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DEFINING COGNITIVE, BEHAVIOURAL AND ENVIRONMENTAL FACTORS IN ENHANCING THE VALUE OF ARTIFICIAL INTELLIGENCE IN BUSINESS

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Abstract. Artificial intelligence is one of the fastest-developing instruments of Industry 5.0. However, research on its impact has not been thoroughly discussed. Therefore, this paper focuses on developing an applicable methodology for measuring the added value of artificial intelligence in business practices, as well as understanding the fundamental factors that underpin the development of Industry 5.0 forces.

This paper presents the results of testing a method for calculating the indirect value added by artificial intelligence (AI) to businesses. It is based on the premise that several factors significantly influence an organization's reputation and overall competitiveness when considering the indirect benefits of using AI. The validation of the model was conducted among 125 business organizations with experience in utilizing various AI-based systems and processes. The study's results indicate a strong statistical correlation between cognitive and motivational factors, as well as a strong correlation between these factors and the added value of AI. Additionally, there is a moderately low statistical correlation between environmental factors and the added value of AI when employing AI tools in practice.

Keywords: AI Added Value; cognitive factors for AI; motivational and environmental factors in business, business competitiveness and AI

JEL: D01, D22, D91

Introduction

The widespread and rapid integration of artificial intelligence (AI) across all sectors of the economy has been recognized as a significant driver of economic development. With its assistance, businesses can manage information that was once restricted, predict customer behavior more accurately, stimulate innovation (Stoyanov 2024), and increase profitability.

AI technologies enable the automation of both routine and increasingly complex tasks, resulting in substantial productivity gains across various industries. Notable examples of AI's impact can be observed in the manufacturing sector, where business processes are optimized and costs are significantly reduced. A considerable portion of the manufacturing industry has already adopted AI solutions, while fintech companies are enhancing their financial services through improved data analytics, risk management, and the provision of customized financial products.

Technology companies are developing their own technology policies to address market demands and trends. Support mechanisms are emerging as a result of technological advancements rather than the reverse (Molhova & Biolcheva 2023). As we enter the age of artificial intelligence, businesses can more effectively differentiate between useful information and humanistic knowledge that fosters wisdom (manager.bg), thereby enhancing their overall value. However, the implementation of artificial intelligence in business necessitates substantial reorganizations and optimizations, which require significant financial investment.

There have been numerous unsuccessful attempts by companies due to incorrectly set goals, misunderstandings regarding the capabilities of artificial intelligence in specific applications, and a lack of quality data, among other factors. These challenges impose constraints on many managers when making decisions about introducing AI into their businesses. To facilitate the decision-making process, managers need to be aware of all potential threats, as well as the added value and returns that AI can provide. Several methods are documented in the economic literature to enhance the sustainability of development (Koleva et al. 2023; El Khatib et al. 2023) and to calculate the added value of AI for businesses (Wamba-Taguimdje et al. 2020). These methods primarily focus on direct returns, utilizing the relationship between changes in business processes that lead to reduced production costs or increased value for consumers (Kulińska 2014). In our previous research, we developed a model to calculate the indirect added value of AI for businesses (Biolcheva and Sterev 2024). This model is based on the premise that the estimation of AI's added value for businesses considers both changes in benefits and the preferences of those businesses.

The primary factors used to calculate indirect value added can be summarized as follows:

– Cognitive factors or factors influencing AI perception;

– Behavioral factors or behavior change factors related to the use of AI;

– Environmental factors or the impact of policies on the introduction or limitation of AI usage (Biolcheva and Sterev 2024).

With the current research, we aim to test this model and demonstrate its capability to calculate the indirect added value of artificial intelligence (AI) for businesses. To achieve this, the following chapters will sequentially present: a brief description of the model, the research methodology, the results, and the conclusion.

