3. Social presence theory. This theory allows for the examination of the degree to which, in a given relationship, a person feels they are interacting with another person rather than operating a tool. This perception influences engagement in teamwork, willingness to rely on the team, and motivation to contribute one's own effort.

4. Task-Technology Fit (TTF). This theory examines the fit between task characteristics and AI

capabilities. It also considers user competencies. Such a comparison provides a basis for forecasting the effectiveness of AI applications and formulating recommendations for AI design that account for the characteristics of tasks to be entrusted to it (Nostrati et al., 2025). Current research considers TTF theory in conjunction with technology acceptance theories TAM/UTAUT and trust (Sha et al., 2025). A high degree of technology-task fit positively influences perceived usefulness and, through high-quality results, user trust.

5. **Neural-Adaptive AI Leadership Model.** This concept serves to model AI applications in leadership. AI handles the algorithmic side of management processes, including data analysis, priority setting, and risk assessment (Riti et al., 2025). The leader utilises these recommendations while considering ethical values, social consequences, and legal implications. This theory focuses on algorithm tuning and modelling the boundaries of AI autonomy.

6. **Psychological theories.** Self-Determination Theory (SDT) highlights the role of human needs, such as autonomy, competence, and relatedness, in motivating collaboration with AI and evaluating its outcomes (Faas et al., 2024). Regulatory focus theory and job crafting draw attention to two tactics of AI use - one oriented towards development, growth, and the exploitation of opportunities, and the other oriented towards safety, loss avoidance, and error prevention (He & Zhao, 2025). Cognitive load theory provides the basis for analyses of the impact of mental workload and attention on the quality of human-AI collaboration (Mollah & Kudapa, 2022).

7. The literature also features models and frameworks that emphasise the role of adaptive human-AI collaboration, such as the Human-AI Collaboration Model (Mahajan, 2025) and the ACT cycle framework, which focuses on dialogue and trust (Hall et al., 2025).

1.2. ARCHITECTURE OF HUMAN-AI RELATIONSHIPS

The directions and concepts of research outlined above lead to the conclusion that the actual use of AI potential at the level of teams, organisations, or the economy as a whole would require authentic integration of human persons and AI. Authenticity is understood as intellectual understanding, as well as trust, emotional engagement, and a shared value system. For such deep integration and engaged interaction to actually exist, a synergy of two processes is required:

the implementation of high-quality AI tools and employees' readiness to adopt a partnership attitude towards AI. The research presented in this study focuses on the second of these. Its aim is to empirically identify factors influencing employees' attitudes towards AI. The study considered selected organisational and individual factors. These include:

1. **Digital culture of the organisation.** Digitalisation leads to a profound transformation and improvement of the organisation (Warner & Wäger, 2019). Alongside the technical, organisational, and strategic components, these changes are accompanied by a transformation of organisational culture. It is both a result of the implemented changes and a factor determining the dynamics, effectiveness, and coherence of the broadly understood digital transformation process (Vial, 2019). Digital culture has its specificity. It is a set of values, beliefs, and practices that favour the adoption of digital technologies in conditions of dynamic change. It highly values learning, knowledge sharing, and relatively high autonomy of individuals and teams (Panasiewicz & Myśliwiecka, 2023).

2. **Leadership.** Leaders' role in organisational digitalisation is key (Malik et al., 2025). Proper leadership supports the formation of a digital organisational culture and influences employees' attitudes towards digitalisation (Gilli et al., 2024,).

3. **Digital skills.** This issue relates to the technical aspect of digitalisation within the organisation's IT. It includes physical resources: hardware, networks, data centres, software and systems, as well as the technical competencies of employees. Given the widespread availability of hardware and software, the latter component has become a key factor in the effectiveness of organisational IT (Obermayer et al., 2022), as well as a key factor influencing employee attitudes towards AI (Bharti et al., 2026). The diversity and pace of IT development mean that (at least) two types of competencies can be distinguished: IT user and IT specialist. User competencies focus on the ability to use technology, while a specialist can design and implement IT system architecture or develop software. The areas of these competencies are not disjoint but overlap. The high availability of IT knowledge means interested users may have highly specialised knowledge in this field.

