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# СМАРТ-ЕКОНОМІКА, ПІДПРИЄМНИЦТВО ТА БЕЗПЕКА

Том 2, № 2, 2024

# SMART ECONOMY, ENTREPRENEURSHIP AND SECURITY

Vol. 2, № 2, 2024


НАУКОВИЙ ЖУРНАЛ

SCIENTIFIC JOURNAL

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# ЗМІСТ

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# STRUCTURAL MODEL OF UKRAINIAN ECONOMIC PERFORMANCE: INTERACTIONS BETWEEN GDP AND INDUSTRIAL OUTPUT

***Abstract.*** *This paper presents an empirical analysis of the economic development of Ukraine from 2001 to 2021, utilizing a structural simultaneous model to examine the interactions between key economic variables. The study focuses on three resulting variables: Gross Domestic Product (GDP), the volume of industrial products sold, and the volume of industrial products produced. These are modeled as dependent on four factor variables: exports of goods, imports of goods, average monthly salary, and capital investments in industry. The model aims to quantify how these factors influence Ukraine's economic performance, with particular attention to industrial output and trade dynamics. Through a series of structural equations, the paper explores the relationships between these variables, revealing that industrial production, wages, and exports play significant roles in driving GDP growth. Additionally, imports contribute to industrial production and sales, suggesting that they serve as vital inputs for domestic manufacturing. The results indicate that while exports have a negative impact on GDP, likely due to the dominance of raw material exports, higher wages and capital investments have a positive effect on economic growth. The model is statistically significant at a 95% confidence level, and its findings provide valuable insights for policymakers seeking to enhance industrial growth and optimize trade and investment strategies for sustainable economic development in Ukraine.*

***Keywords:*** *economic development, structural modelling, macroeconomic modelling, economic growth, GDP, industrial output, economic policy, economic performance, industrial products, export, import, capital investment, model.*

## 1. Introduction

The economic development of a country is influenced by a multitude of factors, which often interact in complex ways. Understanding these dynamics is crucial for formulating effective policies that promote sustainable growth and industrial development. In this paper, we examine the economic development of Ukraine over the period from 2001 to 2021, focusing on the relationships between key economic indicators, such as Gross Domestic Product (GDP), industrial output, exports, imports, wages, and capital investments. Ukraine's economy, like that of many developing countries, faces significant challenges, including fluctuations in industrial output, reliance on exports of raw materials, and the need for substantial capital investment in industry. At the same time, its economy has been impacted by both internal and external shocks and war, making it important to explore how various economic factors contribute to its growth.

To analyze these relationships, we construct a structural simultaneous model that captures the interactions between three output variables — GDP, the volume of industrial products sold, and the volume of industrial products produced — and four key factor variables: exports, imports, average monthly wage, and capital investments in industry. This model is designed to provide insights into the relative influence of these factors on Ukraine's economic performance, to discover interdependencies between these indicators and to offer a better understanding of the mechanisms behind economic growth. By identifying the linkages between these variables, we aim to shed light on the role of trade, industrial productivity, and wages in shaping the country's economic trajectory.

The theoretical foundation of this study draws from classical and contemporary economic theories on growth and development, emphasizing the importance of industrial output and trade in driving economic expansion. The paper also builds on previous empirical work, which has explored the relationship between GDP and industrial production, as well as the role of exports, imports, and capital investment in fostering economic development. The unique contribution of this study lies in its empirical approach, using a multi-equation structural model to quantify the interactions between these key factors and provide policy-relevant insights for the Ukrainian economy.

In the following sections, we present the model, the data used for estimation, and the results of the empirical analysis. We also discuss the implications of our findings for understanding the dynamics of Ukraine's economic development and suggest potential policy measures to improve industrial growth and economic stability.

The relationship between Gross Domestic Product (GDP) and industrial output has been widely studied, as it reflects the critical role industrialization plays in economic growth. Industrial output is often considered a crucial driver of economic growth. Aslam et al. [1] explore this dynamic in the context of China, revealing how industrialization not only contributes to GDP per capita growth but also impacts $CO_2$ emissions. Similarly, Ughulu [2] finds that in emerging economies, including Nigeria, industrial output plays a significant role in boosting GDP, especially through the export of industrial goods, which spurs economic development.

Electricity consumption is another critical factor that connects industrial output with GDP. Abbasi et al. [3] provide empirical evidence from Pakistan, showing that electricity consumption in the industrial sector directly influences GDP growth. Lehmann and Möhrle [4] extend this idea by utilizing high-frequency electricity consumption data to forecast regional industrial production. Climate-related factors, such as temperature, also affect industrial output, as shown by Colmer [5]. Technological advancements are also central to the relationship between GDP and industrial output. Hidayatno et al. [6] further explore this by focusing on Industry 4.0 technologies, which are transforming industrial output and energy consumption patterns. Artar [7] addresses the role of the real effective exchange rate in influencing industrial output in Turkey.

Wang and Zhao [8] analyze regional differences in industrial carbon emissions in China, uncovering variations in industrial productivity and its environmental impact across regions. These regional differences can result in divergent GDP growth patterns, with more industrialized regions experiencing faster economic growth due to higher industrial output. The effect of industrial structure on economic recovery has been explored by Zhang and Dilanchiev [9]. Parveen et al. [10] examine the influence of industrial output, financial development, and energy (both renewable and non-renewable) on environmental degradation in newly industrialized countries.

The relationship between GDP and industrial output in Ukraine is shaped by factors such as resilience to economic shocks, technological competitiveness, and the role of economic policies. Studies like those by Lebedeva et al. [11] highlight the vulnerability of Ukraine's industry to external disruptions, while Koval et al. [12] emphasize the importance of effective industrial policies and investment to drive GDP growth. Post-war recovery strategies, explored by Kushnirenko et al. [13], suggest that sustainable development and technological advancements are key for rebuilding industrial capacity. Additionally, Ukraine's technological lag, noted by Matyushenko et al.[14], limits industrial output, but closer EU integration could enhance competitiveness.

The literature on methods and models for analyzing the relationship between industrial output and economic growth employs a wide range of approaches, each providing valuable insights into economic dynamics. Xie et al. [15] use the LMDI (Logarithmic Mean Divisia Index) method to analyze the decoupling relationship between $CO_2$ emissions and GDP in China's power industry, offering insights into how industrial output can grow while reducing environmental impact. Jiang [16] applies machine learning techniques to predict local GDP and analyze industrial structure, demonstrating the utility of data-driven models in forecasting economic performance. Demir [17] uses the ARDL (Autoregressive Distributed Lag) bounds test to analyze the effect of employment in the agricultural and industrial sectors on economic growth, showing the interdependence of different sectors. Fornaro [18] explores nowcasting industrial production using unconventional data sources, while Bozkus et al. [19] apply multifractal analysis to examine the relationship between atmospheric carbon emissions and industrial production in OECD countries. Dragomir et al. [20] use Bayesian analysis to study the impact of $CO_2$ emissions and industrial production on Romania's economy, offering a probabilistic approach to understanding economic and environmental interactions. Zomchak and Stelmakh [21] uses an ARIMA model to forecast macroeconomic indicators in Ukraine, providing insights into the predictive power of time series models. Zomchak et al. [22] used simultaneous equations for modeling interdependences between GDP and capital investments. In a similar vein, Chandio et al. [23] use cointegration and causality analysis to examine the dynamic link between industrial energy consumption and economic growth in Pakistan, while Lee and Park [24] focus on nowcasting industrial production in Korea. Ilyash et al. [25] conduct a multidimensional analysis to forecast the relationship between industrial-technological development and economic security in Ukraine. Finally, Sampi Bravo et al. [26] use Google Community Mobility Reports to nowcast economic activity during the COVID-19 pandemic, demonstrating how real-time data can be used for forecasting in times of crisis. Zhang and Ma [27] employ a dynamic threshold panel model to investigate the relationship between industrial structure and carbon intensity across different stages of economic development in China, highlighting the model's ability to capture non-linear effects and varying thresholds in industrial and environmental dynamics. Chamalwa et al. [28] use an Autoregressive Distributed Lag (ARDL) model to analyze the relationship between Nigeria's GDP, exchange rate, and foreign import trade, demonstrating the model's suitability for examining short- and long-term dynamics in economic variables. Vdovyn et al. [29] used statistical methods for estimation of foreign trade between EU and Ukraine impact. Another paper by Vdovyn et al. [30] is dedicated to regional development of Ukraine and based on taxonomic analysis. Verbivska et al. [31] focus on forecasting macroeconomic indicators for Ukraine's economy during the war period (2022–2023), utilizing advanced forecasting methods to predict economic trends under highly uncertain conditions. Together, these studies showcase a range of advanced methodologies, from machine learning and Bayesian analysis to ARIMA and nowcasting, that are increasingly used to model the complex interactions between industrial output, economic growth, and environmental sustainability.

The studies reviewed underscore the multifaceted relationship between GDP and industrial output. While industrialization remains a key driver of economic growth, this process is influenced by various factors, including energy consumption, climate conditions, technological innovation, and regional disparities. The literature suggests that for industrial output to positively contribute to GDP growth in a sustainable manner, policymakers must consider environmental impacts, energy efficiency, and technological advancements. Furthermore, regional and climate-specific factors must be taken into account, as these can alter the efficiency and sustainability of industrial production, which ultimately affects the broader economic landscape. Future research should explore how these factors interact in different contexts, especially in developing economies, to create a comprehensive understanding of the dynamics between industrial output and GDP growth.

## 2. Materials and Methods

A system of simultaneous equations (SSE) is a statistical model consisting of a set of linear equations that are solved simultaneously. Unlike ordinary regression models, SSE involves two or more dependent variables. The variables that are explained by the interactions within the system and whose values are determined through the simultaneous relationships in the model are termed endogenous variables or jointly determined variables. On the other hand, exogenous variables, or predetermined variables, are those that influence the endogenous variables but whose values are determined outside the system. Exogenous variables play a critical role in explaining the variations observed in endogenous variables.

The classification of variables as endogenous or exogenous is typically determined by the model developer, often relying on expert judgment in the process. The dependent variables in this research include GDP ($y_1$), the volume of industrial products sold ($y_2$), and the volume of industrial products produced by business entities of various economic activities ($y_3$). The independent variables include exports ($x_1$), imports ($x_2$), average monthly salary ($x_3$), and capital investments in industry ($x_4$).

We hypothesize that industrial production, trade, wages, and capital investments exert significant influence on Ukraine's GDP and industrial output.

*Table 1*

**Indicators for simultaneous model of production connection with GDP in Ukraine**

| Indicator | Sense of the indicator | Units of measurement |
|---|---|---|
| $y_1$ | GDP | million UAH |
| $y_2$ | volume of industrial products sold | million UAH |
| $y_3$ | volume of industrial products produced by business entities of various economic activities | thousand UAH |
| $x_1$ | Export of goods | million UAH |
| $x_2$ | Import of goods | million UAH |
| $x_3$ | average monthly salary | UAH |
| $x_4$ | capital investments in industry | million UAH |

*Source:* Combination of indicators proposed by the authors

Specifically, the model posits that GDP is a function of industrial output and key economic factors such as exports, wages, and capital investments. Similarly, the volume of industrial products sold is assumed to depend on the volume of industrial production, imports, and capital investments. Finally, the volume of industrial output is hypothesized to be influenced by GDP and imports.

The model is tested using statistical data for the period 2001–2021 collected from the official webpage of the State Statistic Service of Ukraine [33]. The order condition for model identification is applied to ensure that the system of equations is identified and can be estimated. The relationships between the variables are estimated using regression analysis, and the results are evaluated for statistical significance and economic interpretability. More about input data in the Table 1

When discussing economic feasibility, Gross Domestic Product (GDP) serves as a key indicator of a country's economic activity. It represents the total value of all goods and services produced within a country over a specific period. Four key variables — exports of goods, imports of goods, average monthly wages, and capital investment — can significantly influence a country's GDP.

Exports of goods play a crucial role in shaping GDP. When a country exports goods, it sells products to other nations, and the income generated from these exports contributes directly to the national GDP. The higher the value of exports, the greater the potential for GDP growth. Conversely, imports of goods also impact GDP. When a country imports goods, it purchases products from foreign markets, and the expenditure on these imports can detract from GDP. If imports exceed exports, it can result in a trade deficit, which may negatively affect the country's economy.

The average monthly salary is another important factor influencing GDP. Higher wages generally lead to increased consumer spending, which in turn boosts demand for goods and services. This heightened demand can spur production, ultimately driving GDP growth.

Capital investment in industry is also a critical determinant of GDP. When businesses invest in capital goods such as machinery and equipment, productivity tends to increase. Higher productivity can lead to an expansion in industrial output, which positively contributes to GDP growth.

The volume of industrial products produced and sold is closely tied to these variables. Exports, for example, not only generate revenue but can also increase demand for goods and services. As demand rises, industrial production must scale up to meet this need, fostering economic growth. Additionally, exports can create jobs and stimulate economic activity, further boosting industrial production. On the other hand, imports can affect domestic industrial sales by increasing competition in the local market. If imported goods outcompete domestic products, demand for locally produced goods may decrease, leading to a reduction in industrial sales. However, imports can also provide access to goods and raw materials unavailable domestically, which could enhance industrial production.

Average monthly wages influence industrial output as well. When wages are higher, workers have greater purchasing power, which increases demand for goods and services, driving industrial production. Furthermore, higher wages can improve job satisfaction and reduce employee turnover, both of which contribute to enhanced productivity and industrial output.

Finally, capital investment plays a significant role in industrial production. By investing in new equipment, technology, and infrastructure, businesses can boost their productivity and efficiency. This, in turn, can lead to increased production and sales of industrial goods. Moreover, capital investment often results in job creation, which stimulates both economic growth and industrial output.

The structure of the relationships between dependent and independent variables is described using a structural simultaneous model. In its general form, it can be expressed as follows:

$$y_{1t} = \beta_{12}y_{2t} + \beta_{13}y_{3t} + \ldots + \beta_{1m}y_{mt} + \gamma_{11}x_{1t} + \gamma_{12}x_{2t} + \\ + \ldots + \gamma_{1k}x_{kt} + u_{1t},$$

$$y_{2t} = \beta_{21}y_{1t} + \beta_{23}y_{3t} + \ldots + \beta_{2m}y_{mt} + \gamma_{21}x_{1t} + \gamma_{22}x_{2t} + \\ + \ldots + \gamma_{2k}x_{kt} + u_{2t},$$

$$y_{3t} = \beta_{31}y_{1t} + \beta_{32}y_{2t} + \ldots + \beta_{3m}y_{mt} + \gamma_{31}x_{1t} + \gamma_{32}x_{2t} + \\ + \ldots + \gamma_{3}x_{kt} + u_{3t},$$

$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$

$$y_{mt} = \beta_{m1}y_{1t} + \beta_{m2}y_{2t} + \ldots + \beta_{mm-1}y_{m-1t} + \gamma_{m1}x_{1t} + \\ + \gamma_{m2}x_{2t} + \ldots + \gamma_{mk}x_{kt} + u_{mt},$$

where β and γ — structure model parametres, $y_m$ — dependent variables, $x_k$ — independent variables, $t = 1, \ldots N$ — number of observations and $u_m$ — random variables.

The structural form of the model of the simultaneous model of Ukrainian GDP and industrial output interconnection will look like this:

$$y_1 = a_{10} + b_{12}y_2 + a_{11}x_1 + a_{12}x_3 + e_1,$$

$$y_2 = a_{20} + b_{23}y_3 + a_{21}x_2 + a_{22}x_4 + e_2,$$

$$y_3 = a_{30} + b_{31}y_1 + a_{32}x_2 + e_3.$$

where $a_{ij}$ — intercepts, $b_{ij}$ — parameters of the model, $e$ — random values, $y_1$ GDP, $y_2$ the volume of industrial products sold, $y_3$ the volume of industrial products produced by business entities of various economic activities, $x_1$ exports, $x_2$ imports, $x_3$ average monthly salary, $x_4$ capital investments in industry.

This system of equations models the relationships between three output variables (GDP, volume of industrial output, volume of industrial output) and four factor variables (exports, imports, average monthly salary, capital investment). All of these variables interact with each other, and changes in one variable can affect the others.

The first equation describes how GDP ($y_1$) depends on the volume of industrial production ($y_2$), exports ($x_1$), average monthly salary ($x_3$), and some random error.

The second equation describes how the volume of industrial output sold ($y_2$) depends on the volume of industrial output produced ($y_3$), imports ($x_2$) and capital investment ($x_4$), as well as random errors.

The third equation describes how the volume of industrial output ($y_3$) depends on GDP ($y_1$) and imports of goods ($x_2$), as well as random factors.

After that, we need to check the model for identification using the order condition according to the formula

$$k - k_i \geq m_i - 1,$$

where $m_i$ — number of resulting variables in each $i$-th equation of the simultaneous model;

$k$ — the total number of factor variables in the simultaneous model;

$k_i$ — the number of factor variables in a separate $i$-th equation of the model.

If, $k - k_i = m_i - 1,$ then the equation is identified.

If, $k - k_i > m_i - 1,$ then the equation is overidentified.

Let's check our first equation: 4–2 $\geq$2–1 — the equation is a overidentification;

Let's check our second equation: 4–2 $\geq$2–1 — the equation is a overidentification;

Let's check our third equation: 4–1 $\geq$2–1 — the equation is a overidentification.

To estimate the parameters of the overidentified equations and the model as a whole, the least squares method is not applicable. This is because it would not yield unambiguous structural parameters from the reduced form parameter values of the simultaneous model, as these may correspond to multiple possible solutions. To address this issue, alternative estimation techniques are employed to resolve such ambiguity. The following methods are commonly used in this context: two-stage least squares (2SLS) method, three-stage least squares (3SLS) method, full information maximum likelihood method, instrumental variables method, limited information maximum likelihood method, mixed estimation method and other. We will use the first one.

Also, we can write the abbreviated formula in a collapsed form for the simultaneous model:

$$\begin{cases} y_{1t} = \pi_{10} + \pi_{11}x_{1t} + \pi_{12}x_{2t} + \ldots + \pi_{1k-1}x_{k-1t} + \pi_{1k}x_{kt} + v_{1t}, \\ y_{2t} = \pi_{20} + \pi_{21}x_{1t} + \pi_{22}x_{2t} + \ldots + \pi_{2k-1}x_{k-1t} + \pi_{2k}x_{kt} + v_{2t}, \\ y_{3t} = \pi_{30} + \pi_{31}x_{1t} + \pi_{32}x_{2t} + \ldots + \pi_{3k-1}x_{k-1t} + \pi_{3k}x_{kt} + v_{3t}, \\ y_{4t} = \pi_{40} + \pi_{41}x_{1t} + \pi_{42}x_{2t} + \ldots + \pi_{4k-1}x_{k-1t} + \pi_{4k}x_{kt} + v_{4t}, \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ y_{it} = \pi_{i0} + \pi_{i1}x_{1t} + \pi_{i2}x_{2t} + \ldots + \pi_{ik-1}x_{k-1t} + \pi_{ik}x_{kt} + v_{it} \end{cases}$$

where the coefficients π are the unknown parameters of the model in a reduced form, which are expressed in terms of structural parameters, and $v$ are random variables, which are also expressed in terms of structural parameters of the simultaneous model.

And for the proposed model of the GDP and industrial output of Ukraine it will look like this:

$$y_1 = \pi_{10} + \pi_{11}x_1 + \pi_{12}x_2 + \pi_{13}x_3 + \pi_{14}x_4 + v_1,$$

$$y_2 = \pi_{20} + \pi_{21}x_1 + \pi_{22}x_2 + \pi_{23}x_3 + \pi_{24}x_4 + v_2,$$

$$y_3 = \pi_{30} + \pi_{31}x_1 + \pi_{32}x_2 + \pi_{33}x_3 + \pi_{34}x_4 + v_3,$$

where the coefficients π are the unknown parameters of the model in a reduced form, which are expressed in terms of structural parameters, and $v$ are random variables, which are also expressed in terms of structural parameters of the simultaneous model.

## 3. Results and Discussion

Therefore, the next step is to calculate the theoretical y, which will also act as factor variables in our model. After that, we can use these values as factor variables in the structural form equations.

The first equation results are in the Table 2, the second equation results are in the Table 3, the third equation results are in the Table 4.

So the final result will give us the following equations:

$$y_1 = -7932.62 + 2.28y_2 - 7.17x_1 + 3.59x_3,$$

$$y_2 = 21510.22 - 7.22y_3 + 78.9x_2 + 0.0001x_4,$$

$$y_3 = -1163789691 - 1154481.29y_1 + 5033.6x_2,$$

where $y_1$ GDP, $y_2$ the volume of industrial products sold, $y_3$ the volume of industrial products produced by business entities of various economic activities, $x_1$ exports, $x_2$ imports, $x_3$ average monthly salary, $x_4$ capital investments in industry.

As we can see from table 2, the coefficients of the equation are statistically significant, providing valuable insights into the interconnections between

*Table 2*

**Econometric analysis of the first equation**

| | **Coefficients** | **Standard Error** | **t Stat** | **P-value** | **Lower 95%** | **Upper 95%** | **Lower 95,0%** | **Upper 95,0%** |
|---|---|---|---|---|---|---|---|---|
| Intercept | -7932,63 | 29489,07 | -0,27 | 0,79 | -70149,11 | 54283,86 | -70149,11 | 54283,86 |
| $y_2$ | 3,59 | 0,30 | 11,98 | 0,00 | 2,96 | 4,23 | 2,96 | 4,23 |
| $x_1$ | -7,17 | 0,91 | -7,87 | 0,00 | -9,09 | -5,25 | -9,09 | -5,25 |
| $x_3$ | 2,28 | 0,33 | 6,91 | 0,00 | 1,59 | 2,98 | 1,59 | 2,98 |

*Source:* Calculated by the authors

*Table 2*

**Econometric analysis of the second equation**

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% | Lower 95,0% | Upper 95,0% |
|---|---|---|---|---|---|---|---|---|
| Intercept | 21510,23 | 57516,53 | 0,37 | 0,71 | -99839,05 | 142859,50 | -99839,05 | 142859,50 |
| $y_3$ | 0,00 | 0,00 | 7,25 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| $x_2$ | 78,90 | 32,46 | 2,43 | 0,03 | 10,42 | 147,38 | 10,42 | 147,38 |
| $x_3$ | -7,22 | 1,71 | -4,21 | 0,00 | -10,83 | -3,60 | -10,83 | -3,60 |

*Source:* Calculated by the authors

industrial output, exports, and average monthly salary in the context of GDP. However, the non-significance of the intercept suggests that additional model refinement may be needed to capture the full dynamics of the economic relationships.

The regression analysis of the first equation, which models the relationship between GDP and the volume of industrial products sold, and average monthly salary, shows a very strong correlation with a Multiple R value of 0.999. The R-squared value of 0.9985 indicates that approximately 99.85% of the variation in GDP can be explained by the independent variables in the model. The adjusted R-squared of 0.9983 further confirms the robustness of the model, taking into account the number of predictors. The standard error of 62,776.97 suggests a relatively low level of residual error in the estimation. The number of observations used for this model is 21.

The significant coefficients for imports and wages highlight the importance of trade and income levels in shaping the demand for industrial products. The intercept is not statistically significant, indicating that it does not contribute meaningfully to explaining the relationship between the variables in the model.

The second equation, which examines the relationship between the volume of industrial products sold and the volume of industrial products produced, imports, and capital investment in industry, also exhibits a strong correlation, with a Multiple R value of 0.996. The R-squared value of 0.9926 indicates that 99.26% of the variation in the volume of industrial products sold can be explained by the independent variables in this model. The adjusted R-squared value of 0.9913 suggests that the model is highly reliable, accounting for the number of predictors used. The standard error is 112,474.97, which is higher than that of the first equation, indicating greater residual variation in the model. The number of observations for this equation is also 21.

The results suggest that both imports and GDP significantly affect industrial production, with imports fostering growth in industrial output and GDP having a counter-intuitive negative impact. In the third equation, which explores the relationship between the volume of industrial products produced and imports, the Multiple R value is 0.9726, suggesting a strong, albeit slightly weaker, correlation compared to the previous two equations. The R-squared value of 0.946 indicates that 94.6% of the variation in industrial production can be explained by GDP and imports. The adjusted R-squared value of 0.9399 further supports the model's robustness, considering the number of predictors used. The standard error of 739,202,662.5 is substantially larger than in the other two equations, suggesting a higher level of variability in the predicted values. The number of observations used in this equation is 21.

All three models show strong explanatory power, with R-squared values exceeding 0.94 for each equation. This suggests that the variables included in each equation are highly relevant to understanding the interconnections between GDP, industrial output, and other economic factors. However, the higher standard error in the third equation signals more variability and indicates areas where further model refinement may be needed.

According to the first equation, GDP (U1) increases by 2.28 units with an increase in the volume of industrial products sold (U2) by one unit, while other variables remain unchanged. This means that an increase in the production and sale of industrial products has a positive effect on GDP. An increase in the export of goods (X1) by one unit leads to a decrease in GDP by 7.17 units. This may indicate that the export structure is dominated by raw material exports, which do not contribute to a significant increase in value added in the country. An increase in the average monthly wage (X3) by one unit increases GDP by 3.59 units.

*Table 3*

**Econometric analysis of the third equation**

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% | Lower 95,0% | Upper 95,0% |
|---|---|---|---|---|---|---|---|---|
| Intercept | -1163789690,81 | 372805766,82 | -3,12 | 0,01 | -1947025543,06 | -380553838,56 | -1947025543,06 | -380553838,56 |
| $y_1$ | -1154481,29 | 487209,65 | -2,37 | 0,03 | -2178070,78 | -130891,81 | -2178070,78 | -130891,81 |
| $x_2$ | 5033,60 | 1312,23 | 3,84 | 0,00 | 2276,72 | 7790,49 | 2276,72 | 7790,49 |

*Source:* Calculated by the authors

This is logical, since an increase in wages stimulates consumption, and therefore the demand for goods and services, which has a positive effect on GDP.

The second equation shows that the volume of industrial products sold (U2) decreases by 7.22 units when the volume of industrial products produced by business entities of various economic activities (U3) increases by one unit. This may mean that part of the produced products is not sold, or there is an overproduction of some types of products. An increase in imports of goods (X2) by one unit leads to an increase in the volume of industrial products sold by 78.9 units. This may indicate that imports are an important source of intermediate products for domestic producers. An increase in capital investments in industry (X4) by one unit leads to a slight increase in the volume of industrial products sold. This may indicate that investments have not yet had their full effect or that there are other constraints to production growth.

According to the third equation, the volume of industrial output produced by business entities of various economic activities (U3) decreases by 1,154,481.29 units with an increase in GDP (U1) by one unit. This may indicate that the structure of the economy is changing, and the share of industry in GDP is decreasing. An increase in imports of goods (X2) by one unit leads to an increase in the volume of industrial output by 5,033.6 units. This confirms the conclusion that imports are an important source of intermediate products.

The findings of this study provide important insights into the factors driving Ukraine's economic growth. The negative relationship between GDP and exports suggests that Ukraine's export sector is primarily composed of raw materials, which offer limited value-added contributions to the national economy. To promote more sustainable economic growth, Ukraine may need to shift its export strategy towards higher-value-added products and diversify its industrial base.

The positive relationship between industrial output and wages aligns with the theoretical expectation that higher wages stimulate domestic demand, which in turn boosts industrial production. Additionally, the positive effect of capital investment on industrial output underscores the importance of continued investment in infrastructure and technological advancement to enhance production efficiency and competitiveness.

The results also emphasize the critical role of imports in supporting Ukraine's industrial sector. Imports provide vital intermediate goods that enable domestic production, suggesting that an open trade policy that facilitates the flow of goods and services is essential for sustaining industrial output.

