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CORPORATE MANAGEMENT OF FINANCIAL AND MARKETING SUPPORT FOR CLUSTER-BASED STARTUP ENTREPRENEURSHIP IN TRADE WITHIN AN INNOVATION-DRIVEN ECONOMY

ABSTRACT

This research study elaborates on the theoretical and methodological aspects of the adaptive management of financial and marketing tools for retail startup clusters within the context of a knowledge- and innovation-based economy. It establishes that optimizing corporate support for startups does not always depend on investment funding; rather, it is primarily determined by a top manager's ability to adapt to changing market conditions through scaling, sales dynamics, and the effective allocation of available resources. The study substantiates the need for neural network modeling to forecast the optimal scaling of retail startups and to formulate policies for their continued support. It details the set of input indicators for neural network modeling that constitute the startup's system of economic, social, financial, and marketing tools. Using scenario modeling, the study evaluates the necessary avenues for marketing and financial support for startups operating in an unstable environment. It provides a detailed characterization of the concept of "neural network sensitivity to corporate support", a metric used to forecast the financial resources required for a startup's effective development. Finally, the study demonstrates that investment should be directed not only toward startups with high profitability but also toward emerging enterprises where such investment fosters the long-term growth of specific financial indicators, thereby enabling the creation of operational reserves to safeguard against potential bankruptcy. Scenario-based options for potential management actions — specifically regarding scaling, adaptive support, and reactive marketing are proposed to ensure the startup's continued effective operation. These options lay the groundwork for startups to make an adaptive transition from traditional, steady development to a reactive model within a cluster-based retail network.

Keywords: adaptive entrepreneurship, startups, neural networks, modeling, corporate support, management, economics, trade, clusters, finance, innovation, profitability, marketing, external environment

JEL Classification: L81, M10, G32, O33

INTRODUCTION

The growth of the knowledge economy places particular emphasis on the need to develop startups in the retail sector, as these ventures act as engines for innovative digital solutions, modernized sales tools, new marketing channels, and optimal customer engagement mechanisms. However, a high level of innovation within a startup does not guarantee its successful progression through all stages of its lifecycle. Startups commonly face severe financial constraints, volatile consumer demand, exorbitant marketing costs, scaling challenges, and a lack of adequate corporate support. In this context, cluster groupings take on special significance, offering unique access to scarce financial, social, human, and marketing resources that would be difficult for an individual startup to secure on its own.

Corporate management plays a pivotal role here, enabling the assessment of a startup's potential and determining the scope, type, and timing of support required to ensure its effective development. Within this study, corporate management is defined as a system

of managerial decisions implemented by a parent company or cluster coordinator to allocate financial and marketing resources among startups. This decision-making entity determines investment priorities, the intensity of marketing support, and the feasibility of scaling entrepreneurial initiatives.

The conventional startup assessment practices that analyze marketing, production, financial, or other management activities are applicable to linear cluster development models but are unsuited to current conditions. In this context, the use of neural network modeling is significant, as it allows us to move beyond viewing a startup merely as a linear phenomenon and instead determine the potential for its future development. These aspects formed the methodological basis of our research, which focuses on identifying effective predictive tools for managing the resources of early-stage enterprises. At the same time, we recognize the immense challenges involved in corporate governance, particularly within trade clusters and startups. Management tools in this sphere have long since evolved beyond mere investment or social support measures; the agenda now includes the need to test specific startup clusters against harsh market realities. A balanced approach to determining the level of investment required to sustain the cluster's viability is particularly crucial. Such support must be fully aligned with various cluster development trajectories, as irrational financial backing can lead to a failed experiment for both the investor and the trade startup cluster as a whole.

LITERATURE REVIEW

Corporate governance issues regarding startup development are extensively addressed in academic literature. For instance, Roper and Grimes (2005) conducted in-depth research on financing innovation and identifying ways to boost productivity.

Wonglimpiyarat and Khaemasunun (2015), Shumilova et al. (2023), and Baporikar (2017) examined key aspects of forming innovation clusters and processes for improving cluster communication, paying particular attention to measuring social entrepreneurship and human capital.