4. **Personal attitude towards digitalisation.** Attitude is a relatively permanent set of feelings, beliefs, and tendencies towards certain behaviours towards specific people, groups, or ideas (Baron & Byrne, 1984). Attitude includes three components: cognitive (beliefs), affective (feelings), and conative

(behaviours) (Jain, 2014). A positive attitude is associated with commitment to the subject of the attitude (Rogozińska-Pawelczyk, 2014). Commitment can concern the organisation as a whole; it can be limited to a selected part of it (Becker & Billings, 1993), and it can also concern professional work (Sungu et al., 2019). The research presented focused on attitudes towards digitalisation. Commitment affects work efficiency (Sungu et al., 2019). In the case of digitalisation, it will be expressed by paying special attention, time, and effort to the use of digital tools in one's professional work.

5. Formalisation. The inclusion of the issue of formalisation in the research stems from its potentially bidirectional impact on the process of enterprise digitalisation, including the degree of acceptance of AI. The characteristics of digital culture are intensive human communication and cooperation, creativity, innovation, and initiative (Pradana et al., 2022). These are features of a post-bureaucratic organisation (Pesch et al., 2021), in which activity coordination occurs based on processes other than formalisation. On the other hand, formalisation can make the implementation of a specific project more effective, and such a project is digital transformation itself (Pesch et al., 2021).

The degree of AI acceptance as a partner in the work process represents the construct of "openness to AI collaboration". It constitutes a result of the respondent's assessments of readiness to recognise the following three AI roles:

1. Everyday co-worker. Acceptance of AI as an everyday co-worker indicates readiness to treat AI as

a full-fledged participant in the organisation, partners in problem-solving processes, decision-making, and task execution (Georganta & Ulfert, 2024; Siemon, 2022).

2. Advisor or supervisor. Acceptance of AI as an advisor or supervisor signifies readiness to genuinely subordinate one's own actions to AI's arguments and recommendations. Research indicates that AI recommendations function as powerful semiotic signals that direct users' cognitive, affective, and pragmatic dimensions, leading to noticeable changes in their behaviour and choices (Arkhipova, 2024; Liel & Zalmanson, 2025).

3. Planner. AI technologies support decision-making processes across a broad spectrum of sectors: business, healthcare, administration, and finance (Khan & Ambadekar, 2024). Acceptance of AI as a planner is conditional (Paul et al., 2024; Khan, 2025) and indicates consent for AI systems to co-decide on goals, action sequences, and resource allocation, signifying a high level of trust in AI's cognitive capabilities.

The characteristics of the studied AI roles are presented in Table 1.

The studied "openness to AI collaboration" has a broader scope than related concepts presented in the subject literature:

1. Technology acceptance, derived from TAM/UTAUT theory, concerns perceived usefulness and ease of use and presupposes an exclusively instrumental treatment of AI.

2. Trust in AI, as considered within the socio-cognitive model of trust (SCMT), encompasses the

Tab. 1. Characteristics of dependent variables

NO.	AI ROLE	VARIABLE NAME	RESEARCH STATEMENT	THE DEGREE OF ACCEPTANCE INDICATES
1.	Everyday collaborator	AI as a partner	I am ready to recognise artificial intelligence as a full-fledged partner in the problem-solving and decision-making process.	Openness to working in a mixed network of relationships, connecting biological persons and AI on equal terms.
2.	Advisor or supervisor	Acceptance of AI influence on the course of work	I am ready to change the way I perform my professional tasks under the influence of arguments and recommendations from artificial intelligence.	Readiness to give AI high trust, expressed by changing personal decisions regarding the direction and content of performed activities.
3.	Planner	AI as a planner	I am ready to implement plans and tasks even when I know that their author is an artificial intelligence.	High trust of the respondent in the cognitive abilities of AI, consisting of the ability to analyse the current situation and generate practical action plans.