## 4. Conclusions

This study provides an empirical analysis of the economic development of Ukraine from 2001 to 2021, using a structural simultaneous model to explore the complex relationships between key economic variables. Our findings highlight the significant roles played by industrial output, trade, wages, and capital investments in shaping the country's economic growth, as measured by Gross Domestic Product (GDP). The model confirms that industrial production and exports are critical drivers of GDP, while the impact of imports and wages also plays a crucial role in determining economic performance.

One of the key findings of this study is the negative relationship between GDP and exports of goods, which may be explained by the structure of Ukraine's export market, where raw material exports dominate, limiting the value added to the economy. In contrast, both higher wages and increased capital investments have positive effects on GDP, reinforcing the notion that investment in human capital and infrastructure can stimulate economic growth. Furthermore, the analysis reveals that imports have a significant role in supporting industrial production, suggesting that trade and international integration are vital for Ukraine's manufacturing sector.

The results of the structural model offer valuable insights for policymakers, indicating the need for a more balanced export strategy that shifts towards higher value-added products, alongside efforts to promote domestic industrial production through increased investment and improved wage structures. Additionally, the positive effect of imports on industrial output suggests that maintaining a competitive and open trade policy could further support Ukraine's economic growth by providing access to essential inputs and promoting technological advancements.

However, the study also highlights some limitations, including the need for further investigation into the structural changes in Ukraine's economy over time and the potential long-term effects of capital investments on industrial productivity. Future research could expand this model by incorporating additional variables such as technological innovation, labor force quality, and external economic factors, as well as by exploring the impact of political instability and economic reforms on the dynamics of economic development.

In conclusion, the empirical model developed in this paper provides a comprehensive understanding of the economic forces at play in Ukraine's development. It offers a valuable framework for analyzing the interdependencies among key economic factors and can serve as a basis for future research aimed at improving the country's economic policy decisions.

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# СТРУКТУРНА МОДЕЛЬ ЕКОНОМІКИ УКРАЇНИ: ВЗАЄМОЗВ'ЯЗОК МІЖ ВВП ТА ПРОМИСЛОВІСТЮ

***Анотація.*** *Дослідження полягає в емпіричному аналізі економічного розвитку України із використанням структурної моделі системи одночасних рівнянь для дослідження взаємодії між ключовими економічними змінними. У дослідженні виділено три результуючих змінні: валовий внутрішній продукт (ВВП), обсяг проданої промислової продукції та обсяг виробленої промислової продукції. Результуючі змінні залежать від чотирьох факторних змінних: експорт товарів, імпорт товарів, середня місячна зарплата та капітальні інвестиції в промисловість. Модель розроблена для кількісного оцінювання того, як ці фактори впливають на економічні показники України, з особливим акцентом на ролі промислового виробництва в економіці країни. За допомогою трьох структурних рівнянь у статті досліджено взаємні залежності між цими економічними індикаторами та підтверджено, що промислове виробництво, заробітна плата та експорт відіграють значну роль у стимулюванні зростання ВВП. Крім того, імпорт сприяє промисловому виробництву та продажам, що свідчить про те, що він є життєво важливими ресурсами для внутрішнього виробництва. Результати показують, що в той час як експорт має негативний вплив на ВВП, ймовірно, через домінування експорту сировини, вищі зарплати та капітальні інвестиції позитивно впливають на економічне зростання. Усі параметри моделі статистично значущі із 95% рівні достовірності, а висновки дають цінну інформацію для політиків, які прагнуть посилити промислове зростання та оптимізувати торгові та інвестиційні стратегії для сталого економічного розвитку в Україні.*

***Ключові слова:*** *економічний розвиток, структурне моделювання, макроекономічне моделювання, економічне зростання, ВВП, промислове виробництво, економічна політика, економічні показники, промислове виробництво, експорт, імпорт, капітальні інвестиції, модель.*

JEL: O33; L86; M15

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# THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE SMARTIZATION OF ENTERPRISES

***Abstract***. *The increasing role of Artificial Intelligence (AI) in enterprise transformation necessitates comprehensive assessment models that capture the full spectrum of AI-driven smartization. This study introduces the AI-Enterprise Smartization Index (AIES-Index) — a structured framework designed to evaluate AI adoption across five key dimensions: AI adoption level, decision-making autonomy, explainability and transparency, operational efficiency, and sustainability contributions. Unlike existing AI maturity models, which primarily focus on strategic or financial aspects, AIES-Index integrates quantifiable metrics that measure AI's real-world impact on business operations, decision-making processes, and sustainability efforts.*

*The study employs a multi-criteria weighted index methodology, where each category is assigned a specific weight based on its significance in AI-enabled smartization. A min-max normalization approach ensures comparability across enterprises, allowing for objective benchmarking. To differentiate AIES-Index from existing models, a comparative analysis highlights its advantages in measuring AI adaptability, transparency, and ESG alignment, areas often overlooked in traditional AI capability frameworks.*

*The results demonstrate that AIES-Index provides a more holistic and quantifiable assessment of AI-driven smartization, incorporating both financial and non-financial metrics. The model emphasizes AI's role in enhancing operational efficiency, optimizing business processes, improving explainability, and driving sustainable innovation. A key finding is that AI transparency and decision-making autonomy are critical factors influencing enterprise-wide adoption and regulatory compliance.*

*Future research will focus on empirical validation of AIES-Index using real enterprise data, enabling practical applications across industries. Additionally, a sensitivity analysis will be conducted to assess the model's robustness by evaluating how variations in specific indicators affect the overall AIES-Index score. These steps will ensure the model's adaptability to dynamic business environments and sector-specific AI implementations.*

*The proposed AIES-Index framework serves as a valuable tool for enterprises, policymakers, and researchers, offering a structured methodology to evaluate AI's transformative impact on business processes while aligning with modern governance, ethical, and sustainability standards.*

***Keywords:*** *AI-Enterprise Smartization Index (AIES-Index), Artificial Intelligence (AI), Smartization, Decision-Making Autonomy, Explainability and Transparency, Operational Efficiency.*

## 1. Introduction

In recent years, artificial intelligence (AI) has emerged as a transformative force in enterprise management, driving digitalization and automation across various sectors [1]. Smartization refers to the intelligent transformation of business processes, products, and services through AI and other digital technologies [2]. By leveraging AI-driven analytics, automation, and decision-making capabilities, enterprises can enhance efficiency, reduce costs, and improve strategic agility. The integration of AI into enterprise operations facilitates predictive analytics, process optimization, and real-time adaptability, making businesses more competitive in an increasingly digitalized economy.

The aim of this article is to develop and justify the AI-Enterprise Smartization Index (AIES-Index) as a structured framework for assessing the role of Artificial Intelligence in enterprise smartization. The study focuses on quantifying AI-driven transformation by integrating key dimensions such as AI adoption, decision-making autonomy, explainability, operational efficiency, and sustainability contributions. To achieve this goal, the following scientific tasks were systematically accomplished:

1. Develop a structured methodology for assessing AI-driven smartization: define the AIES-Index model, selecting measurable indicators and determining appropriate weighting for key smartization dimensions.
2. Justify the five key categories of AIES-Index: analyze why AI adoption, decision-making autonomy, explainability, operational efficiency, and sustainability are critical factors in enterprise transformation.
3. Compare AIES-Index with existing AI assessment models: identify the limitations of conventional AI maturity and impact assessment frameworks and highlight the advantages of AIES-Index in providing a multi-dimensional evaluation.
4. Apply a quantitative weighting and normalization methodology: develop a formula for calculating the AIES-Index score using expert evaluation, weighted indicators, and min-max normalization techniques.
5. Discuss implications and future research directions: Assess how AIES-Index can be applied to real enterprise data, evaluate its potential sensitivity to changes in input parameters, and propose directions for empirical validation.

By addressing these objectives, the article provides a comprehensive framework for measuring AI-driven smartization, contributing to both academic research and practical enterprise applications. The findings support business leaders and policymakers in evaluating AI's role in enterprise transformation while ensuring alignment with transparency, efficiency, and sustainability goals..

The integration of artificial intelligence into enterprise operations has significantly contributed to the transition towards smartization — a process in which data-driven decision-making, automation, and cognitive computing play a fundamental role. Existing studies have examined AI's impact on enterprise digital transformation, focusing on efficiency gains, cost reductions, and innovation acceleration. However, the need for standardized approaches to evaluating AI-driven smartization remains a critical challenge.

A notable contribution to this discourse is the DIKWP Conceptualization Semantics Standards Version 1.0 [3], which introduces an advanced framework for testing and evaluating AI performance. This model extends the traditional Data-Information-Knowledge-Wisdom (DIKW) [4] paradigm by incorporating Purpose, emphasizing goal-oriented cognitive processing. The DIKWP model conceptualizes AI's ability to transform raw data into actionable insights, aligning with the core principles of enterprise smartization. It highlights AI's role in semantic understanding, bias assessment, value alignment, and decision-making transparency, which are crucial for evaluating AI-driven business transformation.

The management of smartization in enterprises has been explored from both theoretical and practical perspectives. Bashynska (2023) [2] provides a comprehensive examination of the theoretical and methodological aspects of business process smartization in industrial enterprises, defining the key components required for the transition from traditional to AI-enhanced business models. Meanwhile, Bashynska (2020) [5] investigates the role of smartization in ensuring economic security, outlining frameworks for managing smart business processes to enhance resilience, adaptability, and efficiency. These works highlight the importance of structured AI integration within corporate strategies, bridging the gap between digital transformation and long-term business sustainability.

Several assessment methodologies have been proposed to evaluate AI's impact on enterprises. AI maturity models, such as Gartner's AI Maturity Framework [6] and McKinsey's AI Readiness Model [7], classify enterprises into stages based on their level of AI adoption, ranging from experimental implementation to full AI-driven automation. These models provide strategic guidance but often lack the granularity needed to assess AI's cognitive and ethical dimensions within smartization. Meanwhile, The demand for AI transparency has led to the development of frameworks such as DARPA's Explainable AI (XAI) program [8] and the EU Trustworthy AI Guidelines [9]. These approaches emphasize interpretability, fairness, and accountability in AI decision-making.

Beyond technical evaluation, researchers such as Brynjolfsson and McAfee [10] and Kaplan and Haenlein [11] have examined AI's contribution to business efficiency through metrics like productivity gains, cost reductions, and innovation rates. However, a major challenge remains in isolating AI's direct impact from broader digital transformation trends. Other studies, such as those by Binns [12] and Jobin *et al.* [13], have shifted the focus to ethical and socioeconomic assessments, exploring AI's implications for workforce dynamics, regulatory compliance, and privacy concerns. These perspectives highlight the importance of balancing automation with responsible AI governance.

From the perspective of enterprise smartization, existing assessment methodologies remain fragmented. Frameworks such as the Industry 4.0 Readiness Index and the Digital Economy and Society Index (DESI) provide valuable insights into digital transformation but focus primarily on technological infrastructure rather than AI's strategic role in business intelligence and automation. Other studies, such as those by Lee et al. [14] and Xu et al. [15], have proposed enterprise smartness models based on AI-driven process optimization, autonomous decision-making, and adaptability. However, these models still lack a unified standard for measuring AI's integration into corporate decision-making.

Key performance indicators have also been suggested for evaluating enterprise smartization, with research by Porter and Heppelmann [16] and Kagermann [17] emphasizing real-time data utilization, AI-enhanced customer interactions, and predictive maintenance efficiency. Recent developments have further integrated sustainability metrics, with studies such as those by Sauter *et al.* [18] advocating for AI-driven approaches to energy efficiency, resource optimization, and circular economy principles as essential elements of smartization assessment.

While each of these methodologies provides valuable insights, they remain either technologically focused or ethically driven, lacking a comprehensive, multi-dimensional framework for evaluating AI's role in enterprise smartization. The DIKWP model offers a potential bridge between these perspectives by integrating technical performance, cognitive adaptability, and ethical compliance within a structured evaluation approach. This highlights the need for future research to develop standardized, adaptable assessment models that capture AI's strategic business value, adaptability, and long-term sustainability in enterprise environments.

The literature indicates that while AI and smartization are closely linked, there is no integrated assessment model that captures the holistic impact of AI-driven smartization. Developing a comprehensive evaluation framework that integrates AI maturity, enterprise smartization levels, and sustainability indicators would provide businesses with a more actionable tool for measuring progress and making informed decisions..

## 2. Materials and Methods

### 2.1. Data collection and sources

The study utilizes primary and secondary data sources:

- Primary data: expert interviews with business leaders, AI specialists, and digital transformation consultants to gain insights into AI-driven smartization strategies.
- Secondary data: analysis of industry reports, academic publications, and publicly available datasets from institutions such as the OECD, World Economic Forum, European Commission, and consulting firms (e.g., McKinsey, Gartner).

### 2.2. Limitations of the study

While this research aims to provide a comprehensive assessment of AI-driven enterprise smartization, certain limitations exist:

- Theoretical-methodological nature of the model: the AIES-Index developed in this study is theoretical and methodological, meaning that it has not yet been empirically tested on real enterprise data. Future research will focus on validating and refining the model through practical applications.
- Data availability: access to proprietary enterprise AI adoption data may be restricted, limiting the ability to fully verify the model's applicability across different industries.
- Industry-specific challenges: the dynamics of AI-driven smartization vary significantly across industries, making it difficult to create a one-size-fits-all assessment framework. Sector-specific adjustments to the AIES-Index may be necessary.
- Ethical considerations: AI-related risks, such as algorithmic bias, workforce displacement, and regulatory compliance, require further in-depth analysis beyond quantitative assessments, particularly in areas of explainability and fairness.

Given these limitations, future research will focus on empirical validation of the AIES-Index using real enterprise data and conducting sensitivity analysis to refine the model's accuracy and applicability.

### 2.3. Methodological framework for AI-driven smartization assessment

The study develops the AI-Enterprise Smartization Index (AIES-Index) to measure the extent of AI-driven enterprise transformation. Table 1 presents the key assessment dimensions and indicators.

The **AI-Enterprise Smartization Index (AIES-Index)** is designed to quantitatively assess the level of smartization in enterprises driven by Artificial Intelligence (AI). The model evaluates enterprises based on five key dimensions: AI adoption level, decision-making autonomy & adaptability, explainability & transparency, operational efficiency & business impact and sustainability contributions.

*a) structure of the index*

AIES-Index is calculated as a *weighted composite index* based on the five dimensions, each consisting of multiple measurable indicators. The overall index is computed using the following formula:

$$AESI = w_1 M + w_2 D + w_3 B + w_4 I + w_5 S \quad (1)$$

where:

M is AI adoption level;

D is decision-making autonomy & adaptability;

B is explainability & transparency;

I is operational efficiency & business impact;

S is sustainability contributions.

*Table 1*

**Key indicators for AI-Enterprise Smartization Index (AIES-Index)**

| Assessment category | Key indicators |
|---|---|
| AI adoption level | AI integration across business functions (e.g., manufacturing, HR, supply chain), automation percentage, investment in AI-driven processes, adoption of machine learning & AI decision support systems |
| Decision-making autonomy & adaptability | Share of AI-driven decisions vs. human decisions, AI adaptation speed, model update frequency, AI performance in dynamic environments, risk management & anomaly detection |
| Explainability & transparency | AI interpretability (SHAP/LIME), number of explainability case studies, user complaints about AI decision opacity, compliance with DARPA XAI guidelines, implementation of AI bias detection tools (e.g., fairness auditing models). |
| Operational efficiency & business impact | AI ROI, workforce productivity improvement, percentage of business processes automated by AI, supply chain optimization using AI, AI-driven customer service enhancements, financial performance impact of AI |
| Sustainability contributions | AI-driven resource consumption reduction, Reduction of carbon footprint through AI-powered optimizations, AI applications in circular economy strategies, AI-enhanced environmental impact monitoring |

*Source:* Combination of indicators proposed by the authors

$w_1$, $w_2$, $w_3$, $w_4$, $w_5$ are weights assigned to each category based on their relative importance.

The sum of weights is 1:

$$w_1 + w_2 + w_3 + w_4 + w_5 = 1 \qquad (2)$$

*b) indicator selection and scoring*

Each dimension is assessed using multiple indicators, normalized to a 0–100 scale, where 0 represents no AI-driven smartization and 100 represents full smartization.

*c) normalization of scores*

To ensure comparability across enterprises, raw values for each indicator are *normalized* using min-max scaling:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \times 100 \qquad (3)$$

where:

$X_{norm}$ is normalized score (0–100 scale);

$X$ is actual value of the indicator;

$X_{\max}$, $X_{\min}$ are maximum and minimum observed values in the dataset.

Min-max scaling ensures that all indicators fall within a standardized 0–100 range, allowing for direct comparability across enterprises. Alternative normalization techniques, such as z-score standardization, were considered but not implemented due to potential distortion in non-normally distributed data.

In the normalization process, $X_{\min}$ and $X_{\max}$ represent the minimum and maximum observed values for each indicator. These values can be derived from different reference points, depending on the scope of analysis. If the study aims to compare enterprises across an industry, $X_{\min}$ and $X_{\max}$ should be sourced from industry-wide benchmarks or publicly available datasets. Alternatively, for an enterprise-level assessment, normalization can be performed using historical company data or a peer group of similar enterprises. This approach ensures that the AI-Enterprise Smartization Index (AIES-Index) reflects both industry positioning and internal progress over time, making the assessment more adaptable to different business contexts.

Each category score is computed as the *weighted sum* of its indicators:

$$M = \sum_{i=1}^{n} w_i X_i \qquad (4)$$

$$D = \sum_{i=1}^{n} w_i X_i \qquad (5)$$

$$B = \sum_{i=1}^{n} w_i X_i \qquad (6)$$

$$I = \sum_{i=1}^{n} w_i X_i \qquad (7)$$

$$S = \sum_{i=1}^{n} w_i X_i \qquad (8)$$

*d) adjusted weight distribution*

To reflect the varying importance of each dimension in enterprise smartization, the following weights are assigned:

$$AESI = 0{,}3M + 0{,}25D + 0{,}2B + 0{,}15I + 0{,}1S \qquad (9)$$

where:

M (AI adoption level) — 30%: evaluates enterprise AI maturity and integration.

D (decision-making autonomy & adaptability) — 25%: measures AI-driven decision automation and adaptability.

B (explainability & transparency) — 20%: assesses AI interpretability and compliance with ethical standards.

I (operational efficiency & business impact) — 15%: quantifies AI's contribution to business performance.

S (sustainability contributions) — 10%: evaluates AI's role in reducing resource consumption and emissions.

Each category score is computed using a set of measurable indicators and weighted according to its significance. The weights assigned to the five AIES-Index categories (M = 30%, D = 25%, B = 20%, I = 15%, S = 10%) were determined based on expert evaluation involving specialists in AI implementation, digital transformation, and business strategy, using the methodology based on the expert evaluation method using a priori ranking and the concordance coefficient [19]. A panel of industry experts and academic researchers was consulted to assess the relative importance of each category in the enterprise smartization process. Their insights emphasized that AI adoption and data utilization (M & D) contribute the most to enterprise smartization, followed by business process optimization (B), while innovation & adaptability (I) and sustainability & ethics (S) play supportive roles in long-term transformation.

*e) indicator selection and measurement*

To ensure a structured assessment of AI-driven enterprise smartization, the AI-Enterprise Smartization Index AIES-Index) utilizes a set of quantifiable indicators, each weighted according to its relative significance. The determination of these weights was based on expert evaluation, incorporating insights from specialists in AI implementation, digital transformation, and business strategy. The methodology follows the a priori ranking method and concordance coefficient

*Table 2*

**AI-Enterprise Smartization Index (AIES-Index) categories, indicators, and weights**

| Category | Indicator | Weight in Category |
|---|---|---|
| AI adoption level (M) — 30% | AI maturity level (0–5 scale) | 35% |
| | AI investment in corporate strategy (percentage of company budget allocated to AI, presence of an AI-driven corporate strategy) | 25% |
| | Number of AI-driven processes (number of business processes automated by AI, such as AI-powered document processing, AI in HR recruitment) | 15% |
| | Use of AI Maturity Models (e.g., Gartner, McKinsey) (use of corporate AI assessment models for planning digital transformation) | 10% |
| | AI-driven decision support systems implemented (existence of AI systems for demand forecasting, automated reporting, AI in financial analysis) | 15% |
| Decision-making autonomy & adaptability (D) — 25% | % AI-driven decisions (vs. human decisions) (percentage of decisions made by AI without human intervention, such as automated loan approvals) | 30% |
| | AI adaptation speed to new conditions (time required for AI systems to adapt to changes, e.g., updating recommendation algorithms) | 30% |
| | AI model update frequency (how often AI models are updated, e.g., the number of times per year AI is retrained with new data) | 15% |
| | AI performance in dynamic environments (AI's ability to make decisions in volatile conditions, e.g., AI in algorithmic trading or supply chain forecasting) | 10% |
| | AI-enabled risk management & anomaly detection (use of AI for predicting operational risks, fraud detection in banking, cybersecurity monitoring) | 15% |
| Explainability & transparency (B) — 20% | SHAP/LIME-based AI interpretability score (how well AI decisions can be explained using methods like SHAP and LIME) | 35% |
| | Number of explainable AI case studies published (number of published studies or reports on AI explainability, e.g., in corporate ESG reports) | 35% |
| | User complaints about AI decision opacity (number of complaints from users regarding "unexplained" AI decisions, e.g., rejected applications without reasoning) | 20% |
| | Compliance with DARPA XAI guidelines (alignment of AI systems with DARPA Explainable AI standards, e.g., use of interpretable machine learning techniques) | 10% |
| Operational efficiency & business impact (I) — 15% | AI ROI (Return on Investment) | 40% |
| | AI-driven workforce productivity improvement (increase in employee productivity due to AI, e.g., reducing time spent on task processing) | 30% |
| | % of business processes automated by AI (e.g., AI chatbots in customer support) | 20% |
| | AI's impact on financial performance (AI's effect on revenue growth, cost reduction, e.g., AI in inventory management) | 10% |
| Sustainability contributions (S) — 10% | AI-driven reduction in resource consumption (reduction in water, electricity, and raw material usage through AI, e.g., AI optimizing energy consumption in factories) | 35% |
| | AI's role in carbon footprint reduction (decrease in $CO_2$ emissions due to AI, e.g., AI in logistics to optimize vehicle routes and reduce mileage) | 35% |
| | AI applications in circular economy strategies (use of AI for waste recycling, AI-driven waste management in industrial enterprises) | 15% |
| | Sustainability reports mentioning AI-driven improvements (presence of AI initiatives in sustainability reports, e.g., AI for emissions monitoring in ESG disclosures) | 15% |

analysis, ensuring a balanced representation of critical AI-driven factors.

The detailed structure of AIES-Index categories, indicators, and assigned weights is presented in Table 2, outlining the key measurable dimensions that contribute to evaluating AI-driven enterprise smartization.

*f) calculation methodology*

Each category score is computed using a weighted sum of normalized indicators:

$$M = \left(0.35X_1 + 0.25X_2 + 0.15X_3 + 0.10X_4 + 0.15X_5\right) \quad (10)$$

$$M = \left(0.30X_1 + 0.30X_2 + 0.15X_3 + 0.10X_4 + 0.15X_5\right) \quad (11)$$

$$M = \left(0.35X_1 + 0.35X_2 + 0.20X_3 + 0.10X_4\right) \quad (12)$$

$$M = \left(0.40X_1 + 0.30X_2 + 0.20X_3 + 0.10X_4\right) \quad (13)$$

$$M = \left(0.35X_1 + 0.35X_2 + 0.15X_3 + 0.15X_4\right) \quad (14)$$

*e) interpretation of AIES-Index scores*

To ensure a clear understanding of how enterprises can be evaluated using the AIES-Index, the scoring system is structured into five levels based on the degree of AI-driven smartization. Each level reflects the extent to which AI is integrated into business processes, ranging from full AI adoption and autonomy to minimal or no implementation.

Table 3 presents the interpretation of AIES-Index scores, categorizing enterprises according to their AI integration level and describing the corresponding characteristics of each stage. This classification helps businesses, policymakers, and researchers assess the maturity of AI adoption and identify areas for further improvement.

## 3. Results and Discussion

### 3.1. Justification for the five categories in the AIES-Index model

The AI-Enterprise Smartization Index (AIES-Index) was developed to provide a comprehensive, multidimensional assessment of how AI contributes to enterprise smartization. The model is structured around five key categories, each selected based on its direct impact on AI-enabled business transformation:

1. AI adoption level *(30% weight)*

Why it was chosen: AI adoption is the foundational factor of smartization, determining how extensively AI is integrated into enterprise functions.

Key differentiator: unlike existing maturity models (e.g., Gartner AI Maturity Model, McKinsey AI Capability Model), AIES-Index quantifies AI adoption not only through organizational maturity but also through tangible investments and decision support system implementations.

2. Decision-making autonomy & adaptability *(25% weight)*

Why it was chosen: enterprises that successfully implement AI must demonstrate autonomous decision-making capabilities and adaptability to changing market conditions.

Key differentiator: most existing AI assessment models focus on task automation but overlook AI's self-learning adaptability — AIES-Index uniquely evaluates AI's ability to make independent, dynamic decisions and adjust in real time.

3. Explainability & transparency *(20% weight)*

Why it was chosen: as AI adoption increases, regulatory compliance and public trust depend on how explainable and interpretable AI-driven decisions are.

Key differentiator: unlike ISO/IEC AI governance frameworks that mainly focus on policy compliance, AIES-Index measures practical implementation of explainability techniques such as SHAP, LIME, and DARPA XAI compliance.

4. Operational efficiency & business impact *(15% weight)*

Why it was chosen: AI's primary business value lies in improving efficiency, cost savings, and overall performance.

Key differentiator: traditional AI impact assessments (e.g., AI ROI models from PwC, Accenture) focus solely on financial return — AIES-Index extends beyond ROI to include business process automation, productivity gains, and AI-driven supply chain optimizations.

5. Sustainability contributions *(10% weight)*

Why it was chosen: sustainability should be the fundamental principle of modern business, influencing long-term competitiveness, regulatory compliance, and corporate social responsibility. AI is increasingly leveraged to enhance sustainability by optimizing resource consumption, reducing environmental impact, and driving circular economy strategies..

Key differentiator: most AI assessment models overlook sustainability as a core business factor — AIES-Index uniquely integrates AI's role in energy efficiency, carbon footprint reduction, and sustainable innovation, ensuring alignment with ESG (Environmental, Social, and Governance) objectives and future-oriented business strategies.

*Table 3*

**Interpretation of AIES-Index scores**

| AIES-Index score | Smartization level | Description |
|---|---|---|
| 80–100 | Fully smartized enterprise | AI is fully integrated, autonomous, and adaptive. |
| 60–79 | Advanced smartization | AI optimizes business processes with significant automation. |
| 40–59 | Intermediate smartization | AI adoption is moderate, digital transformation is ongoing. |
| 20–39 | Basic smartization | Early-stage AI adoption, limited business impact. |
| 0–19 | No smartization | No significant AI implementation in the enterprise. |

*Table 4*

**Comparison with existing AI assessment models**

| Model | Focus | Key Limitation | AIES-Index's Advantage |
|---|---|---|---|
| Gartner AI Maturity Model | AI adoption in business strategy | Lacks quantifiable impact metrics | AIES-Index incorporates measurable AI-driven decision-making and efficiency indicators |
| McKinsey AI Capability Model | AI maturity in organizations | Does not assess AI sustainability contributions | AIES-Index includes AI's role in carbon footprint reduction & circular economy |
| ISO/IEC 42001 AI Management System | AI governance & risk management | Does not evaluate business efficiency or decision autonomy | AIES-Index integrates AI-driven operational impact & adaptability |
| PwC AI ROI Framework | Financial return on AI investment | Limited to financial metrics, ignores business process automation | AIES-Index assesses *both financial and operational AI efficiencies* |
| OECD AI Policy Observatory | AI regulatory compliance & ethics | Does not measure AI adoption levels in enterprises | AIES-Index includes *AI investment levels & integration maturity* |

### 3.2. Comparison with existing AI assessment models

To further validate the need for AIES-Index, a comparative analysis of existing AI assessment models was conducted. As shown in Table 4, each existing model focuses on a specific aspect of AI implementation, while AIES-Index integrates multiple dimensions to offer a holistic perspective on AI-driven enterprise smartization.