Building on this work, Farinha and Bagchi-Sen (2018) demonstrate the need to strengthen the competitiveness of high-tech economic sectors through startups and small businesses by comprehensively implementing innovations, knowledge, and new technologies.

Duginets et al. (2023) strongly advocate for a knowledge-based economy, with Hu et al. (2022) specifically highlighting the territorial distribution of such knowledge. Krammer (2017) emphasizes that tangible results can be achieved through smart specialization and by generating economic benefits for startup founders.

Kowalski (2022) examines the subject through the lenses of regionality and the stimulation of innovative development. Researchers led by Audretsch et al. (2019) advocate for the active expansion of cluster policy across all entrepreneurial sectors, highlighting the need for business adaptation.

Mazur et al. (2021) distinguished themselves through unconventional approaches, employing a wide range of tools to drive innovation and enhance enterprise performance. Richardson (2024) investigates the role of social entrepreneurship in shaping an innovative cross-border environment.

Prokopenko et al. (2021) examine models for managing clustering and marketing processes, linking cluster-related issues with market development management mechanisms. Yang et al. (2015) identifies economic clusters as a tool for aligning economic and spatial policies.

Wessner and Howell (2017) use the example of a high-tech cluster to explore the potential of smart specialization and the concentration of innovation resources.

Prylipko et al. (2021) investigate the modeling of regional innovation management, taking into account financial-credit, human resource, and foreign economic factors. Shenkoya (2025) analyzes the role of innovation clusters in fostering sustainable development and demonstrates how their performance depends on the institutional and economic environment.

Tiwari (2026) examines the institutional and legal prerequisites for entrepreneurial growth in emerging markets. Purdenko et al. (2023) explore the financial management of innovative entrepreneurship and highlight the importance of financial mechanisms for implementing innovation initiatives.

Ferilli et al. (2026) analyze the interrelationship between FinTech transformations, corporate strategies, and the performance of financial institutions, demonstrating the growing role of technological factors in corporate governance. Mykhailichenko et al. (2021) examine competitive strategies for business process management in the context of digitalization.

Putera et al. (2022) provide a comprehensive systematization of the scholarly discourse regarding science, technology, and innovation within national innovation systems. Balanovska et al. (2021) substantiate the use of marketing management as a factor in ensuring enterprise competitiveness, which is crucial for shaping the marketing component of startup support.

Researchers such as Palacios-Hernandez et al. (2026) and Voznyuk et al. (2022) demonstrate that the digital environment drives significant transformations in innovative business, compelling enterprises to adapt and evolve.

This diverse landscape of scholarly discourse underscores the high relevance and importance of the issue we have chosen to address, particularly in the context of Ukraine, where startups operate amidst an unstable external environment. Particular relevance to this study is attributed to research on startup financing, marketing resource allocation, corporate cluster governance, and the application of machine learning methods to entrepreneurial development forecasting.

AIMS AND OBJECTIVES

The aim of the article is to develop an adaptive methodological framework for the corporate governance process—utilizing financial and marketing support tools within the startup sector of the trade industry, employing scenario-based and neural network modeling.

To achieve this aim, the study involves:

- identifying the specific features of establishing corporate support for startups within a trade cluster;
- formulating a system of financial, marketing, and market parameters for neural network modeling;
- developing a model to forecast startup scaling potential;
- determining startup sensitivity to changes in financial and marketing support;
- formulating scenarios regarding the impact of corporate resources while substantiating appropriate management decisions for the future development of the startups.

