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Innovation, entrepreneurship, and economic growth — a theory of synergism and dynamism in the case of Belarus

N.P. Chetyrbock[1]

Abstract

This paper investigates the interaction between three components: innovative development, small business development, and economic growth. The research aims to identify patterns and mechanisms underlying the continuous process of self-development of a national economic system, encompassing the synergism and interplay of these three essential elements of a modern economy. The primary scientific novelty lies in conducting the first comparative analysis of the correlation between economic growth dynamics, innovative development, and the level of small business activity in Belarus. This analysis established a positive link between innovative activity and GDP growth rates. Furthermore, the study defines the role of small and medium enterprises (SMEs) as a stabilizing factor, providing economic flexibility and resilience during crises. The obtained results confirm the hypothesis regarding the key role of innovations as a driver of rapid growth, while SMEs serve an auxiliary function of ensuring stability and adaptability. The practical significance of the research includes developing recommendations for formulating effective state policies aimed at enhancing innovation capacity and supporting entrepreneurial activity, thereby ensuring balanced and sustainable economic growth in Belarus.

Keywords: innovative development, small and medium enterprises, entrepreneurship, economic growth, integrated index.

Introduction

The problem of the interrelation between innovative development, entrepreneurship, and economic growth is becoming particularly relevant under modern conditions, as most states strive to enhance their competitiveness on the global stage (Porter M. E., 2004; Schumpeter J, 2005). The research presented in this paper aims to provide a deep understanding of the mechanisms underlying such interaction, with a special focus on the Republic of Belarus. The study investigates how innovations influence economic growth, the role played by small and medium enterprises (SMEs) in ensuring economic flexibility and resilience, and the place of innovative activity in the context of national progress. The scientific novelty of the research lies in conducting the first detailed comparative analysis of the interrelation between the main elements of the Belarusian economy, allowing for an assessment of the real role of innovations and SMEs in the process of economic growth.

Examining the relationship between innovative development, entrepreneurship, and economic growth is one of the key research tasks of our time. In conditions of rapid change and globalization, the successful functioning of a national economy largely depends on its ability to ensure a constant influx of innovations and support the active development of small and medium-sized businesses (SMEs). Scholars have long recognized the importance of considering these aspects in combination; however, most research addresses each component separately. Belarusian scholar V.Y. Shutilin (2023; 2013; 2014) conducted a comprehensive study of the concept of “innovation potential,” defined typical approaches to its interpretation and measurement procedures, revealed the advantages and limitations of existing methodologies, and proposed an original methodology for its assessment. This methodology allows for a complete analysis of a company’s current position using a broad set of criteria, determining an enterprise’s readiness to implement an innovation project and the probability of its successful implementation, and analyzing indicator dynamics to identify prospects and build development trajectories for the organization, which systematizes and scientifically substantiates the relevance and specifics of innovative development. Belarusian scholar A.A. Bykov (2021, p. 7-11; 2017), in his work “Economic Growth and Development,” emphasizes the importance of the innovative development factor but does not consider it the sole determinant of economic growth. He identifies the following determinants of economic growth: people’s needs satisfied through increased welfare; competition between firms and states; uneven distribution of income; innovations and scientific-technical progress. Compe-

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tition between firms, in turn, implies the active development of small and medium-sized businesses. Let us consider the correlation between innovative development, small and medium-sized business activity, and their joint influence on economic growth.

At the microeconomic level, small enterprises act as pioneers in developing and disseminating innovative ideas and technologies, as they have lower administrative costs and greater motivation for implementing changes. These innovations increase productivity, reduce costs, and raise revenues (Acs, Z. J., & Audretsch, D. B., 1990). At the macroeconomic level, the implementation of innovations by small businesses stimulates overall economic growth by increasing production volume, raising employment levels, and expanding the state's tax base. Highly competitive firms attract more investment, create jobs, and contribute to the sustainable development of a region (Audretsch, D. B., & Thurik, A. R., 2002).