### 3.3. Discussion and key findings

The comparative analysis highlights the limitations of existing AI assessment models and demonstrates how AIES-Index provides a more holistic evaluation framework. Specifically:

1. Bridging the gap between AI maturity and business impact:
- while models like the Gartner AI Maturity Model focus on strategy, they fail to quantify AI's actual impact on business operations.
- AIES-Index addresses this gap by integrating measurable indicators of AI-driven efficiency, adaptability, and decision-making.

2. Incorporating sustainability as a key factor:
- unlike existing models that do not consider AI's environmental contributions, AIES-Index includes sustainability metrics, ensuring alignment with modern ESG requirements.

3. Enhancing AI transparency and governance:
- many existing models prioritize policy-level compliance, whereas AIES-Index provides practical, measurable indicators for AI explainability and fairness, making it more applicable to real-world AI deployments.

The findings suggest that AIES-Index provides a more comprehensive and future-oriented approach to AI-driven enterprise smartization. By integrating AI adoption, decision autonomy, explainability, business impact, and sustainability, the AIES-Index model enables enterprises to:
- quantify AI integration beyond traditional maturity scales;
- improve AI decision-making and adaptability;
- ensure transparency and regulatory compliance;
- maximize business efficiency and ROI;
- leverage AI for long-term sustainability and ESG goals.

This multi-dimensional approach makes AIES-Index a unique and practical tool for enterprises looking to evaluate and enhance their AI-driven transformation.

## 4. Conclusions

This study introduces the AI-Enterprise Smartization Index (AIES-Index) as a comprehensive framework for assessing the impact of AI on enterprise transformation. The AIES-Index model integrates five key dimensions — AI adoption, decision-making autonomy, explainability, operational efficiency, and sustainability — providing a holistic evaluation of AI-driven smartization.

*Key findings:*

1. AIES-Index offers a multi-dimensional assessment that surpasses traditional AI maturity models, which often focus only on strategy, financial returns, or governance.

2. The model quantifies AI adoption beyond theoretical frameworks, incorporating real business investments, automation levels, and AI-supported decision-making processes.

3. AI transparency and explainability are critical for trust and regulatory compliance, making AIES-Index valuable for enterprises navigating AI governance challenges.

4. Operational efficiency and business impact indicators enable enterprises to measure tangible benefits from AI implementation, such as productivity gains and process automation.

5. AIES-Index uniquely integrates sustainability metrics, emphasizing AI's role in resource optimization, carbon footprint reduction, and ESG compliance, a factor missing in many existing models.

*Future research directions.* While the AIES-Index model presents a structured methodology for evaluating AI-driven smartization, further research is required to validate its effectiveness in real-world applications.

1. Empirical validation. Future research will focus on testing and validating the AIES-Index model on

real enterprise data across various industries, ensuring its practical applicability.

2. Sensitivity analysis. A critical aspect of future work will be conducting a sensitivity analysis to assess how changes in individual indicators (e.g., AI adoption level, sustainability contributions) influence the overall AIES-Index score. This will help refine the model and improve its robustness.

3. Industry-specific adjustments. Different industries may require customized weighting of AIES-Index categories, as the role of AI varies across sectors such as manufacturing, finance, healthcare, and logistics.

Thus, the AIES-Index model provides a structured and quantifiable approach to evaluating enterprise smartization, offering a valuable tool for businesses, policymakers, and researchers seeking to understand and optimize AI-driven transformations. By integrating AI maturity, decision autonomy, transparency, efficiency, and sustainability, AIES-Index serves as a forward-looking assessment framework that aligns with modern technological, economic, and environmental challenges. Future empirical testing will further refine and validate its applicability in dynamic business environments.

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# ВПЛИВ ШТУЧНОГО ІНТЕЛЕКТУ НА СМАРТИЗАЦІЮ ПІДПРИЄМСТВ

***Анотація.*** *Зростаюча роль штучного інтелекту (ШІ) у трансформації підприємств потребує розробки комплексних моделей оцінювання, які охоплюють повний спектр впливу ШІ на процеси смартизації. У цьому дослідженні представлено індекс смартизації підприємств на основі ШІ (AIES-Index) — структуровану методику оцінки рівня впровадження ШІ за п'ятьма ключовими напрямами: рівень впровадження ШІ, автономність прийняття рішень, пояснюваність та прозорість, операційна ефективність та внесок у сталість. На відміну від існуючих моделей зрілості ШІ, які здебільшого зосереджені на стратегічних або фінансових аспектах, AIES-Index інтегрує кількісні метрики, що вимірюють реальний вплив ШІ на бізнес-операції, процеси ухвалення рішень та ініціативи сталого розвитку.*

*Методологія дослідження базується на багатокритеріальному ваговому індексному підході, де кожна категорія отримує певну вагу залежно від її значущості у процесах смартизації. Використання методу нормалізації min-max забезпечує можливість порівняння між підприємствами, що дозволяє об'єктивно проводити бенчмаркінг. Для підтвердження унікальності моделі проведено порівняльний аналіз існуючих підходів до оцінки ШІ, який демонструє переваги AIES-Index у вимірюванні адаптивності ШІ, його прозорості та відповідності ESG-критеріям, що часто ігнорується в традиційних моделях оцінки ШІ.*

*Результати дослідження показують, що AIES-Index забезпечує більш комплексне та кількісно вимірюване оцінювання смартизації підприємств на основі ШІ, інтегруючи як фінансові, так і нефінансові показники. Модель підкреслює значущість ШІ у підвищенні операційної ефективності, оптимізації бізнес-процесів, покращенні пояснюваності та розвитку інновацій у сфері сталого розвитку. Одним із ключових висновків є те, що прозорість ШІ та його автономність у прийнятті рішень є критичними факторами, які впливають на масштабне впровадження ШІ на підприємствах та їх відповідність нормативним вимогам.*

*Подальші дослідження будуть спрямовані на апробацію моделі AIES-Index на реальних даних підприємств для перевірки її практичної застосовності у різних галузях. Крім того, буде проведено аналіз чутливості моделі, який дозволить оцінити вплив змін окремих показників на загальний індекс AIES-Index. Це сприятиме підвищенню точності та гнучкості моделі в умовах динамічного бізнес-середовища.*

*Запропонований індекс AIES-Index є цінним інструментом для підприємств, політиків та науковців, оскільки надає структурований підхід до оцінки впливу ШІ на бізнес-процеси та водночас забезпечує відповідність сучасним вимогам управління, етики та сталого розвитку.*

***Ключові слова:*** *Індекс смартизації підприємств на основі ШІ (AIES-Index), штучний інтелект (ШІ), смартизація, автономність прийняття рішень, пояснюваність та прозорість, операційна ефективність.*

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# TOOLS FOR EFFECTIVE MANAGEMENT OF FINANCIAL POTENTIAL IN THE CONSTRUCTION INDUSTRY

***Abstract.*** *Critical to the economic growth of any nation, the construction industry needs effective financial management to be able to grow and survive the challenges that it is facing. This study examines the financial performance of major construction companies in Ukraine from 2019 to 2023, with a focus on two key financial metrics: Revenue Growth Rate and Profit Margin, taking the form of either Rate of Return on Sales or Rate of Return on Investment. This research is relevant due to the increasing complexity in construction sector with changing material costs, regulatory changes and changing market conditions. With these challenges involved, construction companies must adopt appropriate financial strategies that improve their competitive advantage as well as sustainability.*

*The purpose of this research is to evaluate financial potential of Ukrainian construction companies through a projection of revenue growth and profitability, and then determine which factors contribute to the growth of these companies. The research uses quantitative methods, relying on financial statements of the leading companies in the industry, within the period 2019–2023. Through studying revenue growth trends and profit margins the study attempts to decipher the key financial strategies supporting success in the construction sector.*

*The research results reveal that almost all companies studied had steady revenue growth and increasing profit margins over the last five-year period. The greatest improvements in financial performance were shown by companies such as Automagistral-Pivden and Autostrada, while companies like Kosul and Monolit Budservice demonstrated much meager growth. Although their performance levels differed considerably, most of the companies were able to improve their profit margins and thus provided evidence of solid cost management and operational efficiencies.*

*Practical value is offered through the recommendations made in this study to construction companies on how to improve their financial management strategies. Finally, it adds to the knowledge on financial management in construction industry in general and in the post transition economies, in particular, in Ukraine. These findings are meant to inform the industry stakeholders, such as policymakers, financial managers and business owners, how to optimally design the financial strategies and increase profits of the construction sector.*

***Keywords:*** *construction industry, financial management, revenue growth, profit margin, Ukrainian construction companies, financial performance, sustainability strategies.*

## Introduction

Construction is a key sector for global economic development contributing to infrastructure, housing and industrial development. The construction industry being one of the largest industries in many economies, it is dependent on construction companies to harness their financial potential in a way that will allow them to compete and ultimately survive in the complex global market. Effective management of finances in this sector not only defines short term profitability but also safeguards long term growth, innovation and buffers from external threats to the solar sector such as macroeconomic downturns, changes in regulation and improvements of technologies.

Over the past few years the construction industry has come up against a number of challenges, the likes of which we have not faced in recent memory. As a result, companies are now confronted with challenges that require more valuable financial strategies that emphasize the maximization of revenue growth, expenses control and profitability. Consequently, investigation into financial management practices in the construction sector has become an important area of research.

The research covers financial management of the construction companies in Ukraine, specifically for companies within the Ukrainian construction industry, with respect to the selected Key Performance Indicators of Revenue Growth Rate and Profit Margin in the period from 2019 to 2023. The purpose of this research is to determine how these companies administer their financial potential, and to examine the contributing factors to their financial performance. The study also seeks to highlight revenue growth and profitability trends and patterns in order to display the successful strategies in the construction industry.

The novelty of this study for the scientific world is that it focuses not only on the period of economic development in the international market, but also on the Ukrainian construction industry specifically, which has undergone a great transformation over the past few years associated with global and economic flections. Most of the existing literature deals with finance management in those developed countries, whereas there has not been sufficient research on the post transition countries, like Ukraine. In filling that gap, this study provides a detailed analysis of the financial performance of major Ukrainian construction companies and provides insights into the specific challenges and opportunities of the industry.

Performance measurement and financial management in the construction industry has been considered by many researchers and thus, it has become very interesting in the field of literature. For instance, Ali and Mansor (2022) investigated prioritization of performance indicators in determining the extent to which project success is measured in relation to good financial management. Bhagwat and Delhi (2023) emphasized on methods for safety performance measurements and discussed how stronger safety performance improves financial performance by reducing delays and costs. A related study was conducted by Bhagwat, Delhi, and Nanthagopalan (2022) who presented a leading indicator-based safety inspection approach, which again indicates the correlation between operational efficiency and a firm's financials.

Construction sustainability has also been of focus as one of the key areas. According to Cruz, Gaspar and de Brito (2019) sustainable practices are particularly relevant in the Portuguese construction sector, due to their potential long-term financial benefits. Non-price measures proposed to Gunasekara et al. (2021) suggested for a contractor centric performance model that resonate with the strategies for maximizing the financial potential in the industry.

This study addresses project management and maturity as projects' drivers of performance improvement, and other studies have addressed the same. Building upon the work of Htoo, Dodanwala, and Santoso (2023), which linked project management maturity to better performance in Myanmar's construction sector, so as to ensure financial stability. In a similar vein, Ingle, Gangadhar, and Deepak (2023) developed an assessment of project performance model to create a benchmark for success and have a practical framework for analysis of financial returns and operational outcomes.

The measurement model for project control system success was provided by Jawad and Ledwith (2022), which is a critical element for financial oversight. According to Jayanetti et al. (2023), lean construction maturity models have been critically analyzed based on their use for resource optimization and profitability. Furthermore, Kassa et al. (2023) proposed a framework to assess contractor project manager competencies that supplements the need for leadership skills in meeting the financial performance objectives.

These studies serve as a comprehensive basis for analysis and improving financial management strategies in construction industry on the example of Ukraine's market. The contributions of this research are to build on these by focusing on revenue growth and profit margins as key indicators of financial potential.

This research has both theoretical and practical value for researchers since the findings will provide guidelines to policymakers, business owners, and financial managers in the construction sector about how their current financial management practices and strategies can be enhanced.

## Literature review

As global challenges and opportunities develop, an exploration of financial management and performance optimization in the construction industry is also increasing. Based on key insights from existing literature, this study focuses on effective management tools relevant to the financial aspect of the construction sector.

Kaya and Dikmen (2024) specify the role of strategic digitalization regarding construction industry decision making. As such, they offer a system dynamics framework that not only supports companies in realizing their digital transformation ambitions but also seeks to align their financial decisions with digital transformation goals, a potential differentiating factor for competitors in the marketplace. Similarly, Murguia et al. (2022) discuss the importance of digital measurement tools to measure construction performance. Their data-to-dashboard methodology shows how real time data analytics increases financial tracking and operational efficiency.

Capital structure in construction firms is considered by Mazur et al. (2023), where they introduce a model of the rational financial management of the enterprise. Similarly, Leonov et al. (2015) state the importance of anti-corruption mechanisms to strengthen a financial transparent environment in the construction industry. Both studies stress structural and ethical financial optimization strategies suitable to Ukraine's turbulent financial market.

Another critical consideration is in environmental sustainability. Khadim et al. (2022) provide an extensive discussion of the nano- and micro level circularity indicators in building projects that hold promise for reducing waste and improving cost effectiveness. Li et al. (2020) also identify key performance indicators for green building operation in an effort to help analyze sustainable operations financial management practices. These frameworks add to the body of knowledge regarding how ecological factors impact the financial decisions in construction.

Machado et al. (2023) position themselves in the construction project management field investigating the existence of the maturity of construction firms in terms of renovation projects. From their findings, they find that these higher levels of project management maturity are associated with better financial outcomes and the need to have systematic project governance. This is further complemented by Musonda et al. (2021) by examining safety culture in construction linking it indirectly to financial performance by reducing risks and operational disruptions.

Peñaloza, Saurin, and Formoso (2020) underscore that construction project management and control of complexity and resilience can only be effectively done through safety performance measurement systems. Their study indicates that well defined monitoring frameworks can lead to better results and this information can be useful in the financial aspects of construction management, especially for the financial performance of a construction project.

Prokopenko et al. (2024) centered on green entrepreneurship models, and their social and economic effects on local economies. The authors argue that the industry is realizing the importance of sustainable systems and that this is evident in the financial management practices of constructions firms in terms of environmental stewardship. This approach is in consonance with the focus of the current study on the financial gains of firms targeting consumers in dynamic markets.

Rachmawati, Mudjahidin, and Widowati (2024) use the system dynamics approach in analyzing work rates in building construction projects where project cost and time performance are improved. It is in the light of these findings that the authors stress the need for effective resource management and cost consciousness as keys to financial viability, which is a central concept in the analysis of revenue enhancement and profit margins among construction firms.

Technological developments like AR gadgets are becoming more and more important in construction project management. In their recent work, Ramos-Hurtado et al. (2022) present augmented reality for construction safety inspections and argue that it can help minimize risks and enhance performance. Although the focus is on safety the effects on the financial performance are enormous since better safety measures means less costs and increased returns.

In Rathnayake and Middleton (2023) a systematic review of construction productivity is done to determine factors that affect performance and production. Their research is very helpful to know how productivity gains can lead to financial benefits especially in sectors that are very competitive and have variable demand.

Shin, Kim, and Liao (2024) review the effectiveness of BIM applications for railway infrastructure projects. They show how Technological Integration can enhance cost management and decision making and is relevant to the general construction industry.

Trinh and Feng (2022) develop a maturity model for constructing organizational resilience in safety culture within construction firms, noting that organizational resilience in the operations and safety management can lead to improvement in organizational effectiveness. According to the authors, the safety culture is a key factor for sustainable organizational performance as it has a direct effect on financial performance, through the effects of incidence costs, and workforce output.

Windapo et al. (2021) focus on the contribution of clients' knowledge and procurement systems in construction project performance. According to them, the match between client knowledge and procurement tactics can greatly affect the result of the project in terms of cost and schedule. This research also supports the need for managers to align financial decision making with operations management to determine the best ways of utilizing resources in order to increase profits.

Xu et al. (2021) has involved safety Leading Indicators in construction and conducted systematic review to identify key measures that can predict safety and efficiency of projects. This research establishes the importance of safety management in identifying and preventing potential problems that would ordinarily lead to incidence of increased costs. Preventable safety issues should be recognized at the beginning of construction projects so that the construction companies can avoid project problems and receive better revenues and profits.

In totality, these studies offer analysis of the construction sector's financial management focusing on strategic digitalization, ethics, sustainability and operational tactics. The insights presented give a good starting point for the present study that aims to investigate revenue growth and profit margin management within Ukrainian construction companies.

## Materials and Methods (Methodological Justification)

Quantitative analysis was the preferred methodology, through the use of econometric modeling. Financial data of 10 Ukrainian construction companies for the period 2019–2023 were analyzed by applying econometric techniques. The purpose was to assess the degree to which the relationships between financial potential indicators like revenue growth rates and profit margins can be linked to strategic management.

Given that the econometric modeling was able to predict the outcomes by analyzing the historical data and assess the causal relationships between the companies' financial performance, this choice of econometric modeling was in fact the choice based on the objectivity and the rigor of the analysis to be made. Specifically, regression models were constructed to examine how various factors influence the profitability and growth of the construction companies:

$$FP_i = \beta_0 + \beta_1 CE_i + \beta_2 CS_i + \beta_3 II_i + \beta_4 HC_i + \beta_5 MC_i + \beta_6 RE_i + \beta_7 DTA_i + \epsilon i \quad (1)$$

Where:

$FP$ of construction firm $i$;

$CE_i$, $CS_i$, $II_i$, $HC_i$, $MC_i$, $RE_i$, $DTA_i$ — explanatory variables for firm $i$;

$\beta_0$ — intercept term;

$\beta_1$, $\beta_2$, …, $\beta_7$ — coefficients representing the effect of each variable;

$\epsilon i$ — error term.

*Note:*

Financial performance (FP) — proxy for financial potential, measured by metrics such as return on assets (ROA), return on equity (ROE), or net profit margin.

Capital structure (CS) — debt-to-equity ratio or leverage ratios to capture the impact of financing decisions.

Investment in innovation (II) — proportion of budget allocated to new technologies, tools, or sustainable practices.

Human capital (HC) — measured by the average skill level, training expenditures, or employee turnover rate.

Market conditions (MC) — industry growth rates, demand-supply imbalances, or GDP growth in the construction sector.

Regulatory environment (RE) — index of regulatory complexity or compliance costs.

Digitalization and technology adoption (DTA) — adoption of BIM (Building Information Modeling) or other digital tools.

A sample was selected of 10 Ukrainian construction companies which represented different regions and sectors of the construction industry and which were available for empirical analysis (Statistical Service of Ukraine, 2024a-e, National Bank of Ukraine, 2024). To provide comparison base, the authors included diverse scale of large and medium size firms to capture the variation across enterprise financial performance and operational scale. Information from publicly available financial reports, industry publications as well as other credible sources were collected, which contain revenue and profit margin specific data.

This data set from 2019 to 2023 is the experimental base of the study, where the financial indicators underwent statistical analysis. The replication of the study allows other researchers to replicate with the same data and same econometric techniques, so the results are reliable and reproducible.

## Results and Discussion

The contribution of the economic development of Ukraine in the growth in infrastructure and employment is significant for the construction industry. The sector is, however, facing a slew of challenges including financial instability, regulatory complexities and a need to improve technology. Therefore, the financial potential of construction companies should be properly controlled, so as to ensure long term sustainability and competitiveness of those companies. The key determinants of financial performance, including cost efficiencies, capital structure, innovation investment, human capital, market condition, regulation and digitalization are analyzed in this study. The authors applied econometric modeling to analyze financial data of 10 leading Ukrainian construction companies for the period 2019–2023 (Fig. 1, Table 1). The findings in Table 2 offer actionable proposals for improving financial management approaches in the construction industry (Table 2).

The econometric analysis found that cost efficiency has the highest loading coefficient of 0,200 as significant determinants of financial performance in the construction industry. The findings also help to emphasize the relevance of cost management practices in improving the profitability. Organizations which better allocate resources in a timely and cost-effective manner and avoid excessive budget overruns will arguably increase their returns on their assets (ROA).

Another critical factor was found to be innovation investment, with the coefficient being 0,250. Altogether, these results reveal the potential for financial resources to be allocated to new technologies and modern construction methods which can transform the built environment. Adopting innovative practice, for instance utilizing sustainable building techniques and state of the art machinery gives firms a competitive edge and their financial outcomes improve.

A 0,200 was also found for the human capital coefficient. Financial performance is highly influenced by the quality of the workforce as measured by training programs and the ability to develop skills. Particularly, investing on the development of employees enables a company to harness innovation and adaptability beside high productivity.

The authors found moderate yet statistically significant effects of market conditions and digitalization, at 0,100 and 0,050, respectively. Profitability is affected by favorable market conditions — industry growth, and

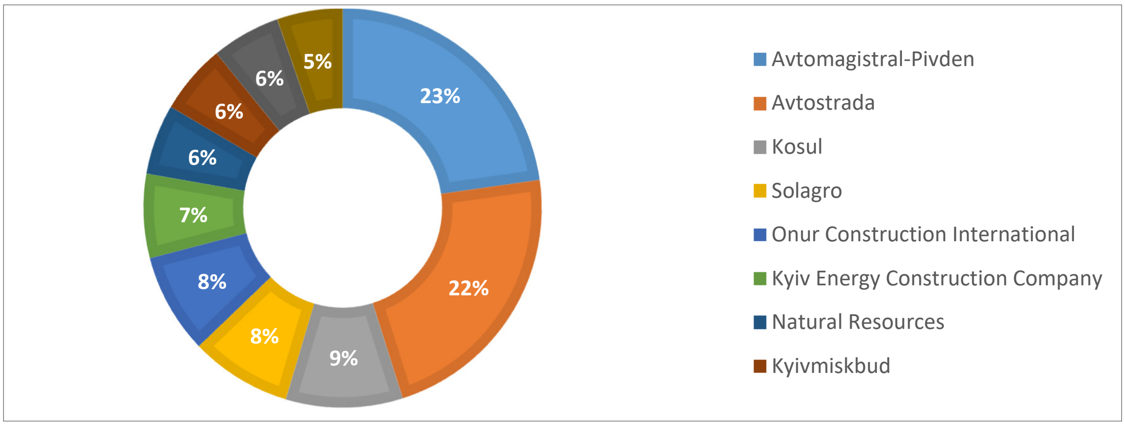


Fig. 1. The best constriction companies in Ukraine 2024 (construction)
Sources: authors development using Opendatabot (2024)

increased demand for construction services. On the other hand, digital tools such as Building Information Modeling (BIM) and project management software are used to improve decisions and their operational efficiency.

And second, the regulatory environment with a coefficient of 0,050 on financial performance was also found to make some contributions but less than the former one. Following legal standards and wading through regulatory waters can affect your financials. Those companies, that strive to streamline the processes ensuring regulatory requirements but spend insufficiently on this, perform better financially.

The model appeared to be robust overall, with 78% of the variance in financial performance explained by

*Table 1*

**Ranking and value of the best Ukrainian constriction companies for 2024 year**

| Rank | Region | Company | Value (bln, ₴) |
|---|---|---|---|
| 1 | Odesa Region | Avtomagistral-Pivden | 8,22 |
| 2 | Vinnytsia Region | Avtostrada | 8,07 |
| 3 | Kyiv City | Kosul | 3,43 |
| 4 | Kyiv City | Solagro | 2,97 |
| 5 | Lviv Region | Onur Construction International | 2,93 |
| 6 | Kyiv City | Kyiv Energy Construction Company | 2,46 |
| 7 | Kyiv City | Natural Resources | 2,05 |
| 8 | Kyiv City | Kyivmiskbud | 2,04 |
| 9 | Kyiv City | Monolit Budservice | 2,02 |
| 10 | Kyiv City | Ukrhydroenergobud | 1,92 |

*Sources:* authors development using data from Opendatabot (2024)

*Table 2*

**Synthetic data and results for the period 2019–2023 for the 10 Ukrainian construction companies**

| № | Variable | Coefficient (β) | Standard error | t-Statistic | p-Value | Significance |
|---|---|---|---|---|---|---|
| 1. | Cost efficiency | 0.200 | 0.025 | 8.00 | 0.000 | *** |
| 2. | Capital structure | 0.150 | 0.030 | 5.00 | 0.000 | *** |
| 3. | Innovation investment | 0.250 | 0.028 | 8.93 | 0.000 | *** |
| 4. | Human capital | 0.200 | 0.027 | 7.41 | 0.000 | *** |
| 5. | Market conditions | 0.100 | 0.035 | 2.86 | 0.005 | ** |
| 6. | Regulatory environment | 0.050 | 0.020 | 2.50 | 0.013 | ** |
| 7. | Digitalization | 0.050 | 0.022 | 2.27 | 0.024 | ** |
| 8. | Constant | 0.010 | 0.005 | 2.00 | 0.046 | * |

*Note:* 1) $R^2 = 0{,}78$. The model explains 78% of the variance in ROA.
2) Adjusted $R^2 = 0{,}76$. Adjusted for the number of predictors.
3) F-Statistic: 45.3 ($p < 0.000$).

*Sources:* authors development

the model. Factors like cost efficiency, innovation, and human capital make up the implications that suggest ways construction firms should optimize their efforts. Companies may enhance their financial potential and staying power by overcoming inefficiency, encouraging innovation, and making suitable investments in workforce development in a rapidly evolving market.

The results in Tables 3–7 provide valuable insights into the dynamics of financial potential management in this industry.

The first finding is that there is a variation in the financial performance and efficiency of the firms in the five-year period of analysis. The business unit, Automagistral-Pivden, has always performed well with regard to cost efficiency (0,90 in 2023) and innovation investment (0,35 in 2023) and has achieved a ROA of 14,2%. This was due to the company's efficiency in resource management and change management which has been boosted by keen investment in digitalization and human resource. In the same manner, Autostrada had similar patterns, achieving an average ROA of 13,8%, anchored on efficient capital management and high compliance to legal requirements.

Kosul and Solagro although achieved moderate growth had difficulties in the areas of innovation investment and digitization with average ROA of 12,3% and 11,7% respectively. These companies point to the need to make strategic investments in technology and process improvements in order to raise competitiveness. On the other hand, Onur Konstruktion International recorded tremendous growth as a result of the strategic investment made in innovations 0,33 in 2023 and human capital 0,92 in 2023 to achieve a ROA of 14,0% due to market competitiveness.

