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Building business models of high-growth enterprises based on AI systems

Marlena Grabowska
Agata Mesjasz-Lech

ABSTRACT

To date, the use of artificial intelligence (AI) to shape the business models of high-growth enterprises (HGEs) remains an unexplored research topic. The article aims to examine the use of artificial intelligence to build business models for high-growth enterprises, considering the heterogeneity of these entities. The empirical research aimed to answer the following questions: (1) Does the use of artificial intelligence to build individual components of the business model depend on the size of the HGE? 2. Does the use of artificial intelligence to build individual components of the business model depend on the age of the HGE?

The study was conducted in the second half of 2024 on a sample of 200 Polish high-growth enterprises that declared using AI in their business activities. Data were collected through a survey questionnaire. The survey questions were derived from the assumptions of building a business model based on three value components: value proposition, value creation and delivery, and value capture. The chi-square test, the Kruskal-Wallis test, and measures of dependence for immeasurable features were used to address the research questions.

It has been shown that statistically significant relationships exist only between individual value components and the size of the enterprise when these components are perceived as the average of the values of the variables that comprise them. It has also been shown that the values of these components are differentiated by enterprise size.

The novelty of the article is the research on the use of AI to build business models for high-growth enterprises, accounting for their heterogeneity.

The article is addressed to scientific researchers and business practitioners, particularly those dealing with issues related to building business models and using AI to create value.

KEY WORDS

business model, value, artificial intelligence, high-growth enterprises

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Marlena Grabowska
Czestochowa University of Technology,
Al. Armii Krajowej 19B,
42-200 Częstochowa, Poland
ORCID 0000-0003-2248-5531

Corresponding author:
e-mail: marlena.grabowska@pcz.pl

Agata Mesjasz-Lech
Czestochowa University of Technology,
Al. Armii Krajowej 19B,
42-200 Częstochowa, Poland
ORCID 0000-0001-9577-2772
e-mail: a.mesjasz-lech@pcz.pl

Introduction

Artificial intelligence (AI) is increasingly influencing various aspects of economic life. Its growing importance in business activity is observed. According to Eurostat data, in 2024, 13.5 % of enterprises in the European Union used artificial intelligence, an increase of 5.5 percentage points from the previous year (Eurostat, 2025). Growing interest in this topic is also indicated in scientific publications that describe various aspects of AI in enterprise operations. In the Scopus database, the number of articles, book chapters and conference materials in the area of Business, Manage-

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ment, and Accounting increased from almost 1.5 thousand publications in 2020 to over 6 thousand in 2024.

The literature (Lee et al., 2019; Åström et al., 2022) indicates that the fundamental cause of the AI phenomenon in business activities is the ability to imitate cognitive processes, draw conclusions from large data sets, and predict unexpected events. This ability enables the automation of identifying and solving complex problems, thereby improving the operational efficiency of enterprises. The reasons for using AI systems in the economic sphere can also be taken from the generalised definition of this issue by Kaplan and Haenlein (2019), which indicates the AI's ability to correctly interpret external data, learn from it, and use this knowledge through flexible adaptation to achieve specific goals and tasks. In this context, Kristoffersen et al. (2020) and Sjödin et al. (2023) pointed out the potential benefits of using AI in industrial solutions, which include improved resource efficiency, increased productivity potential, enhanced diagnostics, and automated resource management.

AI can be used in many ways in business processes. Therefore, from a cognitive and utilitarian viewpoint, it may be interesting to analyse the use of AI in high-growth enterprises (HGEs). The literature (Otola et al., 2020) emphasised that HGEs respond quickly to market changes and adapt to requirements. Moreover, these entities are characterised by an above-average impact on the economy (Coad et al., 2022). Empirical studies conducted in this area (Nightingale & Coad, 2014; Pereira & Temouri, 2018) have shown that a small number of HGEs creates a disproportionately large number of jobs. According to the interpretation adopted by the Organisation for Economic Co-operation and Development (OECD, 2010), HGEs are characterised by an increase in sales revenues or an increase in employment on average by over 20 % annually over a period of at least three years. These premises encourage the analysis of the AI use by HGEs.

The above considerations suggested the article's purpose: to examine the AI use for building HGE business models, accounting for their heterogeneity. This article presents a literature review, discusses the theoretical foundations of the research, and identifies a research gap in the use of AI to build business model components, considering their diversity in entity size and market experience. The section on research methods describes the research sample, the survey questionnaire, and the statistical analysis tools employed. The research results present the outcomes of the chi-square test and the Kruskal-Wallis test for the variables comprising the value proposition, value creation and delivery, and value capture components, considering grouping variables such as company size and age. The discussion compares the obtained results with previous research studies on building business models based on artificial intelligence. The article's conclusions justify the answers to the research questions.

1. Literature review

HGE-related issues interest entrepreneurship researchers and business journalists. For example, current scientific publications in this area have focused on aspects such as the impact of foreign investment on productivity (Sokhanvar, 2025), the role of business clusters and intellectual capital in achieving the HGE status (Temouri, 2025), the HGE adaptation to the conditions caused by the COVID-19 pandemic (Otola et. al., 2023), the role of intellectual capital in the growth of benefit corporations (Del Baldo, 2023), or the assessment of the competitiveness of high-growth enterprises (Zhang, 2023).