METHODS

The research methodology is based on a combination of neural network modeling, scenario analysis, and corporate management tools. The study adopts a conceptual and methodological approach, with scenario calculations based on hypothetical startup indicators to illustrate the potential application of neural network modeling in assessing financial and marketing support. Further empirical testing will require real-world data, specification of the neural network architecture and training parameters, and evaluation of predictive accuracy using an independent test dataset. Unlike traditional startup valuation based on a set of static financial ratios, the proposed approach focuses on establishing a non-linear relationship between a startup's current state, the intensity of its financial and marketing support, and its projected scalability within a trade cluster. Within the proposed framework, a cluster is considered a network of interconnected startups, trade enterprises, investors, and infrastructure partners sharing resources and common economic interests. Cluster interaction is represented through the intensity of partnership ties and resource exchange, while actual cluster structures and membership criteria require further empirical examination. The object of modeling is defined as a trade-oriented startup operating within a corporate or cluster environment and accessing financial, marketing, informational, and partnership resources:

$$X = (F, M, SG, CR, RR, CG, OM, CI),$$

where F represents investments raised by startups; M represents marketing expenditures; SG represents the dynamics of consumer demand; CR represents the conversion of customer leads into purchases; RR represents the rate of repeat purchases; CG represents changes in the customer base; OM represents the operating margin; and CI represents the speed of interaction among startup participants.

In this context, the speed of startup implementation will be measured on a scale of 0 to 1:

$$Pscale = fNN(X).$$

The hidden layers enable the detection of non-linear interdependencies between resource provision and the market characteristics of startups, while the output layer generates a forecast of their scalability. Model training is based on retrospective observations of startup projects, with the dataset divided into training, validation, and test subsets. A key feature of

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the proposed approach is that the resulting forecast is not viewed as the final outcome of the analysis. For each startup, after determining the baseline value P_{scale}^{0}, alternative scenarios of corporate resource impact are modeled. Four scenarios are envisaged: maintaining the current resource configuration; increasing financial support; enhancing marketing support; and simultaneously increasing both components.

To determine a startup's response to additional resources, the concept of neural network sensitivity to corporate support is introduced. For the financial component, this is defined as:

$$SF = P_{scale}^{F+} - P_{scale}^{0},$$

and for the marketing one:

$$SM = P_{scale}^{M+} - P_{scale}^{0}.$$

Thus, corporate governance is more predictable and effective when a startup's resources are allocated purposefully.

RESULTS

The corporate governance system for startups should not follow a traditional model based on the classic allocation of innovations and investments. It is essential to consider that startups develop amidst harsh external conditions, a reality particularly evident in the retail sector, where consumer preferences shift rapidly. Consequently, any uncontrolled market impulse could lead to a catastrophic outcome for the cluster itself. Therefore, there is a need to establish a logic for evaluating the retail cluster's strategy using neural network modeling.

Table 1. Evaluation of the retail cluster strategy using neural network modeling.

Parameter	Economic substance	Managerial purpose
Financial support	Corporate resources allocated to startup development	Determining funding adequacy
Marketing expenses	Resources for promotion and customer acquisition	Assessing the pace of market development
Sales growth	Commercial performance trends	Identifying market acceleration
Conversion rate	Conversion of marketing activity into purchases	Evaluating the quality of customer acquisition
Repeat purchases	Customer retention after the initial transaction	Determining demand stability
Customer base growth	Expansion of market reach	Assessing growth potential
Operating margin	Financial performance of current operations	Monitoring economic viability
Cluster intensity	Utilization of cluster partnership opportunities	Evaluating startup integration

Let us represent this process as a system of interconnected, synchronous, and phased actions.

Scenario-based neural network modeling

To facilitate the practical application of the model, it is proposed to conduct repeated neural network forecasting following scenario-based adjustments to financial and marketing support parameters. The baseline forecast characterizes the startup's prospects under current conditions, whereas alternative forecasts reflect its potential response to managerial intervention. Scenario testing involves a 10% increase in the respective type of corporate support to assess startup sensitivity to changes in financial and marketing resources. The 10% scenario adjustment was selected to ensure comparability of results under a moderate change in financial and marketing resources. Future research should extend the scenario analysis to alternative adjustment levels (±5%, ±10%, and ±20%) to assess the robustness of the results. This scenario serves not as a universal funding standard, but rather as a standardized experimental intervention required to compare the responses of different startups (Table 2).

Table 2. Corporate support scenarios for startups.

