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ARTIFICIAL INTELLIGENCE AS A TOOL FOR DEVELOPING BUSINESS STRATEGIES AND FORMING ADVANTAGES FOR HIGH-TECH STARTUPS

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Abstract

This study examines whether the strategic integration of artificial intelligence (AI) into managerial decision-making is associated with the development of sustainable *competitive advantages. Addressing a gap in the literature on AI adoption in resource-constrained startup ecosystems, the research focuses on startups operating in the Baltic countries. Using a mixed-methods approach that combines survey data, financial analysis, and expert interviews, the study develops an original composite index to capture AI-driven competitive advantages across innovation, operational efficiency, and customer value. The empirical results demonstrate that deeper and more strategic AI integration is positively associated with stronger competitive advantages. The findings further reveal that this relationship is non-linear and significantly strengthened by access to financial resources. Overall, the study highlights that AI generates competitive benefits for startups only when implemented strategically and supported by adequate funding and human capital, offering important implications for startup founders, investors, and policymakers. Given the cross-sectional nature of the data, the reported relationships should be interpreted as associative rather than strictly causal.*

Keywords: artificial intelligence, startup, Baltic countries, competitive advantages, business model, strategic integration, innovation

1. INTRODUCTION

In the modern digital economy, artificial intelligence (AI) has become one of the most transformative technologies, reshaping business models, strategic decision-making processes, and the foundations of competitive advantage. For high-tech startups, AI represents not only a tool for improving operational efficiency but also a strategic instrument that enables companies to innovate, scale rapidly, and compete globally. Unlike large corporations, startups often face resource constraints and heightened uncertainty; however, they demonstrate agility and adaptability, making them ideal candidates for implementing AI-based strategies. The Baltic countries, particularly Estonia, offer a unique context for analyzing the role of AI in startup strategy development. Estonia is internationally recognized as a leader in digital technology, known for its advanced e-government infrastructure, favorable innovation ecosystem, and strong emphasis on digital entrepreneurship. Through initiatives such as e-Residency and Startup Estonia, as well as significant investments in digital infrastructure, the country has created fertile ground for the emergence of high-tech startups that increasingly integrate AI-based solutions into their business strategies. This makes Estonia a vivid example of how AI is increasingly associated with the development of sustainable competitive advantages in startup ecosystems. Although the adoption of AI among startups in the Baltic countries is steadily growing, a gap remains in scholarly research on how these companies strategically leverage AI to ensure long-term competitiveness. Existing studies tend to focus on the technical implementation of AI or its impact on large corporations, while the specific strategic implications for high-tech startups have been less explored. At the same time, issues such as the ethical use of AI, resource optimization, and compliance with international markets have become critically important for startups striving to maintain their competitiveness. This study aims to contribute to the academic literature by examining the relationship between strategic AI integration and competitive advantages for high-tech startups in the Baltic countries, with a special focus on Estonia. The research emphasizes how AI can facilitate the development of business strategies that foster innovation, resource efficiency, and sustainable competitive advantages. By analyzing the Baltic context, this work seeks to provide insights not only into regional startup ecosystems but also into broader global trends where AI is reshaping the trajectory of entrepreneurship.

2. LITERATURE OVERVIEW

2.1. Fundamental economic and strategic foundations of AI

Artificial intelligence (AI) is increasingly conceptualised in economic and strategic literature not merely as a technological tool, but as a general-purpose strategic resource that reshapes value creation, coordination mechanisms, and competitive advantage. This perspective aligns with broader economic analyses that identify knowledge and innovation as foundational pillars for building sustainable competitive advantages at both firm and national levels (Rončević & Ostojić, 2022). Within the resource-based view and dynamic capabilities framework, AI enhances firms' abilities to sense, seize, and reconfigure opportunities under conditions of uncertainty (Agrawal et al., 2018; Enholm et al., 2021). For high-tech startups, AI differs fundamentally from traditional digital tools. Its strategic value lies not in automation alone, but in enabling data-driven learning, adaptive decision-making, and scalable experimentation, which are critical under severe resource constraints. Unlike incumbents, startups rely on speed, flexibility, and rapid recombination of capabilities, making AI particularly relevant as a lever for strategic differentiation rather than cost optimisation. Existing studies, however, tend to analyse AI either at a macroeconomic level or within large corporate settings, focusing on productivity gains, labour substitution, or governance challenges (Kaplan & Haenlein, 2018; Agrawal et al., 2019). As a result, the strategic logic of AI adoption in startups – especially its role in shaping competitive advantages – remains underexplored. The following subsection therefore focuses more specifically on how AI-driven capabilities translate into innovation outcomes and business model transformation at the firm level.

2.2. AI as a driver of innovation and business model transformation

A substantial body of literature demonstrates that AI influences innovation not only incrementally but structurally. Recent reviews further systematize AI's role by developing taxonomies of its applications in innovation management, highlighting how different AI capabilities enable distinct types of innovation (Gama & Magistretti, 2023). AI enables firms to redesign how value is created, delivered, and captured, thereby acting as a catalyst for business model innovation rather than a supporting technology (Borges et al., 2020; Mariani et al., 2022). Bahoo et al. (2022) conceptualise AI as a strategic resource that reshapes corporate innovation processes by automating analytical and creative tasks. Building on this view, Sjödin et al. (2021) show that AI-driven innovation is inherently dynamic, relying on feedback loops and continuous learning across organisational and ecosystem boundaries. Similarly, research on emerging technologies positions AI as a pivotal force in business model innovation, where its integration leads to novel value creation and capture mechanisms (Lee et al., 2019). For startups, this implies that competitive advantage emerges when AI is embedded into core strategic processes, not when it is used in isolation. This view is supported by research on digital startups, which finds that the strategic design and components of a startup's business model are critical predictors of its success (Schumacher, 2022). Building on earlier frameworks that categorize how startups capture value from data (Hartmann et al., 2016), business model research further highlights the ecosystem dimension of AI. Burström et al. (2021) argue that AI reconfigures industrial ecosystems by transforming data into a central strategic asset. This perspective is particularly relevant for startups, which typically operate within platform-based and networked environments. AI thus supports scalability and cross-border expansion – key success factors in global startup competition. Overall, the literature suggests that AI-driven competitive advantages depend on the depth of strategic integration, reinforcing the need to distinguish between experimental, operational, and strategic uses of AI – an issue directly addressed in the present study. This underscores the importance of a nuanced understanding of AI's impact on business models, which can yield transformative benefits but also introduce new complexities and risks (Sena & Nocker, 2021).

2.3. Empirical evidence and sectoral applications of AI in startups

Empirical studies increasingly show that the performance effects of AI in startups depend less on sectoral affiliation and more on the depth of strategic integration. In energy and infrastructure, AI enables demand forecasting and system optimisation, giving rise to new startup business models (Anton et al., 2021). In healthcare, AI-driven diagnostics and data analytics underpin next-generation value propositions (Garbuio & Lin, 2018; Kulkov, 2021). Marketing and digital services literature highlights AI’s contribution to personalisation, customer retention, and predictive analytics (Davenport et al., 2019). Similarly, in the travel and tourism sector, expert evaluations confirm AI's transformative role in creating new opportunities and enhancing customer-centric business models (Štilić et al., 2023). Across these sectors, a common pattern emerges: startups derive sustainable advantages when AI is central to the value proposition rather than an auxiliary tool. However, most empirical studies remain sector-specific or descriptive, offering limited insight into how AI integration translates into broader competitive advantages across different startup contexts. Moreover, comparative and quantitative analyses linking AI integration intensity to competitive outcomes remain scarce – particularly in smaller regional ecosystems. This pattern reinforces the need for cross-sectoral empirical analysis that captures strategic intensity of AI use rather than industry-specific applications.