Source: authors elaboration.

cognitive and affective aspects of the relationship with technology but does not account for readiness for partnership-based collaboration.

3. AI readiness is an organisational construct, referring to infrastructure, resources, and institutional capabilities (Jöhnk et al., 2021), rather than a personal one, and does not encompass personal values, emotions, or the employee's sense of professional identity.

In contrast, the three AI roles merged into "openness to AI collaboration" delineate an area covering the full continuum of interaction - from utilising AI as a tool to subordinating oneself to it, as well as the full span of the decision-making horizon: from operational to strategic. Only the variant of complete replacement of the human was omitted, as it falls beyond the scope of the present study.

"Openness to AI collaboration" and the individual components of the construct serve as the study's dependent variables.

2. RESEARCH METHODS

The research aims to identify the conditions conducive to accepting AI as a partner in the work process. The influence of organisational and individual factors on employee attitudes towards AI will be studied. 43 detailed variables were included, divided into five previously discussed groups:

- digital culture (12 variables),
- leadership (4 variables),
- digital skills (10 variables),
- personal attitude towards digitalisation (9 variables),
- formalisation (8 variables).

The study used the diagnostic survey method and an original research questionnaire. Respondents rated the survey statements using a five-point Likert scale. The questionnaire also included 11 demographic questions.

The research was conducted via an online survey in February 2025. The condition for including responses in the research set was meeting two criteria: current professional activity carried out for at least $\frac{3}{4}$ of a full-time position and work experience in the current place of employment of not less than two years. The imposition of these restrictions resulted from the desire to obtain responses from people whose experiences in the field of participation in digital transformation are current and have been shaped by continuity of experience for at least two

years. Six hundred fourteen complete responses were obtained that met the above criteria simultaneously. The respondents were people of different genders and ages, employed in different industries, positions, and organisations of different sizes. The influence of these factors on openness to AI collaboration was not the focus of the discussed research. The following quantitative analysis tools were used in the analysis:

1. Exploratory factor analysis enables the identification of hidden dimensions that explain observed changes in variable values (Yong & Pearce, 2013), thereby helping to interpret relationships and patterns among the studied variables (Yong & Pearce, 2013).

2. Cluster analysis enables classification of responses based on the degree of openness to AI collaboration. Three variables jointly indicate the nature of this attitude, and cluster analysis allows them to be considered simultaneously (Hair et al., 2019).

3. Linear regression enables the examination of the relationships between the explained dependent variable and a set of explanatory independent variables (Biecek, 2013), thanks to which it becomes possible to more fully and precisely understand the relationships between these variables (Biecek, 2013; Hair et al., 2019). The results were refined using the Akaike Information Criterion (AIC). This criterion aims to minimise the number of explanatory variables (Yamashita et al., 2007), thereby allowing the identification of key explanatory variables affecting respondents' openness to AI collaboration, as represented by three dependent (explained) variables.

Thus, the procedure structure presented below was divided into three stages. In developing the results, the following weights were assigned to response options on the Likert scale: definitely not: -2; rather not: -1; hard to say: 0; somewhat yes: 1; definitely yes: 2.

3. RESEARCH RESULTS

The first stage of the study involved conducting an exploratory factor analysis to identify latent factors underlying the data variability. The data set was inspected using the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests (Howard, 2016, p. 52). Both tests showed the possibility of applying exploratory factor analysis to the respondents' answers. A KMO value of 0.958 was obtained, while values above 0.9 are assessed as excellent. Bartlett's test allowed the rejection of the hypothesis of no correlation between