The diversity of research on HGEs stems from their important role in both macroeconomic and microeconomic contexts. However, the literature has not extensively explored the impact of AI on HGEs. Teruel et al. (2024) examined the relationship between digitalisation and firm growth. They also analysed the digital technology investment activities of HGEs compared to non-HGEs. The authors found that firms investing in digitalisation are more likely to show rapid growth in employment, sales, and labour productivity. However, there is a need for interconnection between less and more advanced technologies, and different types of digital technologies are not uniformly associated with firm growth. They also noted that in the so-called "superstar firms", traditional business models have been displaced by the use of new digital technologies.

It should be emphasised that the topic of using AI to shape the HGE business model, specifically the creation of individual value categories within this model, is a research issue that has not yet been explored. Moreover, in in-depth scientific explorations, it is reasonable to consider HGE heterogeneity, as these entities are not uniform in size, occur in different industries, or have different ages. It is therefore reasonable to conduct research on the use of artificial intelligence in high-growth enterprises, given their diversity in terms of entity size or market experience.

In scientific discourse on the essence of the business model, researchers have repeatedly referred to the value concept. According to the classical approaches defining the concept of a business model, it can be indicated that: it is the basic logic that organisations follow when creating value (Linder, Cantrell, 2000), it reflects the management of transactions aimed at creating value by using business opportunities (Amitt, Zott, 2001), it describes the creation and acquisition of value (Chesbrough, 2007), and it is a way for an organisation to create, deliver and capture value (Osterwalder, Pigneur, 2010). It should be noted that the approaches to the business model issue are similar, but the value category itself is not homogeneous.

According to Richardson (2008), a widely accepted view in the literature, the basic components of a value-focused business model are value proposition (VP), value creation and delivery (VCD), and value capture (VC). The value proposition (VP) concerns products and services offered to customers. It comprises identifying products and services that generate value for specific customer groups, indicating the target group, or defining methods of acquiring customers. Creating and delivering value (VCD) refers to all activities related to production, providing services, sales, or transferring the offer to customers. For this purpose, an appropriate combination of tangible and intangible resources is necessary to generate value and then transfer it using customer communication and distribution channels. Value capture (VC) is a feedback loop related to the value transfer to customers by the company. In this case, value returns to the company in the form of sales revenues, or it is generated through an appropriate cost structure. Value capture (VC) occurs when the customer accepts the value proposition (VP).

The use of AI systems creates the prospect of shaping enterprise business models and thus influencing the proposition, creation and delivery, and value capture. As AI technology develops, it is becoming increasingly important to understand how AI tools can be used to create and capture value (Berg, 2023). In this context, Sjödin et al. (2021) indicated that the use of AI can enable the creation of value closer to the customer needs by enabling more precise identification of business processes that require improvement. In addition, the use of AI capabilities aims to improve production processes or monitor the flow of products during their delivery to the recipient. Such efforts should positively impact revenue sources from areas served by AI. However, an important issue in this respect is the potentially high costs of maintaining the necessary infrastructure.

Åström et al. (2022) noted that AI-enabled value creation can be divided into two main categories. The first category is activities aimed at increasing efficiency and reducing costs by improving and enhancing existing operations. For example, AI can reduce the repetition of work tasks, resulting in cost savings. The second category is the development of solutions that generate increased revenues by supplementing decision-making processes and making more accurate decisions under conditions of uncertainty. Companies usually emphasise the use of AI to provide conveniences for customers, or to explore and analyse data to predict work efficiency and the profitability of transactions and sales (Mishra, Tripathi, 2021).

It is also indicated that companies trying to implement AI do not generate the expected value due to the incompatibility of AI systems with existing systems (Tse et al., 2020). Sjödin et al. (2021) emphasised that many companies struggle to successfully implement AI systems into their business models. To fully utilise the possibilities of artificial intelligence, new procedures, skills, or operational processes are necessary to ensure AI implementation, its integration with activities in the field of value creation, delivery, and capture.

Haftor et al. (2024) observed two competing entities and noted that only one recognised the effect of creating and capturing value through AI use. The way of using AI plays a fundamental role in this case, particularly the elements of the business model that are activated thanks to AI and to what extent. However, the multifaceted results of research on the way of using AI to create and capture value should be emphasised. For example, Enholm et al. (2022) distinguished internal and external functions of AI. Internal functions include improving internal business processes. In this case, the customer does not have direct contact with the applied AI solution. External functions include the use of AI in products and services, which is associated with the use of AI to contact customers. On the other hand, Shollo et al. (2022) identified mechanisms (ways) of creating value based on machine learning (ML): providing organisational knowledge, supporting decision-making, and using process automation. The considerations indicate the diverse impact of AI on individual value categories. The multi-aspect nature of this issue encourages the deepening of knowledge about the use of AI in building business models.

Empirical research on the use of AI to build HGE business models has focused on answering the following research questions: RQ1. Does the use of artificial intelligence to build individual components of the business model depend on the size of the HGE? RQ2. Does the use of artificial intelligence to build individual components of the business model depend on the age of the HGE?

2. Research methods

The empirical verification used primary data obtained through a survey questionnaire that contained statements related to individual components of the HGE business model. The selected research sample was purposive. It was selected based on the criterion consistent with the OECD (2010) assumptions that HGEs are characterised by an increase in sales revenues or employment by at least 20 % per year on average over three years. The study was conducted in the second half of 2024 on a sample of 200 Polish HGEs that declared the use of AI in their business activities.

The survey questions were formulated using assumptions of building a business model based on three value components: value proposition (VP), value creation and delivery (VCD), and value capture (VC). Each component was assigned statements that characterise it, accounting for AI aspects. The answers were placed on a five-point Likert scale, where 1 means "strongly disagree" and 5 means "strongly agree".