2.4. Strategic management and implementation of AI in startups

The success of AI adoption depends critically on managerial and organisational factors. This is supported by broader management literature, which consistently finds a strong positive relationship between a firm's entrepreneurial orientation – encompassing innovation, proactiveness, and risk-taking – and its overall performance (Morić Milovanović et al., 2022). Mishra and Tripathi (2021) emphasise that AI-based value creation requires alignment between technology, strategy, and organisational structure. Ransbotham et al. (2017) identify a persistent gap between firms' AI ambitions and realised business value, often due to fragmented implementation. Agile and co-creation approaches are frequently cited as effective mechanisms for managing AI projects under uncertainty (Sjödin et al., 2020). For startups, such approaches are especially important, as they allow iterative learning while controlling implementation risks. Another critical issue concerns performance measurement. Wamba-Taguimdje et al. (2020) show that AI positively affects efficiency indicators, but the translation of these gains into sustainable competitive advantage depends on strategic coherence and access to complementary resources, such as funding and human capital. This insight directly informs the empirical design of the present study.

2.5. AI, entrepreneurship, and startup dynamics

Entrepreneurship research increasingly recognises AI as a transformative force reshaping opportunity recognition and venture creation (Obschonka & Audretsch, 2020). This has given rise to a distinct profile of 'digital entrepreneurs' who specialize in leveraging AI and data analytics to identify and exploit market opportunities (Chae & Goh, 2020). Digital technologies act as external enablers that reduce entry barriers and accelerate scaling (Von Briel et al., 2017). This is exemplified in studies of innovative startups, where cultivating a data-driven orientation – often enabled by AI – is critical for strategic agility and competitive positioning (Visvizi et al., 2021). At the same time, AI-intensive startups face distinct challenges, including high capital requirements, talent scarcity, and regulatory uncertainty. This dual nature of AI – as both an opportunity and a constraint – necessitates a strategic perspective that goes beyond technological adoption. Recent studies also highlight the social and inclusive dimensions of AI-driven entrepreneurship. Shcherbak et al. (2025) demonstrate how AI-enabled startups contribute to economic integration and resilience in the Baltic region, reinforcing the broader socio-economic relevance of AI strategies.

2.6. The Baltic startup ecosystem and research gap

The Baltic countries, particularly Estonia, represent an advanced digital ecosystem characterised by strong public digital infrastructure, proactive innovation policy, and international orientation. Initiatives such as e-Residency and Startup Estonia create favourable conditions for AI-driven entrepreneurship. Despite these advantages, empirical evidence on how startups in the Baltic region strategically integrate AI to build competitive advantages remains limited. Existing studies focus either on technological adoption or on large firms, leaving a gap in understanding the strategic mechanisms at work in startup contexts. This study addresses this gap by empirically examining the relationship between the strategic level of AI integration and competitive advantages in high-tech startups operating in the Baltic countries.

2.7. Research hypothesis and objectives

Based on the reviewed literature, the central theoretical proposition of this study is that AI creates competitive advantages for startups only when it is strategically integrated into business models and decision-making processes.

Research Hypothesis (H1):

High-tech startups in the Baltic countries that strategically integrate artificial intelligence into their business models and decision-making processes exhibit higher levels of sustainable competitive advantages than startups that use AI fragmentarily or primarily for operational purposes.

The study aims to:

- identify strategic patterns of AI use among Baltic high-tech startups;
- assess how AI-based business models contribute to competitive advantages;
- evaluate the moderating role of ecosystem factors such as funding and talent availability;
- provide evidence-based recommendations for founders, investors, and policymakers.

3. MATERIALS AND METHODS

3.1. Initial data and methods of their processing

This section outlines the data sources, variable construction, and empirical strategy used to test Hypothesis H1. The qualitative component consisted of semi-structured interviews with startup founders and ecosystem experts conducted between March and June 2024. Interviews focused on strategic motivations for AI adoption, perceived barriers, and enabling factors. The qualitative data were used to contextualize and interpret the quantitative findings rather than to generate independent causal claims. The empirical strategy is designed to identify statistical associations between AI integration and competitive advantages. Due to the cross-sectional nature of the dataset, the models do not aim to establish causal relationships. The methodological approach follows a structured logic: first, indicators of AI integration and startup performance are operationalized; second, a composite competitive advantage index is constructed; third, regression, threshold, and moderation models are applied to assess both linear and non-linear effects. Given the exploratory nature of the study and the focus on high-tech startups in the Baltic countries, a targeted sample of 40 startups was used, which allows for in-depth analysis while acknowledging limitations in terms of generalizability. From a methodological perspective, the sample size of 40 startups is consistent with prior empirical studies in startup and innovation research, where access to firm-level strategic and technological data is inherently constrained. The use of multiple regression, threshold, and moderation models with this sample size is justified by the relatively low number of predictors, the inclusion of fixed effects, and the exploratory aim of identifying structural relationships rather than producing population-level forecasts. Moreover, the consistency of results across alternative model specifications (linear, threshold, and moderated regressions) strengthens the internal validity of the findings despite the limited sample size. To test hypothesis H1, we used comprehensive data, including indicators of artificial intelligence integration, financial investments, innovation activity, and startup characteristics. The initial data and sources of receipt are given in Table 1. These indicators form the basis for empirically verifying the hypothesis, and initial data are provided in Appendix A.

Table 1 Initial data for testing hypothesis H1

Initial data	Description	Symbol / Unit of measurement	Data source
AI integration level	The extent to which AI is embedded in decision-making processes.	X_i (dimensionless index, 1-5)	Questionnaire survey of founders and top managers
AI development investments	The amount of funding specifically targeted at AI projects	$R\&D_{AI}$ (kEUR/ year)	Financial reporting of a startup, questionnaire
Total R&D budget	Total R&D Expenditure	$R\&D_{total}$ (kEUR/ year)	Startup financial reporting
Number of new AI products	Number of AI products or services launched during the reporting period	$NewProd_{AI}$ (units)	Startup internal reporting, interview
Total number of products	Total number of startup products/services	TotalProd (units)	Internal reporting of a startup, website
Product launch speed	Average time from idea to product launch	$Speed_{scale}$ (months)	Internal reporting of a startup, interview
Costs before AI implementation	Operating costs of the target process before implementing the AI solution	$Cost_{before}$ (kEUR)	Financial and management reporting
Costs after AI implementation	Operating costs of the target process after implementing the AI solution	$Cost_{AI}$ (kEUR)	Financial and management reporting
Process time before AI	Target business process execution time before AI implementation	$Time_{before}$ (hours / unit)	Timing, internal reporting
Process time after AI	Target business process execution time after AI implementation	$Time_{AI}$ (hours / unit)	Timing, internal reporting
AI decision accuracy	Prediction accuracy or percentage of correct decisions made by AI	Ass_{AI} (%)	Internal quality metrics, testing
NPS of AI service customers	Net Promoter Score loyalty index among users of AI-based services	NPS_{AI} (from -100 to 100)	Customer surveys (NPS survey)
Retention rate	Percentage of customers who continue to use the service after a certain period	$Retention_{AI}$ (%)	CRM systems, analytics
Personalization level	Degree of personalization of services or content using AI	Personalisation (index1-10)	Customer surveys, platform metrics
Startup size	Number of employees in the company	Employees (persons)	Questionnaire, databases
Startup age	Time since the company was founded	Age (years)	Databases (CrunchBase)
Startup industry	The sector of the economy in which the startup operates	Industry (categorical variable: HealthTech, FinTech, etc.)	Questionnaire, databases (Startup Estonia, etc.)
Country	Jurisdiction of startup registration	Country (categorical variable: EE, LV, LT)	Databases
Volume of attracted investments	Total External Financing	Funding (kEUR)	Databases (CrunchBase), questionnaire
Comprehensive competitive advantage index	An integral indicator that assesses the overall competitive advantage of a startup	CICS (dimensionless index)	Calculated indicator