Tab. 2. Characteristics of distinguished factors

FACTORS 1-3			
INTERPRETATION - FACTOR NAME	LEVEL OF DIGITALISATION OF THE ORGANISATION	LEVEL OF FORMALISATION OF THE ORGANISATION	OPENNESS TO AI COLLABORATION
VARIABLES	• seeking and testing new, useful digital tools • using AI • presence of plans for AI application development • digital nature of internal communication and cooperation • increase in digitalisation of products/services • using AI and ML-based DSS • IT support practices	• strictness and unambiguity of organisational solutions • clarity and unambiguity of goals • clear rules regarding team composition • work in accordance with applicable procedures	• AI as a partner • acceptance of AI influence on the course of work • AI as a planner
% OF EXPLAINED VARIANCE	7.983	2.612	2.520
CRONBACH'S ALPHA	0.895	0.776	0.871
FACTORS 4-6			
INTERPRETATION - FACTOR NAME	ENGAGEMENT IN KNOWLEDGE FLOW	IT COMPETENCIES	BELIEFS REGARDING PLANNING AND HIERARCHY
VARIABLES	• sharing knowledge with colleagues • promoting ideas in the field of digitalisation • interest in novelties in terms of implementation possibilities	• knowledge of programming languages • ability to independently train AI • career plans in IT • formal education in IT	• belief in the importance of planning • impact of hierarchy on operational efficiency • role of planning in innovation efficiency
% OF EXPLAINED VARIANCE	2.941	3.643	1.685
CRONBACH'S ALPHA	0.834	0.855	0.745

Source: author's elaboration.

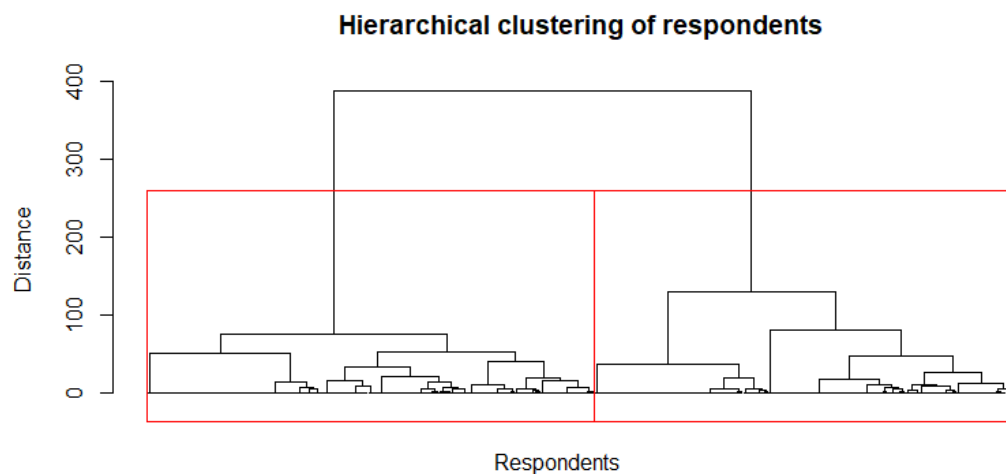


Fig. 1. Dendrogram of clusters distinguished according to the criterion of openness to AI collaboration

Source: author's elaboration.

Tab. 3. Characteristics of clusters distinguished due to respondents' openness to AI collaboration

VARIABLE CLUSTER	AI AS A PARTNER	ACCEPTANCE OF AI INFLUENCE ON THE COURSE OF WORK	AI AS A PLANNER
1. "Enthusiasts"	0.76	0.94	0.85
2. "Sceptics"	-0.79	-0.5	-0.73

Source: author's elaboration.

the variables at the 95% confidence level. Six factors were distinguished based on the scree plot and eigenvalue analysis. Such a model explains 47.5% of the variance in the data. The distinguished factors are characterised by good (Cronbach's $\alpha > 0.8$) or at least acceptable ($0.8 > \text{Cronbach's } \alpha > 0.7$) reliability. The first two factors characterise the organisation, and the remaining four characterise the respondent: their views on work organisation and AI, engagement in knowledge flow, and the level of IT competencies. A detailed presentation of individual dimensions is contained in Table 2.