1. Added value model definition

There remains a lack of common understanding regarding how AI technologies create value within business organizations (Enholm et al. 2022). It is evident that technological advancements aim to identify solutions that foster positive change (Ivanov & Molhova 2023). Various researchers are exploring the added value of AI across different business sectors. For instance, Kim and his team (2011) assert that AI enhances both internal and external connections within organizations, thereby increasing their flexibility. According to Wamba-Taguimdje and colleagues (2020), the value added by AI is reflected in the improved efficiency of company processes. We have identified certain gaps in this area, which motivates us to develop a model based on our perspectives on the subject.

The model for calculating the indirect added value of artificial intelligence (AI) for businesses is discussed in detail in our previous publication (Biolcheva and Sterev 2024). For the purposes of this study, we will briefly outline three main hypotheses: (H1) a higher degree of AI adoption, driven by more complex changes in business processes, (H2) increased trust and motivation resulting from the introduction of AI, leads to a greater economic impact of AI utilization in business. Additionally, environmental factors may indirectly influence the strength of this relationship (H3). In addition, the fundamental indicators are also calculated: the production costs of one product, the revenue from sales of a product, and the added value of a product, considering the changes in the aforementioned values before and after the implementation of AI.

The evaluation of the primary factors is conducted using a 5-point Likert scale (Joshi et al., 2015) to assess the strength of the statements ranked by the respondents. The summary score for each participant within the factor groups is calculated as a simple arithmetic mean. The final score for each of the three factors—cognitive, behavioural, and environmental—along with the overall value-added score, is determined by adjusting the mean scores using the Balassa method on a degree scale. After collecting the evaluations and making the necessary adjustments, the three hypotheses regarding their direct or indirect influences on one another are tested through correlation and regression analysis (Biolcheva and Sterev 2024).

2. Methodology

To evaluate the model for calculating the indirect added value of artificial intelligence in business, a survey was conducted involving 125 business organizations operating in Bulgaria. The respondents included both national and multinational companies. To ensure a diverse and knowledgeable respondent pool, assistance was sought from members of BACS (Bulgarian Association of Corporate Security), who hold positions of expertise in large technology firms, as well as from the Southeast Digital Innovation Hub and other experts. The respondents' fields of activity encompass companies in the high-tech sector and those in the service sector. The selection of these specific companies is driven by their higher degree of innovativeness and their inclination to adopt smart technologies based on artificial intelligence.

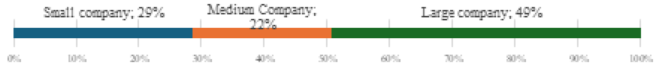
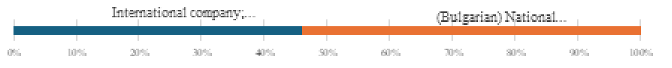
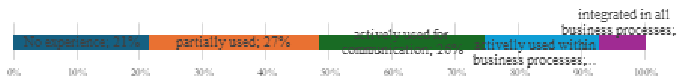
The decision to utilize an online survey for data collection is driven by the opportunity it affords respondents to express their opinions freely and anonymously. The study was conducted using an online survey that comprised 20 questions with closed-ended responses. The first section of the questions serves an introductory purpose, aiming to identify the type and size of the respondent's company. The second section seeks to clarify attitudes toward artificial intelligence (AI), the types of intelligent tools employed, and the extent of their usage by the respondents. The third section requires respondents to assign a score from 1 to 7 (in ascending order) regarding the contribution of AI in specific areas. The survey was conducted during the second quarter of 2024. Three of the monitored companies do not utilize AI tools, and the analysis is based on 122 accurately completed questionnaires. The survey data were processed using SPSS. To perform the necessary analyses, the selection of specific statistical methods focused on correlation and regression analysis.