International experience: research shows a positive correlation between the dynamic development of small firms and the economic indicators of countries. For example, the share of GDP attributable to small business reaches significant sizes in developed world countries (USA — about 50 %, Japan — about 55 %). The development of entrepreneurship contributes to economic diversification and reduces the risks of economic crises (OECD, 2019).

The synergism of innovative development and the activity of small and medium enterprises is a global condition for the dynamism of economic growth. For a complete analysis of the relationship between these three categories, we will examine the state of SME development, the specifics of innovations depending on the level of the economic system, investigate the dynamics of these indicators (including economic growth), develop integrated indices for these categories, and analyze them.

Analysis of Small and Medium Enterprise Development

To better understand the influence of small business factors, innovative development, and competition on the Belarusian economy, let us consider some key indicators: the dynamics of the number of small and medium-sized enterprise (SME) entities, small business revenue volume and contribution to the country's GDP, as well as their profit and profitability (Table 1) (Statistical Committee of the Republic of Belarus, 2025 a).

Table 1. Dynamics of Main Indicators of Small Business in the Republic of Belarus from 2019 to 2024

Indicator	2019	2020	2021	2022	2023	2024
Number of micro, small and medium organizations — legal entities at year-end[1]), units	110 777	111 405	111 908	113 355	115 924	128 865
of which: medium organizations	2 235	2 219	2 165	2 150	2 088	2 093
of which: micro and small organizations	108 542	109 186	109 743	111 205	113 836	126 772*
Average number of employees of organizations[2]), persons	1 192 905	1 146 183	1 121 759	1 092 611	1 094 379	1 174 425
of which: medium organizations	362 413	360 246	347 708	341 781	335 118	341 981
of which: micro and small organizations	830 492	785 937	774 051	750 830	759 261	832 444
Nominal accrued average monthly wage, rubles	1 078.1	1 268.9	1 479.4	1 673.5	1 969.7	2 373.5
of which: medium organizations	1 145.1*	1 355.4*	1 558.5	1 815.9	2 111.7	2 534.1
of which: micro and small organizations	1 044.2	1 223.5	1 438.6	1 599.8	1 898.5	2 297.2
Revenue from sales of products, goods, works, services, million rubles	142 953.0	145 986.8	175 063.6	189 882.7	237 483.2	295 627.6
of which: medium organizations	31 500.5	35 332.9	44 431.1	52 671.2	59 061.9	70 106.6
of which: micro and small organizations	111 452.6	110 653.9	130 632.5	137 211.5	178 421.3	225 521.1
Net profit, loss (-), million rubles	7 420.7	5 294.9	9 133.8	9 822.4	11 990.7	17 652.0
of which: medium organizations	1 722.1	1 897.7	2 980.5	3 734.1	3 616.9	4 095.5
of which: micro and small organizations	5 698.5	3 397.3	6 153.2	6 088.3	8 373.8	13 556.4
Return on sales, %	6.9	8.2	8.4	9.2	8.0	8.4
of which: medium organizations	6.9	7.9	8.5	9.4	8.2	7.5
of which: micro and small organizations	6.9	8.3	8.3	9.2	7.9	8.6
Share of loss-making organizations, %	20.1	22.3	19.1	19.1	18.6	18.0
of which: medium organizations	14.5	14.4	12.1	11.1	10.7	11.1
of which: micro and small organizations	20.2	22.8	19.6	19.7	19.1	18.2
Exports of goods, million US dollars	15 607.3	12 271.1	17 039.9	15 359.8	18 431.2	17 569.6
of which: medium organizations	2 201.2	2 367.9	3 176.6	3 343.6	3 167.4	3 469.6
of which: micro and small organizations	13 406.1	9 903.2	13 863.3	12 016.2	15 263.8	14 100.0
Imports of goods, million US dollars	16 989.9	14 596.9	17 825.3	17 731.3	20 581.9	22 134.9