Source: Author's methodology

The calculation algorithm is presented in Table 2. It should be noted that the construction of the composite indices (IIC, IOE, ICV, and CICS) involves a degree of subjectivity, as weighting coefficients were derived using expert assessment. While this approach is common in multidimensional performance measurement when objective weights are unavailable, the resulting indices may be sensitive to alternative weighting schemes. Therefore, the indices should be interpreted as analytical tools capturing relative differences across startups rather than as precise absolute measures. The developed methodology enables a comprehensive measurement of the impact of AI on key parameters of startups, and it facilitates testing of hypothesis H1 using various statistical models. To test hypothesis H1 and construct indices of startup competitive advantages, an analysis of the initial data for 40 observations was conducted.

Table 2 Stages and algorithms for calculating integral indicators

Calculation steps	**Calculation algorithms**
Stage 1. Developing a system of comprehensive indicators to assess the impact of AI on competitive advantages	1.1. Index of innovation competitiveness (IIC): $IIC = \alpha_1 \cdot \frac{R\&D_{AI}}{R\&D_{total}} + \alpha_1 \cdot \frac{NewProd_{AI}}{TotalProd} + \alpha_3 \cdot Speed_{scale},$ (1) where $R\&D_{AI}$ – investments in AI development; $R\&D_{total}$ – total research budget; $NewProd_{AI}$ – number of new AI-based products/services; $TotalProd$ – total number of products; $Speed_{scale}$– coefficient of product launch speed (in months); α_i— weights determined by expert method. 1.2. Operational efficiency index (IOE): $IOE = \vartheta_1 \cdot \frac{Cost_{before} - Cost_{AI}}{Cost_{before}} + \vartheta_2 \cdot \frac{Time_{before} - Time_{AI}}{Time_{before}} + \vartheta_3 \cdot Ass_{AI},$ (2) where $Cost_{before}$; $Cost_{AI}$ – costs before and after the implementation of AI, respectively; $Time_{before}$; $Time_{AI}$ – the time of execution of business processes before and after the implementation of AI, respectively; Ass_{AI}– the accuracy of forecasts or decisions made based on AI; ϑ_i— weights determined by the expert method. 1.3. Index of customer value (ICV): $ICV = \gamma_1 \cdot NPS_{AI} + \gamma_2 \cdot Retention_{AI} + \gamma_3 \cdot Personalisation,$ (3) where NPS_{AI} — net promoter score among users of AI services, $Retention_{AI}$ – customer retention rate; $Personalisation$ – level of personalisation (assessment based on surveys or analytics); γ_i— weights determined by the expert method. 1.4. Comprehensive index of competitive advantages of a startup (CICS): $CICS = \delta_1 \cdot IIC + \delta_2 \cdot IOE + \delta_3 \cdot ICV$ (4)
Stage 2. Testing the reliability of hypothesis H1	2.1. Multiple linear regression to test the hypothesis: $CICS_i = \beta_0 + \beta_1 X_i + \sum_{j=2}^{m} \beta_j C_{ji} + \varepsilon_i$ (5) where X_i — level of AI integration. Hypothesis H1 will be confirmed if $\beta_1 > 0$ and statistically significant (p-value < 0.05). $X_i = \frac{\sum_{k=1}^{n} w_k \cdot Q_k}{\sum_{k=1}^{n} w_k},$ (6) where Q_k — level of integration of answers to the questionnaire questions; w_k — weights of the questions. 2.2. t-test for comparing means. The sample is divided into two groups: Group A: $X_i \geq 4$ (strategic integration of AI) Group B: $X_i \leq 2$ (fragmentary use of AI) $t = \frac{\bar{Y}_A - \bar{Y}_B}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}},$ (7) Hypothesis H1 will be confirmed if $\bar{Y}_A > \bar{Y}_B$ and the t-statistic is significant. 2.3. Threshold regression. Allows for the identification of the "threshold effect" of the level of AI integration: $CICS_i = \begin{cases} \beta_0 + \beta_1 X_i + \sum \beta_i C_{ji} + \varepsilon_i \text{ if } X_i \leq \gamma \\ \beta_0 + \beta_1 X_i + \sum \beta_i C_{ji} + \varepsilon_i \text{ if } X_i > \gamma \end{cases}$ (8) Hypothesis H1 will be confirmed if $\beta_1' > \beta_1$ and the threshold γ corresponds to the level of strategic integration. 2.4. Moderated model. Checking whether the effect depends on external factors (e.g., access to funding): $CICS_i = \beta_0 + \beta_1 X_i + \beta_2 F_i + \beta_3 (X_i \times F_i) + \sum \beta_j C_{ji} + \varepsilon_i$ (9) where F_i — the moderator (e.g., funding level).

Source: Author's methodology

4. RESULTS

4.1. Descriptive analysis and sample profile

Table 3 presents the main descriptive characteristics of the key variables, including mean values, medians, standard deviations, and ranges. The obtained statistical characteristics reveal significant variability in both the level of AI integration into startup business processes and investment and innovation activities. At the same time, a stable trend towards decreasing costs and development time has emerged after the introduction of AI, confirming its role in increasing efficiency and forming competitive advantages.

Table 3 Descriptive statistics of the study variables

Variable	Unit	Mean	Median	Standard deviation	Minimum	Maximum
Age	Years	4,2	4	2,74	1	8
Number of employees	Persons	61,05	62	34,71	8	111
Level of AI integration (Xi)	1-5	2,86	2,8	0,49	1,76	3,73
R&D Costs in AI (R&DAI)	kEUR	654,7	685,5	321,79	83	1324
Total R&D Costs (R&Dtotal)	kEUR	1845,98	1800,25	694,76	395	2993
Number of new products with AI (NewProdAI)	units	1,73	2	0,93	0	5
Total number of new products (TotalProd)	units	8,9	9	3,33	3	14
Speedscale	1-20	13,38	13,5	4,68	6	20
Cost before AI (Costbefore)	kEUR	240,4	244,5	92,6	83	369
Cost after AI (CostAI)	kEUR	168,2	160	72,13	56	322
Development time before AI (Timebefore)	months	18,97	19,87	5,34	8,95	24,93
Development time with AI (TimeAI)	months	12,18	11,685	4,37	5,52	19,24
AI performance assessment (AssAI)	1-100	81,19	81,25	6,36	72,3	95,6
Metric NPS (NPSAI)	1-100	48,93	47	25,64	10	88
Customer retention rate (RetentionAI)	1-100	74,48	73,8	8,91	60,5	94,3
Level of personalisation (Personalisation)	1-10	7,65	8	1,84	5	10
Funding amount (Funding)	kEUR	5067,58	5143	2901,63	525	8658
Level of AI integration into business processes (IIC)	0-1	0,38	0,37	0,13	0,135	0,646
Level of AI integration into operations (IOE)	0-1	0,45	0,45	0,05	0,312	0,559
Level of AI integration into product value (ICV)	0-1	0,75	0,736	0,08	0,568	0,911
Level of AI integration into development (CICS)	0-1	0,53	0,523	0,06	0,415	0,652

Source: Author's calculations

Figure 1 shows the distribution of 40 startups by their countries of origin: Estonia, Lithuania, and Latvia (left); and the distribution of startups in the sample across eight different industries (right).

