

ARTIFICIAL INTELLIGENCE APPLICATION IN ENTERPRISE BASED ON BUSINESS MODEL CANVAS

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Purpose: This article aims to identify the business model canvas (BMC) areas in which enterprises most frequently implement artificial intelligence (AI) tools and to determine the structural and operational factors that determine their use.

Design/methodology/approach: This survey uses a mixed-methods study that combines a systematic literature review with a two-stage quantitative analysis. First, Z-tests and Chi-square tests examined nine BMC areas using a proportion test (50% population share) to evaluate AI tool prevalence. Second, 18 logit models explained the impact of structural and operational variables on AI use.

Findings: The proportion test results showed that in 2024, significant AI tool use was concentrated in key activities and value propositions. In 2025, customer relationships were added as another area with statistically significant AI use. Econometric research results showed that the implementation of an AI tool in one BMC area depends on its implementation in other areas.

Research limitations/implications: Limitations include the survey's geographic sample size and the evolving level of organizational awareness and knowledge regarding AI tools.

Practical implications: The proportion test results indicate that companies should prioritize implementing AI tools in value propositions, key activities, and customer relationships to improve efficiency and competitiveness. Econometric results indicate that the successive diffusion of AI in a single area of a business model generates network benefits, which can reduce psychological barriers and foster the effective adoption of AI tools within enterprises and increase employee competency.

Social implications: The application of AI tools in specific areas of business models can accelerate digital transformation in a broader context, improve user experience, and influence organizational and management practices.

Originality/value: Unlike other studies, a unique hybrid methodology was conducted based on a systematic literature review with a two-stage quantitative study consisting of simple statistical tests and a set of 18 logit models, which allowed for the identification of AI adoption locations and their mechanisms of diffusion in the business models.

Keywords: Artificial Intelligence, Business Model Canvas, value propositions, key activities, customer relationships.

Category of the paper: Research paper.

1. Introduction

Artificial intelligence (AI) tools are solutions based on interdisciplinary advances in computer science. The term "artificial intelligence" was coined by John McCarthy and presented at the Dartmouth Conference in 1956 (McCarthy, Minsky, Shannon, 1955). Kaplan and Haenlein (2019) define AI as "the ability of a system to correctly interpret data from external sources, learn from that data, and use that knowledge to perform specific tasks and achieve goals through flexible adaptation" (Kaplan, Haenlein, 2019). Key technological components of AI tools include machine learning algorithms, deep learning, fuzzy logic, evolutionary algorithms, swarm intelligence, large language models (LLMs) for processing structured and unstructured data, and computer vision (Sarker, 2021). Intermediate components include graphics processing units (GPUs), transistor processors (TPUs), and cloud computing infrastructure (Nikolić, Dimitrijević, 2022). Robotics and automation, including applications of the Industrial Internet of Things (IIoT), are also important (Khang, Gupta et al., 2023; Rath, Khang, Roy, 2024). As a system, artificial intelligence (AI) has the "ability" to perform specific actions based on external "data". Data drives AI. The system's actions on this data allow it to learn to perform specific tasks and achieve goals in an adaptive manner, i.e., in a way that allows it to adapt to the conditions prevailing at a given moment. The challenge of today is undoubtedly the effective adaptation of AI tools and their effective operation in a system such as an enterprise. This is important, otherwise tensions may arise resulting from the strategic and operational assimilation of AI in enterprises. Current macroeconomic literature widely documents the impact of digital transformation (Śledziewska, Włoch, 2023; Westerman, Bonnet, 2014; Brynjolfsson, McAfee, 2014; Zuboff, 2019), including how advanced artificial intelligence algorithms change the structure, dynamics, and trade policy at the macro and global level (Śledziewska, 2025), gross domestic product (Nowakowski, 2026), or how they affect wages, income, productivity (Acemoglu, 2021), fiscal policy, taxation, and the stability of financial systems (Agrawal, Brynjolfsson, Korinek), divergence, and inequality (Cerutti, Pascual, Kido et al., 2025). However, there is still a deficit in empirical research on the adaptation of AI tools in specific areas of enterprise activity. Previous studies have often focused on AI adoption in its entirety (McElheran, Li, Brynjolfsson et al., 2024; McElheran, Yanf, Kroff, Brynjolfsson, 2026; Bonney, Breaux, Buffington et al., 2024; Bonney, Breaux, Dinlersoz et al., 2026), which often boiled down to the statement "AI-using firms". Currently, this research approach is being practiced less and less, in favor of research that examines AI adoption in enterprises from the perspective of internal applications in various business areas of the organization (Pastor-Merino, Martínez-Barbero, Vicente, Domenech, 2026; Acemoglu, 2024). Therefore, the concept based on the BMC (Business Model Canvas) template can be applied to the study of AI adoption in individual areas of the business model. Such research can be carried out at the binary level, showing the progress of AI tool adoption in individual areas

of the business model. However, the problem of dynamics remains. Year-to-year (i.e., two-year) studies cannot capture this dynamics. With respect to the binary approach, a solution may be the use of proportion tests, which do not reflect year-to-year dynamics but show the ongoing change in the use of AI tools not only within the entire BMC template but also in its individual areas. It's important to remember that the market launch of tools like Chat GPT, Copilot, and Gemini is scheduled for the turn of 2022/2023, with practical implementation in enterprises expected in 2024-2025 (McKinsey & Company, 2025; Stanford University Human-Centered Artificial Intelligence, 2026; Alfaro, Cabrales, Roa et al., 2026; Liu, Wang, 2026). Therefore, capturing these dynamics requires a different perspective. By implementing the Business Model Canvas (BMC) template and thus applying it to the study of AI adoption in specific business model areas, it is possible to develop econometric models that can explain how the change in AI application in a given area depends on variables such as company size, business profile, sector type, and the number of areas in which AI tools have been adopted so far.

Taking the above into account, the aim of this article is to identify the areas of the business model canvas (BMC) in which companies most frequently implement artificial intelligence (AI) tools and to determine the structural and operational factors that determine this use. Specifically, the study aims to verify how company size, business profile (manufacturing/services), technological sector type/other, and AI implementation advancement influence the likelihood of using AI in individual BMC components. Methodologically, the work consists of a literature review (SLR) and quantitative research. The work contributes to understanding the real-world digitalization of companies using AI by empirically verifying the research hypotheses using statistical tests and logit models. The research hypotheses are presented below.

H1s was tested using statistical tests of proportions. Hypothesis H1e, in turn, is an overarching hypothesis consisting of four specific sub-hypotheses:

- Hypothesis H1s: "The percentage of companies using AI tools is significantly higher than the percentage of companies not using AI in most of the nine areas of the Business Model Canvas".
- Main Hypothesis (H1e): The likelihood of implementing AI in individual business model canvas (BMC) areas is determined by the structural characteristics of the company (size, industry, technological profile) and the overall intensity of AI use within the organization, with patterns of these relationships showing stability in 2024-2025.
- Specific Hypothesis 1 (H1e-a): The primary and universal determinant of AI implementation in any BMC area is the overall intensity of the organization's digitalization; the more BMC components already use AI, the higher the likelihood of its implementation in the next area (path effect and digital synergy).

- Specific Hypothesis 2 (H1e-b): The impact of overall digitalization intensity on decisions to implement AI in the business model is dependent on enterprise size, revealing statistically significant patterns in selected BMC areas for small and large companies.
- Specific Hypothesis 3 (H1e-c): A company's affiliation with the information technology (IT) sector is a significant structural feature that co-determines (together with digitalization intensity) the likelihood of implementing AI in selected, specific BMC components.
- Specific Hypothesis 4 (H1e-d): A company's affiliation with a service or manufacturing profile is a significant structural feature that co-determines (together with digitalization intensity) the likelihood of implementing AI in selected, specific BMC components.

This work is consistent with the current research on the application of AI tools in enterprise business areas. From a scientific perspective, the work is significant because it demonstrates that the BMC template is no longer merely a descriptive or conceptual tool, but rather a tool that can be applied mathematically. This allows for the presentation of not only a static perspective on BMC (statistical tests) but also a dynamic one (logit models). This allows for replication of the study in other countries and industries. In terms of the theory of innovation diffusion, the work demonstrates a feedback loop, for example, that the level of AI implementation in BMC, as X, increases the likelihood of AI implementation in a specific area Y. The study also allows for the development of new theories at the interface of management and IT, for example, management goals, financial indicators, and other aspects of technology configuration options, change management, understanding business needs and technology capabilities at the interface between management and those responsible for the technical implementation of digital technologies, employee competencies and AI technologies, and reducing the stress resulting from digital transformation as part of the implementation of AI tools in specific positions.

2. Methods

Two research methods were used in the study. The first focused on a systematic literature review. The second quantitative method enabled empirical research based on a developed survey (Creswell, Creswell, 2022; Fisher, 2017).

The systematic literature review aimed to collect scientific articles that showed the applications of AI in the elements of the BMC template. The systematic literature review was conducted by defining relevant keywords or combinations thereof for the purposes of advanced searching in scientific literature databases. Next, the results obtained were used to identify relevant articles for each element of the research area concerning the application of AI tools.

Subsequently, the selected articles were analysed to develop a matrix of AI applications in individual BMC elements. The diagram below shows the successive stages. The result of the systematic literature review is the identification of research gaps, information on the research methods used to date, the possibility of developing new directions for future research, new research questions, as well as information relevant to businesses with practical implications for the use of AI tools in management. The diagram below shows the systematic literature review.

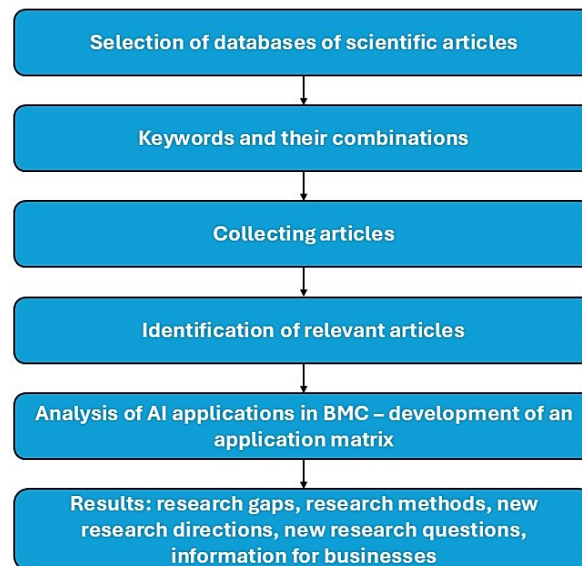


Figure 1. Schematic diagram of the systematic literature review conducted.

Source: Authors own work.

Operationally, the study consisted of the following stages. First, scientific literature databases were selected. The Mendeley and Google Scholar databases were selected for the study. Next, keywords and their combinations were selected. The keywords were based on words such as: Business Model Canvas, BMC, Canvas, value propositions, customer segments, channels, customer relationship, revenue, key resources, key activities, key partnerships, cost structure, AI, artificial intelligence, artificial intelligence tool, artificial intelligence tools. These words made it possible to build combinations of words for advanced searches, e.g.: AI and value propositions; artificial intelligence tool and customer segments, etc. Based on these combinations, the next step was to select relevant articles based on their relevance to the keywords and the research area. Next, the usefulness of the articles was identified in relation to the research objective. The next stage was to build a matrix indicating specific applications of AI in specific BMC elements based on the indications in the identified scientific articles. On this basis, the results were compiled and presented in the form of graphs. In the final step, as part of the discussion of the research results, conclusions were presented regarding research gaps, further research, the methods used, and the results in relation to the research objective. The results of the literature review are intended to answer the research questions.