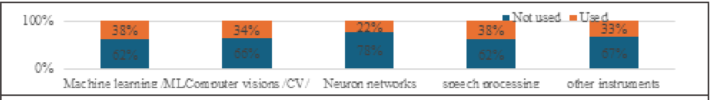
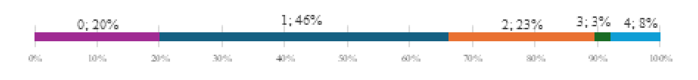
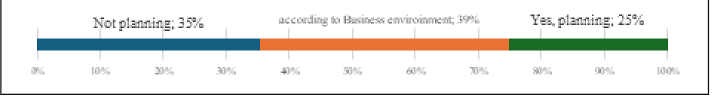
3. Research and results analysis

Five main characteristics were used to classify the observations of the companies: the size of the company (i.e., micro, small, medium, or large); the international scope of the business (i.e., operating solely in Bulgaria or in Bulgaria and abroad); the company's experience with AI tools (measured in years of experience); the types and total number of AI tools implemented and utilized; and the anticipated expansion of AI tool usage in the future. The observations are based on interviews with Bulgarian companies conducted via the Internet. Although the sample is not statistically significant, the interviews include business development specialists to validate the methodology employed.

As a summary of the characteristics of the observed firms, we can derive the following results (Table 1).

Table 1. Characteristics of the observed firms

Q.1 What is the size of the company	
Q.2 What is the internationality of the company	
Q.3 What is the company's experience with AI	

Q.4.1 What AI technologies do you use	
Q.4.2 How many AI technologies do you use	
Q.7 Do you plan to expand the use of AI in the future	

The data indicate that the distribution of responses is relatively balanced, both in terms of size and the respondents' internationalization and experience with AI tools. The tools themselves are also fairly evenly distributed, with the exception of neural networks, which demonstrate lower applicability. Furthermore, 20% of the firms observed do not utilize AI tools, and these firms typically do not intend to adopt AI tools in the future. Notably, nearly 50% of the firms surveyed restrict their use of AI to a single tool.

When examining the degree of dependence among the various qualification characteristics, three stand out as independent (see Table 2):

– Q.1 What is the size of the company;
– Q.6 What is your ethical position regarding the use of AI;
– Q.7 Do you plan to expand the use of AI.

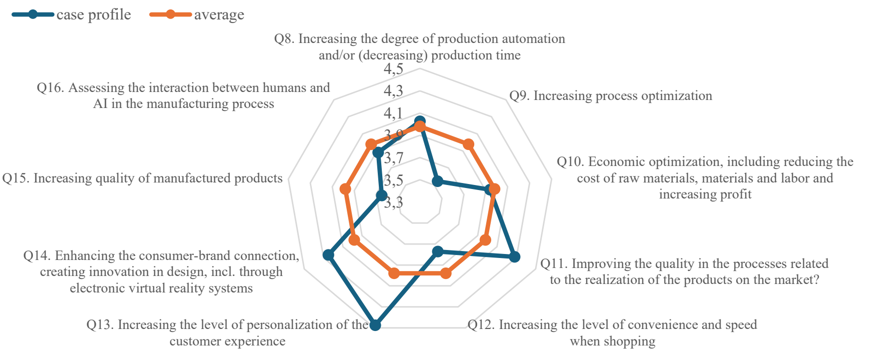
It is these three independent variables that can be used to identify a cluster of firms associated with various patterns of AI usage behavior.

Table 2. Correlations between characteristics of observed firms

	Q1. Size	**Q.2 Internationalization**	**Q.3 Experience with AI**	**Q.4 AI technologies**	**Q.5 AI Challenges**	**Q.6 An Ethical Position for AI**	**Q.7 Expanding use of AI**
Q1	1	-,298**	,405**	,297**	,193*	,162	,133
Q2	-,298**	1	-,172	-,234*	-,207*	-,010	-,281**
Q3	,405**	-,172	1	,415**	,265**	,297**	,285**
Q4	,297**	-,234*	,415**	1	,609**	,212*	,180
Q5	,193*	-,207*	,265**	,609**	1	,065	,102
Q6	,162	-,010	,297**	,212*	,065	1	,132
Q7	,133	-,281**	,285**	,180	,102	,132	1

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

When evaluating the application of AI tools in practice, the following average profile results can be derived. (Fig. 2).