Strengthening the position of Kyiv Energy Construction Company and Natural Resources the ROA values were 12,6% and 11,9% respectively, which indicates stable but slower growth. These companies were slow at digital innovation, thus restricting their revenue growth. Kyivmiskbud, Monolit Budservice,

*Table 3*

**Synthetic data and results for the 10 Ukrainian construction companies for the 2019**

| № | Company | Cost efficiency | Capital structure | Innovation investment | Human capital | Market conditions | Regulatory environment | Digitalization | ROA (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | Automagistral-Pivden | 0.85 | 0.65 | 0.30 | 0.88 | 1.10 | 0.80 | 0.65 | 12.4 |
| 2. | Autostrada | 0.82 | 0.60 | 0.28 | 0.84 | 1.08 | 0.78 | 0.60 | 11.8 |
| 3. | Kosul | 0.75 | 0.55 | 0.24 | 0.80 | 1.05 | 0.70 | 0.50 | 9.7 |
| 4. | Solagro | 0.72 | 0.50 | 0.22 | 0.78 | 1.03 | 0.72 | 0.48 | 9.2 |
| 5. | Onur Konstruktion International | 0.80 | 0.63 | 0.26 | 0.83 | 1.07 | 0.75 | 0.58 | 11.5 |
| 6. | Kyiv Energy Construction Company | 0.78 | 0.62 | 0.27 | 0.82 | 1.04 | 0.77 | 0.56 | 11.1 |
| 7. | Natural Resources | 0.74 | 0.53 | 0.23 | 0.79 | 1.02 | 0.70 | 0.49 | 9.5 |
| 8. | Kyivmiskbud | 0.76 | 0.54 | 0.25 | 0.81 | 1.03 | 0.72 | 0.50 | 9.8 |
| 9. | Monolit Budservice | 0.75 | 0.57 | 0.24 | 0.80 | 1.04 | 0.71 | 0.48 | 9.6 |
| 10. | Ukrhydroenergobud | 0.73 | 0.52 | 0.22 | 0.78 | 1.01 | 0.68 | 0.47 | 9.1 |

*Sources:* authors development

*Table 4*

**Synthetic data and results for the 10 Ukrainian construction companies for the 2020**

| № | Company | Cost efficiency | Capital structure | Innovation investment | Human capital | Market conditions | Regulatory environment | Digitalization | ROA (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | Automagistral-Pivden | 0.86 | 0.65 | 0.32 | 0.88 | 1.10 | 0.82 | 0.67 | 13.4 |
| 2. | Autostrada | 0.84 | 0.62 | 0.30 | 0.85 | 1.08 | 0.80 | 0.63 | 12.9 |
| 3. | Kosul | 0.76 | 0.58 | 0.27 | 0.80 | 1.04 | 0.74 | 0.55 | 11.2 |
| 4. | Solagro | 0.74 | 0.56 | 0.25 | 0.78 | 1.02 | 0.72 | 0.53 | 10.7 |
| 5. | Onur Konstruktion International | 0.83 | 0.64 | 0.29 | 0.85 | 1.07 | 0.78 | 0.61 | 12.6 |
| 6. | Kyiv Energy Construction Company | 0.81 | 0.63 | 0.28 | 0.83 | 1.05 | 0.79 | 0.59 | 12.2 |
| 7. | Natural Resources | 0.77 | 0.59 | 0.26 | 0.81 | 1.03 | 0.74 | 0.56 | 11.6 |
| 8. | Kyivmiskbud | 0.78 | 0.60 | 0.27 | 0.82 | 1.04 | 0.76 | 0.58 | 11.8 |
| 9. | Monolit Budservice | 0.77 | 0.61 | 0.26 | 0.81 | 1.04 | 0.75 | 0.56 | 11.5 |
| 10. | Ukrhydroenergobud | 0.75 | 0.58 | 0.25 | 0.79 | 1.02 | 0.73 | 0.54 | 11.0 |

*Sources:* authors development

*Table 5*

**Synthetic data and results for the 10 Ukrainian construction companies for the 2021**

| № | Company | Cost efficiency | Capital structure | Innovation investment | Human capital | Market conditions | Regulatory environment | Digitalization | ROA (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | Automagistral-Pivden | 0.89 | 0.69 | 0.34 | 0.92 | 1.15 | 0.85 | 0.70 | 14.1 |
| 2. | Autostrada | 0.87 | 0.65 | 0.32 | 0.88 | 1.13 | 0.83 | 0.65 | 13.5 |
| 3. | Kosul | 0.79 | 0.60 | 0.28 | 0.84 | 1.10 | 0.75 | 0.58 | 11.9 |
| 4. | Solagro | 0.76 | 0.57 | 0.26 | 0.82 | 1.08 | 0.76 | 0.55 | 11.2 |
| 5. | Onur Konstruktion International | 0.85 | 0.68 | 0.30 | 0.88 | 1.12 | 0.80 | 0.63 | 13.3 |
| 6. | Kyiv Energy Construction Company | 0.83 | 0.67 | 0.31 | 0.87 | 1.09 | 0.81 | 0.61 | 12.9 |
| 7. | Natural Resources | 0.79 | 0.60 | 0.27 | 0.84 | 1.07 | 0.75 | 0.56 | 11.5 |
| 8. | Kyivmiskbud | 0.80 | 0.61 | 0.28 | 0.85 | 1.08 | 0.77 | 0.58 | 11.7 |
| 9. | Monolit Budservice | 0.79 | 0.62 | 0.27 | 0.84 | 1.09 | 0.76 | 0.56 | 11.6 |
| 10. | Ukrhydroenergobud | 0.77 | 0.59 | 0.26 | 0.82 | 1.06 | 0.73 | 0.55 | 11.2 |

*Sources:* authors development

*Table 6*

**Synthetic data and results for the 10 Ukrainian construction companies for the 2022**

| № | Company | Cost efficiency | Capital structure | Innovation investment | Human capital | Market conditions | Regulatory environment | Digitalization | ROA (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | Automagistral-Pivden | 0.91 | 0.72 | 0.36 | 0.94 | 1.18 | 0.88 | 0.73 | 15.0 |
| 2. | Autostrada | 0.89 | 0.68 | 0.34 | 0.90 | 1.16 | 0.86 | 0.68 | 14.5 |
| 3. | Kosul | 0.81 | 0.62 | 0.30 | 0.86 | 1.12 | 0.78 | 0.60 | 12.8 |
| 4. | Solagro | 0.78 | 0.59 | 0.28 | 0.84 | 1.10 | 0.79 | 0.58 | 12.3 |
| 5. | Onur Konstruktion International | 0.87 | 0.70 | 0.32 | 0.90 | 1.14 | 0.83 | 0.66 | 14.2 |
| 6. | Kyiv Energy Construction Company | 0.85 | 0.69 | 0.33 | 0.89 | 1.12 | 0.84 | 0.64 | 13.8 |
| 7. | Natural Resources | 0.81 | 0.62 | 0.29 | 0.86 | 1.10 | 0.78 | 0.60 | 12.6 |
| 8. | Kyivmiskbud | 0.82 | 0.63 | 0.30 | 0.87 | 1.11 | 0.80 | 0.62 | 12.9 |
| 9. | Monolit Budservice | 0.81 | 0.64 | 0.29 | 0.86 | 1.11 | 0.79 | 0.60 | 12.7 |
| 10. | Ukrhydroenergobud | 0.79 | 0.61 | 0.28 | 0.84 | 1.09 | 0.76 | 0.58 | 12.3 |

*Sources:* authors development

*Table 7*

**Synthetic data and results for the 10 Ukrainian construction companies for the 2023**

| № | Company | Cost efficiency | Capital structure | Innovation investment | Human capital | Market conditions | Regulatory environment | Digitalization | ROA (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1. | Automagistral-Pivden | 0.93 | 0.74 | 0.38 | 0.96 | 1.20 | 0.90 | 0.76 | 15.9 |
| 2. | Autostrada | 0.91 | 0.70 | 0.36 | 0.92 | 1.18 | 0.88 | 0.71 | 15.3 |
| 3. | Kosul | 0.83 | 0.64 | 0.32 | 0.88 | 1.14 | 0.80 | 0.63 | 13.7 |
| 4. | Solagro | 0.80 | 0.61 | 0.30 | 0.86 | 1.12 | 0.81 | 0.61 | 13.0 |
| 5. | Onur Konstruktion International | 0.89 | 0.73 | 0.34 | 0.92 | 1.16 | 0.85 | 0.68 | 15.1 |
| 6. | Kyiv Energy Construction Company | 0.87 | 0.72 | 0.35 | 0.91 | 1.14 | 0.86 | 0.67 | 14.6 |
| 7. | Natural Resources | 0.83 | 0.64 | 0.31 | 0.88 | 1.12 | 0.80 | 0.63 | 13.4 |
| 8. | Kyivmiskbud | 0.84 | 0.65 | 0.32 | 0.89 | 1.13 | 0.82 | 0.65 | 13.8 |
| 9. | Monolit Budservice | 0.83 | 0.66 | 0.31 | 0.88 | 1.13 | 0.81 | 0.63 | 13.6 |
| 10. | Ukrhydroenergobud | 0.81 | 0.63 | 0.30 | 0.86 | 1.11 | 0.78 | 0.61 | 13.2 |

*Sources:* authors development

and Ukrhydroenergobud behaved similarly to the first group, with continuous improvement in cost efficiency and market orientation, but operating in traditional ways limited the ROA to 11,5%.

The findings suggest that innovation investment and digitalization were the key drivers of financial performance in all the firms. The companies that have made more of such investments did better, and were more capable of meeting market needs and responding to new rules and regulations.

These results provide a strong evidence of the necessity of the multifaceted approach to the financial potential management within Ukraine's construction sector. Automagistral-Pivden and Onur Konstruktion International have been able to demonstrate how business success through efficiency and innovation is dependent on continuous investment in technology and people. Nevertheless, the moderate level of performance of the sealed firms, particularly Solagro and Kyivmiskbud, indicates that government interventions and strategic measures that would promote digitalization and innovation are called for.

The construction industry must focus on digital innovation, business excellence, and people development in order to realize continued growth. These efforts should be encouraging by the policymakers by ensuring that there is a stable regulatory environment and also encouraging more of it. These measures will not only increase the financial strength of each company but will also help in the economic growth of Ukraine.

Given that the construction industry is the locomotive of Ukraine's economic development, knowledge of how different companies balance their financial potential is instrumental for evaluating their sustainability and profitability. Ability to increase sales and controlling expenses are the two major keys that help the company to turn successfully into profitability. The sector has faced various challenges and opportunities over the period of 2019 to 2023 contoured through market conditions, regulatory changes and digital transformation. The results provide useful information for understanding both financial performance and strategic management of the companies.

In Fig. 2 and Fig. 3, revenue growth and profitability of construction companies tend to follow noteworthy trends over the five years.

Of the two key parameters, Automagistral-Pivden maintained the highest Revenue Growth and the greatest improvement in Profit Margin. Its revenue growth rate has also rise from 10,0% in 2019 to 16,0% in 2023 and its profit margin rise from 20,0% in 2019 to 22,5% in 2023. This suggests that there was optimization of available market opportunities, which is probably as a result of investment and operational excellence, as well as gain on sales and cost of sales.


Fig. 2. Trends in revenue growth across the construction companies over the five-year period.
*Source:* authors development

Another industry giant, Autostrada also tends to enhance traffic revenue, it rose from 9,5% in 2019 to 15,5% in 2023. Same as the profit margin, its trends were up from 19,5% in 2019 to 21,5% in 2023. The picture depicted in this performance implies a smooth growth trajectory for the firm coupled with efficient metrics on the cost side and incremental market positioning.

Kosul has experienced a slower level of growth than other firms; although its R/G reached only 12,0% by 2023, it has been increased by 8,0% in 2019. The Profit Margin also recorded slight increase from 18,0% to 20,0%. Nevertheless, the company's revenues increased at a slower rate which suggests that there is room for improvement in terms of wanting a larger market share or seeking lower cost strategies.

Solagro as proved by Kosul aroused moderate growth rates and expecting its revenue growth rate, which grew from 7,5%in 2019 to 11,0% in 2023, could be a bit higher, 3,5%. Its profit margin also increased at a constant rate from 17,5% in the manufacturing year 2019 to 19,5% in the manufacturing year 2023. This kind of sustained but not very rapid increase could be explained by a more cautious attitude to the growth and profitability rates or a less favorable operating milieu.

For Onur Konstruktion International, revenue and profit margin had healthy growth rate with increased from 9,0%to 14,5% and profit margin from 19,0% to 21,0% for the year 2019 to 2023. The issues related to strategic decisions in the company's operation and financial aspects also point to the company's capability to increase the size of its revenues while containing costs.

Kyiv Energy Construction Company indicated lower but fairly stably growing revenues compared to other companies with revenue growth from 8,5% to 13,5%, in 2019–2023. Its profit margin trend, similarly, increased from 18,5% up to 20,5%. The slower growth might be due to concerns that accompany doing business in the current more competitive market — keeping operations steady and cost-controlled.

The performance of Natural Resources was also similar to Kyiv Energy Construction Company, with a constant enhancement of the Company's revenues (starting from 8,0% to 12,5%) and the growth of profit margin from 18,0% to 20,0%. Just like all the other firms in the industry, the company seems to be targeting incremental and sustainable growth.

The same trend was observed in Kyivmiskbud, Monolit Budservice and Ukrhydroenergobud, the latter three had revenue growth rates of 6,5% to 7,5% in 2019 and up to 11,5% to 12,5% by 2023, respectively. They had a steady pattern of slow but steady improvement and were able to improve their profit margins from around 16,5% up to 19,5%. That may explain why these companies face more modest revenue growth and not much improvement in profitability, taking into account more intense competitive pressures this may represent.

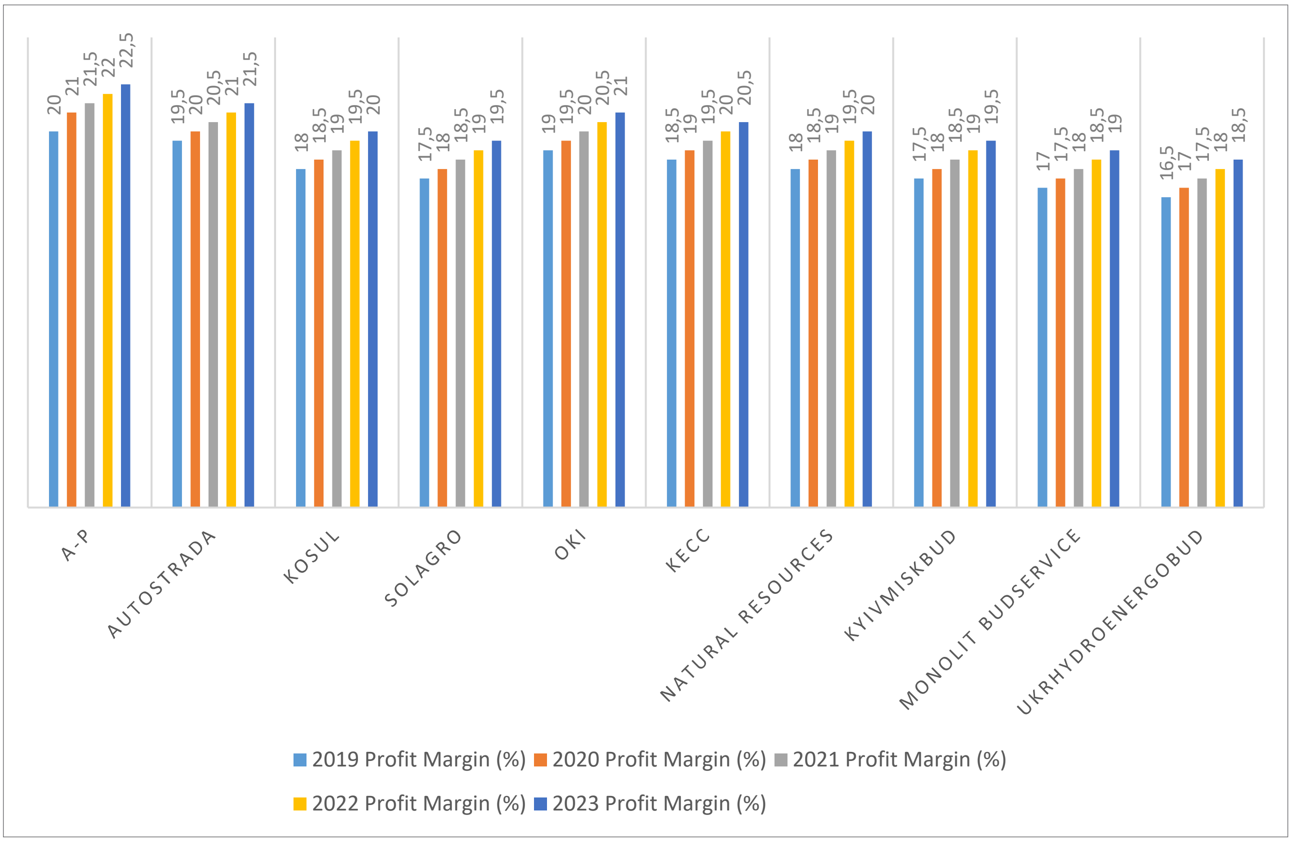


Fig. 3. Trends in profitability across the construction companies over the five-year period.
*Source:* authors development

Analysis of the revenue growth and profit margin trends suggests a pattern of development of most Ukrainian companies under review. Automagistral-Pivden, Autostrada and Onur Konstruktion International are companies that posted strong financial performance with both vibrant revenue growth and large profit margin expansion. All these things are good management in terms of operational efficiencies and market expansion, cost control.

However, Kosul, Solagro, Kyivmiskbud, and especially Monolit Budservice demonstrated more conservative growth. Importantly, these companies did indeed grow over time still compared to rivals, but their growth rates were more subdued and that can be grounded in steadier strategies, saturation of the market, or other external drivers such as competition and regulation.

For companies with slower growth there may be levers to pull to improve their financial potential, such as focusing on innovation, digitalization or diversifying their market. Since the construction sector is capital and labor intensive, the market and regulatory forces have made the construction sector to continuously respond to these dynamics. To improve profitability and maintain long term growth in the highly competitive business environment however, moving forward will require optimizing cost structures, leveraging technology, and exploring new markets.

In order to find the best strategies for the use of funds in construction business and the improvement of its revenue, it is crucial for the construction industry to pay more attention to cost control in the use of resources and procurement functions. In order to improve the financial forecasting, financial managers should consider purchasing new technologies and data analysis tools. Policy makers should encourage a more predictable policy environment for the long-term strategic planning and minimize uncertainties. The findings of this research study strongly suggest that business owners should make innovation, service variety, and market development their top priorities as a way of ensuring sustainable profitability and market competitiveness.

## Conclusions

The construction industry in Ukraine is an important element of the country's economic growth, and the know how the management of financial potential in this sector is critical to ensure its sustainable progress. This research has aimed to analyze the financial performance of key construction companies in Ukraine from 2019 to 2023, focusing on two key parameters: Revenue Growth Rate, and Profit Margin. The authors picked these indicators to see if the companies can grow their operations but also control cost more or less.

Looking at the numbers on the result, most of the companies examined had a positive end in terms of revenue growth and profit margin over the five-year period. Additionally, companies such as Automagistral Pivden, Autostrada and Onur Konstruktion International showed major revenue and profit improvement, which confirms their proper management and investments in the right area. opposite side, with limited growth by Kosul, Solagro, Kyivmiskbud, and Monolit Budservice as potential result of conservative approach or market saturation. But these companies also showed slow improvement in their profit margin, indicating a good job done in managing costs and operational efficiencies.

The results imply that a lot of firms are able to grow between 5–20% year on year, but there are also firms growing more slowly, and not by much more than inflation. These companies focused on innovation, digitalization and new market exploration, could set the table for further financial potential. In addition, while growth will be sustained, the need to address external factors (competition, regulatory changes) will be a requirement for further success.

Additional future research should investigate what factors have influenced development of these financial trends in the Ukrainian construction industry and provide an in-depth analysis of government policy, technological developments and competitive situation within the Ukrainian construction industry. Additionally, research of the relationship between financial management practices and the market conditions could be explored further so that best practices could be applied across the industry.

The final conclusion of this study is pointed to the fact that financial management in the construction industry matters and draws out the important aspects that companies can utilize for better financial performance through strategic planning and financial management as well as operational efficiencies.

**Thank you notes.**
None.

**Conflict of interest.**
None.

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# ІНСТРУМЕНТИ ЕФЕКТИВНОГО УПРАВЛІННЯ ФІНАНСОВИМ ПОТЕНЦІАЛОМ У БУДІВЕЛЬНІЙ ГАЛУЗІ

***Анотація.*** *Будівельна галузь, яка має вирішальне значення для економічного зростання будь-якої країни, потребує ефективного фінансового управління, щоб мати змогу розвиватися та виживати у кризових ситуаціях. У цьому дослідженні розглядаються фінансові показники великих будівельних компаній в Україні з 2019 по 2023 роки, зосереджуючись на двох ключових фінансових показниках: темпі зростання доходу та маржі прибутку, які приймають форму рентабельності продажів або рентабельності інвестицій. Це дослідження є актуальним через зростаючу складність будівельного сектору зі зміною вартості матеріалів, нормативними змінами та зміною ринкових умов. З огляду на ці виклики, будівельні компанії повинні прийняти відповідні фінансові стратегії, які покращать їхню конкурентну перевагу, а також стійкість.*

*Метою цього дослідження є оцінка фінансового потенціалу українських будівельних компаній через прогноз зростання виручки та прибутковості, а потім визначення факторів, які сприяють зростанню цих компаній. Дослідження використовує кількісні методи, спираючись на фінансову звітність провідних компаній галузі за період 2019–2023 рр. Вивчаючи тенденції зростання доходу та норми прибутку, дослідження намагається розкрити ключові фінансові стратегії, які підтримують успіх у будівельному секторі.*

*Результати дослідження показують, що протягом останнього п'ятирічного періоду майже всі досліджувані компанії мали постійне зростання доходів і підвищення норми прибутку. Найбільше поліпшення фінансових показників показали такі компанії, як «Автомагістраль-Південь» і «Автострада», тоді як такі компанії, як «Косул» і «Моноліт Будсервіс», продемонстрували значно менше зростання. Незважаючи на те, що їхні показники значно відрізнялися, більшість компаній змогли підвищити свої прибутки і таким чином надали докази надійного управління витратами та операційної ефективності.*

*Рекомендації, подані у цьому дослідженні, пропонують будівельним компаніям практичну цінність щодо того, як покращити свої стратегії управління фінансами. Нарешті, це доповнює знання про фінансовий менеджмент у будівельній галузі загалом і в економіках, що розвиваються, зокрема, в Україні. Ці висновки призначені для того, щоб поінформувати зацікавлених сторін галузі, таких як політики, фінансові менеджери та власники бізнесу, про те, як оптимально розробити фінансові стратегії та збільшити прибутки будівельного сектору.*

***Ключові слова****: будівельна галузь, фінансовий менеджмент, зростання доходів, маржа прибутку, українські будівельні компанії, фінансові показники, стратегії сталого розвитку.*

JEL: M37, M15, M19

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# USE OF THE APPLE SEARCH ADS IN A MOBILE APP PROMOTION SMART-ECONOMY FRAMEWORK: IMPLEMENTATION STUDY

***Abstract.*** *In the context of digitalization and the rapid growth of mobile app markets, selecting the right digital tools is essential for effective brand management and app promotion. As the global economy increasingly embraces digital platforms, businesses turn to app stores like Google Play and Apple App Store to connect with their target audience. Apple's strong presence in the premium mobile market presents a valuable opportunity for app developers, though challenges remain in optimizing app store advertising to achieve cost-effective conversions.*

*Effective app promotion now relies on data-driven strategies that align with user behavior and preferences. Apple Search Ads, an advanced tool within the App Store ecosystem, helps advertisers target users more precisely, fostering a smarter approach to marketing. This study evaluates the effectiveness of Apple Search Ads in promoting mobile applications, focusing on its business model, keyword bidding strategies, and campaign optimization techniques.*

*By examining performance metrics, the study aims to provide app developers with actionable insights on how to leverage Apple Search Ads to maximize downloads and conversions. This aligns with the principles of the smart-economy, emphasizing efficient resource use, data-driven decision-making, and maximizing the return on digital advertising investments.*

***Keywords:*** *Apple Search Ads, mobile app promotion, smart-economy, keyword bidding, digital marketing*

## 1. Introduction

The subject of the study is the implementation of Apple Search Ads within the broader framework of management for mobile app promotion. Apple Search Ads is a tool that can be an important part of the smart economy due to its ability to target ads to specific audiences with maximum efficiency. This allows you to optimize advertising budgets and use data to intelligently manage resources. In a smart economy that focuses on using data and technology to improve productivity, the use of tools like Apple Search Ads contributes to the efficiency of business processes and the market as a whole. Collecting and analyzing user data helps to better understand consumer needs, which improves the quality of services and products.

This research explores the effectiveness of app store advertising through Apple's solutions, comparing Apple Search Ads Basic and Advanced versions for driving app installations and improving app visibility. The study aims to analyze the app promotion strategies on the Apple App Store and evaluate the results for a paid mobile application.

The purpose of the study is to examine the efficiency of Apple Search Ads in promoting a commercial mobile application by comparing the performance of Basic and Advanced campaign options with market average values. Specifically, the study seeks to evaluate the effectiveness of advertisement structuring strategies, conversion rates, and the return on investment (ROI) of different campaign approaches, aiming to provide practical insights for optimizing mobile app promotion strategies.

Various academic studies have explored the role of digital tools and app promotion strategies. In the context of mobile app promotion, works by Lewis and Nguyen [1] examine the competitive effects of display advertising, showcasing the conversion spillovers across digital platforms. Bellman et al. [2] examine how branded mobile apps positively affect user attitudes towards a brand and their purchase intentions, particularly highlighting the success of informational apps over game-like apps. Zhao & Balagué [3] provide systematic guidelines for designing branded mobile apps, categorizing them by five types and business objectives to enhance marketing through mobile applications. Additionally, Morhart, Malär, and Guèvremont [4] stress the role of brand authenticity and consumer trust in driving app downloads, particularly in competitive categories where user loyalty is crucial. Karagkiozidou et al. [5] provide a comprehensive analysis of app store optimization factors for mobile app promotion. Strzelecki [6] proposes a comprehensive framework for app store optimization, while Picoto, Duarte, and Pinto [7] explored top-ranking factors for mobile apps through a multimethod approach. At the same time, currently there are not enough available studies on app store ads and Apple Search Ads in particular. Given the lack of a systematic study of app store search ads strategies, the subject requires further research.

In general, the research shows that the conversion rate for Apple Search Ads was significantly lower than expected, with only several installs recorded during the period of the campaign. Comparing to Apple Search Ads Basic, Apple Search Ad Advanced campaigns yielded some positive results, with moderate impressions and taps. However, overall results highlighted the need for further optimization, especially in keyword selection and budget allocation. The case study of the “WordFace!” app demonstrated that both precise keywords targeting, and correct app’s distribution model are essential for better ad performance.

## 2. Materials and Methods

The research applies both qualitative and quantitative methods to analyze campaign data. The study uses a comparative analysis of advertisement structuring strategies and econometric models to assess the cost-effectiveness and conversion rates of search ads. Additionally, performance metrics such as tap-through rate (TTR), cost-per-tap (CPT), and conversion rate (CR) were examined using a combination of linear regression analysis and comparative industry benchmarking.

## 3. Results and Discussion

*Choosing app promotion platform.* Mobile app promotion could include both general digital advertising tools, such as Google and Facebook PPC platforms, as well as app stores specific tools. The first one of these tools is App Store Optimization (ASO), which is the process of improving app visibility within app stores and increasing app conversion rates. According to Apple, search is the primary way people discover apps on the App Store, with 70% of App Store visitors using search to discover apps [8]. Therefore, ASO is one of the best ways to grow traffic to an app for free. But with 2.2 million apps in the Google Play Store and roughly 2 million in the Apple App Store [9], such optimization will not be a defining method. ASO works in much the same way as search engine optimization (SEO). Like Google and Bing, both Google Play Store and Apple App Store have their own algorithms to decide which app should be ranking the highest. Those algorithms take into consideration many factors including app title, subtitle, keywords, description, downloads, uninstalls and reviews, so any optimization a brand does on its app store presentation will result in higher credibility, more downloads, and thus more revenue.