As shown, the variables adopted in the research assumptions as indicators of openness to AI collaboration (Table 1) formed a single dimension (Table 2). This dimension was used as a criterion for distinguishing clusters of responses. The most precise results were obtained using Ward's method. Using the Caliński-Harabasz index (1974), it was found that the data set should be divided into two clusters. This data set structure is also confirmed by the dendrogram image shown in Figure 1.

The profiles of the clusters are presented in Table 3. Unambiguous differences in the arithmetic mean values for individual clusters allow interpreting them as: (1) the cluster of "enthusiasts" open to collaboration with AI, and (2) the cluster of "sceptics" maintaining a considerable distance from AI. The size of both groups is very similar.

At the next stage of the research procedure, the dimensions identified using factor analysis were used to analyse the relationship between clusters. Charts illustrate these relationships (Fig. 2-6).

MANOVA analysis showed a relatively low value of Wilks' statistic (0.35738) and a very high value of F (181.91), indicating a systematic and significant difference between clusters. This refers to the differences in arithmetic mean values for individual dimensions of both clusters.

These differences are also highly statistically significant ($p < 2.2e-16$). The systemic and statistically significant differences between clusters were also confirmed by ANOVA and Tukey's post hoc tests. At

the same time, these differences are noticeable across two size classes. In addition to the studied dimension, much more significant differences between clusters concern dimensions related to digitalisation: the level of digitalisation of the organisation, IT competencies (of respondents), and engagement (of respondents) in knowledge flow. Differences in beliefs regarding planning and hierarchy, and in the level of formalisation of the organisation, also exist but have much lower values. Two classes of differences can be observed from the provided charts. In charts 4 and 5 (Fig. 5-6), the circles symbolising clusters are positioned more "vertically" because a significant difference between clusters on the vertical axis of openness to AI collaboration is accompanied by a slight difference on the horizontal axes (planning and hierarchy and the level of formalisation of the organisation). The mutual arrangement of circles in charts 1-4 (Fig. 2-5) is clearly "skewed", resulting from the significant values of differences between clusters on both axes.

The third stage of the study, comprising two steps, examines the influence of independent variables on openness to AI collaboration and its components. The first step involved a separate analysis of each dependent variable that comprises openness to AI collaboration. The analysis results using the linear regression method and the AIC criterion are presented in Table 4 in the section "components of openness to AI collaboration".

The second step in studying the influence of the variables included in the study on the level of openness to AI collaboration was to develop a model for the studied dimension as a whole. The arithmetic mean of the three dependent variables was adopted as the dependent variable. Other solutions were also tested, including the sum and product of the dependent variables, but the model using the arithmetic mean yielded the best results. R^2 for this model is 0.5053, which means that the model explains about 50.5% of the variability of the dependent variable: openness to AI collaboration as a whole. The model is statistically significant ($F = 33.96$). Assessments of the

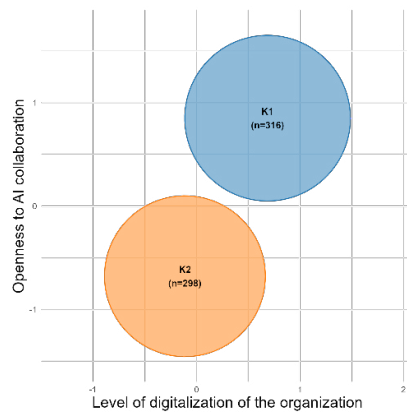


Fig. 2. Level of digitalisation of the organisation vs openness to AI collaboration

Source: author's elaboration.