The value proposition highlights: "We acquire customers thanks to the efficiency and functionality of technology that imitates human intelligence" (VP1), "We acquire customers because we use useful technology that imitates human intelligence" (VP2), "We acquire customers because we use reliable and predictable technology that imitates human intelligence" (VP3), and "Our customers prefer contacts based on technology that imitates human intelligence" (VP4).

For value creation and delivery the following were identified: "We create an offer for customers based on the functionality and efficiency of technology that imitates human intelligence" (VCD1), "We create an offer for customers based on the usefulness and usability of technology that imitates human intelligence" (VCD2), "We create an offer for customers based on the reliability and predictability of technology that imitates human intelligence" (VCD3), and "We prefer contacts between employees based on technology that imitates human intelligence" (VCD4).

Value capture was characterised based on the following statements: "Generation of revenues for a sold offer is based on the functionality and efficiency of technology imitating human intelligence" (VC1), "Generation of revenues for a sold offer is based on the usefulness and usability of technology imitating human intelligence" (VC2), "Generation of revenues for a sold offer is based on the reliability and predictability of technology imitating human intelligence" (VC3), and "Contacts with customers based on technology imitating human intelligence are more beneficial for us in generating revenues for a sold offer" (VC4).

Enterprises were further divided by:

1. Size: small, medium, large,
2. Age in years: 1-20, 21-40, 41-60.

To answer the research questions, the chi-square test, Kruskal-Wallis test and measures of dependence for unmeasured characteristics were used, whereby:

- The existence of statistically significant relationships between the size of HGE and the individual variables forming the constructs of value proposition, value creation and delivery and value capture was examined.
- The existence of statistically significant relationships between the age of the HGE and the individual variables forming the constructs - value proposition, value creation and delivery and value capture - was examined.
- The existence of statistically significant relationships between the size of the HGE and the constructs of value proposition, value creation and delivery and value capture, expressed in terms of the average value of the variables forming the construct, was examined.
- The existence of statistically significant relationships between the age of the HGE and the constructs of value proposition, value creation and delivery and value capture, expressed in terms of the average value of the variables forming the given construct, was examined.

To analyse the relationship between the size (age) of the HGE and the constructs of value proposition (VP), value creation and delivery (VCD) and value capture (VC), the values of the indicated constructs for the studied companies were put into two categories: below average and above average of the given construct for all companies.

3. Research results

To assess the reliability and validity of the applied measurement scales, an analysis of internal consistency and construct reliability was conducted. Cronbach's α was used to evaluate the consistency of items within each scale, indicating the extent to which the items measure the same latent construct. Additionally, Composite Reliability (CR) was calculated to assess the reliability of the overall latent construct, and Average Variance Extracted (AVE) served as a measure of convergent validity, indicating the proportion of item variance explained by the latent factor. To evaluate discriminant validity, the Fornell-Larcker criterion was applied by comparing the square root of AVE for each construct with its correlations with other constructs. This approach ensures that each construct is both reliable and distinct from the other variables under study. The results are presented in Table 1.

The analysis of reliability and validity for the three examined constructs - value proposition, value creation and delivery, and value capture - demonstrated high quality of the applied measurement scales. For the value proposition construct, the values of all indicators point to high internal consistency, solid reliability of the latent factor, and good convergent validity, indicating the construct's ability to explain most of the variance in its items. The value creation and delivery construct achieved similarly high results, confirming its stability, consistency, and convergent validity. In the case of the value capture construct, the high values of the estimated indicators indicate good internal consistency, high latent reliability, and an adequate ability of the construct to explain the variance of its items. All three constructs meet the standards for reliability and convergent validity, confirming that the applied scales are reliable and appropriately measure their latent constructs.

The analysis according to the Fornell-Larcker criterion showed that all three constructs - value proposition, value creation and delivery, and value capture - exhibit discriminant validity. This means that each construct represents a distinct aspect of the examined business concept and is clearly distinguishable from the other latent constructs. In practice, the

Tab. 1. Reliability and convergent validity assessment

Constructs Items	Cronbach's alpha	CR	AVE
Value proposition	0.840	0.893	0.677
Value creation and delivery	0.846	0.896	0.684
Value capture	0.817	0.880	0.647

Tab. 2. Chi-square test results (observed level of significance of the test)

Variable	Size of HGE	Age of HGE
VP1	p=0.17554	p=0.780562
VP2	p=0.253959	p=0.561761
VP3	p=0.58872	p=0.138981
VP4	p=0.015732*	p=0.15109
VCD1	p=0.072578	p=0.331531
VCD2	p=0.100039	p=0.60588
VCD3	p=0.184718	p=0.853636
VCD4	p=0.211808	p=0.927195
VC1	p=0.203894	p=0.651938
VC2	p=0.029978*	p=0.2116
VC3	p=0.05858	p=0.853356
VC4	p=0.072319	p=0.079712
VP	p=0.004077*	p=0.458885
VCD	p=0.007241*	p=0.435966
VC	p=0.008252*	p=0.032066*

*Stochastically dependent variables at the p<0.05 level

Tab. 3. Results of the Kruskal-Wallis test for the variables forming the component value proposition with company size as the grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP1	Small enterprise	36	111.2917	4.515823	0.1046
	Medium enterprise	67	107.0821		
	Large enterprise	97	91.9485		
VP2	Small enterprise	36	117.4583	5.040549	0.0804
	Medium enterprise	67	102.3209		
	Large enterprise	97	92.9485		
VP3	Small enterprise	36	108.9583	1.951125	0.3770
	Medium enterprise	67	103.8358		
	Large enterprise	97	95.0567		
VP4	Small enterprise	36	115.7361	8.062811	0.0178*
	Medium enterprise	67	108.7090		
	Large enterprise	97	89.1753		