App store search ads is what implemented next after ASO in a mobile app promotion algorithm [10]. In this study we will focus on Apple mobile platform and its provided solutions. One of the primary reasons for choosing Apple App Store over Google Play is the significant difference in the demographic profile of users, particularly in terms of income levels. Several studies [11; 12] have shown that Apple users, on average, tend to have higher disposable incomes compared to Android users. According to the report by Consumer Intelligence Research Partners, iPhone users in the United States, for example, are more likely to have higher household incomes than Android users. This income disparity translates into a greater willingness to spend on in-app purchases, premium app subscriptions, and one-time purchases, directly influencing app profitability. In contrary, Android operating system supports sideloading, which offers numerous ways to avoid paying for apps, whereas on Apple mobile platform a user is locked to app publisher demands and Apple policies. Taking these considerations into account, for a commercially distributed app it would be more relevant to study app store search ads on the example of Apple App Store and an app published there.

*Apple App Store and Apple Search Ads digital solutions.* Although Apple is new to digital advertisement market, its U.S. ad revenues have steadily increased from $3.05 billion in 2021 to a projected $7.32 billion by 2025. Growth peaked at 41.6% in 2022, with forecasts of 21% in 2024 [13]. Eventually company’s ads success leaded to Apple testing an AI-powered ad buying tool for the App Store that would automatically determine where to place ads [14]. Today there are two Apple advertising systems, each designed for different categories of advertisers. The “Advanced” version is similar to other PPC platforms, while the "Basic" is presumably designed for app publishers who have not managed digital advertising before. We can conclude that currently "AI-powered tool" is likely integrated in Apple Search Ads Basic system.

The two Apple Search Ads solutions are designed for varying levels of expertise, resources, budget, and experience with app marketing. Summarized, comparison is given in the table 1.

Apple Search Ads lets brands promote their apps on the App Store, the place that over 650 million people per week go to discover and download apps [16]. App Store advertising inventory includes:

- The Today tab, where users start their journey on the App Store.
- The Search tab, where users begin their search.
- Search results, where users search for something specific to download.
- Product pages, where users browse apps ("You Might Also Like" block).

With an ad on the Search tab, a brand can capture people's interest right when they begin their search. The ad will appear prominently at the top of the suggested apps list. It should be noted that only one ad at time can appear at the top of App Store search results. According to Apple, Apple Search Ads offer 40% lower cost-per-install compared to other similar advertising platforms [17].

*Apple Search Ads digital performance indicators.* Most downloads on the App Store start with a search. In fact, 65% happen directly after a user searches for an app. With an ad at the top of relevant search results, a brand can reach users when they search for something specific. Apple algorithms will match an app with people based on a direct signal of their intent — their search query. By intelligently matching the search term with the app being promoted, Apple Search Ads reportedly delivers an average conversion rate (a percent of people who tap a search results ad and then download the app), which is of over 60% [18]. Although it seems to be extremely high number in comparison to other PPC platforms, it should be noted that search ads per se increase conversion probability by 65.26% [19].

According to SplitMetrics agency (Apple Search Ads Partner), the average conversion rate in 2023 was 65.37%, comparing to 64.96% observed in the second half of 2022 [20]. It is important to understand user behavioral patterns and intent for an app category, as this affects conversion rate. For instance, Finance is the top category in cost per tap (CPT) and cost per acquisition (CPA), but only 14th for conversion rate and outside the top 15 for tap-through rate (TTR). High user acquisition costs result from tough competition and reflect each category's unique customer journey. While users may quickly install a "try for free" game (leading to high conversion rates for this category), it is reasonable to assume that publishers must put more effort to gain the trust of people landing on a product page with a Finance app. All these differences in customer journeys and category specifics show how important are App Store optimization strategy and brand promotion.

*Apple Search Ads mechanism and strategies.* Similar to how Google PPC ads work, with Apple Search Ads, a brand makes bid on keywords to trigger and include its ad within relevant App Store search results — so when an App Store customer types in a search query that uses one of the keywords, an ad could appear. Apple recommends bidding on both general and specific keywords, which should increase ads coverage and help an ad to appear for more App Store searches. Similar to other PPC platforms, Apple offers

*Table 1*

**Comparison of Apple search ads platforms**

| Apple Search Ads Basic | Apple Search Ads Advanced |
|---|---|
| Advantages | |
| • Good as entry point for managing app promotion<br>• Strategic campaign decisions made by Apple<br>• Add monthly budget and capped cost per install<br>• Algorithm is intended to source the most efficient ROAS<br>• Paying only for installs<br>• Automated display<br>• Continuous optimization from the algorithm | • Total control over campaign strategy<br>• Audience targeting<br>• Keyword customization and monitoring<br>• Audience customization and monitoring<br>• Setting up ad groups with different product pages<br>• Unlimited allowed budget<br>• Unlimited allowed app promotions<br>• Full access to attribution API |
| Disadvantages | |
| • Little to no control over strategic decisions<br>• No customization for keywords<br>• No customization for audiences<br>• No transparency over optimization<br>• Automation may attract ill-fitting audience<br>• Automation may attract low-quality users<br>• Limitations on the number of apps to promote<br>• Limited access to attribution API<br>• Budget limit at 10 000 USD per app, per month | • More complex than Apple Search Ads Basic<br>• May use more time and resources than Apple Search Ads Basic<br>• Needs a strategic and competitive approach to succeed |

*Source:* created by authors based on [15] exact match keywords, broad match keywords, and negative keywords.

The unique feature of Apple Search Ads is "Search Match" feature that could be enabled during ad campaign creation. Unlike the match types that is applied to keywords, the "Search Match" feature can be turned on or off anytime in the ad group settings. Apple recommends turning on "Search Match" in search results campaigns and ad groups that are dedicated to keyword discovery (a brand needs to run at least one such campaign). With "Search Match", ads could match to searches based on:

- Metadata from App Store app's product page (as well as keywords added by app publisher in App Store Connect).
- Information about similar apps in the category.
- Other search data that may be relevant for brand's app.

This is especially useful in markets where a brand manager doesn't know the local language, thus not knowing which keywords are used by locals to search certain apps. Also, just like Google Ads, Apple Search Ads system offers ideas for additional relevant keywords from the Keyword Suggestion Tool. It shows related terms and their popularity based on App Store searches.

Conducting a cost-effective app promotion with Apple Search Ads requires separating search results campaigns by keyword themes. The first step in structuring search results campaigns is to divide brand's keywords into four separate campaigns. Each should focus on a different keyword theme, which can be included in the campaign name. Structuring ads account by keyword themes helps to measure results and monitor performance, optimize a campaign, and set up to scale for long-term growth. Apple recommends 4 types of search results campaigns:

- Brand Campaign (exact match keywords). Focuses on keywords that relate to app's specific brand.
- Category Campaign (exact match keywords). Focuses on nonbrand keywords that describe an app's category and what an app does.
- Competitor Campaign (exact match keywords). Focuses on competitor keywords, where an app is in the same or a related category.
- Discovery Campaign (broad match keywords). Focuses on reaching a wider audience and "mining" for popular search terms to add as keywords using broad match and "Search Match" to automatically match an ad to relevant search terms.

Some brand managers might be tempted to import their campaign data into Apple Search Ads account. This is not recommended, as industry experts suggest there would be poor results from following that approach [21].

Once a brand identifies search terms that perform well in their discovery campaign, these can be added to the brand, category, and competitor campaigns as new exact match keywords. Then it is needed to repeat the process of adding these keywords as exact match negative keywords in discovery campaign (to prevent discovery campaign from matching ads to the exact keywords that company is already bidding on).

Apple Search Ads Advanced uses a cost-per-tap (CPT) pricing model, so an advertiser pays only when a user taps an ad [22]. The actual amount paid is a result of a second price auction. Apple recommends applying aggressive bid amounts on exact match keywords, as they are core performance drivers and the most relevant to overall campaign. More investment provides with more control over when brand's ad appears. As a general rule, placing moderate bid amounts on broad match and "Search Match" campaigns is more efficient. These keywords drive discovery but may not drive high efficiency like exact match. For optimal performance, most of the traffic should come from exact match.

Apple Search ads also offer bids recommendations (as well as for keywords and daily budget). Applying these bids can increase the likelihood of an ad showing. Actual outcomes, including changes in spend and average CPA, may vary. However, Apple also notices that its recommendations are suggestions and not directives for how much you should bid. An advertiser can also set the default max CPT bid, which will apply across all keywords in the ad group unless a specific keyword bid is applied. A suggested max CPT bid is provided, based on what Apple knows about an app and what advertisers with similar apps are willing to pay. There are 3 metrics that could help manager to determine which bids to set:

- Impression share, which is a share of impressions an ad received from the total impressions served on the same search terms or keywords, in the same countries and regions. Impression share is displayed as a percentage range, such as 010%, 1120%, and so on.
- Rank, which is how an app ranks in terms of impression share compared to other apps in the same countries and regions. Rank is displayed as numbers from 1 to 5 or >5, with 1 being the highest rank.
- Search popularity, which is popularity of a search term, based on App Store searches. Search popularity is displayed as numbers from 1 to 5, with 5 being the most popular. Search popularity can help identify which keywords may present the greatest opportunities to drive campaign performance.

Unlike on some other PPC platforms, with Apple Search Ads one can also add optional cost-per-acquisition (CPA) cap. This setting will specify the amount a brand is willing to spend for a conversion, for example, no more than app's price. Setting a CPA cap is completely optional and limits impressions and conversions. It should be noted that Apple recommends launching ads campaigns without a CPA cap, giving a campaign some time to run so that a manager could learn from results.

Ads are automatically created using the metadata that a brand provides in App Store Connect, the tool used to upload, submit, and manage apps on the App Store. All ads have an ad disclosure icon and feature brand's app name, app icon, and subtitle. Search results ads can also feature screenshots and app previews from a custom product page that a publisher creates in App Store Connect. Here are authors' recommendations that are part of ASO methods to make app's product page more efficient:

- An app icon is one of the first elements of an app that users see, so it is essential to make a strong first impression that communicates an app's quality and purpose.
- A compelling subtitle can encourage taps and downloads. A concise phrase that resonates with brand's audience should be used to highlight app's most valuable features or uses.
- The keywords in App Store Connect help an app to be more discoverable in organic searches. These keywords are also used as a signal for "Search Match" feature and for determining relevancy for search results ads. Therefore, these keywords must be relevant or unique to an app.
- Screenshots captured from an app can visually communicate app's user experience. Currently, a publisher can upload up to 10 screenshots to a product page. Highlighting app's main benefits or features in the screenshots is required, while also keeping any text overlays simple and easy to read.
- Adding an app preview, which are short videos that show the features and functionality of an app. They can be up to 30 seconds long and use footage captured from the app itself. At the moment a publisher can add up to 3 app previews to the product page. Audio in videos is muted, so videos should be compelling to drive audience engagement.

A brand can create up to 35 custom product pages in App Store Connect to showcase specific app features or content. Each custom product page can include screenshots and app previews that are different from those on app's default App Store product page. Each custom product page includes a unique URL that can be used across marketing communications.

On Apple Search Ads, campaigns are separated by ad placement, meaning a brand can only select one ad placement for the campaign. With all ad placements, a maximum CPT bid can be set during campaign creation, while only for search results campaigns keywords and negative keywords can be chosen. A brand can create campaigns that focus on a single country or region, or that include multiple markets; in this case localized product pages are recommended for search ads, while for Today tab ads localization is mandatory. Whereas for Today tab ads and Product Pages ads a brand cannot choose keywords, an app category could be chosen for Product Pages.

*Apple Privacy considerations and ethical issues.* The thing that should be considered by managers is privacy policy and its restrictions on Apple Search Ads platform. The "Personalized Ads" setting on Apple iOS and iPadOS devices gives customers choice to control how their information is used for Apple-delivered advertising. Starting with iOS 15, Apple presents an active prompt to users when they first open App Store. A growing number of users are choosing to turn off the Personalized Ads setting, limiting the use of their information for advertising delivered by Apple. In fact, 78% of App Store search volume comes from devices with Personalized Ads turned off [22].

This aspect leads to the reduced significance of "Audience" settings in ads campaigns. While it allows to choose either "reaching all eligible users" (automatically matching an ad to all eligible users to reach the broadest audience) or "choosing specific audiences", the latter setting will affect only 22% of App Store users. "Specific audiences" settings in App Store Search Ads include:

- Devices (smartphone, tablet, etc.)
- Customer types (new users, users of publisher's other apps, returning users)
- Demographics: age, gender, location (location refinements is only available for some countries and regions)
- Ad scheduling

*Apple App Store platform strategies specifics.* Like all other digital PPC platforms, Apple Search ads allow to reach customers in more countries and regions, while also making the most of seasonal opportunities. What is unique for Apple Search Ads is engaging with previous customers who deleted an app at some point. For some apps leveraging the value of redownloads could be crucial. People download and delete apps for a variety of reasons, and many of them end up redownloading the same apps. In fact, 92% of surveyed iOS users said they've redownloaded apps. And 33% of returning users said they redownloaded apps specifically to make a purchase [23].

Ads on the App Store can be critical in reminding users to redownload apps. Making redownloads a part of brand's Apple Search Ads strategy can help to renew interest in an app, maximize potential for redownloads, and unlock more revenue. One method is to create a custom product page devoted to redownload strategy in App Store Connect. This page can be used as the basis for redownload ad, promoting new features to both new and previous customers. "New Downloads" and "Redownloads" metrics in Apple Search Ads dashboard help to monitor such campaigns.

*Practical application of app promotion strategies for a commercial app on Apple App Store.* Here and below, we will consider the algorithm of managing app distribution and promotion on the example of "WordFace!" app (fig. 1). This application is a commercial utility for iPhone in the "Education" category. At a cost of 3.99 USD, the app is intended for learning foreign languages and is available in most App Store countries (except PRC and Brazil). The application UI and its App Store product pages are translated into 3 languages.

First, an app promotion campaign on Apple Search Ads Basic was started. Apple Search Ads Basic system did not yield any results in case of "WordFace!" app: during the reported month, with monthly budget set to 1000 USD and Maximum Cost-Per-Install (CPI) set to 4 USD, not a single download of the app was achieved in 68 countries (fig. 2). At the same time, the

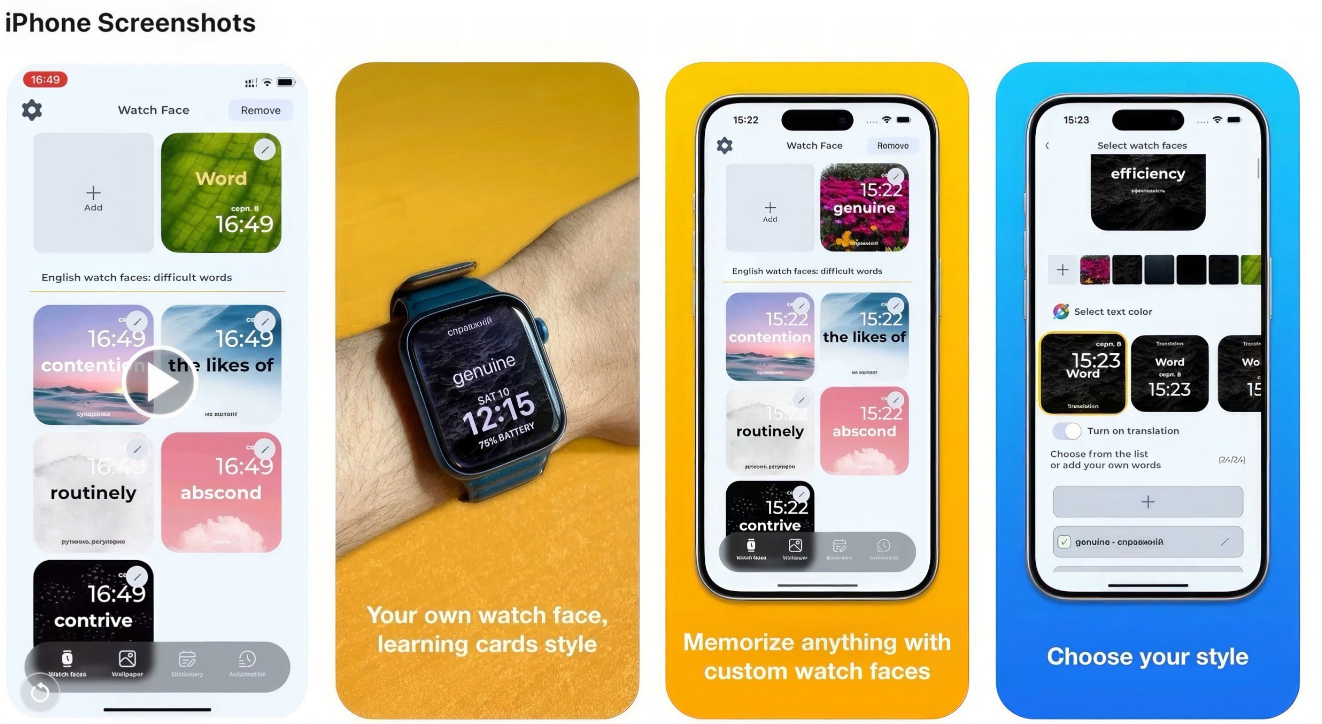


Figure 1. Screenshots from mobile app product page that were used in all ad groups
*Source:* IPhone Screenschots

system does not offer possibilities of further setting and correction.

Next step was launching digital campaigns for "WordFace!" app in Apple Search Ads Advanced. It is important to clarify that this study considers mainly Search ads, since these have more possible applications and are available for more app publishers. Today Tab ad placement, for instance, albeit formally does not have a limitation for smaller app publishers, seems to be currently unavailable for all advertisers. Even though "WordFace!" app complies to current Apple ads policies, still a message "The app you chose is not eligible due to current content policies and restrictions" is shown in Apple Search Ads dashboard. Apple Support, unfortunately, were unable to provide further details.

Following Apple's recommendations, 3 Discovery campaigns with activated "Search Match" were launched first, to the markets of Ukraine, russian-speaking countries (e.g., Kazakhstan) and wealthy English-speaking countries (UK, USA, Australia, Germany, France, etc.). The test budget amounted to 130$. In total 11 546 impressions, 155 taps, and only 2 installs were received over a period of 5 days, so the TTR was at 1.34% with 0.85$ CPT, and the conversion rate was 1.29%. In terms of keyword research, campaigns for several markets did not yield the expected results:

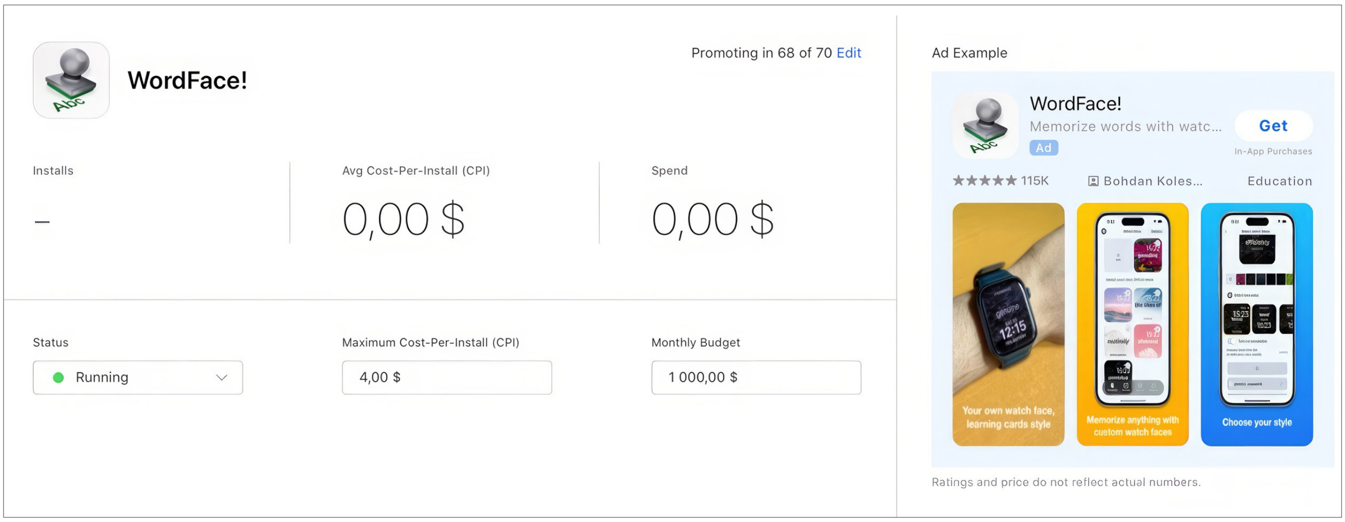


Figure 2. Apple Search Ads Basic results after a month of automatic campaign running
*Source:* WordFace

in the conducted campaigns most of the proposed search terms were labeled as "Low volume terms" (fig. 3), which means a large number of different keywords with less than 10 impressions that cannot be combined into one recommendation. The campaign for one App Store country, Ukraine, was a bit more illustrative: the system recommended to use "English language" keyword, although the number of impressions for this search term in given campaign was rather small.

A week later Competitors and Category campaigns were launched with keywords focused on covering queries on competitors' apps and similar apps, respectively. Both of these campaigns were launched for one App Store country, Ukraine (to maintain a focus considering low test budget). Apps that allow to create learning cards were identified as "WordFace!" app direct competitors.

In Competitors campaign the following keywords were used: *quizlet, anki, flashcards, word of the day*, and others. For the queries that are defined by the system as popular, higher bids for CPT were set. In total 50$ was spent on this campaign during a 3-day period, which resulted in 2 054 impressions, 49 taps, and 0 installs. The TTR was 2.39% with 1.04$ CPT, which is higher than in Discovery campaigns.

The Category campaign was even less successful with keywords like *apple watch, watch face, learning language, spaced repetition*, etc. In total for the same period 15$ were spent, 298 impressions, 8 taps, 0 installs received. CPT was $1.25 with a TTR of 2.68%, which is about the same as in Competitors campaign.

A Product pages campaign with app pages placements was run in parallel. In this campaign keywords cannot be configured, so ads were set to be shown for similar app categories. During a 3-day period 28$ was spent, 2 944 impressions, 32 taps, 0 installs were received. TTR was a paltry 1.09%, with 0.85$ CPT.

To analyze the results, let's turn to the industry statistics. According to SplitMetrics [20], these are the average Apple Search Ads costs in 2023, for apps in "Education" category:

- 1.62$ cost per tap (CPT);
- 8.05% tap-through rate (TTR);
- 59.23% conversion rate (tapping the "GET" button after visiting a product page);
- 1.29$ cost per acquisition (CPA).

From the average market ads values, it follows that although the average price of 0.91$ CPT in the test campaigns for "WordFace!" app was lower than the average in App Store Search Ads, ads were opened about 5 times less often (1.45 TTR), while the overall conversion rate was only 0.82%, which is 72 times lower.

*Building Linear Probability model*. There are very few conversions in our dataset, which makes it challenging for the logistic regression model to compute meaningful results. Linear probability model (LPM) is a simple linear regression applied to binary outcomes. While it is not as robust as logistic regression, it can still provide useful insights when logistic regression fails. Here is the output of the linear regression model based on the dataset (fig. 4):

– R-squared: 0.613, which means that 61.3% of the variation in the conversion (installations) probability is explained by the number of taps and cost-per-tap (CPT). While this is a reasonable explanatory power, the small sample size limits the generalizability.
– Taps coefficient: 0.0083. This suggests that for each additional tap, the probability of conversion (installations) increases by about 0.83%, though this result is not statistically significant ($p = 0.142$).
– CPT coefficient: 0.1247. This indicates that an increase in the CPT slightly increases the probability of conversion, but this is not significant ($p = 0.934$).
– Intercept (constant): –0.1832. This represents the baseline probability of conversion when taps and CPT are zero.

| Search Term | Match Source | Keyword | Default Max CPT Bid | Spend | Avg CPA (Total) | Avg CPT | Impressions |
|---|---|---|---|---|---|---|---|
| (Low volume terms) | Keyword | вчити слова | 0,70 $ | 12,31 $ | 0,00 $ | 0,56 $ | 595 |
| (Low volume terms) | Keyword | циферблаты ар... | 2,50 $ | 12,57 $ | 12,57 $ | 0,97 $ | 401 |
| (Low volume terms) | Search match | —— | 0,70 $ | 0,00 $ | 0,00 $ | 0,00 $ | 134 |
| (Low volume terms) | Keyword | watch | 0,70 $ | 2,14 $ | 0,00 $ | 0,53 $ | 66 |
| (Low volume terms) | Keyword | англійська мова | 0,70 $ | 1,99 $ | 0,00 $ | 0,40 $ | 66 |
| (Low volume terms) | Keyword | карточки для за... | 0,70 $ | 0,36 $ | 0,00 $ | 0,36 $ | 59 |
| (Low volume terms) | Keyword | вивчення картки | 0,70 $ | 0,58 $ | 0,00 $ | 0,58 $ | 53 |
| **англійська мова** | **Keyword** | **вчити слова** | **0,70 $** | **0,00 $** | **0,00 $** | **0,00 $** | **32** |

Figure 3. "Low volume terms" and keywords suggestion for single country App Store discovery campaign in Apple Search Ads Advanced

*Source:* Apple Search Ads

Although the R-squared value is moderately high, neither the number of taps nor the cost-per-tap significantly predicts conversions in this small dataset. The results may not be robust due to the limited sample size and should be interpreted with caution. Expanding the dataset and using a more refined logistic regression model when data allows would provide more reliable results. This linear probability model gives an idea of the relationship between taps, cost-per-tap, and conversions, but further data collection and analysis would improve accuracy.

Taking into account probability model, the drastic difference between average market conversion rate and that for "WordFace!" app from this study cannot be explained by quality of banner ads alone or by poorly designed product page as part of ASO efforts. In this case, the most probable reason is a wrong business model of the app distribution: it seems that a higher conversion rate for clicking "GET" button would be substantially easier to achieve than for clicking "3.99 USD" payment button. At the same time, an app may contain in-app purchases and multiple subscriptions, while not working without them at all (or provide a short-term free trial).

Apple incentivizes the use of subscriptions by app publishers in every way possible, including offering a reduced commission on subscription revenue. For the first year, Apple takes a 30% cut, but after a subscriber stays for a year, Apple reduces its commission to 15% [24]. There are also other stimuli, such as App Store special pages for apps with subscriptions and advanced ways to integrate in-app purchases using Apple StoreKit API. It comes as no surprise that Apple Search ads systems might be also optimized for "free" to install apps with in-app paywalls and free trials that are necessary to perform any action in an app. In that case this research demonstrates that choosing one of "freemium" models [25] is necessary to proceed with Apple Search Ads strategies. Hence, authors recommend considering app's distribution model on "choosing app promotion platform" stage.

## 4. Conclusions

The study of Apple Search Ads in promoting mobile apps provided several insights into the effectiveness of different campaign approaches, particularly when comparing Apple Search Ads Basic with Advanced. The analysis reveals significant performance differences between the two, as well as challenges related to app distribution models and keyword selection. These findings highlight the need for further optimization and strategic planning to fully capitalize on Apple's advertising solutions. The study conclusions are as follows:

1. Limited Effectiveness of Apple Search Ads Basic. The study found that Apple Search Ads Basic failed to deliver any conversions for a tested app. This suggests that the automated nature of Apple Search Ads Basic might not be effective for all app categories, particularly for paid apps.

2. Challenges in Keyword Selection. One of the key challenges identified was the difficulty in selecting effective keywords. In several campaigns, search terms were marked as "Low volume terms," which significantly limited possible strategies of improving visibility and impressions. This reflects the importance of in-depth keyword research to be conducted by brand managers.