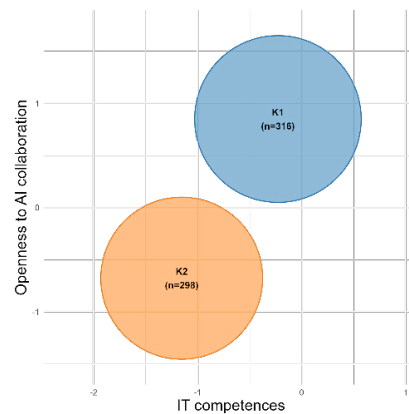


Fig. 3. IT competencies vs openness to AI collaboration

Source: author's elaboration.

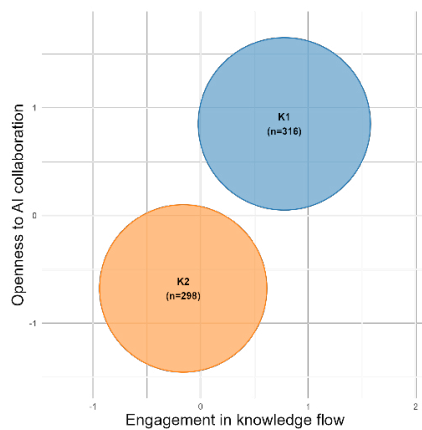


Fig. 4. Engagement in knowledge flow vs openness to AI collaboration

Source: author's elaboration.

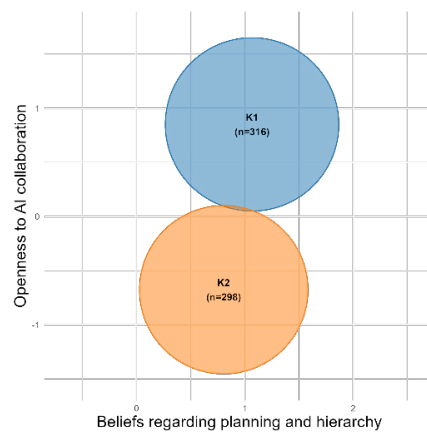


Fig. 5. Beliefs regarding planning and hierarchy vs openness to AI collaboration

Source: author's elaboration.

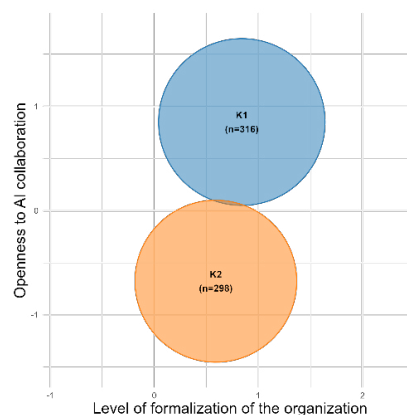


Fig. 6. Level of formalisation of the organisation vs openness to AI collaboration

Source: author's elaboration.

Tab. 4. Variables affecting the degree of openness to AI collaboration

NO.	DEPENDENT VARIABLES INDEPENDENT VARIABLES	COMPONENTS OF OPENNESS TO AI COLLABORATION			OPENNESS TO AI COLLABORATION
		AI AS PARTNER	ACCEPTANCE OF AI INFLUENCE	AI AS PLANNER	
1.	Team meetings according to the schedule	(-) ***	(-) ***	(-) ***	(-) ***
2.	Striving to use digital technologies		(-) *	(-) *	
3.	Support in developing employees' digital competencies			(+) *	
4.	Digital approach to problem solving	(+) *	(+) *		(+) *
5.	Seeking and testing new, useful digital tools		(-) *		
6.	Presence of plans for AI application development	(+) *	(+) ***	(+) ***	(+) ***
7.	Digital leadership of management		(+) *		
8.	Increase in digitalisation of products/services	(-) *			(-) *
9.	Using AI and ML-based DSS	(+) *			
10.	Distance to concerns about AI	(+) ***	(+) ***		(+) **
11.	Enthusiasm for implementing new digital solutions		(+) **	(+) **	(+) **
12.	Belief in the justification of striving for maximum digitalisation of work	(+) ***	(+) **	(+) *	(+) ***
13.	Belief in the competitive benefits of digitalisation			(+) *	
14.	Awareness of the existence of areas for digitalisation	(+) **	(+) **	(+) *	(+) **
15.	Belief in the importance of planning			(-) *	
16.	Ability to create websites		(+) **		
17.	Knowledge of programming languages	(+) *		(+) **	(+) **
18.	Learning IT from colleagues		(+) *	(+) *	(+) *
19.	Career plans in IT	(+) ***	(+) *	(+) **	(+) **
20.	Formal education in IT		(-) *		(-) *
21.	Knowledge of technical aspects of IT				(+) *