The quantitative research method aimed to empirically determine whether the companies covered by the study use AI solutions in individual elements of the BMC or not. The essence of this method is to explain reality based on data that represent the actual state of affairs. In this respect, the quantitative research method allows us to learn about the actual cognitive results, enabling us to draw specific conclusions and interpretations that may serve as a basis for further in-depth research. The basic issue in the quantitative research method is the choice of data collection tool. As part of the study, a questionnaire survey was chosen, in which it was decided to develop closed YES/NO questions. The basis for choosing this type of questions were advantages such as: ease of answering by the respondent resulting from the clarity and unambiguity of the questions, relatively short time needed to complete the survey, and ease of statistical analysis in quantitative research. Another advantage of using closed YES/NO questions is the ability to observe changes indicating the level of AI tool adoption among enterprises. The disadvantage of such a survey is the shallow level of opinion expression, which does not allow for in-depth examination of various issues and nuances related to the use of AI. However, in the broader context of the research strategy, the use of a survey questionnaire is consistent with the logic of the classical research process, in which data is first collected, examined at a general level, and conclusions are drawn that form the basis for separate detailed studies. This process is a deductive approach that is used in many areas of scientific research, including social and marketing research. It also responds to the need to prove a research hypothesis. This process also allows for faster identification of specific areas within a given research field that require in-depth study, e.g. for hypotheses in individual elements of the BMC.

Secondly, to identify the determinants of AI implementation in a given BMC area, 18 logistic regressions (logit models) were estimated – 9 models each for 2024 and 2025. A separate model for each BMC area was used as the dependent variable $Y \in \{0,1\}$. The following explanatory variables (X) were adopted: enterprise size (dichotomous variables for small, medium, and large companies; for micro companies, the intercept serves as the reference base), business sector (manufacturing or services), technological profile (technology company or other; IT industry or other), and digitization intensity (a discrete variable 0-8, denoting the number of other BMC areas with AI tools implemented, which allowed for avoiding multicollinearity). It is also worth emphasizing the advantages of the logit model, e.g., implementing AI in a given BMC area is a binary decision – the company either implemented the technology (1) or did not (0). The choice of the logit model in the study also stemmed from its ability to precisely analyze dichotomous variables and synergy effects, which enabled interpretation of the results using odds ratios (ORs). This tool, unlike linear regression, ensured business realism by limiting predictions to a range of 0-1 and allowed for rigorous assessment of model quality. Determining the effects of a given model through probability of the logit model is also crucial. For example, with use of the logit model ideally indicates a breakthrough moment. When a company implements AI in approximately 4-5 other

BMC areas, the probability of success in the studied area exceeds the 0.5 threshold (50%). That the process is non-linear. It also illustrates changes, for example: at the beginning (values 0-2), the probability increase is slow. Between 3 and 6, a sharp increase (an explosion of adoption) occurs, and above 8, saturation occurs. Thanks to the logit model is possible to received the graph transforms an abstract mathematical algorithm (the logarithm of the odds ratio) into an intuitive roadmap. This allows for immediate understanding of the logical chain of cause and effect: the greater the digital maturity of the entire company, the lower the risk and the greater the ease of implementing AI in a new segment. This approach allows for the identification of technology adoption phases into practical stages. Below is a diagram showing the successive stages of quantitative research.

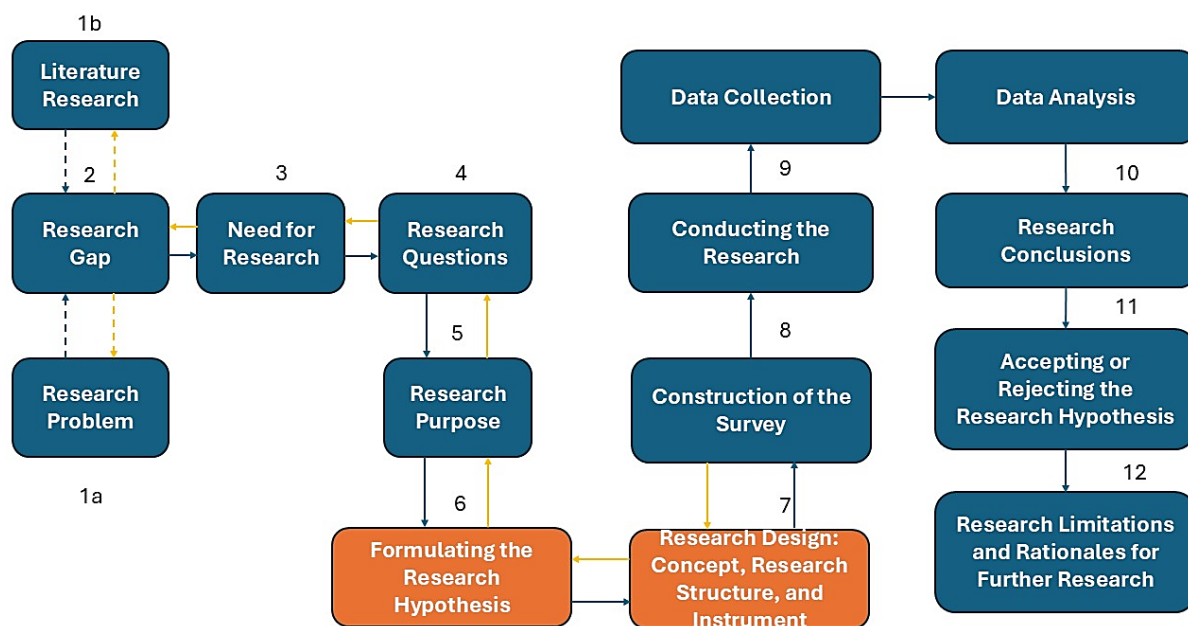


Figure 2. Diagram showing the steps involved in conducting a quantitative study.

Source: Authors own work.

The quantitative research began with stage 1, which was divided into sub-stages 1a and 1b. In sub-stage 1a, theoretical considerations were made regarding the use of AI tools in the enterprise. This stage involved a systemic analysis of the enterprise, its information space and AI tools. A systemic comparison of the enterprise, the information system and AI as a system allowed for the identification of dependencies, relationships and areas that require research, i.e. the need to apply a universal template in the form of BMC. In turn, in sub-stage 1b, literature research was carried out to search for information on completed studies on the application of AI tools in individual elements of BMC. Sub-stages 1a and 1b identified a research gap in stage 2, which indicates that the phenomenon of the application of AI tools in individual areas of business models has not been sufficiently researched. Stage 3 summarises the processes from the sub-stages in the form of the need to conduct research. Formulating the research need in stage 3 leads to research questions in stage 4, such as: In which elements of the business model

do the companies under study use AI tools? In which of these elements are AI applications most numerous? What impact do variables (enterprise size, industry, technological profile) and the overall intensity of AI use in the organization have on the implementation of AI tools in individual areas of the BMC? In turn, in stage 5, the research objective is formulated: to identify the applications of artificial intelligence tools in individual areas of the Business Model Canvas. In stage 6, research hypotheses are formulated: H1s, H1e, H1e-a, H1e-b, H1e-c, H1e-d. This leads to work on the research models in stage 7, specifically on the research concept, its structure and the selection of research tools. This is a very important point, where it was decided that, within the adopted research area, a research questionnaire consisting of nine research questions (stage 8) concerning the use of AI tools in each of the BMC elements would be developed. The following closed YES/NO questions were developed:

Does your organisation use Artificial Intelligence solutions for customer segmentation?

1. Does your organisation use Artificial Intelligence solutions to create value propositions for customers?
2. Does your organisation use Artificial Intelligence to optimise distribution channels?
3. Does your organisation use Artificial Intelligence to build relationships with customers?
4. Does your organisation use Artificial Intelligence solutions to manage key assets?
5. Are key activities in your organisation supported by Artificial Intelligence solutions?
6. Does your organisation use Artificial Intelligence solutions to collaborate with key partners?
7. Is Artificial Intelligence used in your organisation to optimise the revenue structure?
8. Is Artificial Intelligence used in your organisation to optimise the cost structure?

In addition to the above questions, the surveyed entities were asked to indicate the size of their organisation and location data.

It is also worth noting that, including stage 8, we allowed for the possibility of adjusting individual stages, which gave us flexibility in terms of possible changes. Data collection began in stage 9. The data was collected electronically during registration for remote broker meetings and workshops on the applications of artificial intelligence in business and everyday life *AI ABEL AI Applications in Business and Everyday Life (Virtual edition)* in 2024 and 2025. Data was collected from 15 March 2024 to 12 June 2024 and from 14 March 2025 to 12 June 2025 during registration (Digital Economy Lab 2024; Digital Economy Lab 2025). During the study, we also took into account the participation of entities other than companies, i.e. foundations, associations, scientific research and development institutes, and universities, but we limited the results of the study to companies only, in accordance with the research objective and research hypothesis. In total, data was collected from 358 entities during the registration process for the *AI ABEL (AI Applications in Business and Everyday Life)* event in 2024, and from 276 entities in 2025. The sample included companies, universities, research and development institutes, foundations and associations. In accordance with the purpose of the

study, the analysis was limited to enterprises only. As a result of the data cleaning process, in which entities that did not meet the criteria were rejected, the final sample included 200 enterprises in 2024 and 155 enterprises in 2025, respectively. It should be emphasised that participation in the study required consent to the processing of data for scientific purposes. In 2024, 269 entities (74.9%) gave their consent, while 89 entities (24.9%) did not. In 2025, the corresponding figures were 220 entities (79.7%) and 56 entities (20.3%). Only those observations for which consent to use the research data was obtained were included in further analyses. Share of individual companies by size in 2024: micro: 45%; small: 36%; medium: 12%; large: 8%. Share of individual companies by size in 2025: micro: 42%; small: 35%; medium: 14%; large: 9%.

3. Methods

Two research methods were used in the study. The first focused on a systematic literature review. The second quantitative method enabled empirical research based on a developed survey (Creswell, Creswell, 2022, Fisher, 2017).

3.1. Literature research results

The identification of relevant articles published between 2021 and 2025 allowed us to select 100 articles, which were subjected to an in-depth analysis in terms of research methods and areas of application of AI tools within the Business Model Canvas. A detailed list of sources is presented in the Bibliography section: [3], [6-13], [16-17], [25-26], [28-30], [32-33], [36], [38-39], [41-45], [47-50], [52-56], [58-60], [62], [64-73], [75], [77-79], [84-88], [91-92], [97], [99-102], [104], [106-111], [113], [115-121], [123-125], [129], [132-134], [136-140], [143-148].

First, an analysis of the research methods used was carried out. The chart below shows the percentage share of methods used.

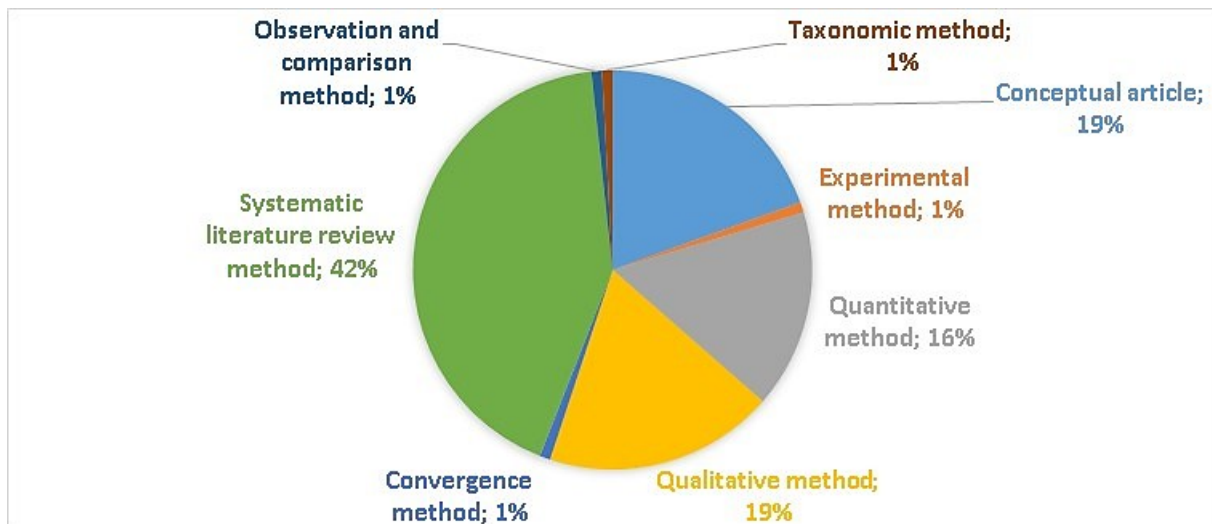


Figure 3. Percentage share of research methods used in the application of AI tools.