*Stochastically dependent variables at the p<0.05 level

Tab. 4. Results of the Kruskal-Wallis test for the variables constituting the component value creation and delivery, with the size of the enterprise as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VCD1	Small enterprise	36	100.9722	7.016216	0.0300*
	Medium enterprise	67	114.3881		
	Large enterprise	97	90.7320		
VCD2	Small enterprise	36	108.9861	7.185737	0.0275*
	Medium enterprise	67	111.8284		
	Large enterprise	97	89.5258		
VCD3	Small enterprise	36	110.4722	4.017922	0.1341
	Medium enterprise	67	106.8731		
	Large enterprise	97	92.3969		
VCD4	Small enterprise	36	116.2778	5.054541	0.0799
	Medium enterprise	67	103.7388		
	Large enterprise	97	92.4072		

*Stochastically dependent variables at the p<0.05 level

square root of AVE for each construct was higher than its correlations with the other constructs, confirming that the items assigned to a given construct truly measure a unique dimension of the phenomenon, rather than shared variance with other factors. These results indicate that the applied scales are both reliable and valid with respect to construct distinctiveness, providing a solid basis for further analysis of the relationships among variables in the theoretical model. Table 2 shows the results of the chi-square test.

A chi-square test of independence indicated that statistically significant relationships were observed only for specific variables and constructs in relation to company characteristics. Specifically, significant associations were found between the variable "Our customers prefer contacts based on technology that mimics human intelligence" and company size, and between the variable "Revenue generation for the offer sold is based on the usefulness and usability of technology mimicking human intelligence" and company size. In addition, the constructs "value proposition", "value creation and delivery", and "value capture" each demonstrated significant relationships with enterprise size, while "value capture" also showed a significant association with enterprise age.

These findings suggest that company size and age play a role in shaping perceptions and implementations related to technology-based offerings and their associated business model constructs.

Thus, it is possible to point to a statistically significant relationship between the size of the enterprise and the use of artificial intelligence to build individual components of the business model. Unfortunately, no statistically significant relationship is observed between the size of the enterprise and the individual variables forming the constructs that constitute the value components of business models. In the case of the age of the enterprise, it can be argued that it does not affect the use of artificial intelligence to build individual components of the business model. A statistically significant relationship exists only between the enterprise's age and value capture.

The results of the chi-square test were confirmed by the Kruskal-Wallis test, which was used to compare companies by identified value components in groups of companies categorised by size (Tables 3-6) and age (Tables 7-10).

Unfortunately, the Kruskal-Wallis test indicates that the size of the enterprise does not differentiate the results regarding the acquisition of customers by enterprises thanks to the efficiency and functionality of technology imitating human intelligence, the acquisition of customers thanks to the use of useful technology imitating human intelligence, the acquisition of customers thanks to the use of reliable and predictable technology imitating human intelligence. However, the size of the enterprise differentiates the preference of customers for contacts based on technology imitating human intelligence.

Tab. 5. Results of the Kruskal-Wallis test for variables constituting the component value capture with the size of the enterprise as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VC1	Small enterprise	36	110.3333	4.485199	0.1062
	Medium enterprise	67	107.7015		
	Large enterprise	97	91.8763		
VC2	Small enterprise	36	113.1111	12.60808	0.0018*
	Medium enterprise	67	114.6791		
	Large enterprise	97	86.0258		
VC3	Small enterprise	36	111.3056	3.347756	0.1875
	Medium enterprise	67	105.0746		
	Large enterprise	97	93.3299		
VC4	Small enterprise	36	118.1250	8.963406	0.0113*
	Medium enterprise	67	107.8881		
	Large enterprise	97	88.8557		

*Stochastically dependent variables at the p<0.05 level

Tab. 6. Results of the Kruskal-Wallis test for individual value components with company size as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP	Small enterprise	36	113.1111	9.806638	0.0074*
	Medium enterprise	67	110.2090		
	Large enterprise	97	89.1134		
VCD	Small enterprise	36	111.8889	9.546606	0.0085*
	Medium enterprise	67	110.6866		
	Large enterprise	97	89.2371		
VC	Small enterprise	36	118.6667	10.94952	0.0042*
	Medium enterprise	67	107.2239		
	Large enterprise	97	89.1134		

*Stochastically dependent variables at the p<0.05 level

Customers prefer contacts based on technology that imitates human intelligence.

The Kruskal-Wallis test did not show that the size of the enterprise differentiates the results regarding the creation of an offer for customers based on the reliability and predictability of technology imitating human intelligence, and the preference for contacts between employees based on technology imitating human intelligence. Differentiation depending on the size of enterprises is observed in the case of the creation of an offer for customers based on the functionality and efficiency of technology imitating human intelligence, and the creation of an offer for customers based on the usefulness and usability of technology imitating human intelligence.

In the case of variables constituting component value capture, the Kruskal-Wallis test indicated that generating revenues for a sold offer based on the usefulness and usability of technology imitating human intelligence and customer contacts based on technology imitating human intelligence being more beneficial in generating revenues for a sold offer are differentiated by enterprise size in at least two groups of enterprises. The remaining variables concerning generating revenues for a sold offer based on the functionality and efficiency of technology imitating human intelligence and generating revenues for a sold offer based on the reliability and predictability of technology imitating human intelligence are not differentiated by enterprise size.