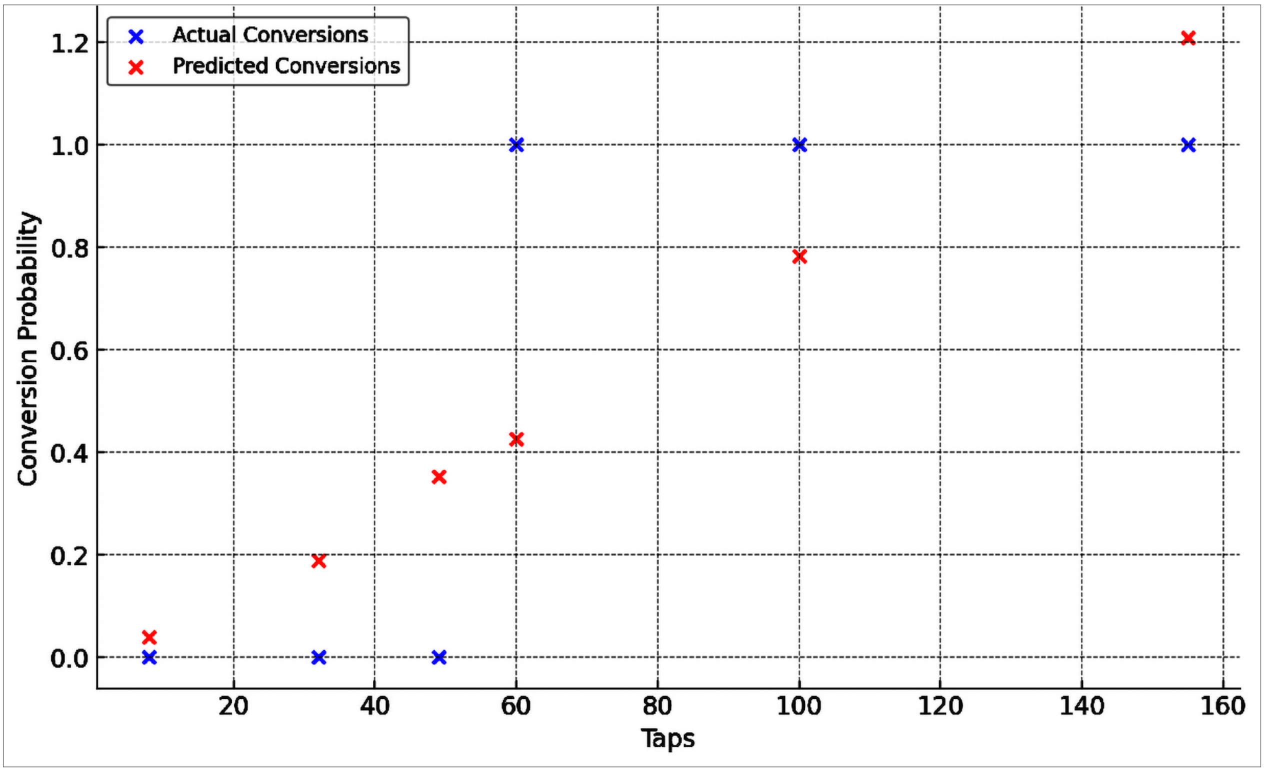


Figure 4. Linear Probability Model: Actual vs Predicted Conversions

*Source:* created by authors

3. Cost-Efficiency Issues and App Distribution Model Impact. The study highlighted a stark difference between the average market conversion rates and those of the tested app. This, in turn, emphasizes the impact of the app's distribution model on the effectiveness of Apple Search Ads. The paid app model used by tested app likely deterred users from converting, as compared to freemium models, which seems to be more compatible with the Apple Search Ads ecosystem.

These findings suggest that while Apple Search Ads offer potential for brands, particularly with the Advanced version, success is contingent on factors like app pricing models, keyword strategies, and campaign optimization.

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# ВИКОРИСТАННЯ РЕКЛАМИ APPLE ПОШУКУ В РАМКАХ РОЗУМНОЇ ЕКОНОМІКИ ДЛЯ ПРОСУВАННЯ МОБІЛЬНИХ ДОДАТКІВ: ІМПЛЕМЕНТАЦІЯ

***Анотація.*** *У контексті цифровізації та швидкого зростання ринків мобільних додатків, вибір правильних цифрових інструментів є важливим для ефективного управління брендом та просування додатків. Оскільки світова економіка все більше охоплює цифрові платформи, компанії звертаються до магазинів додатків, таких як Google Play та Apple App Store, щоб зв'язатися зі своєю цільовою аудиторією. Сильна присутність Apple на ринку преміальних мобільних пристроїв надає цінну можливість для розробників додатків, хоча залишаються проблеми в оптимізації реклами в магазинах додатків для досягнення економічно ефективних конверсій.*

*Ефективне просування додатків тепер спирається на стратегії, засновані на даних, які відповідають поведінці та вподобанням користувачів. Apple Search Ads, передовий інструмент в екосистемі App Store, допомагає рекламодавцям точніше орієнтуватися на користувачів, сприяючи розумнішому підходу до маркетингу. Це дослідження оцінює ефективність Apple Search Ads у просуванні мобільних додатків, зосереджуючись на його бізнес-моделі, стратегіях призначення ставок за ключовими словами та методах оптимізації кампаній.*

*Дослідження має на меті надати розробникам додатків практичну інформацію про те, як використовувати Apple Search Ads для максимізації завантажень та конверсій. Це відповідає принципам розумної економіки, підкреслюючи ефективне використання ресурсів, прийняття рішень на основі даних та максимізацію рентабельності інвестицій у цифрову рекламу.*

***Ключові слова****: Apple Search Ads, просування мобільних додатків, смарт-економіка, ставки за ключовими словами, цифровий маркетинг.*

JEL: M29; M31; O35; Z31

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# FROM FOOD WASTE TO FOOD SUPPLEMENTS: SUSTAINABLE TRANSFORMATION FOR ECONOMIC SECURITY

***Abstract.*** *In this study, we explore the potential for cooperation between hospitality and food supplement manufacturers. The concept aligns with sustainable development principles, addressing both social and environmental concerns. Specifically, it focuses on the collection and upcycling of food waste into food supplements. The paper identifies alternative SWOT strategies to evaluate the feasibility of this idea in the entrepreneurial sector. One key solution to food waste is food upcycling, a growing trend where unused food scraps are transformed into new products. Emerging innovative methods, like advanced food drying technologies, offer effective ways to combat food waste by converting scraps into nutritious products without excessive heat. The study highlights several critical aspects of food upcycling, including: economic efficiency through resource conservation, reduced dependency on external food sources, and enhanced food security. The process also fosters technological development, attracting investments and generating new job opportunities, which strengthens economic stability. Furthermore, upcycling reduces waste and conserves natural resources, positively impacting environmental and economic sustainability. By turning food waste into valuable supplements, this approach contributes to sustainable development goals, such as combating hunger and improving access to nutritious food, thus promoting both social and economic security at the national level.*
***Keywords:*** *sustainable development, food waste, food supplements, food security, economic security*

## 1. Introduction

Food waste is a major issue with widespread implications, negatively affecting society, the environment, and the economy on a global scale. Among the 17 Sustainable Development Goals (SDGs) outlined in the UN 2030 Agenda, signed in 2015, SDG 12 — Responsible Consumption and Production and its associated targets have emerged as a significant challenge due to the ongoing rise in global industrial food waste [1].

The SDGs provide a unique opportunity to transform the concept of sustainability into actionable plans, emphasizing the urgency needed to achieve specific goals that will guide the world toward a more sustainable and resilient future. The primary aim of SDG 12 is to cut global food waste and food loss in half by 2030. Reducing food waste also supports progress toward other SDGs, including Climate Action (SDG 13), Zero Hunger (SDG 2), Sustainable Water Management (SDG 6), and Life on Land (SDG 15).

According to the “Food Waste Index Report” from the United Nations Environment Programme [2], a staggering 931 million tons of food waste were generated worldwide in 2021 across every stage of the food supply chain: production, distribution, retail, markets, and domestic consumption. This report plays a critical role in advancing SDG 12, with new estimates published annually.

Food waste was also a key topic during the side events at the 26th UN Climate Change Conference (COP26) in November 2021, held at the Scottish Event Campus (SEC) in Glasgow.

The food industry is a major contributor to global greenhouse gas emissions, responsible for approximately one-third of all emissions, according to the United Nations [3]. Reducing food waste is key to helping lower these emissions. In regions that rely on local agriculture, food waste often occurs during production. In wealthier areas with a global food supply network, the problem tends to stem more from consumer waste and inefficient food usage

The annual increase in food waste is one of the most significant problems also in the hospitality industry. Every year, around 1.3 billion tonnes of food waste is produced by hotels and restaurants around the world. This is not only a waste of food itself, but also a loss of other resources such as land, water, energy needed to produce all this food. Financial losses are no exception. In the European Union, an impressive 20% of food produced — around 173 kg per person — is thrown away, with the hospitality industry accounting for 12% of food waste in Europe [4]. Given the existing problem, the European Union has declared food waste reduction as a key sustainable development goal in its 2030 agenda. This initiative calls for collective efforts from governments, institutional organizations, businesses and households. By implementing a food waste reduction strategy, both businesses and households can save a lot of money. Not to mention the reduction of their impact on the environment. The financial savings from reducing food waste can be significant. In fact, by solving the problem of food waste, both businesses and individuals can contribute to creating a more sustainable food system, while receiving economic benefits.

One of the directions for solving the problem of food waste is food upcycling — this is a new food trend, according to which previously unused food residues are processed into one or another type of completely new product. Innovative methods, such as advanced food drying techniques, are emerging as effective solutions to combat food waste. Companies are creating technologies that transform food scraps into nutritious flavors and supplements without the need for excessive heat. The focus of food upcycling in this context is on the following aspects:

*Economic efficiency of resources*. The transition from food waste to food supplements contributes to the reduction of resource losses and savings. This is important for ensuring sustainable economic development, which is the basis of the country's economic security. Creating supplements from waste can help increase production efficiency and reduce costs.

*Ensuring food security*. The use of food waste to create supplements allows reducing dependence on external food suppliers, reducing the risks associated with global food crises, shortages and food price inflation. This contributes to market stability and ensuring access to nutrients.

*Innovation and technological development*. The development of technologies for processing food waste into supplements contributes to economic growth and the development of new industries. This process increases the competitiveness of the economy, attracting investment and creating new jobs, which has a positive impact on economic security.

*Impact on environmental and economic sustainability*. Reducing waste by upcycling it into useful products conserves natural resources and reduces waste disposal costs. This can help ensure environmental sustainability, which in turn affects long-term economic security.

*Support for sustainable development and social responsibility*. Using food waste to create supplements also contributes to the achievement of sustainable development goals, in particular in combating hunger and improving access to nutritious foods for all. This is directly linked to social and economic security at the national level.

In this study, we propose the idea of cooperation and interaction between hospitality enterprises — hotels and hotel chains, restaurants, cafes, etc. — and food supplements manufacturers. In fact, this is a reflection of the idea of sustainable development, focused on social and environmental issues and aimed at collecting food waste and its further upcycling to create food supplements. This study identifies alternative SWOT strategies [5] in order to determine the feasibility of using such an idea in entrepreneurship. For example, fruit and vegetable by-products can be used as nutraceuticals due to the content of substances beneficial to health [6]. The term "nutraceuticals," which is a hybrid of the words "nutrition" and "pharmaceutical," refers to nontoxic extract supplements with scientifically proven health benefits for both treatment and prevention [7]. Probiotics, prebiotics, antioxidants, polyunsaturated fatty acids, etc. are the most common food components used as nutraceuticals [8]. In turn, a Chinese food supplement manufacturer has patented an innovative process for producing dietary supplements containing lycopene from tomato by-products [9]. The company has registered a patent for an extraction method that offers the health benefits of the antioxidant through a technology that removes pesticides and improves the quality of lycopene. All this confirms that this new approach to food upcycling, based on circular thinking, can provide the right solutions to new technical, economic, and environmental challenges.

The topic of efficiently utilizing food products and reducing food waste in the hospitality industry remains a significant area of research, as demonstrated by numerous global studies [10–19]. A key focus has traditionally been on the environmental benefits of minimizing food waste in the restaurant sector [Beretta & Hellweg, 2019]. Many researchers explore food waste in the context of sustainable development, particularly considering regional factors [20; 21]. Understanding the quantity, patterns, and causes of food waste is essential for developing strategies to reduce it [22]. From an economic side, McKinsey's research indicates that tackling food waste can reduce retail and manufacturing costs by 3 to 10%, unlocking up to US$80 billion in new market potential [23]. U.S. food waste costs approximately $162 billion annually [24]. One proposed solution is selling suboptimal food that would otherwise be wasted [25]. The global nature of this issue is also reflected in studies focused on strategies to combat food loss and waste [26]. On the other hand, the issue of food additives is also addressed by a number of scientific publications, the vast majority of which focus more on the role of dietary supplements and their impact on human health [27–29]. Díaz, Camara, and Fernandez-Ruiz note that food supplements and functional foods are considered foods that contribute to optimal nutritional well-being, health status, and quality of life by reducing the risk of disease and promoting the proper functioning of human organs and systems [30]. Other studies [31] focus on the sources, models, and human studies that support the health claims of these supplements, followed by sections describing side effects and potential causes for concern.

Overall, food waste in the hospitality sector is a significant and complex issue that requires multifaceted solutions. Existing research highlights the importance of understanding the root causes of food waste and implementing targeted strategies to combat it. However, the idea of food upcycling to address the issue of recycling waste into food supplements is new and not widely used in current scientific literature.

## 2. Materials and Methods

Justifying the need to define alternative SWOT strategies as a tool for determining the feasibility of food upcycling for the purpose of obtaining food supplements, we should note the following. SWOT analysis as an analysis of the weaknesses and strengths of a specific project or business idea, its threats and opportunities involve creating an appropriate matrix for analyzing the life conditions of the idea and its potential.

The definition of alternative SWOT strategies as a tool for determining the feasibility of food upcycling for the purpose of obtaining food supplements was carried out in the context of sustainable transformation. In order to obtain comparative results, a unified system of criteria for assessing the strengths and weaknesses, opportunities and threats of a specific idea was used. A scoring method based on assessments was used to evaluate all of the specified criteria. The assessment was carried out on a 5-point scale, where:

5 points — the maximum significant force of the factor.

4 points — significant influence of the factor

3 points — noticeable influence of the factor

2 points — moderate influence of the factor

1 point — insignificant influence of the factor

The overall assessment of the influence of each group of factors is determined by the sum of the points. The corresponding SWOT map is given below.

In order to determine in which field of interaction of the SWOT matrix influence factors the most optimal strategies are located, which must be followed, it is advisable to find out which combination of factors has the greatest impact on the development process of the object for which the SWOT analysis matrix is being built. For this purpose, the assessment of the strength of the interaction of factors is found as the product of the sum of the scores of the corresponding factors according to formulas (1) — (4) [32].

$$X_{SO} = \sum X_S \times \sum X_O \tag{1}$$

$X_{SO}$ — cumulative score assessment of the feasibility of implementing a strategy combining strengths and opportunities;

$\sum X_S$ — overall assessment of the strength of the strengths, determined by the sum of the points;

$\sum X_O$ — overall assessment of the strength of the capabilities, determined by the sum of the points.

*Table 1*

**SWOT map**

| Opportunities | Point | Threats | Point |
|---|---|---|---|
| – Factor 1<br>– Factor 2<br>– Factor 3<br>– Factor 4<br>– Factor 5… | | – Factor 1<br>– Factor 2<br>– Factor 3<br>– Factor 4<br>– Factor 5… | |
| **Total points** | | **Total points** | |
| **Strengths** | **Point** | **Weakness** | **Point** |
| – Factor 1<br>– Factor 2<br>– Factor 3<br>– Factor 4<br>– Factor 5… | | – Factor 1<br>– Factor 2<br>– Factor 3<br>– Factor 4<br>– Factor 5… | |
| **Total points** | | **Total points** | |

*Source:* created by authors based on [5]

$$X_{ST} = \sum X_S \times \sum X_T \quad (2)$$

$X_{ST}$ — cumulative score assessment of the feasibility of implementing a strategy combining strengths and threats;

$\sum X_T$ — overall assessment of the strength of threats, determined by the sum of the points.

$$X_{WO} = \sum X_W \times \sum X_O \quad (3)$$

$X_{WO}$ — cumulative score assessment of the feasibility of implementing the strategy of combining weaknesses and opportunities;

$\sum X_W$ — overall assessment of the strength of the weaknesses, determined by the sum of the points.

$$X_{WT} = \sum X_W \times \sum X_T \quad (4)$$

$X_{WT}$ — cumulative score assessment of the feasibility of implementing a strategy combining weaknesses and threats.

As a result, we will have a generalizing SWOT matrix for choosing the optimal strategy for the behavior of the object of analysis in the market.

In the analysis matrix, the interaction of factors occurs, resulting in the following areas: S&O — the area of interaction of strengths and opportunities; W&O — the area of interaction of weaknesses and opportunities; S&T — the area of interaction of strengths and threats; W&T — the area of interaction of weaknesses and threats. In accordance with the pair interactions that are in these areas, a further economic business model is built based on a map of alternative strategy vectors. Accordingly, the strategy vector is determined by the area of the rectangles that characterize the corresponding area of interaction of factors of strengths and weaknesses, opportunities and threats. The choice of the optimal strategy of behavior should be carried out in accordance with the maximization of the area of the rectangle of the interaction of factors [33].

$$\begin{cases} S_{S\&O} = X_{SO} = \sum X_S \times \sum X_O \rightarrow \max \\ S_{W\&O} = X_{WO} = \sum X_W \times \sum X_O \rightarrow \max \\ S_{S\&T} = X_{ST} = \sum X_S \times \sum X_T \rightarrow \max \\ S_{W\&T} = X_{WT} = \sum X_W \times \sum X_T \rightarrow \max \end{cases}$$

The optimal strategy will be to combine those factors, the product of the score estimates and, accordingly, the area of the interaction rectangle, which is maximum.

### 3. Results and Discussion

According to the Upcycled Food Association, upcycling food is “the process of transforming by-products, surplus food, and food waste into new, high-quality products for human consumption”. In 2020, a group of specialists from Harvard Law School, Drexel University, the World Wildlife Fund, Natural Resources Defense Council, ReFED, and other organizations officially established the definition of ‘upcycled food’ for applications in policy, research, and beyond: “Upcycled foods use ingredients that otherwise would not have gone to human consumption, are procured and produced using verifiable supply chains, and have a positive impact on the environment” [34].

Food waste can be classified into consumer waste, production waste and post-consumer waste [35]. Production or industrial food waste is usually organic residues defined as unavoidable food waste generated during sorting and cleaning processes, and is mainly represented by plant-based waste such as fruit and vegetable peels or pomace; grains and cereal bran; and animal waste that has no economic value for the producing company, therefore, it is intended to be processed according to the linear model [36]. Except for this waste, if it is intended for reuse by the same company or other organizations, it cannot be considered as waste, but becomes a by-product with a market value.

As world community work toward a more sustainable future, upcycling presents an effective and meaningful solution to cut waste, reduce $CO^2$ emissions, and minimize land use.

Reducing waste: by repurposing food by-products, it can significantly reduce the amount of waste that ends up in landfills, which helps lower methane emissions. The Food and Agriculture Organization states that food waste is responsible for approximately 8% of global greenhouse gas emissions [37].

Lowering $CO^2$ emissions: upcycling typically uses less energy than creating new materials from scratch. For instance, repurposing spent grain into flour instead of growing new crops conserves energy and resources, lowering the overall carbon footprint.

More food, less land: upcycling enables us to maximize the use of existing resources, allowing for the production of more food without the need for additional agricultural land. This is essential for protecting natural habitats and preserving biodiversity.

Everyday examples of food upcycling:

1. From brew to bread. Spent grain, a byproduct of beer brewing, is rich in nutrients and can be upcycled into high-fiber, protein-packed flour. This flour can be used to bake bread, cookies, or even pasta, transforming what would have been discarded into delicious and nutritious foods.

2. Turning fruit scraps into snacks. Some companies upcycle leftover fruit pulp into snacks, dried chips, or smoothie bases, utilizing the remaining fiber and flavor to create tasty and healthy products.

3. Coffee grounds in baking. Leftover coffee grounds are increasingly used in baked goods like brownies and cookies. Not only do they add a rich, earthy flavor, but this practice also helps reduce the waste generated by coffee shops and households.

In general, the process of transforming food waste and leftovers into food supplements is a growing trend in sustainability and the circular economy. It involves recycling food waste (such as peels, stems, seeds, or leftovers) into valuable ingredients that can be used in health-oriented products. This approach not only reduces food waste, but also creates new sources of nutrients and functional ingredients. The main pathways for this transformation are:

*1. Source of food waste.*

Fruits and vegetables: the peels, cores, and other parts of fruits and vegetables that are often thrown away can be rich in vitamins, fiber, and antioxidants. For example, citrus peels contain flavonoids that are beneficial for health.

Grains and seeds: the leftover parts of grains, such as spent grains from brewing or rice husks, can be processed into flours or protein-rich powders.

Coffee grounds and tea leaves: these byproducts may contain antioxidants and nutrients that can be extracted and used in supplements or skin care products.

*2. Processing methods.*

Drying: innovative drying techniques, e.g. freeze-drying or air-drying, are often used to preserve nutrients in food waste without losing as flavor as quality. This method reduces the moisture content, making it easier to process leftovers into powders or concentrates.

Fermentation: companies use fermentation to improve the nutritional profile of food waste, e.g. fermented fruits or vegetables. This not only improves the nutrient content, but can also add probiotics and other beneficial compounds.

Cold pressing: some products, such as fruit pulp or vegetable waste, can be cold pressed to extract juices or oils, which are then concentrated into food supplements.

*3. Creating food supplements.*

Powders and protein supplements: once food waste is processed into powders or concentrated forms, it can be used in food supplements, e.g. protein powders, vitamin-rich shakes, or smoothie boosters. For example, spent grains can be dried and ground into flour that is used in baking or mixed into protein shakes.

Functional products: using processed food waste or leftovers, manufacturers can create functional products that provide additional health benefits. For example, powders from vegetable waste can be added to energy bars or smoothies, increasing the fiber and antioxidant content.

Nutrient-rich extracts: leftovers such as fruit peels or seeds can be processed into extracts rich in vitamins (such as vitamin C from citrus peels) or omega-3 fatty acids from seeds. These extracts can then be incorporated into dietary supplements or used to fortify other foods.

*4. Health benefits.*

Fiber and antioxidants: a lot of food waste byproducts are rich in fiber, which is important for digestion and maintaining gut health. They also often contain antioxidants that help fight inflammation and oxidative stress, which could be the subject of a specific type of food supplement.

Vitamins and minerals: leftovers from fruits and vegetables can be rich in essential vitamins like A, C, and E, which support a healthy immune system, skin, and overall well-being.

*5. Sustainable development.*

Recycling food waste and leftovers into supplements not only reduces the environmental impact of landfills, but also closes the loop in the food production system, aligning with the principles of a circular economy. By turning waste into valuable products, companies are helping to conserve resources and reduce the need for new raw materials. There are some samples of companies with sustainable approach in business:

– Toast Brewing: this company brews beer from leftover bread and also recycles the grains into protein-rich products [38].
– Upcycled Food Association: this non-profit organization helps promote the use of food waste as an ingredient in food products, including supplements [39].

*Table 2*

**SWOT map of food upcycling**

| **Opportunities** | **Point** | **Threats** | **Point** |
|---|---|---|---|
| – reducing food waste | 5 | – safety and quality issues | 5 |
| – using useful food properties | 4 | – non-compliance with food standards | 5 |
| – production of functional supplements | 4 | – loss of nutritional value | 3 |
| – increasing economic efficiency for business and countries | 3 | – psychological barrier of consumers | 4 |
| | | – supply instability | 2 |
| – improving food technology | 5 | – environmental risks | 2 |
| – social responsibility | 4 | | |
| **Total points** | **25** | **Total points** | **21** |
| **Strengths** | **Point** | **Weakness** | **Point** |
| – economic benefit | 4 | – lack of legal basis on this issue | 5 |
| – reducing production costs | 2 | – negative perception by consumers | 5 |
| – innovations development in the food industry | 5 | – social and cultural barriers | |
| | | – high costs for technology and equipment | 4 |
| – improving food security | 3 | – difficulties in scaling production | 4 |
| – stimulating the development of a “circular” economy | 5 | – heterogeneity and instability of raw materials | 3 |
| – increasing awareness of healthy eating | 3 | | 4 |
| **Total points** | **22** | **Total points** | **25** |

*Source:* created by authors

– Upcycled Foods, Inc. (ReGrained): this company takes grains from breweries and recycles them into nutrient-rich bars and flours [40].

In general, converting food waste into food additives is an innovative and effective way to address both food waste and nutrition issues. It's a win-win for everyone in terms of sustainability, reducing waste, and providing valuable nutrients to consumers.

The above gives grounds to assert the unconditional feasibility of converting food waste into food supplements.

Accordingly, we will identify alternative SWOT strategies as a tool for determining the feasibility of processing food waste to obtain food supplements.

The overall assessment of the strength of each group of factors, calculated by summing the individual points, is as follows: the strength of strengths is 22 points, weaknesses total 25 points, the strength of opportunities also amounts to 25 points, and threats account for 21 points. Based on these evaluations, we can construct a comprehensive general SWOT matrix that will guide the selection of the optimal strategy for implementing food upcycling within this context. The general SWOT matrix is presented below.

Based on the results of the calculations, the highest value is observed in the intersection of weaknesses and opportunities, where the cumulative score reaches 625 points. This indicates a significant alignment between the identified weaknesses and the potential opportunities available. To visually represent these findings, the graph below illustrates the chosen vector for the alternative SWOT strategy, providing a clear depiction of the strategic direction based on the analysis.

As it mentioned above the food upcycling process needs a strategy that mitigates the weaknesses of food upcycling while leveraging its opportunities. The structured approach to build such a strategy includes policy and regulatory development addressing the lack of legal basis. The possible way could be collaboration with policymakers, industry experts, and international organizations to establish clear regulations for food upcycling. Opportunities help align legal frameworks with global sustainability trends and use the argument of economic efficiency to advocate for incentives and subsidies.

Consumer education could be reached with awareness campaigns addressing the negative perception by consumers, social and cultural barriers. It includes developing targeted campaigns to change consumer perception about upcycled food products. Opportunities help to emphasize health benefits (functional supplements, improved food technology) and to partner with influencers, chefs, and sustainability advocates to reshape social norms.

*Cost reduction through innovations (addressing: high costs for technology and equipment).*

Action: Invest in R&D to develop cost-effective upcycling technologies and alternative processing methods.

How Opportunities Help:

- Improved food technology can optimize processes and lower costs.
- Economic efficiency for businesses will attract investors and grants.

*Scalable business models (addressing: difficulties in scaling production).*

Action: Foster partnerships between startups, food manufacturers, and hospitality businesses to create scalable production chains.

How Opportunities Help:

- Reducing food waste provides a continuous supply of raw materials.
- Economic benefits will attract investors and facilitate expansion.

*Stable supply chain management (addressing: heterogeneity and instability of raw materials).*

Action: Develop a digital platform for food waste collection and classification, ensuring a steady and quality supply of raw materials.

How Opportunities Help:

- Social responsibility can motivate businesses to join such networks.
- Technology improvements will enhance tracking and quality control.