Markings: *** : $p < 0.001$ (most significant); ** : $p < 0.01$ (significant); * : $p < 0.05$ (moderately significant)

(+) : positive impact; (-) : negative impact.

Source: author's elaboration.

influence of individual independent variables are included in the last column of Table 4.

4. DISCUSSION OF THE RESULTS

The presented study constitutes an attempt to simultaneously capture the full chain of determinants: from the institutional context (digital culture, formalisation), through the agency factor (leadership), the competency factor (digital skills), and the dispositional factor (personal attitudes), to a three-level operationalised construct of AI acceptance as a decision-making partner with increasing autonomy. AI acceptance is not treated as an individual trait but as a result of the interaction among organisational culture, competencies, attitudes, and formal structure (Lazazzara, 2025).

The research identified two distinct attitudes towards collaboration with AI (Fig. 1). They were termed “enthusiasts” and “sceptics”. The category of openness to AI collaboration was designed as a superposition of declarations of respondents’ readiness to collaborate with AI in three areas: everyday, current collaboration, consent to change decisions under the influence of AI arguments and consent to implement plans developed by AI (Table 1). Factor analysis provided empirical confirmation of these assumptions: these three variables turned out to form one dimension with high reliability (Cronbach’s $\alpha = 0.871$ - Table 2). Analysis of the mutual relations of clusters in the six dimensions identified through factor analysis (Table 2) allows stating that openness to AI is clearly favoured by both the level of digitalisation of the organisation and the level of digital competencies of the person and their engagement in knowledge flow (Figures 2-4). In this way, a high connection was indicated between organisational solutions, personal competencies, and organisational culture on openness, and thus readiness to collaborate with AI. Such research results lead to the conclusion that openness to AI collaboration results from the organisation’s systemic advancement in digital transformation, a result of the broadly understood, high level of organisational development in digitalisation.

The research also showed differences between the AI “enthusiasts” and “sceptics” clusters in formalisation. Formalisation is described by two dimensions: beliefs regarding planning (Figure 5) and hierarchy, and the organisation’s formalisation level (Figure 6). The differences are statistically significant, but their values are significantly lower than in dimensions

directly describing organisational digitalisation development.

Regression analysis also explains the significantly lower value of differences in the level of formalisation (Figures 5 and 6) than the level of digitalisation (Figures 2, 3, and 4) between the two distinguished clusters. The organisation of team meetings according to a schedule, one of the variables indicating the level of work formalisation (Gibson et. al., 2019), shows a consistently strong negative impact on all aspects of openness to AI. At the same time, plans for developing AI applications - also fitting into the formalisation thread - have a positive impact. The results confirm the assumption presented in the literary part of this study about the bidirectional impact of formalisation on digitalisation. The explanatory and directive influence of formalisation on employee efforts does not always support actions beneficial to the organisation (Borrey et al., 2018). Such practices, although beneficial, are not in line with the regulations and may occur particularly frequently in new areas that are still being implemented and developed, a category which currently includes the use of AI within an organisation. This conclusion is also supported by the observation that belief in the justification of planning activities moderately, but negatively, affects the level of one of the components of the studied variable (Table 4, Item 15).