Source: Authors own work.

The results of the study indicate that the most commonly used research method is systematic literature review, with a share of 42%. The next most common method is the qualitative method, with a share of 19%. Conceptual articles have the same percentage share. The percentage share of the quantitative method is 16%. The percentage share of tools within the qualitative and quantitative methods was also analysed. In the qualitative method, interviews account for 50% and case studies for the other 50%. In the quantitative method, classical statistics tools account for 47%, machine learning and deep learning tools account for 37%, and econometric tools account for 16%.

The number of individual AI technologies used was also examined. The chart below presents the number of technologies used.

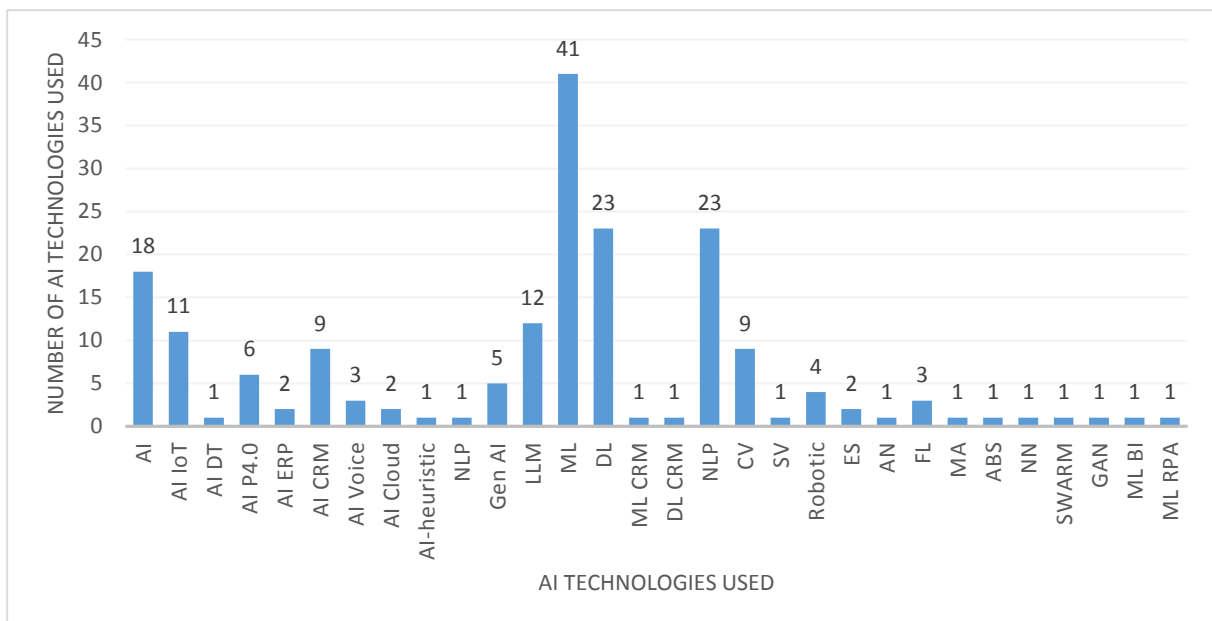


Figure 4. Number of individual AI tools used.

Source: Authors own work.

The results of the study indicate that among the most prominent technologies are Machine Learning (ML) – 41, followed by Deep Learning (DL) – 23, Natural Language Processing (NLP) – 23. The chart also shows the number of technologies used that fall under the generalised acronym AI (Artificial Intelligence) – 18 (the literature review included articles that used the term AI without specifying what it meant). Within the adopted definition and taxonomy, the article classified the Internet of Things (IoT) as part of this group of AI ML and DL algorithms, but it was decided to present this group separately due to the inability to divide it. Among other notable technologies, it is also worth mentioning Large Language Models (LLM) – 12. Others worth noting are AI IoT (Artificial Intelligence Internet of Things) – 11, Computer Vision (CV) – 9, AI CRM (Artificial Intelligence Customer Relationship Management) – 9, AI P.4.0 (Artificial Intelligence Industry 4.0) – 6.

It is worth noting that it is possible to sum up selected technologies that are part of the so-called Industry 4.0. Then the number will increase to as many as 25, assuming that only the following components are included: AI P.4.0, AI IoT, Robotic, AI Digital Twin (DT), AI Cloud, Artificial Intelligence Robotic Process Automation (AI RPA). However, this is problematic due to other components that can also be included in this category. This synthetic approach aims to indicate that some of the components may be of significant importance from the point of view of the Industry 4.0 concept, in particular their application in the optimisation of production processes.

To obtain a more accurate picture based on the SLR, the identified AI technologies were assigned to their main functional roles in the Business Model Framework (BMC). For example, Machine Learning (ML) and Deep Learning (DL) technologies most often support the Key Activities component through process optimization and operational forecasting. Natural Language Processing (NLP) and Large Language Models (LLM) algorithms are primarily implemented in the Customer Relationships and Channels areas, automating communication and personalizing user experiences. Computer Vision (CV) technologies dominate the Key Resources area, responsible for automated quality control in production processes. Within the adopted taxonomy, the Internet of Things (IoT) is not treated as a standalone AI algorithm, but as a critical sensory infrastructure that generates data (data layer), which in the analyzed studies operates in close synergy with ML and DL algorithms (creating the so-called AI IoT – Artificial Intelligence Internet of Things). The creation of the AI IoT category (n = 11) highlights a significant taxonomic dichotomy. While the traditional Internet of Things (IoT) operates solely as an infrastructural connectivity layer for data collection, its convergence integrates edge computing. In the BMC framework, this elevates AI IoT from a mere technological infrastructure to a key enabler of Key Partners (KP) Key Resources (KR) Key Processes, and other effectively combining the digital data stream with algorithms. This is especially important because edge computing can be a crucial implementation element in smaller or medium-sized manufacturing enterprises. The presence of the general "AI" item in the chart reflects publications describing the implementation of integrated, multifunctional

IT systems with a holistic approach. In these cases, companies implemented off-the-shelf commercial platforms (e.g., intelligent enterprise management systems) in which AI operates as a unified system (black box), preventing authors from isolating individual algorithmic techniques.

Table 1.

Functional map of dominant AI technologies in BMC areas based on the conducted SLR

AI Technology (Frequency in Fig. 4)	Main Functional Role in Business	Target BMC Areas (Osterwalder)	Example Enterprise Application
General AI (n = 18)	Unspecified black-box automation and general cognitive computing support, focusing on turnkey commercial software integration, automated administrative workflows, native platform data grouping, and standardized smart asset bundling.	• Key Activities (KA) • Customer Relationships (CR) • Customer Segmentation (CS) • Cost Structure (CS) • Channels (CH) • Key Partners (KP) • Value Proposition (VP)	Out-of-the-box commercial software integration, automated office workflows, and basic cognitive assistance, built-in Suite automation to automate routine scheduling, email drafting, and meeting summarization; out-of-the-box web analytics grouping, standard smart hardware bundles.
Machine Learning (ML) (n = 41)	Predictive analytics, anomaly detection, automation of structural decisions.	• Cost Structure (CS) • Key Activities (KA) • Revenue Streams (RS)	Dynamic pricing, market demand forecasting, logistics cost optimization, energy consumption optimization, back-office process Automation, supplier selection.
Deep Learning (DL) (n = 23)	Advanced pattern recognition, multi-dimensional and unstructured data analysis.	• Key Activities (KA) • Key Resources (KR)	Predictive maintenance, predictive asset lifecycle management, automated machine vision quality control on production lines, intelligent property and infrastructure Digital Twins.
Natural Language Processing (NLP) (n = 23)	Processing, analysis, and structuring of text data and human speech.	• Customer Relationships (CR) • Channels (CH)	Customer feedback clustering, social media sentiment analysis, automated complaint categorization, real-time customer sentiment tracking, multilingual content localization.
Large Language Models (LLM) (n = 12)	Content generation, advanced conversational interaction, real-time knowledge synthesis	• Value Proposition (VP) • Customer Relationships (CR)	AI-driven advisory systems, hyper-personalization of product offers, 24/7 generative technical support.

Cont. table 1.

AI IoT (n = 11)	Integration of digital intelligence with physical infrastructure (sensing + edge computing)	• Key Resources (KR) • Key Partners (KP) • Key Activities (KA)	Autonomous supply chain management (tracking and telemetry), smart warehousing, sensor-based monitoring of resource consumption and processes, edge-powered cyber-physical assets, predictive maintenance-as-a-service, closed-loop autonomous process control, automated energy and emission load balancing.
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Source: Authors own work.

The presented functional map illustrates a clear division between specialized AI technologies (such as NLP or DL) and holistic or infrastructure-based solutions (General AI, AI IoT). This classification demonstrates that while selected algorithms are responsible for the point-by-point optimization of operational processes or customer relationships, integrated and edge systems are cross-cutting factors enabling the transformation of multiple areas of the BMC template simultaneously.

The study identified areas of application for AI tools in specific parts of the Business Model Canvas.

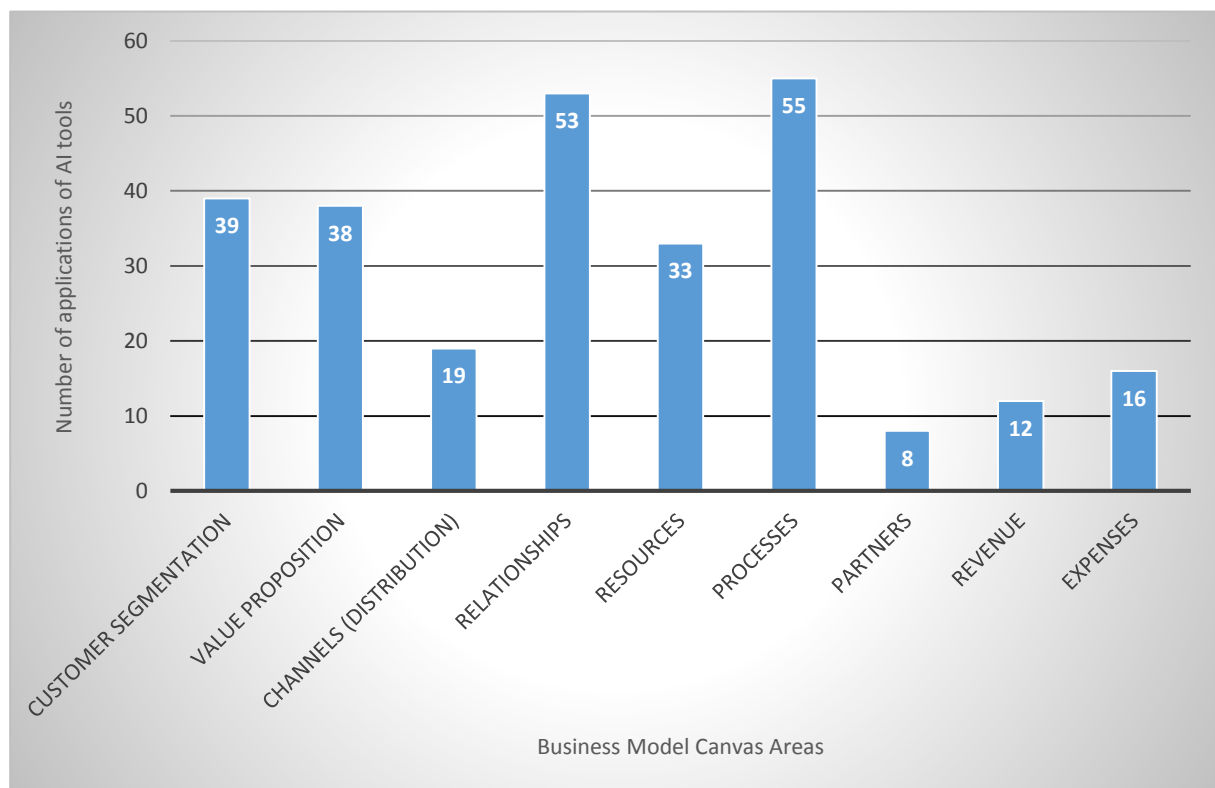


Figure 5. Number of applications of AI tools in specific areas of the BMC.