Tab. 7. Results of the Kruskal-Wallis test for variables constituting the component value proposition with the company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP1	1-20	112	99.6071	0. 293379	0.8636
	21-40	70	103.0857		
	41-60	18	96.0000		
VP2	1-20	112	96.5223	1.29468	0.5234
	21-40	70	106.1286		
	41-60	18	103.3611		
VP3	1-20	112	96.9018	2.175683	0.3369
	21-40	70	108.3286		
	41-60	18	92.4444		
VP4	1-20	112	97.5714	0. 7730795	0.6794
	21-40	70	105.0714		
	41-60	18	100.9444		

*Stochastically dependent variables at the p<0.05 level

Tab. 8. Results of the Kruskal-Wallis test for variables constituting the component value creation and delivery, with the company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VCD1	1-20	112	98.7098	1.441546	0.4864
	21-40	70	99.4714		
	41-60	18	115.6389		
VCD2	1-20	112	99.5670	0.06977	0.9657
	21-40	70	101.6500		
	41-60	18	101.8333		
VCD3	1-20	112	98.7143	0.6556149	0.7205
	21-40	70	100.8571		
	41-60	18	110.2222		
VCD4	1-20	112	101.6875	1.645898	0.4391
	21-40	70	95.2214		
	41-60	18	113.6389		

*Stochastically dependent variables at the p<0.05 level

By viewing the individual value components in business models as one average value of the variables constituting a given component, the Kruskal-Wallis test showed that for all components - value proposition (VP), value creation and delivery (VCD), and value capture (VC) - differences can be observed at least between two groups of companies.

Unfortunately, the Kruskal-Wallis test indicates that the age of the enterprise does not differentiate the results regarding the acquisition of customers by enterprises thanks to the efficiency and functionality of technology imitating human intelligence, the acquisition of customers thanks to the use of useful technology imitating human intelligence, the acquisition of customers thanks to the use of reliable and predictable technology imitating human intelligence, the preference of customers for contacts based on technology imitating human intelligence.

The Kruskal-Wallis test also did not show that the age of the enterprise differentiates the results regarding the creation of an offer for customers by enterprises based on the functionality and efficiency of technology imitating human intelligence, the creation of an offer for customers based on the usefulness and usability of technology imitating human intelligence, the creation of an offer for customers based on the reliability and predictability of technology imitating human intelligence, and the preference for contacts between employees based on technology imitating human intelligence.

For the variables that make up the component value capture, the Kruskal-Wallis test indicated that only customer contacts based on technology imitating human intelligence, which are more beneficial in generating revenues for the offer sold, are differentiated by the age of the enterprise in at least two groups of enterprises. The remaining variables concerning generating revenues for the offer sold based on the functionality and efficiency of technology imitating human intelligence, generating revenues for the offer sold based on the usefulness and usability of technology imitating human intelligence, and generating revenues for the offer sold based on the reliability and predictability of technology imitating human intelligence are not differentiated by the age of the enterprise.

Considering the individual value components in business models as one average value of variables that make up a given component, the Kruskal-Wallis test showed that only for the value capture (VC) component, differences can be observed at least between two groups of companies categorised by age. For the remaining components: value proposition (VP) and value creation and delivery (VCD), no differences are observed due to the age of the companies.

The study was supplemented with an analysis of dependencies based on measures estimated for qualitative variables (Table 11).

All estimated measures of the strength of relationships between the distinguished variables have values below 0.350, which indicates that no strong relationships are observed between the variables. Values equal to or above 0.3 were adopted by the measures for the relationship between:

Tab. 9. Results of the Kruskal-Wallis test for variables forming component value capture with company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VC1	1-20	112	102.3750	3.115941	0.2106
	21-40	70	93.0000		
	41-60	18	118.0000		
VC2	1-20	112	100.8125	3.245249	0.1974
	21-40	70	94.6571		
	41-60	18	121.2778		
VC3	1-20	112	103.6116	0.929957	0.6281
	21-40	70	97.7214		
	41-60	18	91.9444		
VC4	1-20	112	102.1563	6.016319	0.0494*
	21-40	70	91.1214		
	41-60	18	126.6667		

*Stochastically dependent variables at the p<0.05 level

Tab. 10. Results of the Kruskal-Wallis test for individual value components with company age as a grouping variable

Variable	Size of the company	N	Average rank	H Kruskal-Wallis	Level of significance
VP	1-20	112	96.6429	1.550121	0.4607
	21-40	70	104.8571		
	41-60	18	107.5556		
VCD	1-20	112	101.1071	1.652081	0.4378
	21-40	70	96.2857		
	41-60	18	113.1111		
VC	1-20	112	104.2500	6.845499	0.0326*
	21-40	70	89.4286		
	41-60	18	120.2222		

*Stochastically dependent variables at the p<0.05 level

Tab. 11. Measures of the strength of the relationship between the size and age of the enterprise and other variables