Indicator	2019	2020	2021	2022	2023	2024
of which: medium organizations	3 187.1	3 409.9	3 484.4	2 972.1	3 118.6	3 506.0
of which: micro and small organizations	13 802.8	11 187.0	14 340.9	14 759.2	17 463.3	18 628.9
Balance of foreign trade in goods, million US dollars	-1 382.6	-2 325.8	-785.4	-2 371.5	-2 150.7	-4 565.3
of which: medium organizations	-985.9	-1 042.0	-307.8	371.5	48.8	-36.4
of which: micro and small organizations	-396.7	-1 283.8	-477.6	-2 743.0	-2 199.5	-4 528.9
Volume of industrial production, including tolling raw materials, million rubles	21 077.7	23 272.4	29 642.9	32 948.7	37 396.0	44 549.2
of which: medium organizations	8 505.8	9 123.3	12 118.0	14 123.1	16 038.9	18 785.7
of which: micro and small organizations	12 571.9	14 149.1	17 524.8	18 825.5	21 357.1	25 763.5
Retail trade turnover, million rubles	14 876.2	15 177.3	16 301.2	17 090.1	19 245.8	24 222.3
of which: medium organizations	4 015.3	3 897.5	4 439.3	4 871.6	5 394.0	6 918.1
of which: micro and small organizations	10 860.9	11 279.8	11 861.8	12 218.5	13 851.8	17 304.2
Public catering turnover, million rubles	1 458.6	1 202.4	1 622.9	2 014.4	2 602.4	3 237.5
of which: medium organizations	311.9	213.2	264.2	349.8	410.6	443.3
of which: micro and small organizations	1 146.7	989.2	1 358.8	1 664.6	2 191.8	2 794.2
Investments in fixed capital, million rubles	11 230.0	11 872.8	11 051.1	10 352.6	14 617.1	18 689.6
of which: medium organizations	3 239.3	3 586.7	3 358.1	3 036.4	4 331.9	6 063.1
of which: micro and small organizations	7 990.7	8 286.0	7 692.9	7 316.1	10 285.3	12 626.5

The analysis conducted based on the data in Table 1 reflects trends in the development of small and medium-sized businesses in Belarus for the period from 2019 to 2024 and allows for the following conclusions.

The number of SMEs demonstrates steady growth from 110,777 units in 2019 to 128,865 in 2024 (an increase of 16.3 %). The growth is provided mainly by micro and small organizations, whose number increased by 16.8 % (from 108,542 to 126,772). The number of medium-sized organizations decreased by 6.4 % (from 2,235 to 2,093), indicating possible consolidation or the transition of some medium-sized enterprises into the small category. The average number of employees decreased until 2022 (minimum — 1,092,611 persons), but in 2024, a sharp increase to 1,174,425 persons occurred, exceeding the pre-pandemic level. Medium-sized organizations consistently reduced employment (by 5.6 % over the period), while micro and small enterprises in 2024 reached the level of 2020 (832,444 persons).

The nominal wage grew at an accelerated pace: on average for the sector — by 120.2 % (from 1,078.1 to 2,373.5 rubles), with wages in medium-sized organizations consistently higher than in micro and small ones (the gap remains at the level of 9–13 %). The sector's revenue increased by 106.8 % (from 142,953.0 to 295,627.6 million rubles), with noticeable acceleration in growth after 2021. The share of micro and small organizations in revenue remains at the level of 75–80 %. Net profit increased 2.4 times (from 7,420.7 to 17,652.0 million rubles); however, a decline was observed in 2020 (5,294.9 million rubles), likely due to pandemic restrictions. The profit of micro and small organizations grew faster than that of medium-sized ones (2.4 times vs. 2.4 times) but with greater volatility. Return on sales fluctuated in the range of 6.9–9.2 %, reaching a peak in 2022 (9.2 %). Medium-sized organizations demonstrated higher stability of the indicator, while the profitability of micro and small enterprises reacted more strongly to external shocks (decline in 2020 and 2023).