Source: Authors own work.

The results of the study indicate that the largest number of applications of AI tools occurs in the area of so-called key activities – 55. This is followed by customer relations – 53. Next in line are customer segmentation – 39, value proposition – 38, and key resources – 33.

3.2. Survey results – statistic tests

The data collected in the survey enabled quantitative analysis through graphical presentation of the responses obtained from companies and testing of statistical hypotheses. The survey, on the other hand, aimed to obtain answers from the companies themselves regarding the application of AI tools in specific areas of BMC. The answers to closed YES/NO questions made it possible to obtain graphs of the use or non-use of AI tools in a given BMC area by the companies surveyed during brokerage meetings and workshops in 2024 and then in 2025 (Digital Economy Lab 2024; Digital Economy Lab 2025).

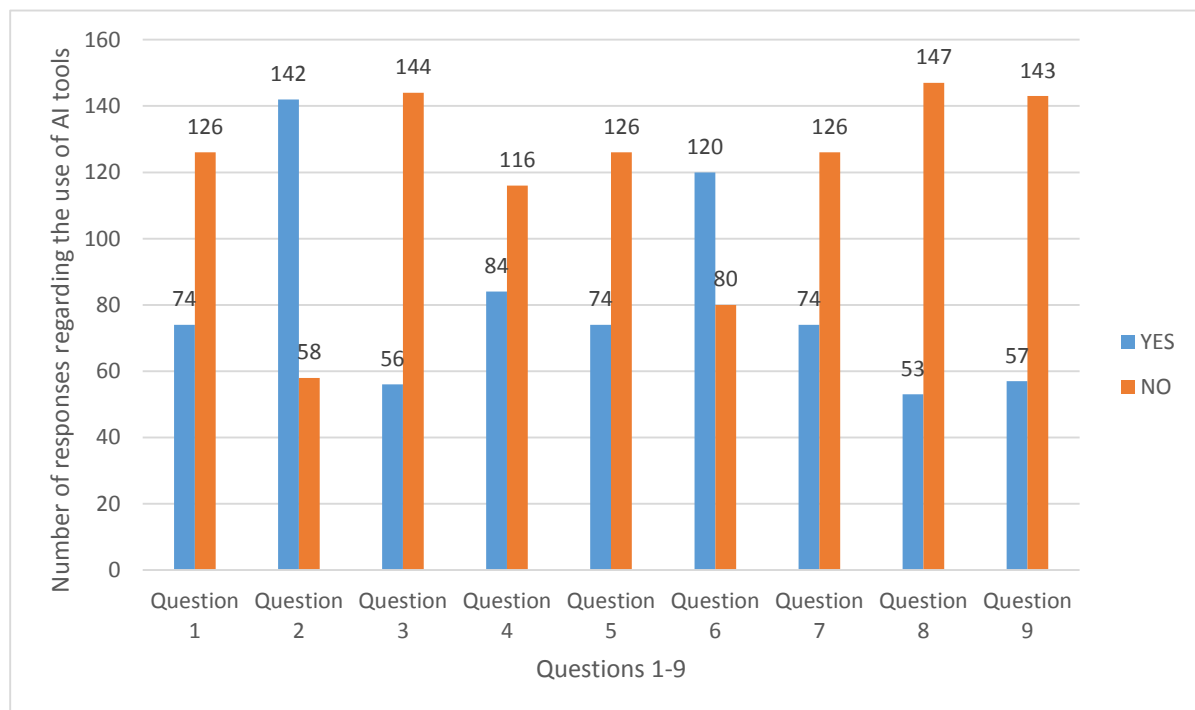


Figure 6. Responses obtained in the survey. YES/NO questions concerning the declaration of the use or non-use of AI tools by the surveyed companies in a given BMC area in 2024.

Source: Authors own work.

The survey results indicate that in most cases, companies declare that they do not use AI tools in specific BMC areas. Figure 6 shows that these areas include: question 1 – customer segmentation (126 responses), question 3 – distribution channels (144 responses), question 4 – customer relationships (116 responses), question 5 – key assets (126 responses), question 7 – partner relationships (126 responses), question 8 – revenue structure (147 responses), question 9 – cost structure (143 responses). The cases in which the use of AI in individual BMC areas was most frequently reported were: question 2 – customer value proposition (142 responses), question 6 – key activities (120 responses) (Digital Economy Lab 2024;).

The results were checked using the unit proportion test, also known as the Z-test, and the Chi-square test, which assumes that the proportion in a given population has a specific value. In this case, it is 50%. This allows us to test the null hypothesis H_0 and the alternative hypothesis H_1 in a given BMC area. The following set of hypotheses was proposed: H_0 : Hypothesis of an equal 50/50 distribution. This means that YES or NO responses do not differ statistically. H_1 : No equal 50/50 distribution. This means that YES or NO responses predominate. The table below presents the results of the proportion test for individual BMC components regarding declarations of artificial intelligence applications in the surveyed enterprises in 2024 (Creswell, J.W., Creswell, D.C. 2022; Fisher, 2017).

Table 2.

Unit proportion test Z and Chi-square test of individual BMC components concerning declarations of AI tools applications in the surveyed companies in 2024

No.	BMC Component	YES	NO	Z-statistic	χ^2 statistic	p-level	Test result $\alpha=0.05$	Advantage
1	Segmentation	74	126	3,68	13,52	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO
2	Value Proposition	142	58	5,94	35,28	<0,05	Statistically significant difference: Rejection of H_0	Advantage YES
3	Distribution Channels	56	144	6,22	38,72	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO
4	Customer Relationships	84	116	2,26	5,12	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO
5	Key Assets	74	126	3,68	13,52	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO
6	Processes	120	80	2,83	8	<0,05	Statistically significant difference: Rejection of H_0	Advantage YES
7	Partner Relationships	74	126	3,68	13,52	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO
8	Revenues	53	147	6,65	44,18	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO
9	Costs	57	143	6,08	36,98	<0,05	Statistically significant difference: Rejection of H_0	Advantage NO

Source: Authors own work.

The results of the proportion tests clearly indicate that statistically significant differences ($p < 0.05$) exist in all nine areas of the BMC template, which allowed us to reject the null hypothesis of an equal distribution of responses. A clear predominance of "YES" responses (Advantage YES) was observed only in the Value Proposition and Processes areas, proving that AI tool implementation in 2024 was strongly focused on generating new value for customers and operational optimization. The remaining seven business model components are dominated by a lack of implementation (Advantage NO), indicating the still untapped potential of AI tools.

The empirical distribution of "YES" and "NO" responses provided in the analysis of nine areas of the Business Model Canvas (BMC) template is presented in Figure X. The visualized data illustrate the structure of declarations regarding the implementation of artificial intelligence tools, constituting a direct starting point for the proportion tests and chi-square analysis.

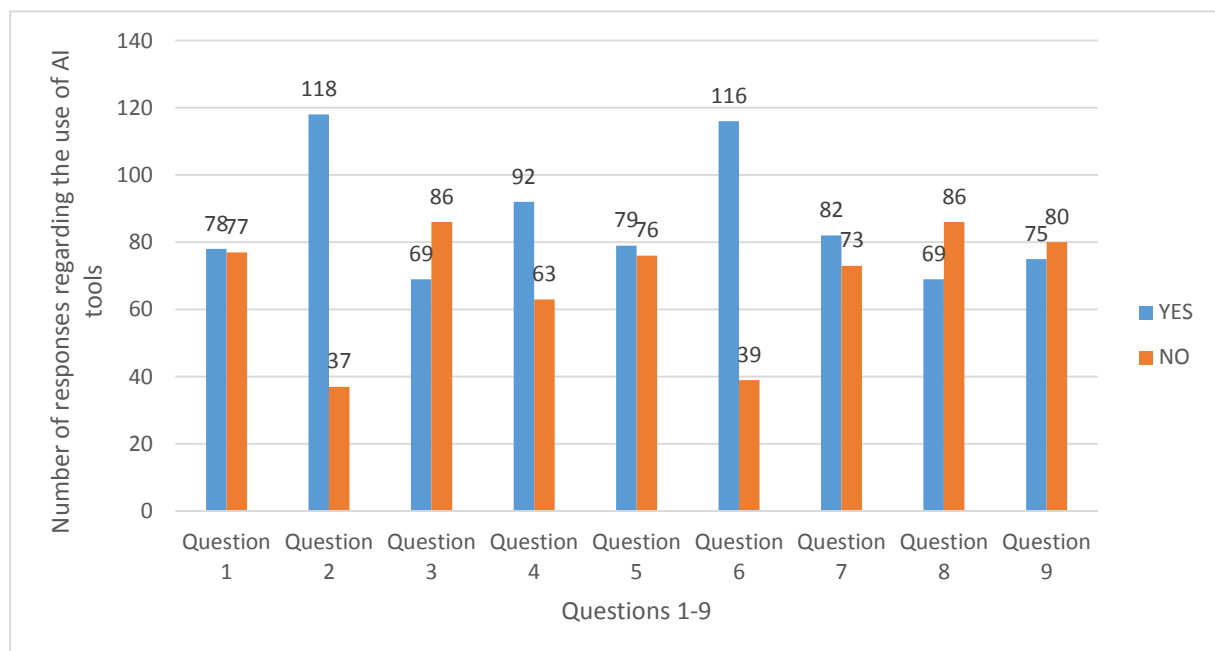


Figure 8. Responses obtained in the survey. YES/NO questions concerning the declaration of the use or non-use of AI technology by the surveyed companies in a given BMC area in 2025.

Source: Authors own work.

The survey results indicate that in most cases, companies declare the use of AI tools in specific BMC areas. Figure 8 shows that these areas include: question 1 – customer segmentation (78 responses), question 2 – value proposition (118 responses), question 4 – customer relationships (92 responses), question 5 – key assets (79 responses), question 6 – processes (116 responses), question 7 – partner relationships (82 responses). The cases in which the majority of respondents stated that AI tools were not used in particular BMC areas were: question 3 – distribution channels (86 responses), question 8 – cost structure (86 responses), question 9 – revenue structure (80 responses).

As in 2024, the results for individual BMC areas were tested using a unit proportion test and Chi-square for 2025 (Creswell, J.W., Creswell, D.C., 2022; Fisher, 2017).

Table 3.

Unit proportion test Z and Chi-square test of individual BMC components concerning declarations of AI tools applications in the surveyed companies in 2025

No.	BMC Component	YES	NO	Z-statistic	χ^2 statistic	p-level	Test result $\alpha=0.05$	Advantage
1	Segmentation	78	77	0,08	0,006	>0,05	There is no basis to reject H0	No advantage (50/50)
2	Value Proposition	118	37	6,506	42,329	<0,05	Statistically significant difference: Rejection of H0	Advantage YES
3	Distribution Channels	69	86	1.365	1,865	>0,05	There is no basis to reject H0	No advantage (50/50)
4	Customer Relationships	92	63	2,329	5,426	<0,05	Statistically significant difference: Rejection of H0	Advantage YES
5	Key Assets	79	76	0,241	0,058	>0,05	There is no basis to reject H0	No advantage (50/50)
6	Processes	116	39	6,185	38,252	<0,05	Statistically significant difference: Rejection of H0	Advantage YES
7	Partner Relationships	82	73	0,723	0,523	>0,05	There is no basis to reject H0	No advantage (50/50)
8	Revenues	69	86	1,365	1,865	>0,05	There is no basis to reject H0	No advantage (50/50)
9	Costs	75	80	0,402	0,161	>0,05	There is no basis to reject H0	No advantage (50/50)

Source: Authors own work.