As we can see, successful implementation of food processing depends on a comprehensive strategy that addresses both threats and opportunities. By focusing on key areas such as policy and regulation development, consumer education, technological innovation, scalable business models and supply chain management, the food processing industry can overcome existing barriers and realize its full potential. Collaboration with policymakers, experts and influencers, as well as investment in research and development, will help create an environment conducive to growth. Seizing opportunities such as global sustainability trends, technological advances and cost efficiencies will not

*Table 3*

**General SWOT matrix of food upcycling**

| | | **Opportunities** | **Threats** |
|---|---|---|---|
| | | $\sum X_O$ = 25 points | $\sum X_T$ = 21 points |
| **Strengths** | $\sum X_S$ = 22 points | S&O<br>$X_{SO}$ = 22*25 = 550 | S&T<br>$X_{ST}$ = 22*21 = 462 |
| **Weakness** | $\sum X_W$ = 25 points | W&O<br>$X_{WO}$ = 25*25 = 625 | W&T<br>$X_{WT}$ = 25*21 = 525 |

*Source:* created by authors

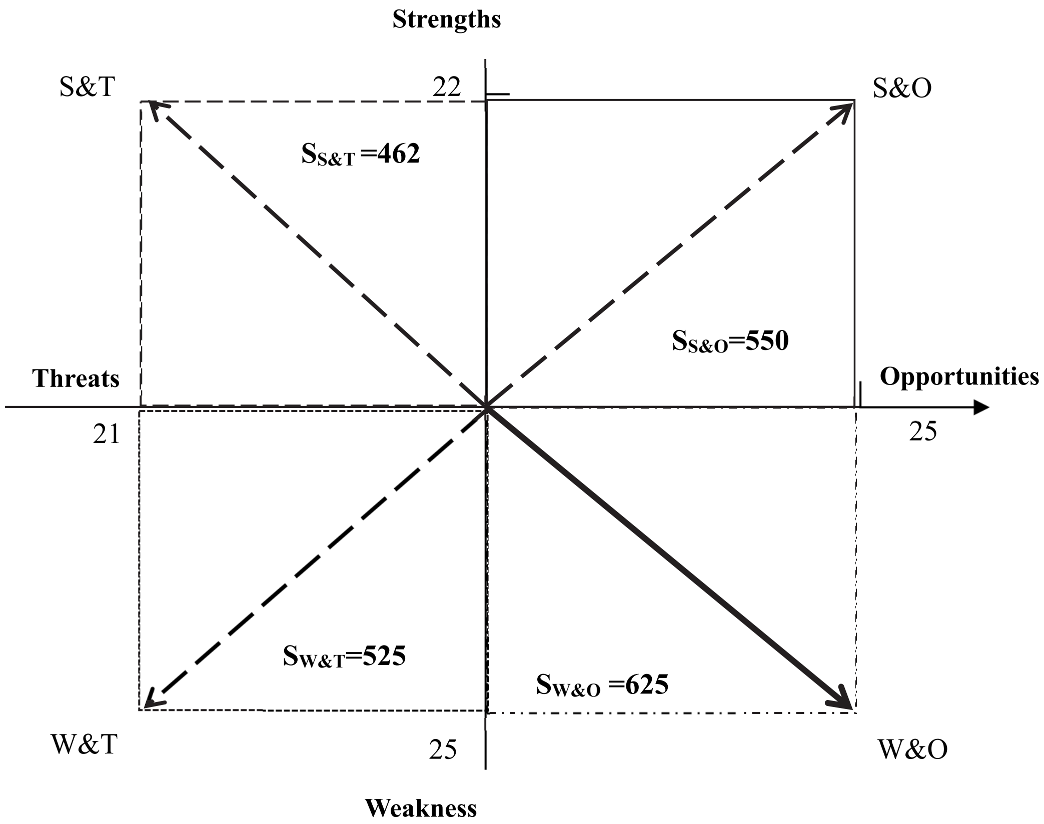


Figure 1. Vector of the alternative SWOT strategy
*Source:* created by authors

only strengthen the industry but also facilitate its widespread adoption. Ultimately, with a strategic and well-coordinated approach, food processing can become a key component of sustainable food systems.

### 4. Conclusions

Addressing food waste is a critical global issue with far-reaching consequences for society, the economy and the environment. Food waste can be described as a significant portion of resources that could otherwise contribute to a more sustainable food system. With global food waste levels reaching staggering levels every year, and sectors such as the hospitality industry contributing significantly to this waste, it is clear that innovative solutions are urgently needed. In this context, food recycling has emerged as an important and promising approach to reducing waste while simultaneously creating valuable products that can contribute to human health.

Food upcycling involves the recycling of food waste, surplus food and food scraps into new, high-quality products for human consumption. It aligns with the principles of the circular economy, transforming waste into valuable resources and closing the loop in the food production system. Examples of beer grounds, fruit pulp, coffee grounds and other food residues confirm the growing recognition of the nutritional potential of these often-discarded leftovers. Food upcycling can provide nutrient-rich ingredients for food supplements, functional foods and even improve the production of everyday food products such as snacks, flours and beverages.

The potential for upcycling leftovers is enormous, not only in terms of solving the problem of food waste, but also in terms of the opportunities it offers for economic and sustainable development. By upcycling food waste into nutraceuticals — food products that promote health — companies are simultaneously addressing two pressing issues: food waste and nutrient deficiencies. Using food waste as ingredients in supplements and functional foods could make a significant contribution to the health and wellness industry, creating a valuable market for these upcycled materials. As research into food upcycling continues to grow, new technologies and processing methods, such as drying, fermentation, and cold pressing, will play an important role in unlocking the full potential of food waste.

However, the successful implementation of food upcycling depends on careful consideration of both the opportunities and the challenges. The SWOT analysis conducted in this study highlighted the need for a strategic approach to address the weaknesses of the current food processing industry while capitalizing on its opportunities. Key areas identified for improvement include regulatory development, consumer education, technological innovation, scalable business models, and supply chain management. Collaboration with policymakers, industry experts, and international organizations is essential to create a clear legal framework for food upcycling that aligns with the global sustainable development goals. By creating policies that encourage and support the adoption of upcycling practices, governments can encourage businesses to invest in innovative technologies and processes.

Equally important is the need for consumer education. Food upcycling is still a relatively new concept, and many consumers remain unaware of the benefits or the nutritional value of upcycled products. Targeted awareness campaigns, which address negative perceptions and social barriers, are crucial to changing consumer attitudes and encouraging the adoption of upcycled foods. Emphasizing the health benefits of upcycled products — such as the presence of antioxidants, fiber, and essential vitamins — can help reshape consumer perceptions and promote the idea of upcycling as a sustainable and healthy alternative.

Technological innovation is another key factor that can drive growth in the food processing industry. High technology and equipment costs have been identified as significant barriers to scaling up production. However, investing in research and development to create cost-effective processing technologies and alternative processing methods will reduce production costs and make processing more financially viable. As technology advances, businesses will be better equipped to optimize processes, improve product quality, and reduce costs, creating a more sustainable food system.

In addition to technological advances, promoting scalable business models is essential to the long-term success of food processing. By forming partnerships between startups, food manufacturers, and hospitality businesses, the food industry can create robust value chains that support the upcycle process. Reducing food waste will ensure a continuous supply of raw materials, and the resulting economic benefits will attract additional investment and expansion opportunities. A scalable approach will be critical to meeting the growing demand for processed foods while maintaining a stable and reliable supply chain.

Finally, sustainable supply chain management is vital to ensure the stability and quality of raw materials used in upcycling food production. Developing digital platforms to collect and classify food waste will help businesses track and manage their raw material supply, ensuring that it meets the required processing standards. Technological advances in this area will also improve supply chain efficiency and transparency, further enhancing the reliability of upcycling. Ultimately, the success of upcycling as a sustainable solution depends on a coordinated, multi-faceted strategy that addresses both the challenges and opportunities present in the current food system. By focusing on policy development, consumer education, technological innovation, scalable business models, and supply chain management, upcycling can play a key role in creating a more sustainable, resource-efficient food system. As the global community works to achieve the SDGs, upcycling can reduce food waste, reduce greenhouse gas emissions, conserve natural resources, and provide consumers with valuable nutrients. With the right strategies, food upcycling can become an integral part of a sustainable future food.

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# ВІД ХАРЧОВИХ ВІДХОДІВ ДО ХАРЧОВИХ ДОБАВОК: СТАЛА ТРАНСФОРМАЦІЯ ДЛЯ ЕКОНОМІЧНОЇ БЕЗПЕКИ

***Анотація.*** *У цій науковій праці ми досліджуємо потенціал співпраці між готельним бізнесом та виробниками харчових добавок. Концепція відповідає принципам сталого розвитку, враховуючи як соціальні, так і екологічні проблеми. Зокрема, вона зосереджена на зборі та подальшій переробці харчових відходів у харчові добавки. У статті визначено альтернативні SWOT-стратегії для оцінки доцільності цієї ідеї в підприємницькому секторі. Одним з ключових рішень проблеми харчових відходів є переробка харчових продуктів, що набирає обертів, коли невикористані харчові відходи перетворюються на нові продукти. Новітні інноваційні методи, такі як передові технології сушіння харчових продуктів, пропонують ефективні способи боротьби з харчовими відходами шляхом перетворення відходів на поживні продукти без надмірного нагрівання. У дослідженні висвітлено кілька критичних аспектів переробки харчових продуктів, зокрема: економічну ефективність завдяки збереженню ресурсів, зменшення залежності від зовнішніх джерел їжі та підвищення продовольчої безпеки. Цей процес також сприяє технологічному розвитку, залученню інвестицій та створенню нових робочих місць, що зміцнює економічну стабільність. Крім того, переробка зменшує кількість відходів та зберігає природні ресурси, позитивно впливаючи на екологічну та економічну стійкість. Перетворюючи харчові відходи на цінні добавки, цей підхід сприяє досягненню цілей сталого розвитку, таких як боротьба з голодом та покращення доступу до поживної їжі, тим самим сприяючи як соціальній, так і економічній безпеці на національному рівні.*

***Ключові слова****: сталий розвиток, харчові відходи, харчові добавки, продовольча безпека, економічна безпека.*

JEL: C55; M31; L81

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# EVALUATING CUSTOMER EXPERIENCE IN E-COMMERCE: MULTILINGUAL SENTIMENT ANALYSIS OF USER REVIEWS USING TRANSFORMER MODELS

***Abstract.*** *This study addresses the challenge of multilingual sentiment analysis in e-commerce, with a focus on Ukrainian and Russian book reviews. We propose a hybrid framework based on transformer architectures that accounts for the linguistic complexity of Slavic languages and the significant class imbalance often present in customer feedback data. Using a dataset of approximately 70,000 user reviews from the Ukrainian online bookstore Yakaboo, we evaluate four model variants based on the XLM-RoBERTa architecture and compare their performance to a monolingual Ukrainian RoBERTa baseline.*

*The classification task is formulated as binary: identifying low-rated reviews (1–3 stars) versus high-rated ones (4–5 stars), with the minority class comprising only 4–5% of the dataset. Our best-performing model — combining partial fine-tuning, a deep classifier, and focal loss — achieves a macro F1 score of 0.73 and an F1 score of 0.47 for the minority class, outperforming the baseline (0.66 and 0.37, respectively). The application of oversampling and focal loss proved effective in mitigating class imbalance.*

*Beyond technical performance, the findings underline the practical utility of accurate sentiment detection for e-commerce platforms. Effective identification of negative feedback enables companies to address customer dissatisfaction, refine product offerings, and inform personalized marketing strategies. This research contributes to advancing multilingual NLP in low-resource settings and provides a scalable solution for real-world sentiment classification in morphologically rich languages.*

*The scientific novelty of this research lies in the integration of multilingual transformer architectures with adaptive classifiers and class imbalance mitigation techniques, specifically tailored for real-world e-commerce review data in morphologically rich languages. The proposed framework demonstrates how domain-specific fine-tuning and architectural customization can significantly enhance sentiment classification performance in low-resource language settings.*

***Keywords:*** *Sentiment analysis, Natural Language Processing, e-commerce, customer experience, multilingual transformer models, XLM-RoBERTa, class imbalance.*

## 1. Introduction

In today's digital-first economy, user-generated content, particularly online reviews, has become a cornerstone of consumer interaction and business intelligence. The proliferation of e-commerce platforms, online marketplaces, and digital publishing environments has led to an exponential growth in the volume of user reviews, which — accompanied by star ratings — form a powerful dual-source of information offering both qualitative textual feedback and quantitative evaluation. According to Statista [1], the global e-commerce market reached $4.3 trillion in 2024, with strong projections for continued growth. On the one hand, this is due to the increased use of AI in digital marketing [2–4], on the other hand, this boom has placed increasing emphasis on companies' ability to monitor and respond to consumer sentiment in real time.

User-generated reviews have become especially critical for publishers, providing immediate feedback on content quality and user satisfaction. However, effectively utilizing this feedback presents substantial challenges. Online reviews are inherently unstructured and written in free-form language that often includes irony, sarcasm, slang, and ambiguity. This complexity is further compounded in Slavic languages, where lexical variation and rich morphological structures complicate text analysis [5]. Moreover, a frequent mismatch exists between the emotional tone expressed in the review text and the numeric star rating assigned by the user, complicating models that rely solely on one of these data sources to infer satisfaction [4, 6].

Sentiment analysis (SA), a key subfield of Natural Language Processing (NLP), seeks to determine the emotional polarity (positive, negative, or neutral) of a given text. With the advent of Deep Learning (DL), particularly transformer-based architectures such as BERT (Bidirectional Encoder Representations from Transformers) and its multilingual variants (e.g., XLM-RoBERTa) [7–8], the field has achieved significant progress. These models leverage pretraining on massive corpora to capture complex syntactic and semantic relationships, enabling more contextually aware sentiment classification. Empirical studies [9–12] have shown that transformer-based models consistently outperform conventional approaches across a wide range of NLP tasks.

Despite these advancements, two practical challenges remain underexplored. First is the issue of class imbalance in sentiment-labeled datasets. Most users are more likely to submit a review when they are highly satisfied or highly dissatisfied, resulting in a skewed distribution of sentiment labels. This imbalance can bias machine learning models, leading to poor performance in identifying underrepresented classes — typically negative reviews. Second is the inconsistent correlation between textual sentiment and star ratings, which can obscure the true emotional content of a review. These challenges are particularly pronounced in book reviews, where literary language, figurative expressions, and subjective interpretation often influence the sentiment expressed.

This paper proposes a novel approach to detecting low-rated book reviews (1 to 3 stars) by leveraging sentiment classification on multilingual (Ukrainian and Russian) data. We frame the task as a binary classification problem focused on identifying negative or neutral sentiment, regardless of the explicit star rating. Our objectives are threefold:

1. To evaluate the effectiveness of multilingual transformer-based models (specifically XLM-RoBERTa) in classifying review sentiment in a binary setting (positive vs. negative/neutral).
2. To assess the performance of a monolingual baseline model (UA-RoBERTa) trained specifically on Ukrainian data.
3. To explore the impact of class imbalance mitigation techniques, such as oversampling and focal loss, on classification performance, with particular emphasis on the underrepresented class of negative reviews (approximately 4%).

Our contributions are as follows:

- We compile and preprocess a real-world dataset of user reviews in Ukrainian and Russian.
- We compare transformer-based sentiment classification models, including monolingual and multilingual variants.
- We experiment with fine-tuning and freezing strategies for large multilingual language models.

By focusing on the sentiment classification of book reviews in a multilingual and imbalanced dataset, this research contributes to both technical and applied aspects of NLP. From a technical standpoint, it demonstrates the viability of large-scale multilingual models in low-resource and morphologically rich language settings. From an applied perspective, the insights generated may inform the development of recommender systems, editorial decision-making tools, and customer experience dashboards in publishing and e-commerce domains.

The remainder of this paper is structured as follows. Section 2, *Materials and Methods*, presents related work, dataset description, identified limitations of existing approaches, and the proposed modeling framework. Section 3, *Results and Discussion*, describes the experimental setup, evaluates model performance, and analyzes classification results. Section 4, *Conclusions*, summarizes the key findings and outlines practical implications and directions for future research.

## 2. Materials and Methods

### 2.1. Review resent papers

Sentiment analysis (SA) has emerged as a critical tool for interpreting user-generated content in e-commerce environments [9]. As noted by Ge et al. [13], the field has evolved significantly from basic rule-based sentiment classifiers to sophisticated deep learning (DL) approaches, with transformer-based models representing the current state of the art.

Numerous studies have investigated the relationship between star ratings and review sentiment. Authors of [6] identified substantial discrepancies between numerical star ratings and textual sentiment, showing that text often conveys nuances not reflected in the rating. Bigne et al. [4] examined this misalignment in the tourism sector, while Pan and Zhang [14] were among the first to explore interactions between review text and rating valence. Subsequent studies, including [15–16] further analyzed these inconsistencies, highlighting how review length and sentiment richness may impact user interpretation and model accuracy.

Several studies have addressed SA in low-resource languages. Authors of [17] evaluated data augmentation techniques to overcome data scarcity, and paper [6] were presented a systematic review of multilingual SA methods for under-resourced languages, emphasizing transfer learning and cross-lingual modeling. Aliyu et al. [18] extended this discussion with a comprehensive overview of models, languages, and datasets applicable to low-resource SA tasks.

The rise of transformer-based architectures has fundamentally reshaped NLP research. Devlin et al. [7] introduced BERT, enabling contextualized bidirectional language representations. Conneau et al. [8] later proposed XLM-RoBERTa, a multilingual transformer trained on a large corpus of 100 languages. Barbieri et al. [19] introduced XLM-T, optimized for Twitter-based multilingual SA. Authors of [20] compared multilingual approaches on social media data, while Miah et al. [21] proposed a multimodal ensemble combining transformers and LLMs. Results of paper [22] were demonstrated the superiority of DL methods including transformer-based architectures over traditional ML in analyzing e-commerce reviews.

In a series of contributions, authors of [11, 23–25] investigated content analysis and sentiment detection in electronic media using ML techniques. Their work includes a methodology for content analysis of mass media texts [23], a study on emotional polarity classification in social networks [24], and an empirical comparison of DL models for sentiment classification in social media [25]. In a separate applied study, they analyzed social media content with ML methods to support sentiment detection pipelines in digital environments [11].

Another well-known challenge in SA is class imbalance. In real-world datasets, positive reviews often dominate, while negative reviews although typically more informative are underrepresented [26–27]. Oversampling methods such as SMOTE [28] have been widely used to address this issue by synthetically generating samples for the minority class. Additional methodological challenges include code-switching, sarcasm detection, negation handling, and cultural variation in sentiment expression.

Several review papers have synthesized the evolving landscape of SA. Authors of [9, 29] analyzed the application of sentiment analysis on e-commerce platforms, while Mao et al. [30] provided a comprehensive review of sentiment methods, challenges, and trends in both traditional ML and modern DL contexts. Results of paper [31] emphasized the importance of feature engineering for Chinese reviews. Authors of [10] surveyed multilingual DL approaches for sentiment analysis in social media.

Research focusing on Slavic languages (especially for Ukrainian) remains relatively limited. Thus, Radchenko [32] proposed fine-tuned RoBERTa model for Ukrainian language, and Prytula [5] benchmarked transformer models including BERT, DistilBERT, XLM-RoBERTa, and UKR-RoBERTa on Ukrainian sentiment classification.

In summary, recent literature demonstrates the rapid advancement of sentiment analysis techniques, particularly in multilingual and low-resource contexts. However, limited research has explored sentiment classification in Slavic languages using deep transformer-based models in imbalanced datasets. Our work builds on this gap by applying multilingual transformers to Ukrainian and Russian reviews and addressing class imbalance through oversampling and loss-based optimization.

### 2.2. Limitations of Existing Approaches

Despite the availability of various sentiment analysis tools and pretrained models, several critical limitations emerge when applying them to the task of analyzing multilingual user reviews, particularly for low-resource and morphologically rich languages such as Ukrainian and Russian. These limitations can be categorized into five key areas:

**1. Insufficient Language Support.** Most widely used sentiment analysis libraries, such as *TextBlob, VADER*, and *Afinn*, are primarily optimized for English-language content. Their performance deteriorates significantly when applied to Slavic languages, which differ substantially in morphology, syntax, and semantics. Furthermore, these libraries typically lack native support for Ukrainian and Russian, leading to unreliable outputs and limited generalization [5, 12, 18].

**2. Constraints of Proprietary Large Language Models (LLMs).** While state-of-the-art commercial models (e.g., OpenAI GPT, Google Gemini, Anthropic Claude) demonstrate strong multilingual capabilities, they are accessible only via API-based interfaces that often involve high usage costs. This poses challenges for large-scale academic studies, particularly those requiring privacy, reproducibility, or transparency. Additionally, their black-box nature limits control over internal processes and domain-specific adaptations [21].

**3. Limited Customization in Cloud-Based Sentiment Platforms.** Cloud-based NLP platforms such as Google Cloud Natural Language API or IBM Watson offer sentiment analysis as part of broader content analytics services. However, these tools are often subscription-based and offer limited ability to fine-tune models for specific domains. Their general-purpose pretrained models tend to oversimplify domain-specific sentiment, especially in contexts such as literary critique or user reviews in e-commerce [25].

**4. Translation-Based Workarounds.** A common workaround involves translating user reviews into English and then applying established English-language sentiment models. While convenient, this approach introduces additional sources of error. Machine translation may distort sentiment-laden expressions, weaken contextual nuance, or omit subtle emotional cues — particularly problematic for reviews that rely on idioms, sarcasm, or domain-specific phrasing. As a result, the final sentiment prediction may deviate significantly from the original intent [12, 31].

**5. Misalignment Between Text and Rating Labels.** In real-world datasets, star ratings and textual sentiment are frequently misaligned. For instance, a user might assign a high star rating while expressing critical opinions in the review text or vice versa. This misalignment undermines the validity of models trained exclusively on rating labels, as they fail to capture mixed or nuanced sentiment expressions that are common in subjective review genres such as book evaluations [4, 6, 24].

Taken together, these limitations underscore the need for domain-adapted and language-specific sentiment models trained on real multilingual data. In this study, we aim to overcome these barriers by applying fine-tuned transformer-based architectures and custom classification components, tailored to the linguistic and structural characteristics of Ukrainian and Russian user reviews.

### 2.3. Dataset Description

This study utilizes the Yakaboo Book Reviews dataset, a large-scale corpus of user-generated reviews collected from the Ukrainian online bookstore Yakaboo [33]. The dataset comprises 69,256 annotated entries, each containing a review text, a star rating (from 1 to 5), and associated metadata, such as publication date, book ID, and review ID. The reviews were published between May 2014 and August 2020, with the median date falling in April 2019.

To frame the sentiment classification task, we restructured the original 5-point star rating system into a binary classification problem. Reviews with ratings from 1 to 3 stars were grouped into the Low (1–3) class (label 1), while 4 and 5-star reviews were grouped into the High (4–5) class (label 0). This framing emphasizes the identification of less favorable feedback, which is both underrepresented and business-critical. The dataset is highly imbalanced, with approximately 83% of reviews rated 5 stars, and only 4–5% rated from 1 to 3 stars (see Figure 1).

Linguistically, the corpus is nearly evenly split between Ukrainian (49.5%) and Russian (51.5%), making it suitable for evaluating multilingual language models. On average, *Low-rated* reviews tend to be longer than *High-rated* ones in both languages (e.g., Russian: 194 vs. 179 words; Ukrainian: 217 vs. 197 words), suggesting that users may express dissatisfaction more elaborately (see Figure 2).

In our analysis, we used a concatenated version of both the review title and the review body as the

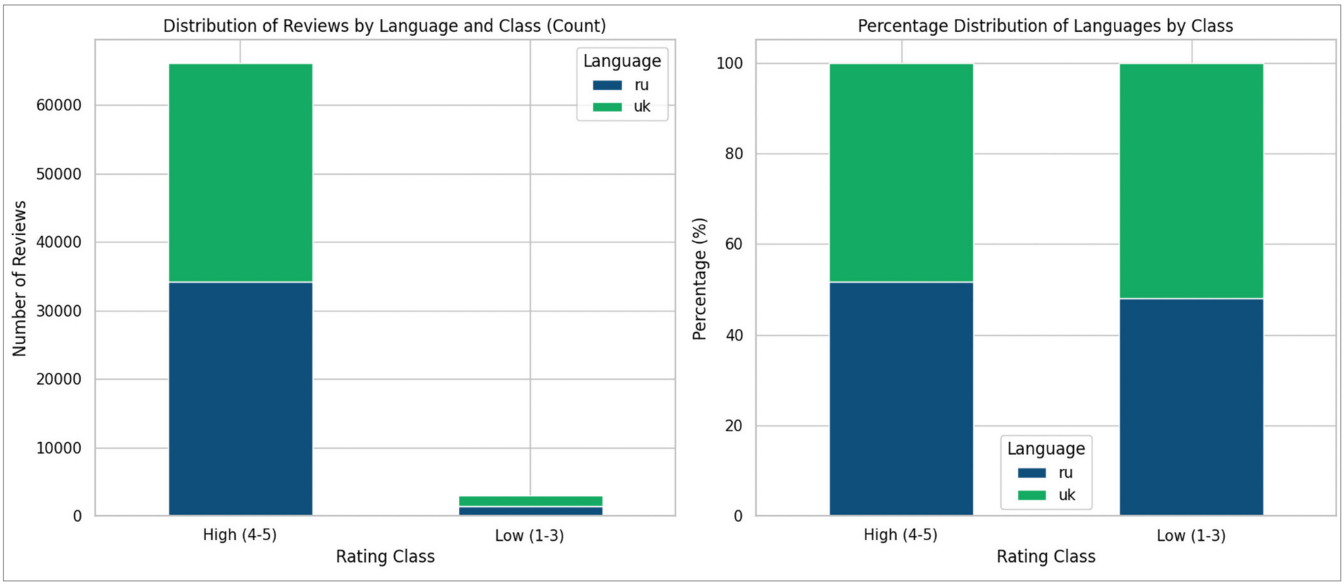



Figure 1. Distribution of Reviews by Language and Class
*Source:* calculated and designed by the authors

input text. To ensure consistency and improve model performance, we applied several preprocessing steps:
- Missing values in both review Title and review fields were replaced with empty strings.
- Excess whitespace and special characters were normalized using regular expressions.
- The final input text (text) was constructed by concatenating the review title and review fields with a space separator, followed by additional cleaning to remove redundant spaces.
- Reviews with empty or invalid text after preprocessing were filtered out.
- All text was lowercased to reduce vocabulary size and improve tokenizer efficiency.
- Potential HTML tags were stripped using regex-based patterns.
- Redundant punctuation (e.g., “!!!” or “???”) was normalized to a single instance to retain emotional intensity while avoiding overfitting.

This preprocessing pipeline ensured cleaner and more semantically meaningful inputs, suitable for tokenization by transformer-based language models.

### 2.4. Proposal Approach

To address the limitations of existing multilingual sentiment analysis tools, we propose a hybrid framework that combines fine-tuned transformer architectures with custom neural classifiers, optimized specifically for imbalanced, multilingual book reviews in Ukrainian and Russian. Our approach prioritizes:
- language-specific adaptability, addressing the morphological richness of Slavic languages;
- class imbalance mitigation, through techniques such as oversampling and focal loss;
- computational efficiency, via partial fine-tuning and frozen embeddings.

The main objective of this study is to predict review ratings (on a 1–5 star scale) using only textual content, with a particular focus on detecting low-rated (1–3 stars) reviews. We frame this as a binary sentiment classification task, targeting negative or neutral sentiment regardless of the explicit star rating. This task presents several challenges, including:
- significant class imbalance;
- subtle linguistic cues;
- the need to capture context-dependent sentiment patterns across two languages.

To address these issues, we implement a multilayer modeling framework that integrates pretrained multilingual transformers with task-specific classifiers.

Transformer-based language models such as BERT, RoBERTa, and XLM-RoBERTa have transformed NLP by effectively capturing semantic and syntactic nuances using self-attention mechanisms [7–8]. These models are pretrained on massive multilingual corpora, enabling strong cross-lingual understanding and robust performance across languages. In particular, XLM-RoBERTa is well suited for our task, as it supports morphologically rich languages and handles informal, user-generated content effectively.

Unlike monolingual models trained on English or Ukrainian, XLM-RoBERTa’s cross-lingual capacity allows us to use a single model for both Ukrainian and Russian reviews, thereby reducing the need for separate pipelines. Moreover, its pretrained embeddings allow downstream classifiers to better interpret idioms, code-switching, and informal sentiment expressions.