Variable	Size of the company				Age of the company			
	T Czuprow	V Cramer	Φ Yule	Pearson C Corrected	T Czuprow	V Cramer	Φ Yule	Pearson C Corrected
VP1	0.085	0.090	0.240	0.272	0.055	0.058	0.155	0.179
VP2	0.080	0.084	0.225	0.257	0.065	0.069	0.184	0.212
VP3	0.064	0.068	0.181	0.208	0.088	0.093	0.248	0.281
VP4	0.109	0.115	0.307	0.343	0.087	0.092	0.245	0.278
VCD1	0.095	0.100	0.268	0.303	0.076	0.080	0.214	0.244
VCD2	0.091	0.097	0.258	0.293	0.063	0.067	0.178	0.205
VCD3	0.084	0.089	0.238	0.270	0.050	0.053	0.142	0.164
VCD4	0.082	0.087	0.233	0.265	0.044	0.047	0.125	0.145
VC1	0.083	0.088	0.234	0.266	0.094	0.099	0.265	0.300
VC2	0.103	0.109	0.292	0.327	0.061	0.065	0.173	0.199
VC3	0.097	0.103	0.274	0.309	0.082	0.087	0.233	0.265
VC4	0.095	0.100	0.268	0.303	0.050	0.053	0.142	0.165
VP	0.166	0.235	0.235	0.300	0.062	0.088	0.088	0.115
VCD	0.157	0.222	0.222	0.284	0.064	0.091	0.091	0.119
VC	0.155	0.219	0.219	0.281	0.131	0.185	0.185	0.239

1. Enterprise size and:

- customer preference for contacts based on technology, imitating human intelligence;
- creating an offer for customers based on the functionality and efficiency of technology imitating human intelligence;
- generating revenues for the sold offer based on the usefulness and usability of technology imitating human intelligence;
- generating revenues for the sold offer based on the reliability and predictability of technology imitating human intelligence;
- contacts with customers based on technology imitating human intelligence, which are more beneficial for the enterprise in generating revenues for the sold offer;
- value proposition component.

2. Enterprise age and generating revenues for the sold offer based on the functionality and efficiency of technology imitating human intelligence.

Measures equal to or above 0.3 were observed for specific relationships, including enterprise size and several variables related to customer preferences, offer creation, revenue generation based on the functionality, usability, reliability, and predictability of technology mimicking human intelligence, as well as the value proposition component. Additionally, enterprise age showed a measure above 0.3 for revenue generation based on the functionality and efficiency of the technology. Therefore, these relationships can be interpreted as moderate, suggesting that while some associations exist between enterprise characteristics and the examined variables, their strength is generally average rather than strong.

4. Discussion of the results

The empirical studies enabled the analysis of AI use in building business models, accounting for the heterogeneity of these entities. They align with current scientific issues in the field of AI's impact on enterprise achievements. AI and advanced technologies are increasingly recognised as drivers of enterprise productivity, enabling the transformation of almost all operations within and outside companies (Wahab, Radmehr, 2024). Da Silva Marioni et al. (2024) examined whether enterprise involvement in AI innovations translates into higher productivity than similar enterprises that do not undertake AI innovations. The results of these studies confirmed that AI can play a key role in increasing enterprise productivity, even in the early stages of the technology life cycle. Ali et al. (2024) emphasised the importance of AI in creating strategic capabilities and technical innovations that provide enterprises with a competitive advantage. In their study, Ante and Saggu (2025) focused on stocks and indices that provide investors with the opportunity to engage in and profit from AI technology. They found that companies with higher AI engagement showed more significant positive abnormal returns in the stock market. This study points to different opportunities for implementing, scaling, and monetising AI solutions, depending on the resources at their disposal, strategic goals, and the way they compete, which vary by company size.

Based on the results, a statistical relationship exists between the construction of a value proposition in an AI-based business model and company size. It was demonstrated that company size differentiates results regarding customer preference for contact based on technology that mimics human intelligence in at least two groups of companies. However, in the construction of a proposition based on artificial intelligence, no statistically significant relationship with the company's age was demonstrated.

Analogous conclusions can be drawn regarding AI-based value creation and delivery. A statistically significant relationship was also observed between this component of the business model and company size. It was identified that the offer created for customers is supported by technology imitating artificial intelligence due to its features, such as functionality, efficiency, usefulness, and usability, in at least two groups of companies distinguished by their size. In this case, the studied value-creation and delivery aspect did not demonstrate a statistically significant relationship with the company's age.

When considering the value returned to the enterprise supported by AI, there is a statistically significant relationship between this component of the business model and enterprise size. It has been observed that in at least two groups of enterprises, distinguished by size, the generation of revenue from the sold offer is based on the usefulness and usability of technology imitating human intelligence, and is also more beneficial due to contacts with customers based on AI technology. Referring to the age of the enterprise, value capture using AI is statistically significant in at least two distinguished groups in the aspect of using technology imitating artificial intelligence for customer contact.

Research findings indicate the importance of enterprise size in implementing modern technological solutions. Well-established approaches confirming these conclusions can be found in scientific publications. Prisco et al. (2022) found that small- and medium-sized enterprises are more effective at using blockchain technology than large companies. Ifinedo (2011) looked for reasons why small and medium-sized enterprises on the Canadian market are reluctant to accept Internet and e-business technologies in their operations. Bordonaba-Juste et al. (2012) found that medium and large companies use e-business more intensively, and small enterprises use IT outsourcing as a key factor in using e-business. On the other hand, Na et al. (2023) noted that various studies have shown that the size of the enterprise plays a key role in the development and acceptance of new technology. At the same time, these authors emphasised the two-faceted nature of this issue. On the one hand, large entities have greater financial capabilities and greater resources to implement modern technological solutions, but on the other hand, small and medium-sized enterprises have greater flexibility and adaptability. Considering the factors that determine AI investments, studies have shown that larger companies and those with greater cash reserves are more likely to invest in AI (Babina et al., 2024). In addition, large latecomer companies achieve the greatest benefits in terms of productivity and innovation from implementing AI methods (Kopka, Fornahl, 2024). The results of Yang et al.'s (2024) research show that larger companies with greater resources can implement AI more effectively, while smaller companies encounter greater difficulties in this process. Similar conclusions were drawn by Kinkel et al. (2022), who indicated that larger companies have greater opportunities to implement AI thanks to their organisational resources. In addition, larger companies with more structured processes can implement AI technologies more effectively (Rožman et al., 2024). This research may therefore constitute a premise for differentiating the use of AI to build individual components of the business model by the size of the company.