Scenario	Change in funding	Change in marketing support	Managerial appointment
Baseline	0 %	0 %	Determining the initial outlook
Financial	+10 %	0 %	Identifying the reaction to additional capital
Marketing	0 %	+10 %	Identifying the reaction to market activation
Combined	+10 %	+10 %	Assessing the combined resource effect

It is advisable to focus not on the absolute forecast value following a resource increase, but rather on the gap between the baseline and scenario-based forecasts. This gap reflects the startup's latent capacity to respond to corporate support. Notably, financial and marketing sensitivities may differ significantly. If SF > SM, a lack of financial resources can be considered the primary constraint on the project's development. Conversely, if SM > SF, intensifying market activity becomes the priority. If both metrics are low, a mechanical increase in resources is ill-advised and necessitates a prior revision of the startup's business model.

Testing the neural network model

To demonstrate the possibilities of the proposed approach, a model population of startups representing various directions of innovations in trade was formed. The values of the indicators at this stage have a scenario-model nature and are used for approbation of methodological tools, and not for characterizing the actual activity of specific companies. The calculations in the table were performed using the formulas described in the article's methodology. The forecast values for the four hypothetical startups were constructed as illustrative scenario-based estimates reflecting potential differences in responses to financial and marketing support rather than as outputs of an empirically trained neural network. These values demonstrate the calculation logic of sensitivity indicators and facilitate comparisons between alternative managerial scenarios. Four conditional startup projects were used for testing: RetailAI, focused on intelligent personalization of sales; SmartShelf, which develops digital solutions for retail space and inventory management; MarketFlow, aimed at automating the interaction of sellers with digital sales channels; LoyaltyTech, specializing in personalized customer loyalty technologies (Table 3).

Table 3. Results of scenario neural network prediction.

Startup	Baseline forecast	+10% funding	+10% marketing	+10% in finance and marketing
RetailAI	0.68	0.72	0.80	0.85
SmartShelf	0.57	0.71	0.61	0.75
MarketFlow	0.49	0.54	0.56	0.60
LoyaltyTech	0.76	0.79	0.83	0.87

The results demonstrate fundamentally different reactions among the startups to identical resource inputs. For RetailAI, marketing sensitivity is more pronounced: increased marketing support raises the forecast from 0.68 to 0.80, whereas additional funding raises it only to 0.72. Thus, the key constraint for this project in the model scenario is not a lack of capital, but insufficient intensity of market promotion. Conversely, for SmartShelf, financial reinforcement yields the greatest impact, raising the forecast from 0.57 to 0.71. On this basis, the management of financial and marketing support becomes selective. It is advisable to focus RetailAI on marketing intensification and SmartShelf on financial reinforcement; MarketFlow requires a revision of key business model elements prior to further investment, whereas for LoyaltyTech, the priority shifts to the organizational support of scaling and the expansion of its cluster connections. The proposed managerial decisions are illustrative, as they are based on hypothetical scenario indicators and demonstrate the potential for differentiated allocation of corporate resources. Their practical effectiveness requires further verification using empirical data from real startups.

A practical outcome of the proposed approach is the creation of a neural network profile representing a startup's resource response. This profile can be updated regularly as new data on sales, customers, expenses, and corporate support outcomes becomes available. This transforms the neural network model from a one-off analytical tool into a component of the corporate system for managing a startup portfolio.

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Generating scenario-based forecasts does not, in itself, resolve the challenges of corporate management. The increased probability of scaling–resulting from an injection of funds or an expanded marketing budget–must be weighed against the volume of additional resources required to achieve that outcome. An identical projected gain can hold vastly different managerial value depending on whether a startup requires only a modest amount of additional funding or a significant expansion of corporate support. To address this issue, the concept of the marginal resource productivity of corporate support for a startup is proposed:

$$MRPi = \frac{P_i^S - P_i^0(1+g_i^S)}{\frac{\Delta Fi}{F_i^0} + \frac{\Delta Mi}{M_i^0}},$$

where $MRPi$ *is the marginal resource productivity of supporting the i-th startup;* P_i^0 *is the baseline projected scaling probability;* P_i^S *is the projection under the selected scenario;* g_i^s *is the projected sales growth rate under the scenario;* F_i^0 *and* M_i^0 *are the baseline volumes of financial and marketing support; and* ΔFi *and* ΔMi *are their scenario-based increases.*