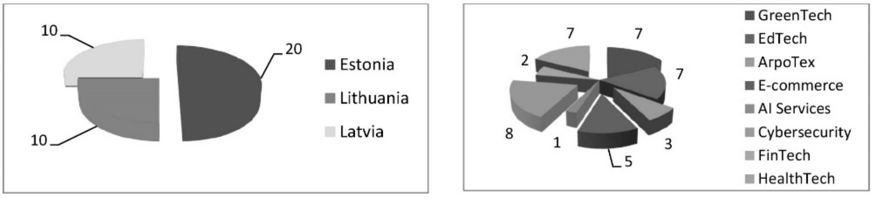

Figure 1 Distribution of startups in the Baltic countries (left) and distribution of startups by industry

Source: Author's analysis

As the data shows, the cybersecurity, healthcare, EdTech, and environmental technology sectors are the most represented in the sample, indicating their importance.

Figure 2 illustrates the distribution of startups in the sample according to the level of integration of artificial intelligence into their business processes, assessed on a scale of 1 to 5. The data in Figure 2 shows that the largest proportion of startups in the sample demonstrate a medium and high level of AI integration, which confirms its growing importance for business.

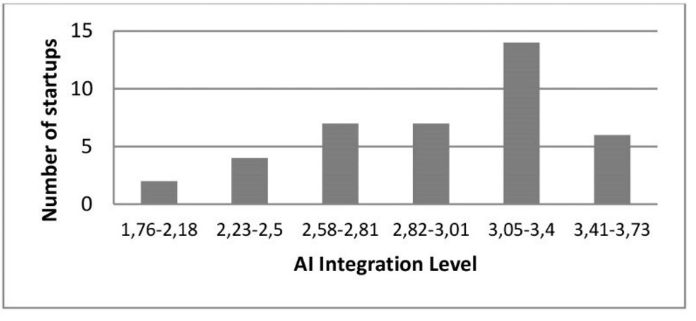

Figure 2 Distribution of startups by AI integration level (X_i)

Source: Author's calculations

4.2. Analysis of the relationship between AI integration level and the comprehensive competitive advantage index (CICS)

Table 4 presents the results of the regression analysis examining the impact of the level of AI integration (Xi) and other control variables on the level of AI integration in the development of competitive advantages (CICS) among startups. The model includes independent variables such as the level of AI integration (Xi), company size, startup age, funding volume, and industry.

Table 4 Results of the regression analysis of the dependence of CICS on the AI integration level and control variables

Variable	Coefficient (β)	Standard error	t-statistic	p-value
AI integration level (X_i)	0.124	0.032	3.875	0.000
Company size (log)	0.045	0.021	2.143	0.038
Startup Age	-0.008	0.006	-1.333	0.190
Funding Amount (log)	0.062	0.018	3.444	0.001
Industry (referent: GreenTech)				
- EdTech	0.031	0.028	1.107	0.275
- HealthTech	0.042	0.030	1.400	0.169
- Cybersecurity	0.050	0.029	1.724	0.092
- E-commerce	0.025	0.027	0.926	0.359
- FinTech	0.038	0.031	1.226	0.227
- AI Services	0.067	0.033	2.030	0.049
Constant	0.211	0.089	2.370	0.022

Source: Author's calculations

The conducted regression analysis, with the results presented in Table 4, enabled us to estimate the influence of various factors on the level of integration of artificial intelligence in the development of competitive advantages (CICS) of startups. The model has a high explanatory power: the P^2 value is 0.712, which means that 71.2% of the variation in the dependent variable CICS is explained by the predictors included in the model. The significance of the F-statistic ($n<0.001$) confirms the adequacy and statistical significance of the entire model as a whole. The central result of the analysis is the confirmation of the hypothesis about the positive impact of the level of AI integration on competitive advantages. The coefficient $\beta=0.124$ is positive and statistically significant ($n<0.001$), which indicates that each additional point in the level of AI integration is associated with a higher value of the CICS index by 0.124 points, provided that other variables remain unchanged. Significant factors were also identified among the control variables. Company size, expressed as the logarithm of the number of employees, has a positive effect on CICS ($\beta=0.045$, $n=0.038$), meaning that larger startups tend to exhibit a higher level of AI-related competitive advantage. Similarly, funding amount also has a statistically significant positive relationship ($\beta=0.062$, $n=0.001$), indicating that startups with more funding are more successful in using AI to create competitive advantage. In contrast, startup age did not show a statistically significant effect ($n=0.190$). In the industry analysis, the AI Services industry stands out, where startups have a statistically significant advantage in CICS compared to the GreenTech reference group ($\beta=0.067$, $n=0.049$). The scatterplot plots the relationship between the AI integration level (Xi) and the competitive advantage index for 40 startups (Figure 3). The figure shows a positive linear relationship, which supports the conclusion that a higher level of AI integration in a startup is directly related to its ability to create competitive advantages.

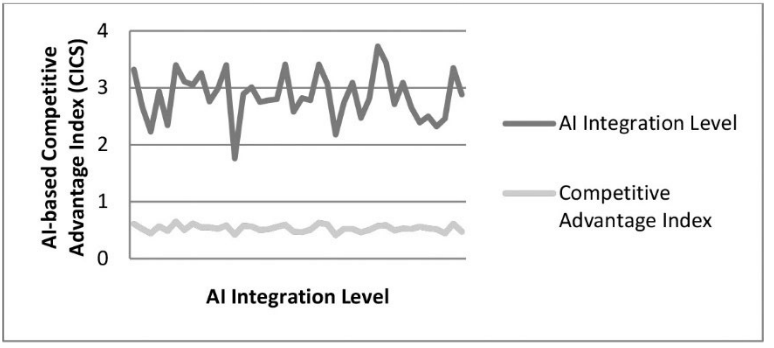

Figure 3 Scatterplot and trend line showing the relationship between Xi (AI Integration Level) and CICS

Source: Author's calculations

4.3. Comparative analysis of startup groups with different levels of AI integration

Table 5 presents a comparison of the average values of the KPIs for startups with high and low levels of AI integration, which allows us to assess the impact of AI on their business performance.