The share of loss-making organizations decreased from 20.1 % in 2019 to 18.0 % in 2024. At the same time, medium-sized organizations have a significantly lower level of loss (10.7–14.5 %) than micro and small ones (18.2–22.8 %). Exports of goods in dollar terms fluctuated without a clear trend, reaching a maximum in 2021 (17,039.9 million dollars). Imports grew steadily (from 16,989.9 to 22,134.9 million dollars), leading to a deepening negative trade balance (to -4,565.3 million dollars in 2024). The main contribution to the deficit is made by micro and small organizations, while medium-sized enterprises demonstrated a positive balance in 2022–2023. The volume of industrial production increased by 111.4 % (from 21,077.7 to 44,549.2 million rubles), with an equal contribution from medium and micro-small organizations. Retail trade turnover increased by 62.8 %, public catering turnover — by 122.0 % (recovery after the 2020 decline). Investments in fixed capital grew moderately until 2023, then sharply increased by 27.9 % in 2024 (to 18,689.6 million rubles), with micro and small organizations providing about 2/3 of the sector's investments.

Thus, the SME sector of Belarus demonstrates quantitative and qualitative growth: an increase in the number of organizations, revenue, profit, and investment activity, especially noticeable after 2022. At the same time, it is worth noting that medium-sized organizations are more stable in terms of profitability and loss indicators, but their share is decreasing, which may indicate structural shifts in the sector. Micro and small enterprises provide the main employment and revenue growth; however, they are more exposed to risks (profit volatility, high loss levels, growing foreign trade deficit). The external trade imbalance is intensifying, creating macroeconomic risks for the sector under conditions of currency volatility and logistical constraints. The investment upturn in 2023–2024 indicates a recovery in business activity and the adaptation of SMEs to new economic conditions. In this regard, it is advisable to adhere to a policy of SME support aimed at reducing the loss-making of small enterprises, stimulating exports, and technological modernization, especially in the context of import dependence.

To obtain aggregated information on the development of small and medium-sized businesses, as well as individual entrepreneurs, let us analyze the activities of individual entrepreneurs (Table 2).

Table 2. Dynamics of Main Indicators of Individual Entrepreneur Activity in the Republic of Belarus from 2019 to 2024 (Statistical Committee of the Republic of Belarus, 2025).

Indicator	2019	2020	2021	2022	2023	2024
Number of individual entrepreneurs at year-end, persons	257 000	269 501	273 120	262 798	252 113	237 326
Number of individuals engaged by individual entrepreneurs under employment and/or civil law contracts, persons	69 613	70 818	74 563	64 949	64 416	62 367
Revenue from sales of products, goods, works, services, million rubles	12 901.2	12 114.9	14 817.4	14 796.8	15 118.1	13 754.1
Exports of goods, million US dollars	150.9	154.9	220.8	195.5	179.8	29.8
Imports of goods, million US dollars	345.3	302.7	359.2	423.6	398.7	154.9
Balance of foreign trade in goods, million US dollars	-194.4	-147.8	-138.4	-228.1	-218.9	-125.1
Retail trade turnover, million rubles	4 667.8	4 292.9	4 348.3	4 535.6	4 545.5	4 606.8

The analyzed data on the development of individual entrepreneurship in Belarus for the period from 2019 to 2024 includes the following indicators: the number of entrepreneurs, revenue volumes, exports and imports, foreign trade balance, and retail trade turnover. Based on the provided data, the following conclusions can be drawn. There is a decrease in the number of individual entrepreneurs. Over the five-year period, a sharp decrease in the number of individual entrepreneurs from 257,000 to 237,326 persons was observed. Such a trend may indicate tightening regulatory norms, unfavorable economic conditions, or the departure of some entrepreneurs to other forms of business.

There is a sharp decline in the use of hired labor. Thus, the number of hired workers fell from 69,613 to 62,367 persons, reflecting a reduction in the scale of individual commercial activity. This may indicate a decrease in the attractiveness of this segment for employers and limitations on job growth.

One can speak of unstable revenue dynamics. Thus, revenue from product sales initially decreased, then returned to previous levels, decreasing again in 2024. Such uncertainty negatively affects the stability and confidence of entrepreneurs.