We designed and tested four architectural variants (Table 1), each exploring different trade-offs in model capacity, fine-tuning depth, and class imbalance robustness:

**UA RoBERTa.** A monolingual model pretrained on Ukrainian corpora [32], fine-tuned on the top two

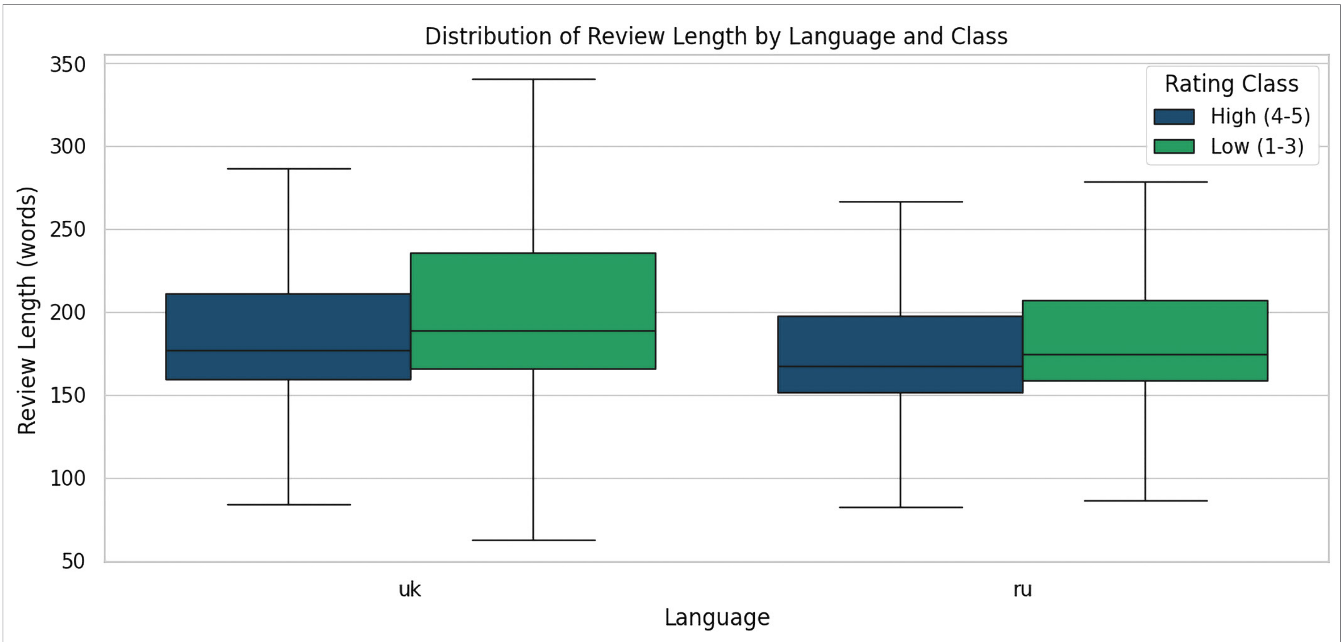



Figure 2. Distribution of Review’s Length by Language and Class
*Source:* calculated and designed by the authors

*Table 1*

**Architectural Variants**

| Variant | Backbone | Fine-Tuning | Classifier | Key Innovation |
|---|---|---|---|---|
| Baseline | UA-RoBERTa | Top 2 layers | Dense layer | Monolingual benchmark tailored for Ukrainian text |
| Variant 1 | XLM-RoBERTa | Top 2 layers | Dense layer | Lightweight multilingual adaptation with reduced training cost |
| Variant 2 | XLM-RoBERTa (frozen) | None | BiLSTM / CNN | Leverages frozen multilingual embeddings and adds sequential feature extraction |
| Variant 3 | XLM-RoBERTa | Top 2 layers | BiLSTM/CNN + Focal Loss | Integrates partial fine-tuning, advanced classifier, and imbalance-aware loss |

*Source:* designed by the authors

transformer layers and equipped with a dense classification head. Serves as a benchmark to compare against multilingual alternatives.

**Fine-tuned XLM-RoBERTa with Dense Classifier.** his configuration partially fine-tunes the top two layers of XLM-RoBERTa and applies a simple dense output layer (typically based on the [CLS] token) to map embeddings to sentiment classes. It offers a balance between performance and training cost.

**Frozen XLM-RoBERTa with Custom BiLSTM/CNN Classifier.** In this setup, the entire XLM-RoBERTa model is frozen, and its output embeddings are passed to a custom classifier composed of:

- BiLSTM: to model long-range dependencies and sequential sentiment patterns;
- 1D CNN: to extract n-gram features and localized emotional signals.

These classifiers are evaluated separately to identify which structure better utilizes the transformer-generated representations.

**Fine-tuned XLM-RoBERTa with BiLSTM/CNN Classifier**. This advanced variant integrates the strengths of both Variant 1 and Variant 2. It partially fine-tunes the top two layers of XLM-RoBERTa while adding a deep classifier (BiLSTM or CNN) and applying **focal loss** to dynamically adjust learning based on class distribution. This configuration directly targets the minority class problem and enhances detection of subtle or mixed sentiment expressions.

These variants represent a spectrum of trade-offs in terms of language specialization, computational efficiency, and classification complexity:

- The UA-RoBERTa baseline is strong for Ukrainian text but lacks multilingual capacity.
- Variant 1 provides an efficient and scalable multilingual alternative with partial fine-tuning.
- Variant 2 eliminates fine-tuning altogether, relying solely on pretrained embeddings and downstream modelling — suitable for low-resource scenarios.
- Variant 3 integrates fine-tuning, advanced classification, and class imbalance optimization, offering the most robust performance for imbalanced multilingual sentiment classification.

This modeling framework allows for a comparative evaluation of how different architectural choices affect classification accuracy, particularly for detecting negative or neutral user feedback in real-world, multilingual e-commerce environments.

## 3. Results and Discussion

### 3.1. Experimental Setup

To ensure comparability across all experiments, we standardized the training and evaluation procedures for each model variant. All models were trained using the Adam optimizer with an initial learning rate of 2e-5 and a linear learning rate scheduler with warm-up steps [34]. Training was conducted for a maximum of 5 epochs, with early stopping based on validation loss to prevent overfitting. The batch size was set to 16.

Considering the average length of user reviews (see Figure 2), we set a maximum input sequence length of 256 tokens for all models to ensure consistency in input representation across architectures.

Two loss functions were evaluated:

- **Binary Cross-Entropy (BCE)**: the standard choice for binary classification tasks;
- **Focal Loss:** employed to address class imbalance by dynamically scaling the contribution of each sample based on prediction confidence, emphasizing harder-to-classify examples [35].

To further mitigate the effects of class imbalance, the following techniques were applied [26]:

- **Class weighting**: weights inversely proportional to class frequency were applied during training;
- **Random oversampling**: minority class instances were oversampled using RandomOverSampler from the *imbalanced-learn* library. This was applied only to the training set to prevent data leakage.

Each of the four model variants based on XLM-RoBERTa was evaluated on the binary sentiment classification task, distinguishing between low-rated reviews (1–3 stars) and high-rated reviews (4–5 stars). Given that only about 4% of the dataset corresponds to low-rated reviews, the task presents a significant imbalance challenge.

To ensure robust evaluation, we used an 80/20 stratified train-test split of the dataset, preserving the proportion of the minority class in both subsets.

All experiments were implemented using the PyTorch DL framework and Hugging Face Transformers

[36], and executed in Google Colab Pro+, leveraging NVIDIA L4 GPUs (24 GB VRAM). Mixed precision training (FP16) was enabled to accelerate training and reduce memory usage.

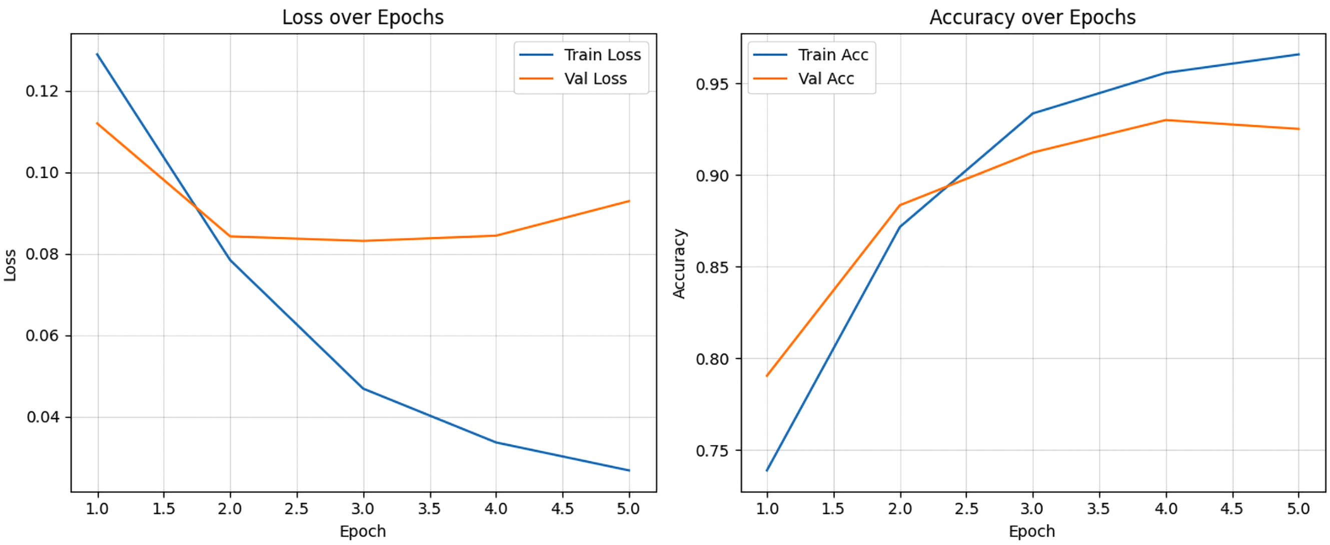
Figure 3 illustrates the training and validation loss and accuracy curves for the Baseline model (a) and Variant 3 (b). The Baseline model shows moderate overfitting: while training loss continues to decrease steadily, validation loss plateaus early and slightly increases after the third epoch. Accuracy follows a similar pattern, with a growing gap between training and validation performance. In contrast, Variant 3 demonstrates smoother convergence, with both loss and accuracy curves stabilizing by the fourth epoch. The smaller gap between training and validation metrics indicates better generalization, confirming the benefits of partial fine-tuning, focal loss, and the deeper classifier used in this configuration.

### 3.2. Classification Performance

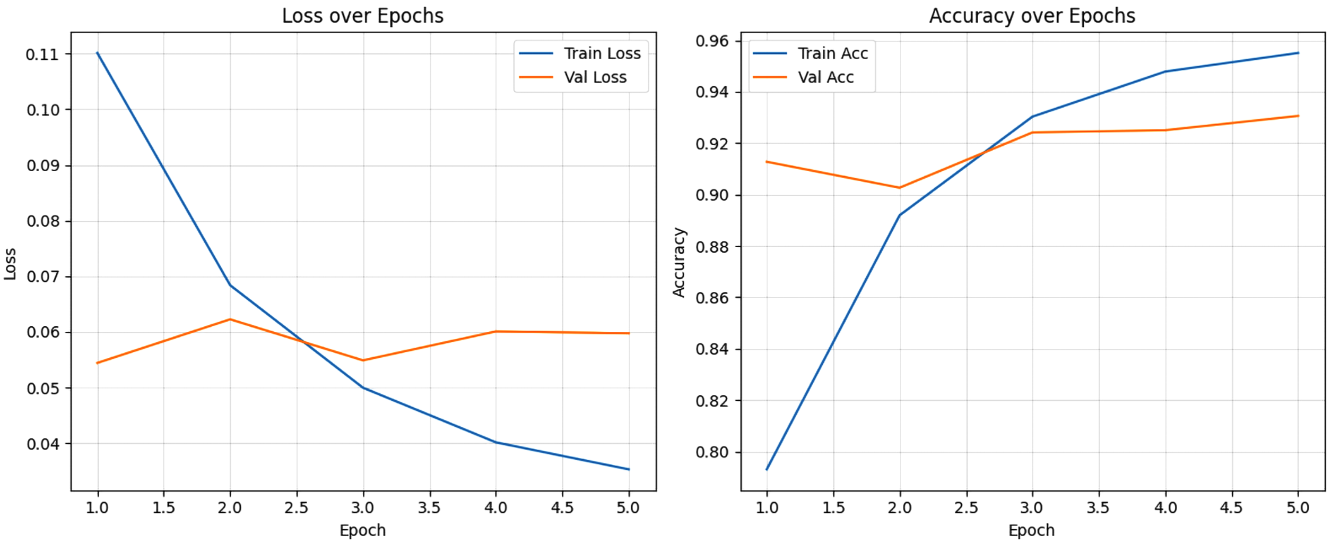
To evaluate model performance, we used a comprehensive set of metrics that reflect both overall accuracy and the models' ability to detect the minority class. Given the imbalanced nature of the dataset, particular attention was paid to performance on low-rated reviews (1–3 stars).

The following evaluation metrics were employed:

- **Macro F1**: the unweighted average of F1 scores across both classes, providing a balanced measure of performance regardless of class distribution;
- **F1 (Low)**: F1 score for the minority "Low-rated" class; a harmonic mean of precision and recall, this metric reflects the model's ability to detect negative/neutral sentiment;
- **Precision (Low)**: proportion of reviews predicted as "Low-rated" that were actually correct;
- **Recall (Low)**: proportion of actual "Low-rated" reviews that were correctly identified;




(a)




(b)

Figure 3. Training and validation loss/accuracy curves for the Baseline (a) and Variant 3 (b) models

*Source:* calculated and designed by the authors

*Table 2*

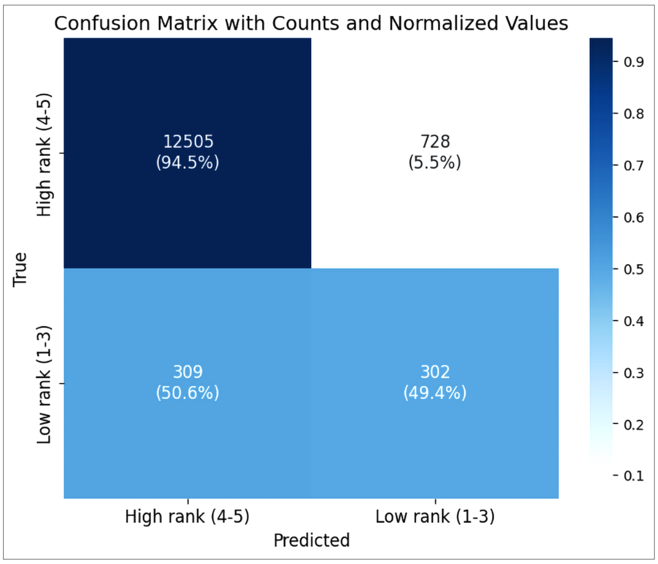
**Classification Performance by Model Variant**

| Variant | Macro F1 | F1 (Low) | Precision (Low) | Recall (Low) | ROC AUC | Inference Time (ms) | Accuracy |
|---|---|---|---|---|---|---|---|
| Baseline | 0.66 | 0.37 | 0.28 | 0.54 | 0.76 | 32 | 0.92 |
| Variant 1 | 0.7 | 0.43 | 0.31 | **0.71** | 0.83 | 36 | **0.93** |
| Variant 2 | 0.61 | 0.27 | 0.29 | 0.25 | 0.75 | **21** | 0.90 |
| Variant 3 | **0.73** | **0.47** | **0.39** | 0.6 | **0.84** | 41 | 0.92 |

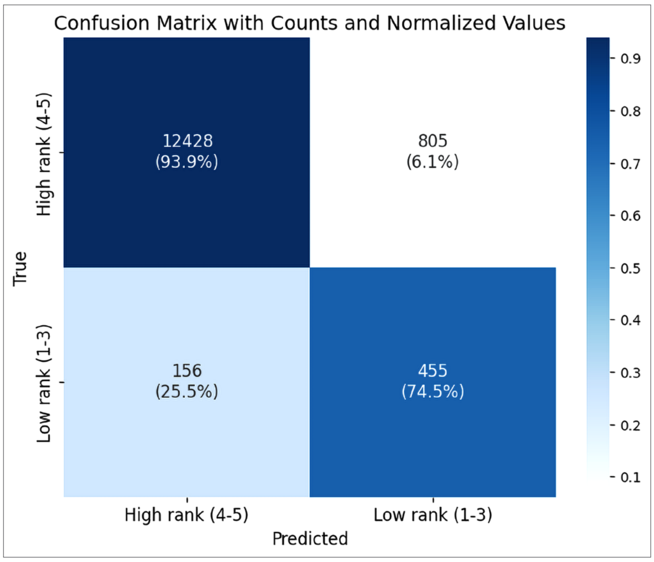
*Source:* calculated by the authors

- **ROC AUC**: the area under the Receiver Operating Characteristic curve, measuring the model's ability to distinguish between positive and negative sentiment across all thresholds;
- **Inference Time (ms)**: average time required to classify a single review; this metric is important for assessing real-world deployment feasibility;
- **Accuracy**: overall proportion of correctly classified reviews, though less informative in imbalanced settings.

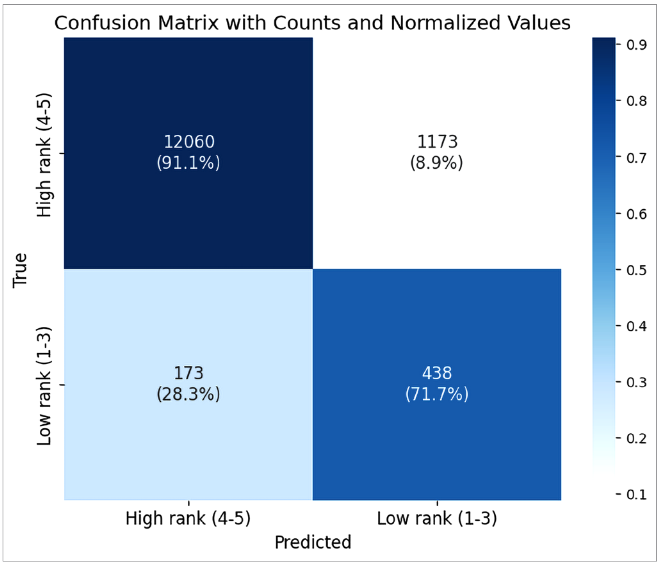
These metrics enable a holistic comparison of model performance, especially in terms of the ability to capture underrepresented sentiment classes. Table 2 summarizes the classification results for all four



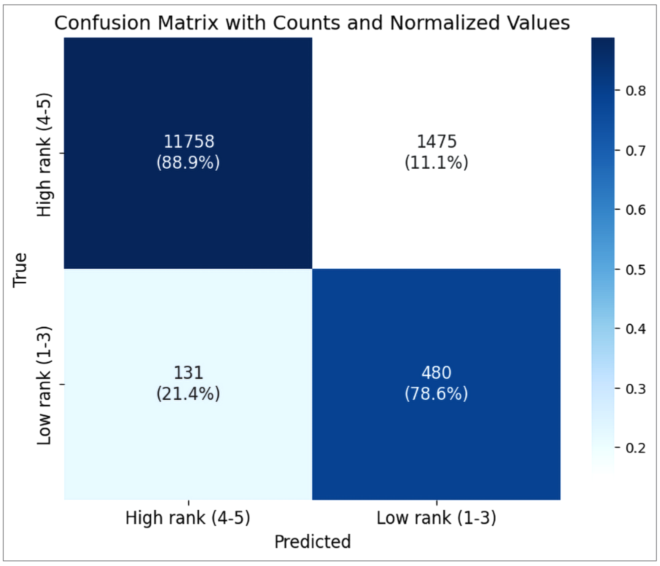

(a)




(b)




(c)




(d)

Figure 4. Confusion Matrixes for Baseline (a), Variant 1 (b), Variant 2 (c), and Variant 3 (d) model's architectures

*Source:* calculated and designed by the authors

model variants tested on the binary sentiment classification task.

The results clearly demonstrate that multilingual transformer models significantly outperform the monolingual baseline in identifying low-rated reviews. Variant 3, which combines partial fine-tuning, an advanced BiLSTM/CNN classifier, and focal loss, achieved the highest Macro F1, F1 (Low), and ROC AUC, indicating its superior ability to detect negative and neutral sentiment in imbalanced data.

Variant 1, which applies a simpler dense classification head, also performed well — particularly in recall, suggesting a strong ability to detect most low-rated cases, albeit with somewhat lower precision. In contrast, Variant 2, which uses frozen embeddings with no fine-tuning, showed the fastest inference time but had the weakest performance across all key metrics, especially on the minority class.

The Baseline model achieved high overall accuracy but exhibited a strong bias toward the dominant class (high-rated reviews), as evidenced by its lower recall and F1 score for the minority class.

These findings validate the effectiveness of using focal loss and partial fine-tuning in improving performance on underrepresented classes, and highlight the importance of classifier architecture in leveraging transformer embeddings effectively.

In addition to quantitative metrics, we also examined Confusion Matrices (Figure 4) to gain deeper insights into how each model handles class imbalance.

- The Baseline model (a) shows a strong bias toward the majority “High-rated” class, with a relatively low number of correctly identified “Low-rated” reviews and many false negatives.
- Variant 1 (b) demonstrates clear improvement, correctly classifying more Low-rated reviews than the baseline, though at the cost of some false positives (i.e., High-rated reviews misclassified as Low-rated).
- Variant 2 (c) exhibits the weakest performance in detecting Low-rated reviews, with a high number of misclassifications and low recall, confirming the limitations of using frozen embeddings without fine-tuning.
- Variant 3 (d) achieves the highest number of correctly identified Low-rated reviews, highlighting its strength in addressing class imbalance. However, it also shows an increased number of High-rated reviews misclassified as Low-rated, indicating a trade-off between recall and precision.

These visualizations support the quantitative findings presented in Table 2 and emphasize the importance of balancing recall and precision when dealing with minority sentiment classes.

To gain deeper insights into model behavior, we conducted a qualitative analysis of misclassified reviews. This analysis revealed several recurring patterns:

**1. Mixed sentiment expressions**: All models struggled with reviews that simultaneously contained both positive and negative opinions. For instance, reviews praising the book’s plot but criticizing its translation or vice versa were frequently misclassified due to the presence of conflicting sentiment cues.

**2. Subtle negation and irony**: Reviews with nuanced linguistic structures, especially involving negation or **ironic phrasing**, posed significant challenges. A typical example is the phrase *“не можу сказати, що книга погана”* (“I cannot say the book is bad”), which was sometimes misinterpreted as negative, despite conveying overall positive sentiment.

**3. Rating-text inconsistency**: A notable proportion of misclassifications occurred in cases where the star rating and textual sentiment were not aligned. For example, reviews written in predominantly positive language but assigned a low rating (or the opposite) often confused the models, highlighting the limitations of using ratings as ground truth sentiment labels.

**4. Code-switching and multilingual noise**: Reviews containing a mixture of Ukrainian and Russian, or incorporating English words and phrases, exhibited higher error rates — especially for the Baseline model. In contrast, Variants 1 and 3, powered by XLM-RoBERTa, demonstrated greater robustness to such linguistic variation due to their multilingual pretraining.

These observations reinforce the importance of handling ambiguous sentiment, multilingual input, and label inconsistency in real-world sentiment analysis applications. They also suggest potential avenues for further improvement, such as incorporating irony detection mechanisms, attention-based alignment with ratings, or code-switching aware tokenization strategies.

## 4. Conclusions

This study addressed the challenge of sentiment classification in imbalanced, multilingual user reviews, focusing on the identification of low-rated book reviews written in Ukrainian and Russian. We proposed and evaluated four architectural variants based on transformer-based models, including multilingual and monolingual backbones, custom classifier components, and class imbalance mitigation techniques.

Our results demonstrate that multilingual transformer models, particularly XLM-RoBERTa, substantially outperform a monolingual baseline (UA-RoBERTa) in detecting low-rated reviews. Among all configurations, Variant 3 — which combines partial fine-tuning, a deep BiLSTM/CNN classifier, and focal loss — achieved the best overall results, with an F1 score of 0.47 for the minority class and a macro F1 of 0.73, representing a substantial improvement over the baseline. The model also achieved a strong ROC AUC of 0.84, indicating high discriminative ability.

In contrast, models relying on frozen embeddings (Variant 2) underperformed in all metrics related to minority class detection, despite offering the fastest inference. This highlights the importance of targeted fine-tuning even when working with powerful pretrained architectures. Variant 1 demonstrated a good balance between recall and speed, showing that lightweight solutions can remain competitive when architectural choices are well-optimized.

Beyond numerical performance, qualitative error analysis revealed important challenges that remain open: handling mixed sentiment, interpreting negation and irony, resolving text-rating inconsistencies, and processing code-switched input. These aspects point to the inherent complexity of real-world sentiment analysis in multilingual and user-generated settings.

From a practical standpoint, the proposed framework offers a scalable approach for automated sentiment monitoring in digital publishing, e-commerce platforms, and recommendation systems, particularly in low-resource linguistic environments. It demonstrates how multilingual pretrained models can be adapted to underrepresented languages and real-world tasks through focused fine-tuning and classifier design.

Future work may focus on the integration of irony detection, multitask learning for sentiment and rating alignment, and the use of code-switching-aware pretraining to further enhance model robustness. Additionally, further evaluation on external datasets and different domains (e.g., product reviews, news comments) will help assess the generalizability of the proposed approach.

Overall, this research contributes to advancing multilingual sentiment analysis in underrepresented language settings, and provides a foundation for building more context-aware, fair, and accurate review classification systems.

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# ОЦІНКА КЛІЄНТСЬКОГО ДОСВІДУ В ЕЛЕКТРОННІЙ КОМЕРЦІЇ: БАГАТОМОВНИЙ СЕНТИМЕНТ АНАЛІЗ ВІДГУКІВ КОРИСТУВАЧІВ З ВИКОРИСТАННЯМ ТРАНСФОРМЕРНИХ МОДЕЛЕЙ

***Анотація.*** *У роботі розглянуто задачу багатомовного аналізу тональності в середовищі електронної комерції на прикладі рецензій українською та російською мовами на книги. Запропоновано гібридний підхід, що базується на трансформерних архітектурах і враховує як мовну складність слов'янських мов, так і суттєвий дисбаланс класів у даних користувацьких відгуків. Для дослідження використано корпус з приблизно 70 000 рецензій, зібраних на українській онлайн-платформі Yakaboo.*

*Класифікаційна задача сформульована як бінарна: виявлення відгуків із низьким рейтингом (1–3 зірки) проти високих (4–5 зірок), причому частка міноритарного класу становить лише 4–5%. Найкраща модель — частково донавчена XLM-RoBERTa з глибоким класифікатором і функцією втрат focal loss — досягла макро-F1 = 0.73 і F1 для міноритарного класу = 0.47, що суттєво перевищує результати базової мономовної моделі (0.66 і 0.37 відповідно). Застосування «передискретизації більшості» (oversampling) та focal loss довело свою ефективність у подоланні дисбалансу.*

*Результати дослідження засвідчують практичну цінність аналізу тональності для платформ електронної комерції — зокрема, для виявлення незадоволених клієнтів, удосконалення товарних пропозицій і персоналізації маркетингових стратегій. Робота робить внесок у розвиток багатомовного аналізу тональності в умовах обмежених мовних ресурсів.*

*Наукова новизна дослідження полягає в поєднанні багатомовних трансформерів із адаптивними класифікаторами та спеціальними методами боротьби з дисбалансом класів для обробки реальних даних ринку електронної комерції. Запропонований підхід може бути адаптований до інших мов і предметних областей, що відкриває перспективи подальших міждисциплінарних досліджень у сфері цифрового маркетингу, онлайн-комунікацій та соціальних медіа.*

***Ключові слова:*** *сентимент аналіз, обробка природної мови, електронна комерція, клієнтський досвід, багатомовні трансформерні моделі, XLM-RoBERTa, дисбаланс класів.*

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