Table 5 Comparison of the average values of the indexes for groups with high and low levels of AI integration

Index	**Average value for the group with a low level of AI integration ($X_i \leq 2,81$)**	**Average value for the group with a high level of AI integration ($X_i > 2,81$)**
AI integration level into business processes (IIC)	0,32	0,43
AI integration level into operational processes (IOE)	0,44	0,47
AI integration level into product value (ICV)	0,72	0,77
AI integration level into competitive advantage development (CICS)	0,5	0,56

Source: Author's calculations

A comparison of average values reveals that startups with a high level of AI integration significantly outperform those with a low level of integration across all key metrics. The average values of the IIC, IOE, ICV, and CICS indices are consistently higher in the group with deeper AI integration. This suggests a direct correlation between the level of AI integration and the overall business outcomes of startups. Companies that more actively and deeply implement AI demonstrate better indicators of business process efficiency, responsiveness, product value, and, as a result, are more successful in creating competitive advantages in the market. The bar chart (Figure 4) presents a comparison of the average values of key performance indices (CICS, IIC, IOE, ICV) for two groups of startups, identified based on their median level of AI integration.

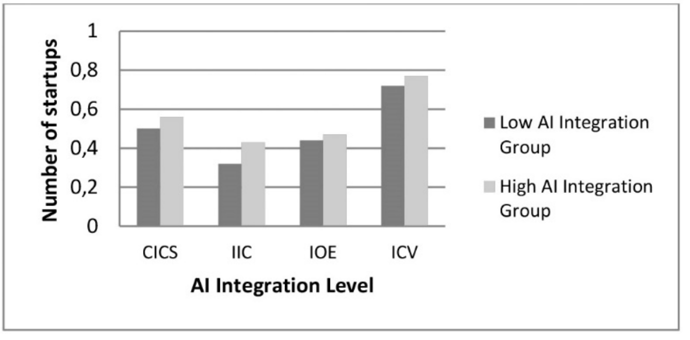

Figure 4 Bar chart comparing average values of CICS, IIC, IOE, and ICV between groups

Source: Author's calculations

It clearly demonstrates that startups with a higher level of AI integration show significantly higher average values for all four key indices compared to those with a low level of AI integration. This confirms that the implementation of AI is a critical factor in improving competitiveness and business efficiency.

4.4. Identifying the threshold effect of strategic AI integration

Table 6 contains the results of the threshold regression (model 8), which allows us to determine at what level of AI integration (variable Xi) its positive impact on the competitive advantages of startups becomes most pronounced. The analysis shows the presence of a “threshold effect”, which confirms that AI implementation must reach a certain strategic level in order to have a significant impact on business indicators.

Table 6 Threshold regression results

Variable	Coefficient	Standard error	t-statistic	P-value
Level of AI integration (Xi)	0,143	0,025	5,72	< 0,001
AI integration (above threshold γ)	0,287	0,041	7	< 0,001
Threshold γ	3	-	-	-
Fixed effects (Country, Industry)	Included			
R2	0,552			
F-statistics	12,56			< 0,001
Number of observations	40			

Source: Author's calculations

The data in Table 6 show that the threshold value $\gamma = 3.00$. This means that the impact of AI integration on competitive advantage increases sharply when the integration level exceeds 3 points on a scale from 1 to 5. Hypothesis H1 is confirmed ($\beta_2 > 0$): The coefficient for the variable "AI Integration (above threshold)" is 0.287, which is positive and statistically significant ($p < 0.001$).

This indicates that for startups that have exceeded the threshold level of integration, the growth of competitive advantage accelerates significantly. The results of the regression analysis revealed the threshold value of γ at 3.00. This means that a startup's competitive advantage increases significantly only after its AI integration level exceeds this threshold. Hypothesis H1 is confirmed, according to which a strategic approach to AI implementation (integration level above 3.00) is a necessary condition for achieving the maximum effect and gaining significant competitive advantages.

Figure 5 illustrates the threshold effect in the relationship between AI integration level (Xi) and its impact on competitive advantages, as well as the change in coefficient β1 when the integration level crosses the critical threshold value ($\gamma = 3.00$).

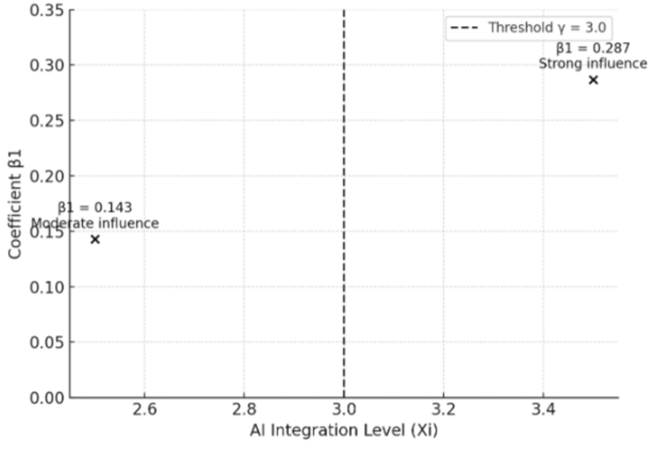

Figure 5 Visualization of the threshold effect: change in the coefficient β_1 when passing through the threshold value γ

Source: Author's calculations

The results demonstrate a significant shift in influence: when $Xi \leq 3.00$, the coefficient $\beta1$ equals 0.143, indicating a positive but moderate contribution to competitive advantages. However, once the integration level exceeds the threshold ($Xi > 3.00$), the coefficient $\beta1$ rises to 0.287, reflecting a strong and substantially more pronounced impact. This confirms the existence of a nonlinear relationship, where higher AI integration yield disproportionately greater competitive benefits.

4.5. Moderator effects: the role of access to funding and industry specificity

Table 7 contains the results of the regression analysis with moderation effects (Model 9). The primary objective of this analysis is to investigate how access to funding (Funding) affects the relationship between the level of AI integration (Xi) and start-up competitive advantage (CICS). This model enables us to test the hypothesis that financial support not only has an independent positive effect but also serves as a strengthening factor, allowing start-ups to fully realize the potential of their AI investments.

Although the main analysis focuses on the effect of funding, the inclusion of industry fixed effects (Industry) in Model 9 revealed that the effect of AI on competitive advantage (CICS) may vary across different industries. For example, in highly capital-intensive sectors such as GreenTech and FinTech, funding may play a more significant role in accelerating AI adoption than in less capital-intensive industries. Thus, having sufficient funding is critical for startups in these areas to fully realize the potential of their AI investments.

Table 7 Results of the regression analysis with the moderation effect (Xi * Funding interaction)

Variable	**Coefficient**	**Standard error**	**t- statistic**	**P- value**
AI integration level (Xi)	0,172	0,028	6,14	< 0,001
Funding	0,000021	0,000008	2,63	0,013
Interaction (Xi * Funding)	0,000045	0,000015	3	0,005
Fixed effects (Country, Industry)	Included			
R2	0,625			
F- Statistics	15,87			< 0,001
Number of observations	40			

Source: Author's calculations

The results clearly confirm the presence of a significant moderation effect, as evidenced by the positive and statistically significant coefficient of the interaction variable (Xi* Funding) ($p < 0.01$). This means that funding is a key factor that significantly amplifies the positive effect of AI implementation on the competitive advantage of start-ups. Thus, the effect of AI investments is not static: its strength is directly proportional to the amount of available funding. Start-ups with a high level of AI integration and sufficient funding demonstrate significantly higher competitive advantage scores, which highlights the synergistic effect between technological innovation and financial support.