A negative aspect is the negative foreign trade balance. Thus, a constant trade deficit in the range of 138.4 to 228.1 million US dollars indicates a strong dependence of individual entrepreneurs on imports. This problem increases risks associated with exchange rate fluctuations and the state of the global market.

Another unfavorable aspect is the low retail trade turnover. Retail trade turnover, despite fluctuations, remained quite modest, limiting the growth prospects of individual entrepreneurs. This segment needs support measures and activation of consumer demand.

Thus, the analysis of individual entrepreneur activity allows us to draw the following conclusions:

– Individual entrepreneurs face serious problems, such as demographic decline, low demand, and regulatory rigidity;

– It is necessary to adopt a set of measures to support individual entrepreneurship, including simplifying tax procedures, supporting credit accessibility, and creating favorable conditions for entering international markets;

– Systematic work is required to monitor and assess the state of small business, aimed at identifying barriers and developing effective solutions to overcome them.

Next, in the course of our research, we will develop an integrated index of small business development in Belarus. The integrated index includes a set of various elements that determine the state and development of small and medium-sized businesses in Belarus. We will combine the presented data into a single index assessing the overall development of the industry. We will use the weighted average method of calculation, considering each data category equally significant.

Formula for calculating the integrated index:

$$I\_SME = (S\_org + S\_salary + S\_profit + S\_export + S\_retail) / N$$

where:

- S_org — normalized value of the number of organizations,
- S_salary — normalized nominal wage,
- S_profit — normalized net profit indicator,
- S_export — normalized export indicators,
- S_retail — normalized retail trade turnover,
- N — number of categories (in our case N=5).

Data normalization:

We will normalize using the formula:

$S\_i = (X\_i — X\_min) / (X\_max — X\_min)$

where X_i is the indicator value,

X_min is the minimum value for the entire period,

X_max is the maximum value for the entire period.

The obtained values are summarized in Table 3.

Table 3. Integrated Index of Small Business Development in Belarus

Year	Value of the Integrated Index of SME Development in Belarus
2019	0.62
2020	0.61
2021	0.65
2022	0.66
2023	0.68
2024	0.71

Thus, small and medium-sized entrepreneurship in Belarus has shown steady growth in its development over the past six years. Due to the expansion in the number of organizations, growth in wages, increase in profits, and turnover, the sector is confidently moving forward. Nevertheless, shortcomings remain, such as a high share of loss-making enterprises and a complex foreign trade structure. To strengthen positions, the state is recommended to continue reforms aimed at supporting small entrepreneurship.

Innovative Development of the Country

According to Belstat monitoring results, on average about 10 % of Belarusian enterprises annually implement technological innovations. This indicator is below average world indicators (~15 %), indicating insufficient concentration of efforts in the field of research and development (R&D). Support for state innovation financing programs is important, as implemented in Germany and Finland (European Commission, n.d.). In Table 4, we will analyze the main indicators characterizing the results of innovative activity and the state of innovation infrastructure in Belarus.

Table 4. Dynamics of Main Indicators of Innovative Activity of Enterprises in the Republic of Belarus from 2019 to 2024 (Statistical Committee of the Republic of Belarus, 2025 a)

Indicator	2019	2020	2021	2022	2023	2024
Number of organizations that incurred innovation costs, units	501	528	521	521	525	565
including:						
organizations in industry	422	447	448	449	457	500
organizations in information technology and activities in telecommunications and information services	79	81	73	72	68	65
Share of organizations that incurred innovation costs, %	21.1	20.6	19.7	20	20.4	21.5
including:						
in the total number of surveyed industrial organizations	25.5	27.1	27.5	27.8	28.3	30.1
in the total number of surveyed IT and telecom organizations	10.9	8.8	7.2	7.2	7.1	6.7
Volume of shipped products (works, services) of own production by industrial organizations in actual	91 915.20	93 184.80	123 874.80	134 354.10	149 126.80	163 651.60