Unlike simple neural network sensitivity, this indicator characterizes not only the forecast's response but also the productivity of the corporate resource intervention. A high value indicates that a relatively small change in resource allocation is accompanied by a significant improvement in the scaling forecast and commercial dynamics. For example, for SmartShelf, a combined scenario raised the baseline projection from 0.57 to 0.75. If financial and marketing support increase by 10% and the projected sales growth in the scenario is 18%, then:

$$MRPSmartShelf = \frac{(0.75 - 0.57)(1 + 0.18)}{0.10 + 0.10} = 1.062.$$

For MarketFlow, given a similar increase in resources, a forecast of 0.60 versus a baseline of 0.49, and a projected sales growth of 9%:

$$MRPMarketFlow = \frac{(0.60 - 0.49)(1 + 0.09)}{0.10 + 0.10} = 0.600.$$

Thus, even with an identical relative increase in corporate resources, the projected productivity for SmartShelf is nearly 1.8 times higher. This establishes an additional basis for prioritizing resources within the corporate startup portfolio.

The effect of financial-marketing complementarity

Under certain conditions, their combined use can generate an effect that cannot be explained merely by the sum of the two separate impacts. To assess this, a neural network complementarity coefficient for corporate support has been proposed:

$$KNCi = \frac{P_i^{FM} - P_i^0}{P_i^F - P_i^0 + P_i^M - P_i^0},$$

where P_i^{FM} *is the forecast given a simultaneous increase in financial and marketing support;* P_i^F *is the forecast under the financial scenario; and* P_i^M *is the forecast under the marketing scenario.*

If $KNC > 1$, the combined impact exhibits signs of resource synergy. A value close to unity indicates a predominantly additive effect of the resources. If $KNC < 1$, the simultaneous expansion of both types of support yields a lower result than would be expected based on their individual effects. The proposed indicators of marginal resource productivity and financial-marketing complementarity represent relative analytical measures of additional resource effectiveness and the interaction between support components. Their economic interpretation depends on the normalization of input parameters, while the robustness of the resulting estimates requires further assessment across different scales of resource adjustments.

For RetailAI:

$$KNC = \frac{0.85 - 0.68}{(0.72 - 0.68) + (0.80 - 0.68)} = 1.063.$$

Thus, for RetailAI, a positive complementarity between financial and marketing support is observed. In contrast, for SmartShelf:

$$KNC = \frac{0.75 - 0.57}{(0.71 - 0.57) + (0.61 - 0.57)} = 1.000.$$

In this case, the combined scenario is virtually equivalent to the aggregate effect of the two separate resource inputs. This implies that there is no need for SmartShelf to automatically combine both forms of support; corporate management can focus primarily on the financial component, which drives the bulk of the projected growth. This result leads to an important principle for corporate management: financial and marketing support for a startup should not be increased in tandem simply because both have a positive impact on its development. A simultaneous increase in resources is justified primarily when the model reveals complementarity between them.

Corporate priority of startups

Next, we adapt the calculations using the example of a startup operating in the trade sector of the economy:

$$CPi = \frac{P_i^* * MRPi * KNCi * (1 + CIi)}{1 + \delta i},$$

where CPi is corporate governance efficiency; Pi is optimal business scale planning; MRPi is the permissible resource limit; KNCi is the integration index; CIi is the permissible interaction limit; and δi is the permissible network margin of error.

In this case, for the first cluster, the forecast is 0.85, MRP = 0.92, KNC = 1.063, the permissible participant synergy is 0.72, and the margin of error is 0.08. Then:

$$CPRetailAI = \frac{0.85 * 0.92 * 1.063 * (1 + 0.72)}{1 + 0.08} = 1.324.$$

For MarketFlow with P_i^*=0,60, MRP=0,60, KNC=0,917, CI=0,48 та δ=0,13:

$$CPMarketFlow = \frac{0.60 * 0.60 * 0.917 * (1 + 0.48)}{1 + 0.13} = 0.433.$$

The results and evaluation of the forecast, including the detailed validation mechanism, are presented in Table 4.