Figure 6 presents the interactive effect of AI integration on CICS, considering different levels of funding. The analysis explores how variations in financial resources (low, medium, and high levels) alter the strength of the relationship between AI integration and competitive performance.

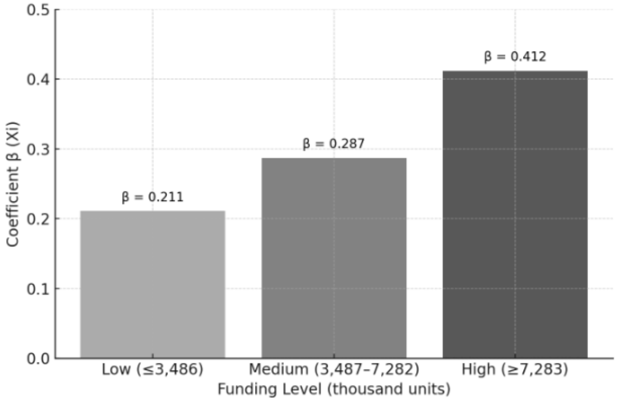

Figure 6 Interactive effect of AI integration level on CICS at different funding levels (low/medium/high)

Source: Author's calculations

The results confirm that funding significantly moderates the impact of AI integration. At a low funding level (≤ 3,486 thousand), the coefficient β equals 0.211, reflecting a positive but weak influence. With medium funding (3,487–7,282 thousand), the effect becomes stronger, with β = 0.287, indicating a moderate and noticeable impact.

At high funding levels (≥ 7,283 thousand), the coefficient β rises sharply to 0.412, revealing a strong and substantially more pronounced effect. This demonstrates that adequate financial support amplifies the benefits of AI integration for enhancing CICS outcomes.

4.6. Qualitative insights: barriers and drivers of strategic AI integration

Qualitative data were analyzed using thematic content analysis. Interview transcripts were coded inductively to identify recurring themes related to barriers and drivers of strategic AI integration. The frequency and consistency of themes across interviews informed the categorization presented in Table 8. Table 8 summarizes the key barriers and drivers of strategic AI integration in Baltic startups, based on content analysis of in-depth interviews with founders and ecosystem experts. Qualitative data provides depth of context by identifying recurring themes across cases and complements the quantitative analysis. This enables us to better understand why some startups fail to reach the critical threshold of AI integration, while others capitalize on the enabling factors to enhance competitiveness and innovation.

Table 8 Key barriers and drivers of strategic AI integration in Baltic startups (based on content analysis of interviews)

Category	Themes Identified	Illustrative Insights (from interviews)	Link to Quantitative Findings
Barriers	• Limited access to AI-specific funding • Shortage of skilled AI talent • Regulatory uncertainty and compliance costs • High implementation costs for early-stage startups • Ethical and trust-related concerns among customers	*"For small startups, the cost of training AI models is prohibitive unless we secure external funding." "We struggle to attract AI engineers; most prefer established companies or move abroad."*	Confirms regression results highlighting the moderating role of ***Funding***; explains why lower-funded startups show weaker CICS gains.
Drivers	• Strong regional digital infrastructure (especially Estonia) • Governmental and EU-level support programs • Network effects within startup ecosystems • Growing demand for AI-enabled products/services • International scalability opportunities	*"The e-Residency program helped us test our AI-based product across markets much faster." "Clients are increasingly asking for AI-driven personalization – this pulls us to invest more."*	

Source: Author's analysis

The qualitative insights from in-depth interviews provide an essential complement to the quantitative results, highlighting both systemic barriers and enabling factors that shape the strategic use of AI in Baltic startups. The barriers – such as limited funding, talent shortages, and regulatory uncertainty – explain why many startups remain below the critical threshold of AI integration, resulting in only moderate performance gains. At the same time, the identified drivers − strong digital infrastructure, supportive policy frameworks, and rising market demand − illustrate the conditions under which startups can surpass this threshold and unlock disproportionately greater competitive advantages. These findings confirm the quantitative evidence of threshold and moderation effects (Figures 5 and 6), while also offering contextual depth on the mechanisms behind these relationships. The qualitative findings are intended to enhance interpretive depth and should not be interpreted as statistically representative of the broader startup population.

5. DISCUSSION

5.1. Empirical associations between AI integration and competitive advantage

The obtained results provide empirical evidence of a systematic association between the level of artificial intelligence (AI) integration and the competitive advantages of high-tech startups, particularly in resource-constrained environments (Agrawal et al., 2018; Huang & Rust, 2020). Given the cross-sectional nature of the dataset, the findings should be interpreted as correlational rather than strictly causal. In particular, potential endogeneity concerns cannot be fully ruled out. Startups with stronger competitive positions may be more capable of investing in AI, leading to reverse causality, while unobserved managerial capabilities or strategic orientation may simultaneously influence both AI integration and performance outcomes. Although the inclusion of control variables and fixed effects partially mitigates these risks, future research employing longitudinal data or instrumental variable approaches would be necessary to more rigorously address endogeneity. Nevertheless, the consistency of the observed relationships with established theoretical frameworks suggests that strategic AI integration plays an important enabling role in shaping competitive outcomes.

The identified threshold effect ($\gamma = 3.00$) indicates a non-linear relationship, whereby higher levels of AI integration are associated with disproportionately stronger competitive advantages. This pattern indicates that deeper strategic AI integration is linked to substantially stronger competitive outcomes rather than incremental performance improvements. While this pattern does not allow for direct causal inference, it aligns with theoretical arguments that emphasize the transformation of business models once AI adoption reaches a strategic level (Borges et al., 2020; Sjödin et al., 2021). Thus, the results support the interpretation that competitive advantages emerge not from the mere presence of AI, but from its deep integration into core processes and value creation mechanisms.

The moderation effect of funding further demonstrates that access to financial resources is strongly associated with the magnitude of AI-related competitive advantages. Although causality cannot be conclusively established within the current research design, the findings are consistent with prior studies highlighting the role of capital availability as a critical enabling condition for effective AI implementation (Agrawal et al., 2019; Ransbotham et al., 2017).

Qualitative insights reinforce these results by providing contextual explanations for the observed statistical associations. Barriers such as talent shortages and regulatory uncertainty help explain why some startups remain below the identified threshold of AI integration, while supportive digital infrastructure and policy frameworks facilitate deeper adoption. These qualitative findings do not establish causation but strengthen the interpretive validity of the quantitative results by illustrating plausible mechanisms underlying the observed relationships (Dwivedi et al., 2021; Nambisan et al., 2019).

Overall, the discussion highlights that AI-based competitive advantages in Baltic startups should be understood as the outcome of interrelated strategic and institutional factors, with the present study identifying robust empirical relationships rather than definitive causal effects. Accordingly, the findings should be understood as evidence of robust empirical associations that are consistent with existing theory, rather than as proof of direct causal effects.

5.2. Practical and Policy Implications

From a policy perspective, the findings suggest that public support measures in the Baltic region should focus not only on promoting AI adoption per se, but on enabling startups to reach a strategic level of AI integration. Government programs and startup accelerators could apply these insights by designing targeted funding instruments for AI-intensive projects, particularly at early growth stages where resource constraints are most binding. In addition, accelerator programs may emphasize the development of AI-related managerial and technical capabilities, helping startups move beyond experimental or fragmented use of AI toward deeper integration into core business models. At the regional level, coordinated policies that combine financial support, talent development, and regulatory clarity could enhance the effectiveness of AI-driven entrepreneurship and strengthen the competitiveness of the Baltic startup ecosystem.