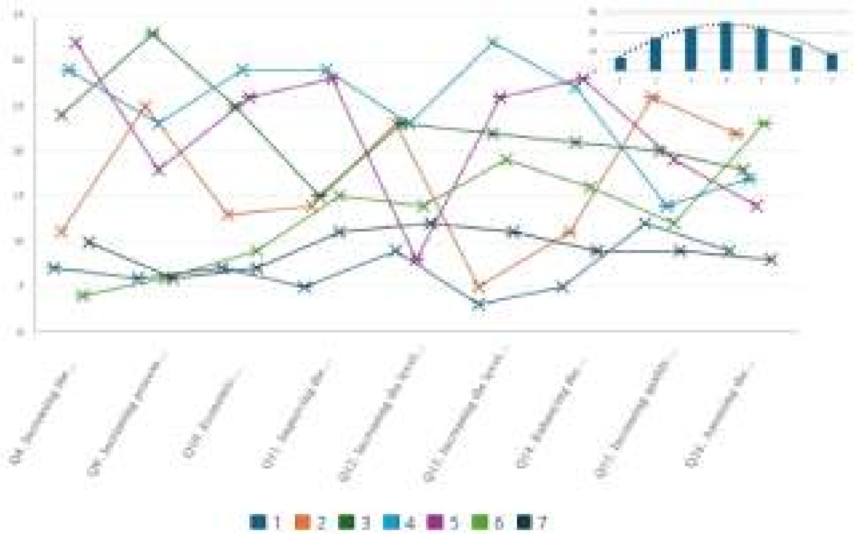


Legend: 1 is the lowest and 7 the highest score for optimization / process improvement

Figure 2. Profile of cognitive factors in using AI tools

From the analysis of the AI tools utilized, it is evident that their primary focus is on enhancing communication with consumers and increasing sales opportunities through artificial intelligence, rather than on improving or optimizing internal processes within the company. Despite the reported outcomes, the average profile score of 4.0 corresponds to the mean value regarding the level of process optimization and efficiency.

An important aspect of this analysis is the degree of variation in the scores (Fig. 3).



Legend: 1 is the lowest and 7 the highest score for optimization / process improvement

Figure 3. Variation of cognitive factors when using AI tools

It is evident from the data that the estimates for the variation of cognitive factors closely resemble a normal distribution. Depending on the extent of utilization by the companies, the average in the distribution shifts either to the left (toward 3.00, indicating a deterioration of the effect) or to the right (toward 5.00, indicating an improvement of the effect).

Statistically, there is a correlation between individual cognitive factors (see Table 3)

Table 3. Correlation dependences between the cognitive factors of AI for the observed companies

	Q.8	Q.9	Q.10	Q.11	Q.12	Q.13	Q.14	Q.15	Q.16	Qcogn
Q.8	1	,605**	,585**	,500**	,439**	,592**	,498**	,391**	,390**	,717**
Q.9	,605**	1	,571**	,508**	,723**	,601**	,452**	,650**	,727**	,840**
Q.10	,585**	,571**	1	,628**	,574**	,645**	,489**	,569**	,440**	,797**
Q.11	,500**	,508**	,628**	1	,377**	,544**	,429**	,344**	,374**	,687**
Q.12	,439**	,723**	,574**	,377**	1	,602**	,373**	,757**	,649**	,803**
Q.13	,592**	,601**	,645**	,544**	,602**	1	,657**	,554**	,561**	,826**
Q.14	,498**	,452**	,489**	,429**	,373**	,657**	1	,354**	,445**	,669**
Q.15	,391**	,650**	,569**	,344**	,757**	,554**	,354**	1	,762**	,792**
Q.16	,390**	,727**	,440**	,374**	,649**	,561**	,445**	,762**	1	,788**
Qcogn	,717**	,840**	,797**	,687**	,803**	,826**	,669**	,792**	,788**	1

*. Correlation is significant at the 0.05 level (2-tailed).

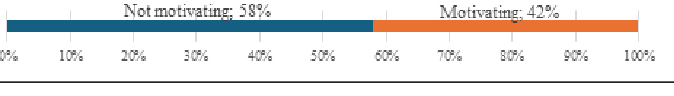
**. Correlation is significant at the 0.01 level (2-tailed).