Table 4. Forecast evaluation and validation of cluster grouping and interaction.

Startup	P_i^*	MRP	KNC	CI	δ	CP	Corporate solution
RetailAI	0.85	0.92	1.063	0.72	0.08	1.324	Combined support with a marketing focus
SmartShelf	0.75	1.062	1.000	0.65	0.07	1.228	Priority financial reinforcement
MarketFlow	0.60	0.60	0.917	0.48	0.13	0.433	Business model refinement
LoyaltyTech	0.87	0.71	0.917	0.81	0.06	0.966	Cluster scaling

To ensure consistent interpretation of the results, Table 4 specifies the projected scaling level (P), marginal resource productivity (MRP), complementarity coefficient (KNC), cluster interaction intensity (CI), permissible error margin (δ), and corporate priority (CP). All indicators are presented in accordance with the proposed calculation framework. A high volume of partnership interactions, unaccompanied by a corresponding resource-driven impact, should not serve as a standalone justification for continued funding.

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Thus, within the proposed approach, neural network modeling serves not merely to mechanically rank startups, but to facilitate digital experimentation with corporate decisions prior to the actual allocation of resources. Management gains the ability to pre-test various financial and marketing impact scenarios, assess the strength of a specific project's response, identify resource interaction effects, and – only then – justify the configuration of support. This enables the concept of a startup's neural-network resource-response profile to be augmented with three characteristics: resource productivity, financial-marketing complementarity, and corporate priority. Together, these form a far more robust foundation for managing cluster-based startup entrepreneurship than the mere one-off forecasting of scaling probability. The primary focus of the corporate decision shifts from the startup itself to its projected capacity to transform a specific configuration of corporate resources into a new quality of entrepreneurial growth.

DISCUSSION

The results of this study expand upon existing concepts in the scientific literature regarding the cluster environment as a space where entrepreneurial, financial, technological, and market opportunities are concentrated. Specifically, Baporikar (2017) links the cluster approach to entrepreneurship development, while Audretsch et al. (2019) emphasize the impact of cluster policy on enterprise performance and the emergence of cross-industry spillover effects.

Our calculations align with the reasoning of Hryshchenko et al. (2023), who detailed changes in entrepreneurial structures. However, our research has deepened the analysis by examining the logic of cluster corporate governance in the context of marketing support, an aspect absents from the aforementioned scholar's work.

Aranchii et al. (2022) proposed a high-level synergy of comprehensive business assessment tools, while Purdenko et al. (2023) investigated innovation management during periods of shock. While we share these authors' views, we emphasize that we approached the issue from the perspectives of proactivity and turbulence, an angle not found in any existing studies. Building on these authors' findings, our study extends existing approaches by incorporating managerial proactivity and external environmental turbulence into the assessment of financial and marketing support for startups.

Our analysis of marketing tools is fully consistent with the work of Balanovska et al. (2021), who demonstrated the relationship between marketing and enterprise competitiveness. Our findings advance the understanding of support mechanisms for startup entrepreneurship in the trade sector, a topic not previously addressed in academic literature.

In our view, Prokopenko et al. (2021) failed to effectively integrate startups and clusters with marketing tools. Our article addresses this gap by successfully incorporating marketing tools into startup business processes.

CONCLUSIONS

The scientific novelty of the study lies in developing a conceptual and methodological framework for corporate management of financial and marketing support for cluster-based startup entrepreneurship, integrating scenario modeling, resource sensitivity assessment, and corporate priority identification. Applying these concepts makes it possible to determine which specific resource – financial, marketing, or a combination thereof can drive the most significant change in a specific startup's projected trajectory.