6. CONCLUSIONS

Based on the conducted empirical research, a key conclusion has been formed: strategic integration of artificial intelligence (AI) is a key factor associated with in the formation of sustainable competitive advantages for high-tech startups in the Baltic countries. The results of regression analysis demonstrate a statistically significant positive relationship between the level of AI integration (Xi) and the composite index of competitive advantages (CICS): coefficient $\beta = 0.124$ ($p < 0.001$) with high explanatory power of the model ($R^2 = 0.712$). This means that a one-point increase in the level of AI integration on a 5-point scale is associated with a 0.124-point higher value in the CICS index, assuming all other factors remain equal. The most important result is the identification of a nonlinear threshold effect ($\gamma = 3.00$). When crossing this critical threshold, the impact of AI on competitive advantages qualitatively intensifies: the impact coefficient increases from 0.143 to 0.287 ($p < 0.001$ in both cases). This confirms that the maximum effect is achieved not through fragmented, but through systematic, strategic implementation of AI into business models and decision-making processes. Access to funding acts as a critically significant moderator, enhancing this effect. The interaction coefficient (Xi × Funding) is 0.000045 ($p = 0.005$), indicating synergy between technological and financial resources.

The analysis revealed that at low funding levels (≤ 3486 kEUR), the impact of AI on CICS is weak ($\beta = 0.211$), while at high funding levels (≥ 7283 tEUR), this effect more than doubles ($\beta = 0.412$). Qualitative data revealed that key barriers limiting the achievement of the threshold level include a shortage of specialized funding for AI projects, a lack of qualified personnel (noted by 40% of interviewees), and regulatory uncertainty. Thus, the obtained results indicate that to realize the competitive potential of AI, startups need not only an internal strategic orientation but also access to external resources – capital and talent pool – as well as support within national and pan-European digital ecosystems.

Research limitations. Despite the comprehensive approach, this study has several limitations that should be taken into account when interpreting the results. First, the sample size, limited to 40 startups from the Baltic countries, while representative for a pilot analysis, does not allow for full extrapolation of the conclusions to the entire population of high-tech ventures in the region, nor to other geographical contexts. Second, the cross-sectional design of the study, which captures a snapshot at a specific point in time, limits the ability to establish causal relationships and analyze the long-term dynamics of AI's impact on competitive advantages. Third, despite the application of weighting coefficients, the calculation of composite indices (IIC, IOE, ICV, CICS) is to some extent subjective and depends on expert assessments when assigning weight values αi, ϑi, γi, δi. In addition, the cross-sectional design of the study limits the ability to control for potential endogeneity between AI integration and competitive performance, which should be addressed in future longitudinal or quasi-experimental research designs. Fourth, the study may have been subject to self-selection effects, as startups already interested in AI and with positive results were more likely to agree to participate in the survey and interviews. Finally, although the model accounted for industry fixed effects, there remains the possibility that unaccounted industry- or country-specific factors may have influenced the obtained relationships. Future research could address potential selection bias by employing random or stratified sampling strategies, expanding the dataset using administrative or platform-based data sources, and applying longitudinal designs or matching techniques to better isolate the effects of AI integration across heterogeneous startup populations.

Directions for future research. The obtained results open several promising directions for future research. The priority is to conduct a longitudinal study to track the evolution of the impact of strategic AI integration on startups' competitive advantages over time, which would enable the establishment of causal relationships and the assessment of the long-term return on investment in AI. Second, it would be advisable to expand the geographical scope by including startups from other Central and Eastern European countries or Scandinavia to test the universality of the identified threshold effects and the role of moderators in different institutional environments. Third, the mechanism of interaction between different types of AI (e.g., machine learning, natural language processing, computer vision) and specific business models requires in-depth study, as well as an analysis of how the stage of startup development (seed, early-growth, scaling) affects the effectiveness of AI implementation strategies. These avenues align with broader calls in the literature to explore the interplay between AI, digital globalization trends, and evolving entrepreneurial strategies (Ratten, 2024). Fourth, the qualitative dimension could be supplemented with in-depth case studies of failed AI implementation cases to identify additional barriers and risks not identified in this study. Ultimately, it would be beneficial to develop and validate a more comprehensive system of metrics for evaluating the strategic maturity of AI use, extending beyond the aggregated index Xi.

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APENDIX A

StartupID	Startup	Country	Industry	Age	Employees (person)	Xi (AI integration level, 1-5)	R&DAI	R&Dtotal	NewProdAI	TotalProd	Speedscale	Costbefore	CostAI	Timebefore	TimeAI	AssAI	NPSAI	RetentionAI	Personalisation	Funding	IIC	IOE	ICV	CICS
S01	Sunly	EE	GreenTech	8	14	3,32	847	1320	5	5	19	317	216	24,27	15,34	74,6	78	67,5	8	764	0,578	0,461	0,789	0,611
S02	eAgronom	LT	EdTech	5	80	2,67	129	395	3	6	12	283	160	19,51	14,57	80,1	14	64,8	6	7209	0,452	0,49	0,606	0,519
S03	Aerones	LV	AgriTech	2	79	2,23	476	2223	2	9	20	297	228	16,2	9,51	76,1	12	60,5	9	5021	0,152	0,445	0,687	0,442
S04	Sonarworks	LV	E-commerce	7	19	2,94	468	2057	2	6	14	118	79	16,38	10,08	87,5	62	72,3	10	5526	0,32	0,51	0,844	0,57
S05	Binalyze	EE	GreenTech	5	41	2,34	786	2832	1	11	17	179	140	9,42	6,14	81,3	32	80,6	9	5522	0,203	0,435	0,788	0,489
S06	BoBo	EE	AI Services	8	40	3,4	682	2578	3	3	10	368	252	9,56	5,63	77,5	62	73,7	10	2046	0,62	0,482	0,849	0,652
S07	Bolt	EE	Cybersecurity	2	55	3,11	99	1978	3	10	6	333	263	18,24	11,71	78,4	46	75,3	5	1318	0,41	0,427	0,662	0,504
S08	Vinted	LT	FinTech	1	30	3,05	453	840	4	9	15	301	201	17,41	12,19	80,6	83	91,6	9	3197	0,456	0,465	0,911	0,618
S09	Origin	LV	EdTech	4	69	3,26	472	1359	3	4	15	102	65	11,62	8,82	78,2	83	72,2	5	6906	0,471	0,452	0,714	0,55
S10	Cenos	LV	HealthTech	4	95	2,76	993	2872	1	10	6	329	238	24,09	18,51	82,9	26	78	8	6270	0,468	0,429	0,736	0,548
S11	Naco	EE	E-commerce	4	44	2,99	701	1483	2	3	20	89	71	21,28	16,77	72,8	87	87,4	6	1931	0,389	0,363	0,804	0,525
S12	Veriff	LT	EdTech	5	106	3,4	388	2022	2	13	7	325	218	9,93	7,55	78,7	82	73,9	10	8572	0,401	0,44	0,883	0,583
S13	Biomatter	LT	HealthTech	1	51	1,76	501	2119	4	14	19	179	157	23,83	17,59	81,9	10	81,8	6	3745	0,202	0,373	0,655	0,42
S14	Roibox	EE	Cybersecurity	5	111	2,89	1224	2925	2	11	11	369	208	24,56	14,32	86,5	60	90,2	5	8073	0,415	0,559	0,735	0,577
S15	PVcase	EE	Cybersecurity	7	93	3,01	988	2904	1	11	14	259	180	24,93	15,96	78,5	54	93,2	10	7349	0,292	0,465	0,899	0,565
S16	Tuum	EE	Cybersecurity	5	98	2,75	762	1897	1	4	13	302	268	8,95	5,97	75,2	86	65,1	6	7282	0,386	0,37	0,729	0,501
S17	Ovoko	EE	HealthTech	1	42	2,78	1012	2993	2	9	18	329	244	20,53	10,86	73,8	13	92,4	9	2306	0,245	0,466	0,794	0,515
S18	Green Genius	LV	EdTech	1	72	2,8	344	1095	1	12	10	226	158	17,28	11,84	94,6	71	77,2	7	3486	0,365	0,499	0,777	0,556