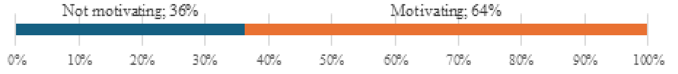
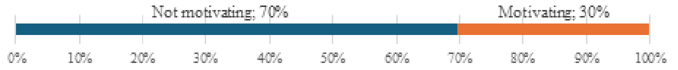
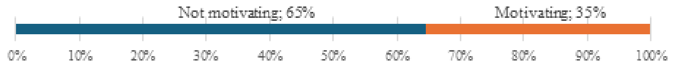
However, some variables are observed to be moderately highly correlated with others. These include:

- Q.14 Increasing the consumer-brand relationship by creating innovation in design, incl. by using virtual reality electronic systems
- Q.11 Quality improvement in the processes related to the realization of the products on the market
- Q.8 Increasing the degree of production automation and/or (decreasing) production time.

The assessment of behavioral factors is closely linked to the evaluation of motivating factors for the implementation and practical use of artificial intelligence (AI) (see Table 4). The primary motivating factors include:

Table 4. Characteristics of the observed companies

Curiosity of AI application	

Increasing the efficiency of production processes	
Competitive or market pressures	
Fulfilment of company goals	

From the data presented in Table 4, it is evident that the primary motivator for implementing AI tools in practice is the enhancement of production processes, cited by 64% of companies. Conversely, the least significant motivator is addressing competitive and market pressures, reported by only 30% of companies. These findings starkly contrast with the stated cognitive effects of process improvements within organizations, where the most pronounced effect is observed in enhancing communication with consumers, while the least significant effect pertains to the optimization of production processes.

In addition to the aforementioned points, trust in AI tools can be examined as a component of behavioral factors (see Fig. 4).

Legend: 1 is the lowest and 7 the highest score for optimization / process improvement

Figure 4. Profile of motivational factors when using AI tools

It is evident from the data that the variance scores of the motivating factors fall below the normal distribution. Specifically, intracompany motivation is significantly lower, scoring 3.10 out of 7.00, which negatively impacts trust. In contrast, the motivating score of the expected effect in the IS instruments exceeds the mean, with a score of 4.20 out of 7.00.

These findings are further supported by the lack of a correlational relationship among individual motivating factors (see Table 5).

Table 5. Correlation dependencies between the motivational factors of IM for the observed firms

	Q17.1	Q17.2	Q17.3	Q17.4	Q17	Q18	Qbehav
Q17.1	1	-,104	,144	-,166	,464**	-,018	,275**
Q17.2	-,104	1	-,038	-,067	,410**	,195*	,385**
Q17.3	,144	-,038	1	,126	,617**	,037	,409**
Q17.4	-,166	-,067	,126	1	,455**	,157	,387**
Q17	,464**	,410**	,617**	,455**	1	,189*	,748**
Q18	-,018	,195*	,037	,157	,189*	1	,794**
Qbehav	,275**	,385**	,409**	,387**	,748**	,794**	1

*. Correlation is significant at the 0.05 leQel (2-tailed).
**. Correlation is significant at the 0.01 leQel (2-tailed).

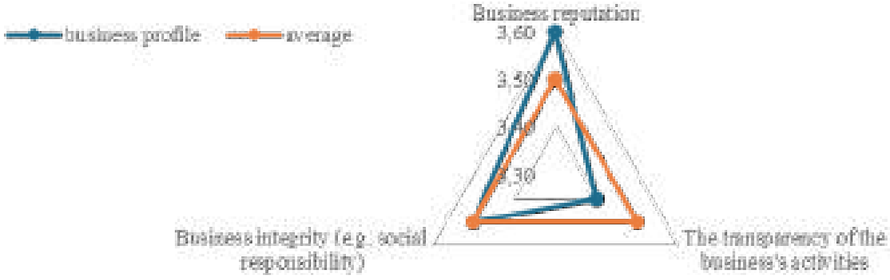
According to the results of the examination of the degree of dependence among the various motivational characteristics, three stand out as independent (see Table 5).