The results of the proportion tests show statistically significant differences ($p < 0.05$) in three areas of the BMC template – Value Proposition, Processes, and Customer Relationships – where a clear predominance of "YES" responses was noted, confirming the focus of AI implementations on value creation, process optimization, and relationship building. In the remaining six components of the business model, there is no basis for rejecting the null hypothesis ($p > 0.05$), which indicates a relatively balanced distribution of responses (50/50). This data pattern indicates that the diffusion of AI technology in these areas is still transitional and has not yet achieved a dominant market position.

The study, using tests, identified which individual BMC areas had significant results regarding the use or non-use of AI tools, or the lack of a significant advantage. In 2024, most companies used AI tools in areas such as value proposition and processes within core activities. In other areas, such as market segmentation, customer relationships, channels, key partners, key resources, revenues, and costs, the majority of responses were "no". These results indicate that in 2024, the working hypothesis H1s is not met for most areas. Therefore, there were more areas within the BMC where a larger percentage of companies did not achieve an advantage in using AI tools. However, it is worth noting the two aforementioned areas where

the percentage of companies using AI tools is higher. In the first case, these are processes within core activities, which also stand out significantly in the systematic literature review. This result indicates that companies are exploring the use of AI tools in processes to increase their effectiveness at both the operational and strategic levels. AI tools can be used in processes in areas such as production. However, they can also be applied more broadly, for example, within the framework of Industry 4.0, for example, they can be used for process optimization within horizontal and vertical integration. They can be used to optimize processes using specific raw materials. Furthermore, criteria regarding energy consumption and pollutant emissions can be included within the same optimization framework. Another important issue for the application of AI tools from a process perspective is the product lifecycle. AI tools contribute to the optimization of processes related to product lifecycle management, from the purely development level to extending the product lifecycle as part of entering markets where the product has not yet appeared. It is also worth noting that the use of AI tools in the product lifecycle area applies not only to processes but also to the creation of value propositions. It is therefore not surprising that most companies are seeking AI tool applications to create value propositions such as specific functionalities, features, price, performance, reliability, etc. It is worth emphasizing that this is also an area that stands out significantly in a systematic literature review. It's also worth noting that areas like customer relationships and market segmentation also stood out in the systematic literature review. However, the results of the 2024 study indicate that most companies have not yet leveraged AI tools in these areas.

In 2025, a similar study was conducted using the same questionnaire. The quantitative analysis was based on the same working hypothesis and statistical hypotheses. However, the study results revealed a completely new picture regarding the application of AI tools in specific areas of BMC. Among the areas where the percentage of AI tool applications was significant were: processes within key activities, value propositions, and customer relationships. Therefore, for the second year in a row, areas such as processes and value propositions showed a higher percentage of applications. Therefore, it can be hypothesized that companies interested in AI tools are choosing to use them in processes and value propositions. The results of the 2025 study also point to a new, prominent area of AI application in BMC: customer relationships. The use of AI tools in this area applies to activities such as acquiring new customers, retaining existing customers, increasing sales, but also to forms of contact and opportunities for engaging customers in relationships, such as co-creation, problem-solving, building awareness of products or services, and tailoring offers to needs. It's worth emphasizing that the customer relationship area ranks second, right after processes, based on systematic literature reviews. The results of the 2025 study also point to an interesting phenomenon regarding the use or non-use of AI tools within companies. In six BMC areas: segmentation, channels, key resources, key partners, revenues, and costs, the significance test indicated statistical hypothesis H_0 , which indicated that H_0 : the hypothesis of an equal 50/50 distribution, meaning that YES or NO responses do not statistically differ. Analyzing the values in individual

areas, it can be seen that there are areas where the percentage of companies using and not using AI is very similar, for example, 78 companies answered YES and 77 NO. Other examples include key resources, where 79 answered YES and 76 answered NO, and channels, where 69 answered YES and 86 answered NO. The results indicate that, in addition to the three main areas of AI tool application mentioned above (processes, value proposition, relationships), YES responses indicating the use of AI tools also occur in areas such as segmentation, key resources, and partner relationships. This could suggest that AI tools are used in most areas of BMC. However, at a statistical level, the differences between the percentage of companies using AI tools and the percentage of companies not using them are similar. The same applies to three areas where the percentage of NO responses is clearly higher than YES, including distribution channels, revenues, and costs. Therefore, the current situation within the applied statistical test indicates that neither the main hypothesis H1s can be confirmed in 2025. The survey results indicate that within just one year (2024–2025), the structure of AI applications in the BMC model has changed. The two previously dominant areas, processes and value proposition, have been joined by customer relations, and in several other areas (segmentation, key resources, partnerships) similar proportions of AI use and non-use have been observed.

3.3. Survey results – logit models

As part of the quantitative study, logit models were estimated. A total of 18 logit models were estimated – one for each identified BMC area. The models were estimated based on data obtained through surveys conducted during brokerage meetings and workshops in 2024 and 2025 (Digital Economy Lab 2024; Digital Economy Lab 2025). Nine models were estimated for 2024 and nine for 2025. The aim of estimating these models was to examine the main determinants influencing decisions related to the implementation of AI tools in individual BMC areas. All estimated models are presented in Appendix 1 and Appendix 2. The initial structure of the logit models consisted of the following variables: X_1 – small company, X_2 – medium-sized company, X_3 – large company, X_4 – application of AI tools in other BMC areas, X_5 – service or manufacturing company, Variable X_5 – service or manufacturing company, Variable X_7 – IT or other company. The intercept serves as a reference base for micro-enterprises. The Y_i variables represent the subsequent BMC areas: Y_1 – segmentation, Y_2 – value proposition, Y_3 – distribution channel, Y_4 – customer relationships, Y_5 – key resources, Y_6 – key activities, Y_7 – key partners, Y_8 – revenue structure, and Y_9 – cost structure.

The results of the study conducted using logit models for 2024 and 2025 indicated that the variable "AI tools used in other areas of BMC" was a significant factor in all 18 models in both 2024 and 2025. Therefore, it can be concluded that this is a universal variable. It can also be concluded that implementing AI in one area generates network benefits and facilitates the diffusion of AI tools to other areas of the enterprise's business model. Furthermore, the greater the number of areas in which AI tools are used, the greater the likelihood of using AI tools in another area of the business model. Therefore, the use of AI tools increases the likelihood of

adopting these technologies in subsequent areas. It can be concluded that a strong feedback effect occurs in the digitalization process – positive experiences with implementing AI tools in one area influence the decision to implement them in the next. A lack of positive experiences with AI can block or delay decisions regarding further implementations.

In 2024, in Model 5, the impact of company size was revealed only in the area of key resources (Model 5). The X_3 variable (large company) proved statistically significant. This result can be explained by the fact that large companies possess larger resources due to their organizational structure. Therefore, there are emerging needs for more effective resource management, and AI tools can meet these needs. It should also be emphasized that large companies have correspondingly large capital resources, for example, large companies can create their own data centers, purchase expensive licenses, or employ scarce specialists (e.g., data scientists). The model confirms this. The positive, very high coefficient for variable X_3 (2.0139; OR = 7.492) clearly demonstrates the existence of a high entry threshold. Developing modern resources—such as advanced data centers, proprietary algorithms, or teams of specialized data engineers—requires significant financial outlays. Large companies have the advantage of free capital, economies of scale, and an existing, mature IT infrastructure. Although being a large company drastically increases the chances of resource transformation (by nearly 650%), this model reveals strong support from the X_4 variable (AI Application; OR = 2.172). This means that large entities not only passively possess resources but also digitize them. Artificial intelligence acts as a "catalyst", enabling more effective management and monetization of resources available only to large organizations (e.g., gigantic data sets – Big Data). For example, previously implemented algorithms become a knowledge base that optimizes resource management, which is crucial in a large company with a significant amount of resources – learning curve effects appear faster. It is also worth noting that resources in the context of BMC include both human resources and assets such as machines, devices, and equipment, which are crucial for process execution. Therefore, resources can be used to optimize a significant portion of processes, including other areas of BMC through processes. It's also worth examining this result from the perspective of the resource-based view (RBV) (Wernerfelt, 1984), a concept from the field of strategic management that suggests that the sources of sustainable competitive advantage are based on a company's internal resources and competencies, not on market structure. Following the assumptions of the resource-based view, it can be concluded that advanced digital technologies and AI are becoming a key, rare, and difficult-to-copy resource that builds sustainable competitive advantage—provided that these solutions are tailored specifically to the company's needs, often based on company-sourced data. It's also worth noting that competencies play a significant role in the resource-based view. Algorithms and data are valuable, but they can also be difficult to replicate—for example, because they feed unique data from internal company sources. However, these are "resources", or more precisely, AI resources. For these resources to create a competitive advantage, they require appropriate human resource competencies related to the use of AI tools,

such as: instruction design (Prompt Engineering), critical thinking, verification and evaluation, analytical and process thinking, the ability to combine data, interpret data, interpret results, digital empathy, task management (which tasks can be performed by AI), organizing work with AI (the process of planning, structuring, and coordinating tasks and AI resources with the daily responsibilities of an employee or team to automate tasks, accelerate processes, and increase efficiency), building workflow automation, digitizing analog resources, and so on. Small and medium-sized companies (X_1 , X_2), due to budget constraints, are statistically much less likely to independently create such defined, modern key resources. Another solution may lie in publicly available AI tools. Advanced models (e.g., from OpenAI, Anthropic, or Google) are publicly available to anyone for a few dollars a month. This creates a certain paradox for RBV. Such AI tools are a common (not scarce) resource and easy to copy. They are a different "resource" than dedicated AI tools. According to RBV, they cannot, therefore, provide a competitive advantage on their own. However, what will continue to determine the use of AI resources is an employee with high universal AI skills, who becomes many times more effective than an employee without these skills. Another important issue from the point of view of RBV is the process of knowledge conversion known within the classic SECI model (Socialization, Externalization, Combination, Internalization) (Nonaka I, Takeuchi H. 1995) or newer versions of GenAI SECI (Uchihira, 2026). Digital organizational culture is also important. Digital Organizational Culture – DOC is a set of shared values, beliefs, norms and everyday behaviors of employees that define the way in which an organization uses digital technologies and tools to create business value (Teguh, Noermijati, Moko et al., 2022) as well as digital innovations as the creation (and resulting changes) of market offers, business processes or business models that result from the use of digital technologies (Nambisan, Lyytinen, Majchrzak, Song, 2022) or more specifically, digital innovations that are transforming the way products and services are developed, produced, and used. For example, innovations using digital technologies enable the "sharing" of resources such as cars, utilities, and accommodation. Such innovations are revolutionizing traditional markets, including media and entertainment, car rental and sales, hospitality, and even temporary labor markets (Bogers, Garud, Thomas et al., 2021).

It's also worth noting model number 2 in 2024, where a company operating in the IT sector significantly increases the chances of developing its value proposition. IT companies possess unique technological competencies that allow them to continuously and dynamically redefine their offerings. In their case, modifying their value proposition is not merely a response to market changes, but a natural element of their product strategy. The combination of artificial intelligence implementation (X_4) and the specific nature of the IT industry (X_7) creates a synergy effect. IT companies have a ready-made infrastructure and know-how, thanks to which implementing AI solutions allows them to create modern, personalized products or services for their customers much faster and more effectively. A positive coefficient value for the X_7 variable indicates that entities in the IT sector have a much higher chance of successfully transforming their value proposition than manufacturing or traditional service companies.