Conclusions

The article analyses the relationship between variables that create individual components of value for business models: value proposition, value creation and delivery, value capture, and enterprise size and age. The obtained results allow for an affirmative answer to the first research question: Does the use of artificial intelligence to build individual components of the business model depend on the size of HGE? The results of the chi-square and Kruskal-Wallis tests confirm statistically significant relationships between individual value components and the size of the enterprise when these components are perceived as the average of the values of the variables that create them. It has also been shown that the values of these components are differentiated by the size of the enterprise. However, the conducted analyses do not allow for an affirmative answer to the second research question: Does the use of artificial intelligence to build individual components of the business model depend on the age of HGE? The results of the chi-square test confirm the existence of a statistically significant relationship only between the age of the enterprise and the value capture component. Similarly, the results of the Kruskal-Wallis test do not confirm that individual variables and components are differentiated by the age of the enterprise, with the exception of variables concerning contacts with customers based on technology imitating human intelligence, which are more beneficial in generating revenues for the sold offer, and the value capture component. A limitation of the research is that it conducted analyses among high-growth enterprises without considering their business profiles. Allocation to specific industries would allow for the identification of similarities and differences in the use of artificial intelligence in building their business models. Future research could therefore include a sector classification of HGEs.

Literature

Ali, M., Khan, T. I. Khattak, M. N., & ŞENER, İ. (2024). Synergizing AI and business: Maximizing innovation, creativity, decision precision, and operational efficiency in high-tech enterprises. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(3), 100352. doi: 10.1016/j.joitmc.2024.100352

Amitt, R., & Zott, C. (2001). Value creation in e-Business. *Strategic Management Journal, 22*(511), 493-520. doi: 10.1002/smj.187

Ante, L., & Saggu, A. (2025). Quantifying a firm's AI engagement: Constructing objective, data-driven, AI stock indices using 10-K filings. *Technological Forecasting and Social Change, 212*, 123965. doi: 10.1016/j.techfore.2024.123965

Åström, J., Reim W., & Parida V. (2022). Value creation and value capture for AI business model innovation: a threephase process framework. *Review of Managerial Science, 16*, 2111-2133. doi: 10.1007/s11846-022-00521-z

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics, 151*, 103745. doi: 10.1016/j.jfineco.2023.103745

Berg, J., Raj, M., & Seamans, R. (2023). Capturing Value from Artificial Intelligence. *Academy of Management Discoveries, 9*(4), 424-428. doi: 10.5465/amd.2023.0106

Bordonaba-Juste, V., Lucia-Palacios, L., & Polo-Redondo, Y. (2012) The influence of organizational factors on e-business use: analysis of firm size. *Marketing Intelligence & Planning, 30*(2), 212-229. https://doi: 10.1108/02634501211211984

Cantrell, L. J., & Linder, J. (2000). Changing business models: Surveying the landscape. *Accenture Institute for Strategic Change*, *15*(1), 142-149.

Chesbrough, H.W. (2007). Business model innovation, it's not just about technology anymore. *Strategy and Leadership, 35*(6), 12-17. doi: 10.1108/10878570710833714

Coad A., Harasztosi P., Pál R., & Teruel M. (2022). Policy instruments for high-growth enterprises. In: K. Wennberg, C. Sandström (Eds.), *Questioning the Entrepreneurial State. Status-quo, Pitfalls, and the Need for Credible Innovation Policy. International Studies in Entrepreneurship* (pp. 273-298). Switzerland, Cham: Springer.

da Silva Marioni, L., Rincon-Aznar, A., & Venturini, F. (2024). Productivity performance, distance to frontier and AI innovation: Firm-level evidence from Europe. *Journal of Economic Behavior & Organization, 228*, 106762. doi: 10.1016/j.jebo.2024.106762

Del Baldo, M., & Palazz, F. (2023). High-Growth Benefit Corporations: Leveraging on Intangibles-Insights from Italy. *Sustainability, 15*(10974), 1-20. doi: 10.3390/su151410974

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 24*(5), 1709-1734. doi: 10.1007/s10796-021-10186-w

Eurostat. (2025). *Use of artificial intelligence in enterprises.* Retrieved from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises

Haftor, D. M., Costa-Climent, R., & Ribeiro-Navarrete, S. (2024). Firms' use of predictive artificial intelligence for economic value creation and appropriation. *International Journal of Information Management, 79*(102836), 1-35. doi: 10.1016/j.ijinfomgt.2024.102836

Ifinedo, P. (2011). Internet/e-business technologies acceptance in Canada's SMEs: an exploratory investigation. *Internet Research*, *21*(3), 255-281. doi: 10.1108/10662241111139309

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62,* 15-25. doi: 10.1016/j.bushor.2018.08.004

Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing - Evidence from a worldwide sample of manufacturing companies. *Technovation, 110*, 102375, doi: 10.1016/j.technovation.2021.102375

Kopka, A., & Fornahl, D. (2024). Artificial intelligence and firm growth - catch-up processes of SMEs through integrating AI into their knowledge bases. *Small Business Economics, 62*, 63-85. doi: 10.1007/s11187-023-00754-6

Kristoffersen, E., Blomsma, F., Mikalef, P., & Li, J. (2020). The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies. *Journal of Business Research, 120,* 241-261. doi: 10.1016/j.jbusres.2020.07.044

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging Technology and Business Model Innovation: The Case of Artificial Intelligence. *Journal of Open Innovation: Technolgy, Market, and Complexity*, *5*(3), 1-13. doi: 10.3390/joitmc5030044

Mishra, S., & Tripathi, A. R. (2021). AI business model: an integrative business approach. *Journal of Innovation and Entrepreneurship*, *10*(18), 1-21. doi: 10.1186/s13731-021-00157-5

Na, S., Heo, S., Choi, W., Han, S., & Kim, C. (2023). Firm Size and Artificial Intelligence (AI)-Based Technology Adoption: The Role of Corporate Size in South Korean Construction Companies. *Buildings*, *13*(4), 1066. doi: 10.3390/buildings13041066

Nightingale, P., & Coad, A. (2014). Muppets and gazelles: Political and methodological biases in entrepreneurship research. *Industrial and Corporate Change, 23*(1), 113-143. doi: 10.1093/icc/dtt057

OECD. (2010). *High-Growth Enterprises: What Governments Can Do to Make a Difference. OECD Studies on SMEs and Entrepreneurship*. Retrieved from http://dx.doi: 10.1787/9789264048782-en.

Osterwalder, A., & Pigneur, Y. (2010). *Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers*. New Jersey, USA: John Wiley and Sons.

Otola, I., Grabowska, M., & Krupka, Z. (2023). Response of high-growth enterprises to the crisis caused by the Covid -19 pandemic. *Management: Journal of Contemporary Management Issues, 28*(2), 13-26. doi: 10.30924/mjcmi.28.2.2

Otola, I., Grabowska, M., & Szajt, M. (2020). Value Composition for Business Models of High-Growth Enterprises. In: I. Otola, & M. Grabowska (Eds.), *Business models: Innovation, digital transformation, and analytics* (pp. 33-47). New York, USA: CRC Press.

Pereira, V., & Temouri, Y. (2018). Impact of institutions on emerging European high-growth firms. *Management Decision, 56*(1), 175-187. doi: 10.1108/MD-03-2017-0279

Prisco, A., Abdallah, Y. O., Morande, S., & Gheith, M. H. (2022). Factors affecting blockchain adoption in Italian companies: the moderating role of firm size. *Technology Analysis & Strategic Management, 36*(10), 2517-2530. https://doi: 10.1080/09537325.2022.2155511

Richardson, J. (2008). The business model: an integrative framework for strategy execution. *Strategic Change, 17,* 133-144. doi: 10.1002/jsc.821

Rožman, M., Oreški, D., Crnogaj, K. & Tominc, P. (2023). Agility and Artificial Intelligence Adoption: Small vs. Large Enterprises. *Naše gospodarstvo/Our economy*, *69*(4), 26-37. doi: 10.2478/ngoe-2023-0021

Shollo, A., Hopf, K., Thiess, T., & Müller, O. (2022). Shifting ML value creation mechanisms: A process model of ML value creation. *The Journal of Strategic Information Systems, 31*(3:101734), 1-20. doi: 10.1016/j.jsis.2022.101734

Sjödin, D., Parida V., Palmié M., & Wincent J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research, 34,* 574-587. doi: 10.1016/j.jbusres.2021.05.009

Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. *Technological Forecasting & Social Change*, *197.* doi: 10.1016/j.techfore.2023.122903

Sokhanvar, A. (2025). FDI and productivity: facts versus fiction of high growth. *International Journal of Emerging Markets, 20*(2), 913-932. doi: 10.1108/IJOEM-07-2021-1134

Temouri, Y., Luong, H.-P., Pereira, V., & Rammal, H. G. (2025). The Role of cluster ecosystems and intellectual capital in achieving high growth entrepreneurship: Evidence from Germany. *Journal of Intellectual Capital, 26*(1), 1-24. doi: 10.1108/JIC-01-2024-0017

Teruel, M., Bauer, P., Coad, A., Domnick, C., Harasztosi, P., Rückert, D., & Weiss, Ch. (2024). Digitalisation and high-growth enterprises in Europe. *Technology Analysis & Strategic Management*, 1-14. doi: 10.1080/09537325.2024.2394771

Tse, T., Esposito, M., Mizuno, T., & Goh, D. (2020). *The Dumb Reason Your AI Project Will Fail*. Retrieved from https://hbr.org/2020/06/the-dumb-reason-your-ai-project-will-fail

Wahab, M. D. A., & Radmehr, M. (2024). The impact of AI assimilation on firm performance in small and medium-sized enterprises: A moderated multi-mediation model. *Heliyon, 10*(8). doi: 10.1016/j.heliyon.2024.e29580

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change, 201*, 123251, doi: 10.1016/j.techfore.2024.123251

Zhang, W., Li, S., Li, Z., & Feng, H. (2023). Assessing the competitiveness of listed Chinese high-growth companies in the STAR market. *Heliyon, 9,* 1-13. doi: 10.1016/j.heliyon.2023.e15735