- Q.17.1 What motivates you to use AI in business: Curiosity;
- Q.17.2 What motivates you to use AI in business: Striving to increase the efficiency of production processes;
- Q.17.3 What motivates you to use AI in business: Competitive or market pressures.

It is these three independent variables that can be used to identify a cluster of firms associated with various patterns of AI usage behavior.

The assessment of the value added by AI to the firm's activities is measured by three key effects: the firm's reputation, the transparency of its activities, and its fairness in the market.

However, the assessment of value added is lower than the anticipated level (at least an average of 4.00), as each of the evaluated value-added elements holds nearly equal significance (see Fig. 5).



Legend: 1 is the lowest and 7 the highest score for optimization/process improvement

Figure 5. Value-added profile when using AI tools

In summary, one can assess the presence or absence of evidence to confirm the hypotheses derived from the model (see Fig. 5). When evaluating the presence or absence of a statistically significant correlation between individual variables, the following correlation matrix can be generated (see Table 6).

Table 6. Correlation relationships between variables: independent and dependent variables related to the use of AI for the observed firms

	Qcogn	Qbehav	Qenviro	QAValue
Qcogn	1	,632**	,718**	,760**
Qbehav	,632**	1	,393**	,537**
Qenviro	,718**	,393**	1	,727**
QAValue	,760**	,537**	,727**	1

*. Correlation is significant at the 0.05 leQel (2-tailed).
**. Correlation is significant at the 0.01 leQel (2-tailed).

Based on this, the defined hypotheses are confirmed.
• H1: There is a strong statistical correlation between cognitive (H1.1) and behavioral (H1.2) factors that influence the independent outcome variable: the added value of AI in the practical use of AI tools.
• H2: There is a strong statistical correlation between cognitive and behavioral factors that determine the added value of AI.
• H3: There is a moderately low statistical correlation between environmental factors and the value added by AI when utilizing AI tools in practice.

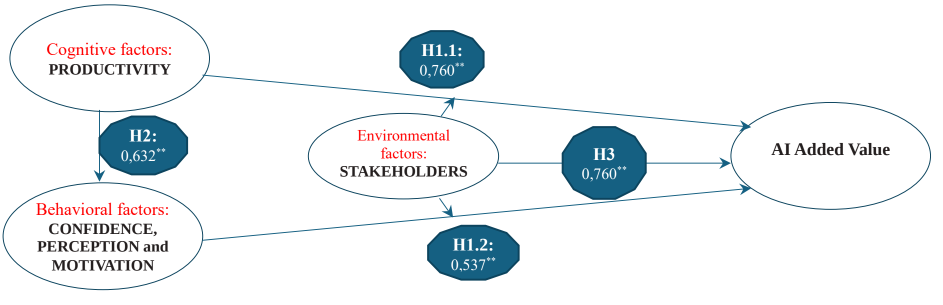


Figure 6. Verification of defined hypotheses using AI tools

In addition, a cluster analysis can be conducted to summarize the differences in firms' behaviors when utilizing AI tools in practice (Fig. 6).