This stems from the fact that for IT companies, technology is the core of the business, not just a supporting tool.

In 2025, in Model 7, the impact of company size was revealed only in the area of key partners (Model 7). The (X_3) variable (large company) proved statistically significant. This result can be explained by the growing competitive advantage of the entire value chain. This is because AI tools make it easier for large companies to exchange data with suppliers. It is also possible that large companies have sufficient capital for supply chain digitization: digitizing common technology platforms, supply chain integration systems (e.g., advanced ERP/CRM systems combined with AI), and network security for secure data exchange; building common APIs and cloud databases; implementing automated ordering and logistics tracking systems; investing in algorithms that forecast demand for suppliers; and ensuring secure, encrypted data transmission channels between companies.

The conducted likelihood ratio (LnL) test analysis revealed a lack of structural stability of the logit model parameters between 2024 and 2025. The study results can be found in Appendix 3. For eight of the nine variables examined, the Chi-square test statistic clearly exceeded the critical value of 5.991. For these items (from item 1 to item 8), the null hypothesis (H_0) of parameter stability was correctly rejected at the significance level ($\alpha = 0.05$). This means that the impact of factors such as segmentation, value proposition, and key resources has changed statistically significantly over time. The exception is the "Cost structure" variable (item 9), for which the test statistic is 2.53, which is lower than the critical value. Therefore, there is no basis for rejecting the hypothesis (H_0) for cost structure, meaning that this parameter has remained stable.

The rejection of hypothesis H_0 in models 1 to 8 (from Segmentation to Revenue Structure) means that the mechanism of diffusion and mutual influence of AI technologies in these areas has completely changed over the course of just one year. This result can be interpreted as indicating that the market is in a phase of profound AI evolution. The way AI use in some areas drove its implementation in others in 2024 became obsolete in 2025. This is evidence of a dynamic digital transformation process. The market learns AI dynamically and, to some extent, chaotically. I am testing AI tools in 8 areas on a "living organism". However, there is something that serves as a benchmark: the stability of the cost-related model parameter, also known as the cost structure in the BMC model. The cost structure proved to be the most stable element in this study. This indicates that the mechanism by which AI tools implemented in the remaining 8 areas generate savings or shape company expenses has already been fully structured and automated. The impact of AI on cost optimization (e.g., process automation, reduced man-hours) in 2025 is based on exactly the same predictable relationships as the previous year. Cost algorithms deliver consistent, repeatable results. What does this mean? A company that implements AI more efficiently than its rival achieves cost leadership. AI is used to optimize costs or cut costs. It can also be argued that cost optimization becomes the first elimination criterion in the competitive game, not a permanent win. Those who fail to

optimize costs with AI are eliminated from the market. However, it's important to remember that if the AI tool is not dedicated, competitors will purchase the same AI tools and achieve the same cost optimization within a few months. A cost advantage with AI may provide a temporary advantage, but it is easily imitated by others. Therefore, companies will have to seek a pattern of applying AI tools in the remaining eight BMC areas to gain a market advantage. Currently, the lack of stability in these eight areas indicates that no one in the market has a ready-made template for success. Companies that develop a unique pattern of AI application in their business model should gain a market advantage over their competitors. Therefore, there is a need to continue this research in the coming years.

Referring to the quantitative study using logit models, it should be emphasized that the most difficult stage of digital transformation is taking the first step and implementing AI in any pilot area. Once the organization has developed internal procedures and competencies related to using algorithms (as reflected by the OtherBMCAI variable), the implementation process in the remaining business segments (in particular, in 2024 in the areas described by model 8: variable Y – Revenues, model 9: variable Y – Costs, model 5: variable Y – Key Assets, and model 3: Distribution Channels, and in 2025, model 2: Value Proposition; Model 8: Y – Revenues; Model Y-9: Costs. These models were the most valuable in formal terms) occurs organically and highly effectively. It is also worth noting that the developed models also allow for the implementation of a practical scale of technology adaptation:

1. Resistance Phase (0-2 implementations): The probability of success increases slowly. The company is learning the technology, and the barrier to entry is high. At this level, it is crucial to build competencies in AI tools if dissemination to other areas of the business model is to occur.
2. Hyper-growth/Breakthrough Phase (3-6 implementations): Each subsequent implementation significantly (even dramatically) increases the chances of digitizing the area under study using an AI tool. This is the phase in which the organization begins to operate in a process-oriented manner. Synergy becomes the main driving force. Reaching a critical mass of 4-5 areas indicates that the probability of the company adopting it in another specific area becomes higher than the probability of inaction.
3. Saturation phase (7-8 implementations). The probability approaches 1 (100%). Implementing AI in the researched area ceases to be a separate, risky project. At this stage, barriers to entry (both competency-based and psychological) are completely eliminated by prior experience.

The logit models also allowed for addressing hypothesis H1e and the sub-hypotheses H1e-a to H1e-d derived from it. The main hypothesis (H1e) was partially confirmed. Considering the results of testing the specific hypotheses, the main hypothesis H1e is considered partially confirmed. The empirical study showed that the likelihood of implementing AI in BMC components is significantly determined by the overall intensity of the organization's digitalization (H1e-a) and company size as a key structural characteristic (H1e-b).

4. Discussion

Research on the use of AI tools in enterprises from a business model perspective can contribute more knowledge not only in terms of theoretical implications but also in the area of practical application of AI in business. A systematic literature review related to the use of AI tools in business, as well as literature presenting research results on digital transformation, indicates the need for further research. Currently, research on the application of AI tools in enterprises in relation to their business models based on the BMC template is still in a phase where literature, conceptual and qualitative research predominate, and quantitative research is rare. However, it should be emphasised that it is thanks to research based on the first three methods, and in particular on the qualitative method as empirical, that we can seek confirmation of the latest results based on quantitative research. We must also not forget the valuable contribution of research based on a systematic review of the literature, the results of which constitute the first point of reference for further research on a given phenomenon. In turn, a large number of qualitative studies can be analysed quantitatively over time. Thus, they are another set that can show in which areas of the BMC template AI tools have been applied. Conceptual research, whose solutions may relate to specific areas of the BMC, can bring similar value. Thus, it also becomes an indicator showing which areas of the template are of interest for in-depth research. It is also worth mentioning the most important selected research works from the point of view of our study. The first one concerns a study conducted by Metzler D., Neuss N., Muntermann J. and refers to the applications of AI in business models of enterprises, in particular the use of AI as a driver of innovation within a given business model (Metzler, Neuss, Muntermann, 2021). The research was carried out in the form of a case study in four traditional industries. In this work, they sought to answer questions such as RQ1: How does the use of AI affect specific elements of the business models of companies present on the market? RQ2: How does AI drive innovation in the business models of companies present on the market? The study was based on expert interviews with senior management of eight companies in four industries: (1) Automotive, (2) Industrial products, (3) Pharmaceuticals, and (4) Consumer goods and retail. The study yielded results in which AI played the largest role as a driving force in areas such as key activities (processes), value proposition, key partners, and key resources. In our study, we obtained similar results for key activities (processes) and value proposition. On the other hand, key partners and key resources in our study are less important for companies, especially in 2024. It is not until 2025 that there are more YES answers in the area of key partners and key resources, but as the statistical test shows, these differences are not yet significant. In our study, after value propositions and key activities, customer relationships took the next statistically significant place. Several aspects should be noted when comparing the results of both studies. Firstly, it is interesting that there are two areas that stand out from the rest in terms of AI applications. These are value proposition

and key activities/processes. From the point of view of the qualitative study results, it was also possible to determine that the impact of AI on the value proposition concerns issues such as:

- 1) The development of products and services based on or supported by artificial intelligence.
- 2) Integration of artificial intelligence components into existing products and services.

In the case of processes, this concerned:

- 1) automation and optimisation of internal processes through artificial intelligence,
- 2) reducing the workload through human-robot collaboration based on artificial intelligence,
- 3) predictive analytics in the field of consumer needs and trend forecasting.

It should be noted that the results of the qualitative study were published in 2021. The consistency of the two areas (key activities, value proposition) with our research results in 2024 and 2025 allows us to hypothesize that in 2022 and 2023, interest in the application of AI tools was concentrated in these two areas. However, this hypothesis needs to be verified. Another issue is the difference between the third area of AI tool applications in the aforementioned qualitative study and the results of our quantitative study in 2025. In the case of qualitative studies, these are key partners. In the case of our quantitative studies, these are customer relations. In this case, we put forward two hypotheses that explain this difference. The first is that the introduction of AI tools such as ChatGPT in 2023 has led to a significant increase in the use of these tools for customer relationship building. The second hypothesis concerns the statement that the diffusion of AI tools among companies applying them in the area of customer relations lasted approximately 2 to 2.5 years. An observation was also made that the qualitative study selected traditional companies producing goods with a physical dimension. In such companies, e.g. in the automotive and pharmaceutical industries, relationships with suppliers within the framework of so-called horizontal integration are important in the area of product manufacturing.

Among other research results identified in a systematic review of the literature, an article by Ma Genoveva Dancausa Millán et al. entitled "An Economic Perspective on the Implementation of Artificial Intelligence in the Restaurant Sector" stands out. The authors of the article conducted qualitative and quantitative research. As part of the qualitative research, three groups related to gastronomy were surveyed – chefs, entrepreneurs and gastronomy experts – to gather their opinions on the use of artificial intelligence in the restaurant sector in Spain. The qualitative research used the Business Model Canvas and Lean Model Canvas, adapted specifically to the restaurant sector. These models, as innovative approaches, allowed for the identification of key success factors based on the respondents' experiences. The division based on the tool used was also interesting. The study was conducted using the Business Model Canvas, which the authors considered to be more focused on the market and the company, and the Lean Model Canvas, which prioritises the market and the product. The results of the qualitative study indicated that value propositions based on creating personalised menus using artificial intelligence algorithms and offering unique and personalised dining experiences stand

out as core values that attract and retain customers. Another area is customer relations and distribution channels, including an online platform for orders and reservations, as well as partnerships with restaurants and catering companies, which are essential for promotion, sales and service delivery. Next are the identified revenue streams and key resources, which include revenue generated from direct sales of personalised menus, commissions on orders placed through the online platform, and artificial intelligence (AI) consulting services for food service establishments. Key resources also include teams of AI developers, experienced chefs and a robust technology platform. Referring to the results of our 2025 study, we can conclude that there are again two common areas of BMC: value proposition and customer relationships. It is worth noting that the second important area, key activities and processes, is not explicitly mentioned, although the authors of the article claim in the part of the study where the Lean Model Canvas is used that "specific problems in the restaurant sector that can be solved with artificial intelligence, such as inventory management, menu personalisation and kitchen process optimisation, helping entrepreneurs strengthen their company's weaknesses and identify key factors, saving costs and improving investment efficiency". It is worth noting that this study, in correspondence with ours, suggests that in-depth research on the application of AI tools should focus on specific industries.