To deepen the assessment, the study proposes determining the marginal resource productivity of corporate support, the neural network complementarity of financial and marketing impacts, and the startup's projected corporate priority status. This made it possible to distinguish between a startup's overall prospects and the advisability of allocating additional corporate resources to its development. High projected scalability does not necessarily imply a need for increased support, whereas a startup with modest current metrics may demonstrate significantly higher resource productivity.

Scenario-based testing confirmed that startups respond differently to identical changes in resource allocation. For some projects, additional funding is the decisive factor for growth, while for others, it is the intensification of marketing support; conversely, a weak response to both types of resources indicates a need to revise the business model.

The findings are conceptual and methodological in nature, relying on illustrative scenarios rather than empirically validated forecasts of real startup performance. The practical application of the proposed approach requires further testing on a representative sample of enterprises using actual financial and marketing indicators. Using scenario modeling, the study evaluates the necessary avenues for marketing and financial support for startups operating in an unstable environment. It provides a detailed characterization of the concept of "neural network sensitivity to corporate support", a metric used to forecast the financial resources required for a startup's effective development. Finally, the study demonstrates that

investment should be directed not only toward startups with high profitability but also toward emerging enterprises where such investment fosters the long-term growth of specific financial indicators, thereby enabling the creation of operational reserves to safeguard against potential bankruptcy.

Scenario-based options for potential management actions — specifically regarding scaling, adaptive support, and reactive marketing are proposed to ensure the startup's continued effective operation. Processes for improving human resource management, as well as retraining and professional development, could serve as avenues for further research. Overall, future research should also focus on expanding case studies regarding the recruitment of young people with technical backgrounds into trade startups, thereby enhancing digitalization within the trade sector.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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КОРПОРАТИВНИЙ МЕНЕДЖМЕНТ ФІНАНСОВО-МАРКЕТИНГОВОЇ ПІДТРИМКИ КЛАСТЕРНОГО СТАРТАППІДПРИЄМНИЦТВА В ТОРГІВЛІ В ІННОВАЦІЙНІЙ ЕКОНОМІЦІ

У науковому дослідженні конкретизовано теоретико-методичні аспекти адаптивного керування фінансово-маркетинговими інструментами стартапкластерів торгівельних підприємств в умовах розвитку економіки знань та інновацій. З'ясовано, що оптимізація корпоративної підтримки підприємств-початківців не завжди залежить від інвестиційного забезпечення, а переважно визначається вмінням топуправлінця адаптуватися до змін ринкової кон'юнктури через масштабування, динаміку продажів і вдалого розподілу наявних ресурсів. Обґрунтовано необхідність використання нейромережевого моделювання з метою прогнозування доцільного масштабування роздрібних стартапів і формування політики їх подальшої підтримки. Деталізовано сукупність вхідних показників для нейромережевого моделювання, які формують систему економічних, соціальних, фінансових і маркетингових інструментів стартапу. Засобами сценарного моделювання здійснено оцінювання необхідних напрямів для маркетингової та фінансової підтримки стартапів в умовах нестабільного оточення. Деталізовано та надано ґрунтовну характеристику категорії нейромережевої чутливості до корпоративної підтримки, результатом якої є прогнозування необхідної кількості фінансових ресурсів для ефективного розвитку стартапу. Доведено, що найбільше інвестиційне спрямування слід направляти не лише на стартапи, які мають високі показники прибутковості, а й на молоді підприємства, де такі інвестиції забезпечать тривале зростання окремих фінансових показників, необхідних для створення операційних резервів

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підприємства на випадок банкрутства. Запропоновано сценарні варіанти можливих управлінських дій щодо масштабування, адаптивної підтримки, реактивного маркетингу, які необхідні для подальшого ефективного функціонування стартапу. Такі варіанти створюють підґрунтя для адаптивного переходу стартапів від традиційно-сталого розвитку, до реактивного в межах кластерної торговельної мережі.

Ключові слова: адаптивне підприємництво, стартапи, нейромережі, моделювання, корпоративна підтримка, менеджмент, економіка, торгівля, кластери, фінанси, інновації, прибутковість, маркетинг, зовнішнє середовище

JEL Класифікація: L81, M10, G32, O33

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