Unsurprisingly, a wide range of variables characterising the level of organisational digitalisation positively affect openness to AI (Table 4, Items 3, 4, 6, 7, and 9), but the influence of external factors on the studied variable cannot be considered dominant. The small influence of digital management engagement is noteworthy (Table 4, Item 7). Some organisational digitalisation processes also showed a small but negative impact on openness to AI collaboration (Table 4, Items 2, 5, and 8). At the same time, elements of the employee’s attitude towards digitalisation had a significant impact on the studied variable. Particularly open to collaboration with AI are people who are not afraid of AI (Table 4, Item 7), are internally convinced of the importance of digitalisation (Table 4, Items 11 and 12), and are planning a professional connection with the IT industry (Table 4, Item 19). Individual digital competencies also positively impact openness to AI collaboration (Table 4, Items 16-19 and Item 21). The above compilation provides a strong basis for concluding that personal and internal factors dominate organisational influences in shaping openness towards AI. This phenomenon can be considered a symptom of qualitative changes in the transition from the first stage of digitalisation, which is instrumental and consists of automat-

ing routines, to the second, based on AI and requiring acceptance of diversity, as well as the importance of digital cognitive perspectives, projects, and decisions. The specificity and power of “digital thinking”. Acceptance of a partnership with such a complex technology as AI engages the employee’s deeper values and views. External influences, even as they are inscribed in the process of digitalisation, are of little or no positive importance, or none at all.

The results discussion can be concluded with the significant observation that the employee’s personal attitude, i.e., enthusiasm about digitalisation, marked by plans to pursue professional development in this field, is completely different from formal education in IT. The latter factor showed only a moderate, and moreover negative, impact on the studied variable (Table 4, Item 20).

CONCLUSIONS

The use of three complementary research methods: factor analysis and linear regression, when analysing survey responses from 614 respondents, allowed for an in-depth analysis of the relationships of 43 studied variables and inference on this basis about the determinants of employee openness to AI collaboration. The research indicates two essential vectors favouring this type of openness:

1. High level of digital transformation.
2. Personal employee engagement in the transformation process.

There is no doubt that a high level of digitalisation and employees’ digital competencies affect their openness to AI. Digitalisation creates distinct organisational culture patterns, emphasising the roles of autonomous teams and spontaneous, intensive cooperation. Hence, the bidirectional impact of formalisation on openness to AI is likely to be predicted at the stage of literature review and confirmed empirically. On the one hand, clear plans and principles of action direct work and give it meaning, which can positively dispose towards AI if plans cover its implementation; on the other hand, formalisation can inhibit processes of spontaneous experimentation with AI, which is an expression of the employee’s engagement and interest in this field.

In the studied context, the thread of personal engagement is particularly important because, as empirically demonstrated, a number of factors that positively affect openness to AI are rooted in employees’ personal attitudes, beliefs, and competencies. Their influence is stronger than that of organisational factors.

Based on the research presented in this article, the following recommendations can be indicated for building employee openness to effective, engaged collaboration with solutions based on artificial intelligence:

1. A high level of organisational digitalisation development is necessary to successfully implement AI. The AI application is just the next stage of digital transformation, not a separate undertaking.
2. The pace of AI development means that its use will be a process of continuous innovation. To use the constantly appearing and changing tools, it is necessary to ensure a pro-innovation atmosphere conducive to searches and experiments conducted by employees, sometimes independently, sometimes in ad hoc teams.
3. Formalisation through plans and procedures favours project implementation. However, the search and shaping of assumptions for these implementations can take the form of spontaneous, creative searches, which formalisation can suppress. Therefore, when formalising digitisation processes, one should ensure that the boundary separating the limitation of ambiguity and lack of direction from limiting development dynamics has not been crossed.
4. Personal attitudes and beliefs play a significant role in openness to AI. Therefore, a solution conducive to AI implementation will be to foster a positive atmosphere around these plans and actions, arousing engagement, internal motivation, and conviction in their application.
5. The emotional factor is also important because the employee is to collaborate with an artificial creation in a formula that previously included only biological persons. In such a situation, employees may expect the organisation to provide support and a sense of security.

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