Among other studies, it is also worth mentioning Julian Marius Muller's article "Business model innovation in small- and medium-sized enterprises. Strategies for industry 4.0 providers and users" Müller JM. (2019). This article presents the results of a qualitative study. The aim of the study was to examine the impact of Industry 4.0 on the business models of SMEs in the manufacturing sector. Although Industry 4.0 includes other technologies in addition to AI tools, our research shows that AI technologies interact with such Industry 4.0 technologies as: IoT, Digital Twin, Cloud Computing, and Robotics. Therefore, it is worth citing the aforementioned study. A representative sample was selected to conduct the qualitative study. The study covered the mechanical and machine construction industry, the automotive industry and the electrical industry. The article concluded that these industries would be most affected by Industry 4.0. Therefore, these three sectors were selected for the study. The study included interviews that focused on changes in the business model in connection with Industry 4.0. A total of 43 interviews were conducted. Of the 43 companies, 24 were from the mechanical engineering and equipment industry, 13 were automotive industry suppliers, and 6 were from the electrical sector. The study showed that key resources were the most frequently mentioned component in the sample (58.14% of respondents). Respondents mainly mentioned two aspects. Firstly, production facilities and equipment must be modified or specially purchased in accordance with specifications, or existing machines must be adapted, also known as "modernisation". This is a very interesting result, as it is somewhat related to the view of the application of various Industry 4.0 technologies not only in relation to the acquisition of new assets but also in relation to their integration with existing ones. In our study, key resources begin to play a role in 2025. Most companies indicate the use of AI tools in key resources,

but this is not yet a significant difference compared to companies that do not use AI tools in this area. Value proposition is the second most frequently mentioned component (53.49% of respondents). Respondents mainly describe new products, services or a combination of both, to be offered to customers. In our research, the value proposition is also of significant importance. Key partners rank third on the list of the most frequently mentioned components (48.84% of respondents). According to respondents, IT experts are important for the implementation of Industry 4.0 solutions. In our research, relationships with key partners begin to be recognised in 2025. However, as with key partners, we see greater use of AI tools in companies in this area, but not to the extent that it is significant compared to companies that do not use them. In turn, the results of Julian Marius Muller's study Müller JM. (2019) indicate that it is worth examining key partners from the point of view of AI tool providers in the future. Customer relations also rank third on the list of the most frequently mentioned structural elements (48.84% of respondents). Similarly, in our study, this area is important in relation to the use of AI tools in 2025. However, from the perspective of Industry 4.0, customer relations in Julian Marius Muller's study Müller JM. (2019) are more focused on the reliability of Industry 4.0 technologies. What is interesting, however, is the difference in Julian Marius Muller's study, which shows that key activities are the second least frequently mentioned components of the business model (23.26% of respondents). In our research, key activities in the area of processes played an important role in AI applications in both 2024 and 2025. This is an interesting difference that requires further research in the future.

In the case of the quantitative study using logit models based on the collected empirical data for the entire BMC framework, it should be emphasized that it was an extension of previous fragmented studies in the area of digital transformation using other research methods. In this respect, the study stands out from others – it uses logit models to empirically operationalize the entire Business Model Canvas (BMC). It is worth emphasizing, however, that the study fits into the trend of econometric analyses of innovation diffusion, including digital innovation, but transfers it to the level of the full BMC framework. It is worth mentioning here slightly older articles focusing on the diffusion of technology, such as: *Inter- and Intra-Firm Diffusion Of Ict In The United Kingdom (Uk) And Switzerland (Ch) An Internationally Comparative Study Based On Firm-Level Data*, Giuliana Battisti, Heinz Hollenstein, Paul Stoneman, Martin Woerter (Battisti, Hollenstein, Stoneman et al., 2007) or *Inter- and intra-firm diffusion of technology: The example of E-commerce: An analysis based on Swiss firm-level data* Heinz Hollenstein, Martin Woerter, (Hollenstein, Woerter, 2008). Among other recent scientific studies, one should undoubtedly mention *The Influence of Generative AI on Business Management* by Rodríguez Benito, M.E., Hernández Zelaya, S.L., Reyes Reina, F.E. (Rodríguez, Hernández, Reyes, 2026) where the authors developed a logit model that predicted the probability of a company implementing a broad portfolio of AI technologies (binary variable: implementing at least two different AI typologies simultaneously), based on the fact of prior adoption of Generative AI as a starting point. Another interesting article is *Applications*

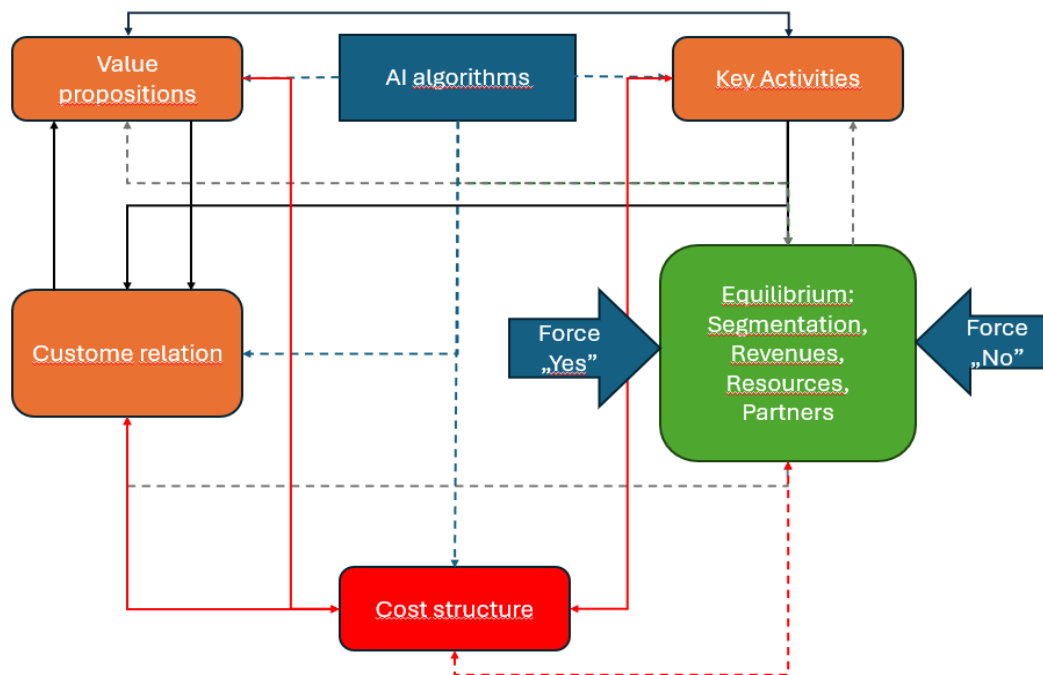
of Artificial Intelligence in Small and Medium Scale Business (Kamruzzaman, Sujoy, Siddiki et al., 2025). As part of this article, econometric models were developed that revealed a strong influence of organization size on the probability of advanced AI diffusion. The study showed that medium-sized companies are statistically twice as likely to fully implement Business process remodeling under the influence of AI is more likely than microenterprises.

The study using logit models revealed interesting results regarding the involvement of large enterprises in AI adoption in terms of resources in 2024 and key partnerships in 2025. Although company size was a noticeable factor in the study, it cannot be ruled out that small companies are experiencing asymmetric, spotty implementations, while large corporations are implementing AI systematically. This interpretation is consistent with the information contained in the reports AI adoption by small and medium-sized enterprises: Emerging gaps across G7 and OECD economies (OECD, 2025) and Use of artificial intelligence in enterprises (Eurostat, 2025). This indicates the need for more detailed research on the use of AI tools by SMEs.

As part of the discussion, we also consider the research results regarding the hypotheses and the resulting conclusions. In summary, quantitative research based on the 2024-2025 series of tests demonstrates a dynamic evolution in AI implementations, with key areas including processes and value propositions, as well as customer relationships. This change, supported by the lack of structural stability of logit model parameters in as many as eight BMC areas, signals a deep, even chaotic, search by companies for a unique template for market success. The only stable element proved to be the cost structure, proving that the mechanisms for automation and cost optimization using AI have been mastered. In the context of competitive strategy, however, this means that cost reduction has become merely a fundamental criterion for survival (easily replicated), not a source of sustainable success. Ultimate strategic advantage will be achieved by those organizations that develop their own, difficult-to-imitate model for AI use in the remaining, still unstable business areas, one that is not only focused on cost-based competitive advantage but is primarily based on market advantage. The series tests indicate that the aforementioned areas—value proposition, processes, and customer relationships—may be the first to emerge from these volatile areas in the future. However, this requires further research in the coming years.

As part of our discussion of the results, we also propose a working model of the AI causal engine within BMC. The overwhelming statistical significance ($p < 0.05$) and clear dominance of "YES" indicate that the model's key components are the Value Proposition and Key Activities/Processes area, as well as the cost/cost structure area, which reflects companies' current efforts to gain cost-based competitive advantage. In the proposed model, AI tools are essentially the key driver of impact. Cost optimization using AI is the first step and the primary goal of companies. In turn, series tests indicate that in the early stages of diffusion, organizations implement AI where the return on investment is immediate: internal operational efficiency (processes) and product or service improvement (value proposition) are among these.

Data from 2025, in turn, reveal the emergence of a new important area: Customer Relationships are moving into a statistically significant dominance of "YES" ($Z = 2.329$, $p < 0.05$). Companies are exploring these three areas to use AI to build a competitive market strategy.



The blue dashed line indicates the impact of AI algorithms on 4 key BMC areas: value proposition, key activities/processes, customer relationships, costs; the green dashed line shows the overall impact of AI algorithms on areas in equilibrium; the black arrows show the relationships between the 4 BMC elements; the gray dashed line shows the relationships between the 4 elements and the 4 elements in equilibrium; the red line shows the relationships between the 4 areas: value proposition, key activities/processes, customer relationships, and costs; the red dashed line shows the relationships between costs and the 4 areas in equilibrium.

Figure 9. AI Causal Engine Model for Business Models.

Source: Authors own work.

The causal mechanism is the democratization of generative AI, primarily LLM architecture. Unlike complex, often dedicated AI tools in the supply chain, customer-facing AI tools, such as chatbots and CRM systems with generative AI, are highly effective. Consequently, the causal impact of AI shifts from internal processes directly to the customer, explaining the statistical significance of customer relationships in 2025. The six areas in which equilibria occur in 2025 remain controversial. It cannot be ruled out that these are due to sample limitations, but the fact that significant effects occur for the areas of value proposition, processes, and customer relationships demonstrates that equilibria can be considered in terms of the interaction of forces responsible for the implementation of AI tools in BMC areas, as well as the interaction of forces responsible for the lack of implementation. The former include: market and competitive pressures, customer needs and expectations, the desire to reduce operating costs, management's awareness of digitalization, evolving employee attitudes towards digital transformation, employee digital competencies, government-created conditions (programs supporting digital transformation among enterprises), and others. The latter include: technological debt, low data

levels, low competencies, especially digital competencies, financial barriers, an unclear business model, resistance to change, risk, and others. These two forces may block AI expansion in other areas of BMC. It cannot be ruled out that the transition to AI expansion for many companies requires a profound reorganization that goes beyond the technical installation of AI tools. The proposed working model of the AI engine requires further research, which will primarily demonstrate whether the six areas mentioned will remain in balance or whether they will be incorporated into areas where AI tools are used or not.

Based on the obtained results of the logit models, the verification of the hypothesis regarding company size is crucial. This clearly indicates that large organizations demonstrate significantly higher dynamics and effectiveness in adopting AI tools. Basing these findings on the classical resource-based view (RBV), it can be assumed that larger entities possess unique, difficult-to-copy technological, human, and structural capital. Even if they use readily available AI tools, they master them more quickly thanks to their human resource competencies, their tendency to be a digital organization, a learning organization, and their propensity for digital innovation. It is precisely this configuration of resources and competencies that allows them to build market asymmetry and achieve a sustainable competitive advantage, and perhaps even a market advantage in the future. Consequently, a distinct polarization may occur in the market: companies capable of transforming AI potential into unique strategic value will begin to clearly outperform their competitors.

Using the scale of technology adoption, the overall research results can be discussed. In 2024, most companies were in the resistance phase (implementation in only two areas: processes and value proposition). In 2025, thanks to the addition of customer relationships and dynamic trial tests in other areas, such as segmentation or resources, companies entered the initial hypergrowth/breakthrough phase (3-6 areas). The explanation for the lack of structural stability (LnL tests) indicates that the hypergrowth phase is inherently chaotic, dynamic, and based on real-world experiments with AI tools. This explains why the parameters of the logit models for the eight BMC areas proved unstable between 2024 and 2025 – the market learns as it transitions from phase 1 to 2. The scale also links to the Resource Based Value (RBV) and large companies. Reaching the saturation phase (7-8 areas) requires enormous capital and unique competencies. This is confirmed by the result of the logit model on company size: only large organizations have the resources to enter this phase currently and thus maintain a sustainable competitive advantage, while smaller companies are in the resistance or transition phase.