S19	Nord Security	EE	Cybersecurity	7	106	3,41	763	1351	2	5	6	175	131	20	13,05	82	74	69	5	8552	0,646	0,451	0,689	0,593
S20	Mapon	EE	AgriTech	1	108	2,58	991	1943	1	9	18	336	253	24,47	19,1	85,9	41	76,1	6	6150	0,28	0,422	0,689	0,473
S21	Koala	LV	GreenTech	8	54	2,82	83	1663	2	14	12	83	67	19,7	16,59	94,1	43	94,3	5	1462	0,234	0,407	0,719	0,464
S22	Better Medicine	EE	HealthTech	1	85	2,78	1305	2281	2	12	20	95	56	22,23	15,44	74	81	77,2	5	2376	0,279	0,478	0,728	0,506
S23	Salu Health	EE	HealthTech	4	10	3,41	1114	1654	1	11	10	359	229	22,74	13,94	93	48	71,5	10	1696	0,511	0,54	0,818	0,628
S24	Flowstep	EE	EdTech	8	8	3,07	1050	1963	1	6	11	326	246	22,25	11,47	85,2	35	82,2	10	6629	0,457	0,499	0,831	0,603
S25	Sention Technologies	EE	HealthTech	8	12	2,18	581	1829	0	14	18	337	288	15,24	12,55	76	43	68,4	7	8041	0,17	0,339	0,7	0,415
S26	Atrandi Biosciences	LT	HealthTech	7	97	2,74	577	2338	1	3	12	239	178	11,78	9,68	81,9	63	62,7	9	525	0,37	0,401	0,781	0,525
S27	Sentinel	EE	Cybersecurity	3	21	3,09	825	1796	0	4	8	231	146	14,74	8,68	90,7	12	64,5	5	5032	0,441	0,543	0,568	0,521
S28	Drafter AI	LV	EdTech	3	110	2,47	652	2537	1	3	17	257	203	23,16	17,22	83,5	59	64,5	6	6688	0,267	0,412	0,681	0,463
S29	Lokalise	LV	Cybersecurity	1	34	2,81	689	1708	1	14	15	242	196	10,49	5,52	95,6	21	65,3	8	3996	0,29	0,505	0,685	0,504
S30	ÄIO	EE	GreenTech	8	16	3,73	589	1700	3	7	8	112	71	16,73	9,34	81	74	64,9	5	6568	0,524	0,522	0,675	0,576
S31	Printful	LV	E-commerce	3	86	3,44	856	1606	2	7	10	258	176	11,96	6,89	90	63	82,4	5	7961	0,513	0,524	0,714	0,587
S32	Arbonics	EE	GreenTech	3	22	2,71	869	2980	2	13	11	180	133	17,88	10,78	81,4	14	66,4	7	8658	0,356	0,468	0,644	0,496
S33	Naco Technologies	EE	E-commerce	1	97	3,09	844	2975	2	9	14	347	251	22,67	19,24	91,9	66	72,1	9	632	0,309	0,432	0,817	0,53
S34	Rrr.lt	LT	Cybersecurity	3	49	2,65	517	1272	3	11	18	144	99	22,97	17,09	85,7	26	91,4	8	6771	0,287	0,459	0,78	0,52
S35	Eneba	LT	GreenTech	5	84	2,39	1324	2068	2	11	19	247	162	12,02	7,63	73,5	56	76,6	10	4606	0,332	0,468	0,848	0,56
S36	Printify	LT	EdTech	2	58	2,5	573	1582	1	5	17	122	71	23,43	17,76	72,9	32	83,4	10	8343	0,269	0,458	0,83	0,532
S37	Glia	EE	FinTech	7	70	2,32	290	1009	0	5	10	123	70	18,06	14,82	75,2	88	66	6	7291	0,329	0,452	0,736	0,514
S38	Bisly	EE	Cybersecurity	2	103	2,46	851	1779	2	5	20	364	322	13,95	11,66	72,3	23	66,7	8	7138	0,311	0,312	0,693	0,445
S39	Zeew	LV	E-commerce	1	110	3,35	794	1734	2	6	6	91	77	20,04	10,43	73,8	75	61,4	10	2872	0,583	0,427	0,83	0,615
S40	Tule	EE	AgriTech	4	59	2,88	197	948	1	10	19	174	117	16,19	10,33	88,6	84	65,9	6	3139	0,135	0,505	0,728	0,472

Source: https://www.seedtable.com/best-startups-in-lithuania; https://www.seedtable.com/ best-startups-in-latvia;

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UMJETNA INTELIGENCIJA KAO ALAT ZA RAZVOJ POSLOVNIH STRATEGIJA I STVARANJE PREDNOSTI ZA VISOKOTEHNOLOŠKE *STARTUPOVE*

Sažetak

Ovo istraživanje ispituje je li strateška integracija umjetne inteligencije (UI) u menadžersko odlučivanje povezana s razvojem održivih konkurentskih prednosti. Uzimajući u obzir nedostatak u literaturi o primjeni umjetne inteligencije u startup ekosustavima s ograničenim resursima, istraživanje se usredotočuje na startupove u baltičkim zemljama. Primjenom mješovitog istraživačkog pristupa, koji kombinira anketne podatke, financijsku analizu i intervjue sa stručnjacima, studija *razvija kompozitni indeks za mjerenje konkurentskih prednosti temeljenih na umjetnoj inteligenciji u okviru dimenzija inovacija, operativnih učinkovitosti i vrijednosti za korisnike. Empirijski rezultati pokazuju da je dublja i strateška integracija umjetne inteligencije pozitivno povezana s jačim konkurentskim prednostima. Nalazi dodatno otkrivaju da je taj odnos nelinearan i značajno ojačan dostupnošću financijskih resursa. U cjelini, istraživanje naglašava da UI donosi konkurentske koristi startupovima samo kada se implementira strateški i uz odgovarajuću financijsku potporu i ljudski kapital, nudeći važne implikacije za osnivače startupova, investitore i donositelje politika. S obzirom na presječni karakter podataka, utvrđeni odnosi trebaju se tumačiti kao asocijativni, a ne strogo uzročni.*

Ključne riječi: umjetna inteligencija, startup, baltičke zemlje, konkurentske prednosti, poslovni model, strateška integracija, inovacija.

JEL klasifikacija: M15, L26, O31, O33.