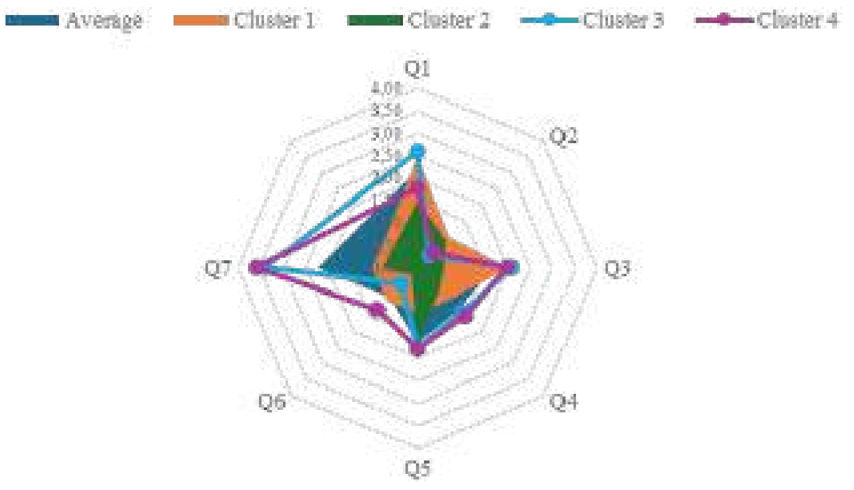


Figure 7. Cluster defining by difference in using AI tools

– Cluster 1 primarily consists of medium and large national companies that possess significant experience in the practical application of AI tools. However, they utilize a limited range of AI tools, typically around one, and the challenges associated with the AI usage environment are relatively minimal. Their decisions regarding the further development of AI tools largely depend on changes in the environment.

– Cluster 2 comprises the smallest and some medium-sized national companies. While they have experience with AI tools, most of these companies do not utilize such tools in practice. The environmental impact assessment is relatively low; however, most of these representatives do not intend to adopt AI in the future.

– Cluster 3 comprises the largest and some medium-sized international companies that utilize AI tools to optimize one or more processes within the organization. On average, these companies employ 1 to 2 AI tools in practice. Recognizing the significant role of environmental challenges, they plan to introduce additional AI tools in the future.

– Cluster 4 comprises small and medium-sized international companies that possess considerable experience in implementing AI tools. Below are the representatives that utilize the highest number of AI tools in practice. For these companies, environmental challenges are of utmost importance, and they are primarily focused on expanding their use of AI tools.

Based on the primary differences in the key characteristics of the typical representatives of each cluster, the interaction of the individual variables in the application of AI can be summarized:

– Cluster 1 is situated in an optimal environment for evaluating the cognitive and behavioral factors associated with the use of AI in practice. However, the assessment of the environmental impact is minimal, and due to the limited use of AI tools, the added value of AI in their practice remains insufficient.

– Cluster 2 representatives rate the importance of cognitive factors as mediocre and may feel demotivated to use AI tools in practice. For this group, the influence of the environment on the use of AI is minimal, as is their assessment of the added value of AI tools for their practice.

– For Cluster 3, the rating of cognitive factors was highest when combined with a high rating of behavioral factors. This combination also indicates the greatest influence of the environment on the use of AI, as these representatives derive the highest added value from the practical application of AI.

– Finally, the representatives of Cluster 4 demonstrate a greater awareness of the cognitive factors of AI and surpass the representatives of Cluster 3 in terms of motivation. However, their assessment of the added value of AI in their practice is moderate—significantly higher than that of representatives from Clusters 1 and 2, yet still notably lower than that of Cluster 3 regarding the added value of AI.

Conclusions

In summary, there is no doubt that realizing high added value from the use of AI is closely linked to a thorough assessment of the market and competitive factors that influence this impact. National companies, particularly small and medium-sized enterprises, urgently require additional training on the potential applications of AI tools to enhance processes and achieve improved economic and organizational outcomes across various functions—not just in user communication. Developing the necessary knowledge and skills to utilize different AI tools will also foster a greater willingness to adopt new technologies in the future.

Following the aforementioned points, it is essential to identify relevant information that can enhance the cognitive and motivational attitudes of these firms towards utilizing AI as a means to achieve greater added value from its implementation and practical use. This rationale supports the team's ongoing efforts to explore the indirect value that AI contributes to businesses. Future research should focus on complementing the relationships among the key drivers of AI adoption in business and measuring their added value.

The findings of this research could be highly beneficial for strategy developers, as the results may encourage small and medium-sized enterprises (SMEs) to adopt and implement more tools associated with Industry 5.0. Furthermore, the research indicates that SMEs encounter not only environmental challenges but also cognitive and behavioral limitations. These cognitive barriers can be addressed through various training programs offered at universities, while behavioral limitations can be mitigated through additional practical training sessions.

Nevertheless, the challenge of analyzing the effects of AI implementation in practice still remains. While this paper presents one possible model for defining the added value of AI, it requires further evidence from other regions, with an increasing number of respondents and business representatives.

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