5. Summary

The study, based on a systematic literature review, allowed us to identify which technologies are interesting from the perspective of AI tool applications and which of the nine BMC areas are most frequently used. The systematic literature review thus provides insight into the appropriate selection of research methods for further research, and also provides insight into which AI application areas within BMC should be selected for, for example, in-depth studies.

The quantitative survey-based study yielded unique results, demonstrating changes in enterprises regarding the non-use and use of AI tools in specific BMC areas. The study captured a crucial moment of digital transformation in the area of AI applications in specific BMC areas. As recently as 2024, most enterprises were not interested in using AI tools in specific BMC areas. Only the key activity areas related to processes and value propositions indicated that most enterprises were using AI tools. However, in 2025, the situation is changing in favor of AI tool adoption among enterprises. In addition to the two areas mentioned above, customer relationships will be added in 2024. In the next four areas: customer segmentation, key assets, and partner relationships, we see a higher number of companies using AI than those not using it. However, the differences between these companies are small, confirming the statistical insignificance. There are also areas where a slight majority of those not using AI tools remain. These include distribution channels, revenues, and costs. However, the differences are also too small, as statistically confirmed. This study indicates that significant changes are taking place in the use of AI tools in companies' business models. Based on the results, we can expect that in 2026 and 2027, a significant shift towards a majority of companies using AI tools should be observed. It would be a significant surprise to see a shift away from the use of AI tools. It does not seem that such a scenario will occur in the form of some form of "AI winter". However, further quantitative research is planned to confirm the direction of change. In turn, logit model studies from 2024-2025 indicate that the use of AI tools in BMC areas is a universal factor stimulating digitization through a feedback effect. This creates conditions for increasing employee competencies in AI tools and also reduces the psychological barriers to using new technology. It is worth emphasizing that both competencies related to the use of AI tools and reducing the psychological barriers associated with using these tools are interesting research topics. The results of quantitative studies using logit models indicate that large enterprises demonstrate an advantage in AI adoption due to greater capital resources, optimizing key resources (2024) and key partnerships (2025).

The quantitative study, conducted using both batch tests and logit models, can also be considered jointly in terms of common conclusions. The starting point is triangulation, which allows for combining these conclusions. In this respect, the study answers the questions "Where?" and "How does it work?" The batch test answered the question "Where" (in which BMC areas) is the AI activity of companies concentrated, i.e., Value Proposition, Processes,

and Communication. Logit models, in turn, revealed the mechanism and consequences of this concentration. They showed how implementations in some areas influence the probability in others. Drawing analogies from a systemic perspective, one can say that the quantitative study based on batch tests indicated what was happening in the system areas at time t , while quantitative study 2 showed how these areas interacted. For example, the key processes area is key in the batch tests, but the logit model, in which this area was the Y variable, was not a model that distinguished itself from the others in formal terms. This is also understandable in terms of the company's business model, which implements AI in processes not to "have processes", but to reduce costs, improve the value proposition, and increase revenue. Processes are the engine, not the result, although this engine is integrated into the synthetic variables of the degree of digitization based on AI tools. In turn, the value proposition, which is key in both the series tests and the logit study in 2025, allows us to conclude that companies are experimenting with AI in this area (series test), and the overall level of digitization based on AI tools in the company strengthens this area.

From the perspective of logit models, it's worth paying attention to large enterprises, particularly in the context of the resource-based theory. Large companies have sufficient resources to implement AI tools. However, what may limit them in implementing AI are employee competencies in using AI tools. This isn't just about technical understanding of the tool, although this is also important, but also a broader context of competencies, including soft skills such as critical thinking, creativity, curiosity, willingness to experiment, systems and process thinking, adaptability and openness to change, perseverance, and patience, allowing the tool to be used to increase the efficiency of workplace processes within a given business model and the implemented corporate strategy. However, if the resource-based theory removes the limitation related to AI tools and makes them readily available, then employee competencies become a key factor, crucial for the implementation of AI tools not only in large enterprises but also in SMEs. Furthermore, new models for transforming knowledge regarding the use of AI tools in organizations will also play a significant role. Companies that employ highly skilled AI-enabled employees and incorporate knowledge transformation mechanisms related to AI application into their business models will have a competitive and market advantage. However, this requires further research.

The results of the study, conducted using both series tests and logit models, including parameter stability, allowed us to build a situational picture of how companies are implementing AI tools in their business models. Currently, it can be concluded that companies are focusing on using AI tools to optimize their cost structure. This is the first concrete step towards achieving tangible results from AI tools as part of their so-called competitive strategy. The study results indicate that companies are dynamically testing various AI tools in various areas of their business models. It can be concluded that, on the one hand, they are learning them, and on the other, they are trying to implement them for a specific purpose within the existing business model and strategic assumptions. It is worth noting that a cost-based competitive

strategy has its limits. Companies will need to seek applications for AI tools for market strategy, which requires the application of AI tools in other areas of the BMC. The study results in the testing area indicate that these areas may include value propositions, customer relationships, and also processes. It is therefore important to continue research on the use of AI tools in various business models in order to capture not only the diffusion process within the organization but also to observe how the use of these tools may change at the level of the implemented strategy, i.e. the transition from a cost-based competitive strategy to a market strategy based on, for example, value proposition, customer relationship, or appropriate segmentation.

The results of the study, based on a systematic literature review and a quantitative survey, indicate that further research into AI BMC applications is worthwhile. In particular, it is worth focusing on selected individual BMC areas, such as distribution channels, or conducting studies on different configurations of areas, such as the front office or back office. From the perspective of implementing this study, it is necessary to consider its limitations. One such limitation was the design of the survey, in which we used YES/NO responses. From the perspective of the obtained results, this choice allowed us to capture the change in the use of AI in business models and also enabled the construction of logit models. On the other hand, expanding the survey with questions such as: "What specific tools do companies use in a given BMC area?" could contribute to a better understanding of which tools and in which areas of BMC play a key role.

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Appendix I

Year 2024	Lp. Model	Variable Y _i	Independent variables statistically significant (p<0.05)										OR - Odds Ratio	Confidence Interval for the Odds Ratio (95% CI for OR)	Pseudo R ² (McFadden's)	Test H-L (-value)	Accuracy (ACC)	Sensitivity (TPR)	Specificity	Indicator (AUC)	Indicator (AIC)
			Coefficients standing next to variables							const											
			Variable X1 - small company	Variable X2 - medium-sized company	Variable X3 - large company	Variable X4 - Application of AI in other areas of BMC	Variable X5 - Service or manufacturing company	Variable X6 - technology company or other	Variable X7 - IT company or other												
			-	-	-	-	0,6076	-	-	-	-2,7124	1,836 [1,555;2,167]	0,3064	0,73	80%	60,80%	91,30%	0,8452	186,832		
			-	-	-	-	0,6559	-	-	0,8040	-0,9619	1,927;2,234 [1,512;2,455][1,082;4,615]	0,2594	0,0429	79,90%	86,50%	61,00%	0,8295	185,682		
			-	-	-	-	0,6507	-	-	-	-3,5974	1,917 [1,603;2,284]	0,349	0,5208	84%	63,20%	92,30%	0,8701	159,628		
			-	-	-	-	0,691	-	-	-	-2,6088	1,966 [1,651;2,412]	0,3383	0,061	76%	66,70%	82,80%	0,8686	184,064		
			-	-	2,0139	0,7756	-	-	-	-	-3,4452	7,492;2,172 [1,789;31,379][1,760;2,680]	0,4073	0,3699	82%	68%	90,40%	0,8835	162,836		
			-	-	-	0,4809	-	-	-	-	-0,8269	1,617 [1,373;1,905]	0,1868	0,0924	69%	76,90%	57%	0,7786	222,252		
			-	-	-	0,6165	-	-	-	-	-2,7513	1,852 [1,567;2,190]	0,3119	0,0171	79,50%	59,50%	91,30%	0,8433	185,37		
			-	-	-	0,8363	-	-	-	-	-4,6882	2,308 [1,847;2,884]	0,4547	0,0912	88,50%	73,60%	93,90%	0,9036	130,112		
			-	-	-	0,7888	-	-	-	-	-4,2404	2,201 [1,787;2,710]	0,427	0,1454	87,50%	70,20%	94,40%	0,891	140,97		

Appendix II

Year 2025	Independent variables statistically significant (p<0.05)										OR - Odds Ratio		Confidence Interval for the Odds Ratio (95% CI for OR)	Pseudo R ² (McFadden n)	Test H-L (-value)	Accuracy (ACC)	Sensitivity (TPR)	Specificity	Indicator (AUC)	Indicator (AIC)
Lp.	Model	Variable Yi	Coefficients standing next to variables							const										
			Variable X1 - small company	Variable X2 - medium-sized company	Variable X3 - large company	Variable X4 - Application of AI in other areas of BMC	Variable X5 - Service or manufacturing company	Variable X6 - technology company or other	Variable X7 - IT company or other											
1	Model 1	Segmentation	-	-	-	-	0,7575	-	-	-3,5031	2,133	[1,721;2,644]	0,4311	0,1562	81,30%	83,30%	79,20%	0,9033	126,23	
2	Model 2	Value Proposition	-	-	-	-	0,898	-	-	-1,2725	2,455	[1,785;3,376]	0,4442	0,4797	85,20%	90,70%	67,60%	0,9140	98,692	
3	Model 3	Distribution Channel	-	-	-	-	0,6671	-	-	-3,5463	1,949	[1,607;2,363]	0,3725	0,1988	77,40%	73,90%	80,20%	0,8876	137,658	
4	Model 4	Customer Relationship	-	-	-	-	0,701	-	-	-2,4006	2,016	[1,643;2,473]	0,3995	0,3365	80,60%	83,90%	75,80%	0,8912	129,282	
5	Model 5	Key Resources	-	-	-	-	0,5611	-	-	-2,5256	1,753	[1,486;2,067]	0,3129	0,036	75,70%	77,20%	73,70%	0,8580	151,608	
6	Model 6	Key Activities	-	-	-	-	0,5718	-	-	-0,7229	1,771	[1,447;2,169]	0,2941	0,0552	82,60%	88,80%	64,10%	0,8569	127,434	
7	Model 7	Key Partners	-	-	1,8685	-	0,7457	-	-	-3,3437	2,108;6,479	[1,701;2,612];[1,353;31,027]	0,4216	0,1454	81,30%	83,10%	79,20%	0,8996	129,83	
8	Model 8	Revenue Structure	-	-	-	-	0,8444	-	-	-4,4309	2,326	[1,825;2,964]	0,4659	0,2584	83,20%	80,00%	85,90%	0,9146	117,99	
9	Model 9	Cost Structure	-	-	-	-	0,8925	-	-	-4,2737	2,441	[1,892;3,150]	0,4967	0,1305	83,90%	85,50%	82,30%	0,9270	112,114	

Appendix III

No.	Variable Name Yi	K - Degrees of Freed	Adjusted LnL 2025	Statistic χ^2	Critical Value $\alpha=0,05$	Test Result
1	Segmentation	2	78,858	24,916	5,991	Rejection H_0
2	Value Proposition	2	61,092	62,253	5,991	Rejection H_0
3	Distribution Channel	2	86,231	16,830	5,991	Rejection H_0
4	Customer Relationships	2	80,827	18,410	5,991	Rejection H_0
5	Key Resources	2	95,231	26,000	5,991	Rejection H_0
6	Key Activities	2	79,635	58,982	5,991	Rejection H_0
7	Key Partners	2	83,672	14,025	5,991	Rejection H_0
8	Revenue Structure	2	73,542	20,970	5,991	Rejection H_0
9	Cost Structure	2	69,751	2,530	5,991	Not rejection H_0