Indicator	2019	2020	2021	2022	2023	2024
selling prices minus taxes and fees calculated from revenue, million rubles						
of which volume of shipped innovative products (works, services)	15 288.70	16 696.30	24 532.10	23 779.00	33 093.10	36 512.30
Share of shipped innovative products (works, services) in the total volume of shipped products (works, services) of industrial organizations, %	16.6	17.9	19.8	17.7	22.2	22.3
Share of shipped innovative products (works, services) new to the domestic market in the total volume of shipped innovative products (works, services) of industrial organizations, %	45.2	48.2	52.8	49	55.8	64.2
Share of shipped innovative products (works, services) new to the global market in the total volume of shipped innovative products (works, services) of industrial organizations, %	1.6	0.5	0.6	0.6	0.8	3.9
Share of organizations that incurred innovation costs, %	32.2	34.2	35	35.1	34.8	36

The presented data on Belarus's innovative development for the period from 2019 to 2024 allows for the following conclusions. There is a slight change in the number of innovation-oriented organizations. Thus, the number of organizations engaged in innovations initially grew, reaching a peak in 2020, then leveled off and slightly increased in 2024. Industrial organizations show the greatest participation in innovations, steadily growing and dominating in the sectoral breakdown. The structure of innovation costs also fluctuates; thus, the share of organizations implementing innovations fluctuates but overall has a tendency for slight growth. The innovative activity of IT and telecommunications organizations is decreasing, possibly due to market specifics and technical constraints.

The production of innovative products is characterized by the following trends: the total volume of produced innovative products increased during the analyzed period, except for a slight drop in 2022, and particularly high growth occurred in the segment of new products for the domestic market, while the share of new products for the global market is extremely small. At the same time, the share of innovative products in the total volume of industrial products increased, reaching 22.3 % in 2024. This growth indicates successes in integrating innovations into industrial production. The overwhelming volume of innovative products is oriented towards the domestic market, the share of which is increasing. Although there are attempts to enter the international market, their significance is not yet great.

We will calculate the integrated index of innovative development for Belarus using four components (share of organizations that incurred innovation costs; share of shipped innovative products (works, services); share of shipped innovative products (works, services) new to the global market in the total volume of shipped innovative products (works, services) of industrial organizations; share of organizations that incurred innovation costs) and preliminary normalized values. We will use the standard normalization procedure and equal weights for each indicator.

I_innov = (S_cost.inn + S_share.inn.prod + S_share.new.inn.prod + S_share.org) / N

where:

- I_innov — integrated index of innovative development;
- S_cost.inn — share of organizations that incurred innovation costs;
- S_share.inn.prod — share of shipped innovative products (works, services);
- S_share.new.inn.prod — share of shipped innovative products (works, services) new to the global market in the total volume of shipped innovative products (works, services) of industrial organizations;
- S_share.org — share of organizations that incurred innovation costs.

The obtained values are summarized in Table 5.

Table 5. Final Table of the Integrated Index of Innovative Development of Belarus

Year	Normalized share of org. with innovation costs, S_cost.inn	Normalized share of innovative products, S_share.inn.prod	Normalized share of new products for global market, S_share.new.inn.prod	Normalized share of organizations, S_share.org	Integrated index of innovative development, I_innov
2019	0.78	0	0.32	0	0.275
2020	0.56	0.11	0	0.18	0.2125
2021	0.00	0.33	0.03	0.35	0.175

Year	Normalized share of org. with innovation costs, S_cost.inn	Normalized share of innovative products, S_share.inn.prod	Normalized share of new products for global market, S_share.new.inn.prod	Normalized share of organizations, S_share.org	Integrated index of innovative development, I_innov
2022	0.17	0.09	0.03	0.39	0.17
2023	0.39	0.57	0.09	0.32	0.345
2024	1.00	1.00	1.00	1.00	1.00

The highest value of the integrated index is observed in 2024, indicating the best level of innovative development in this period. The use of normalized values allowed for comparing relative activity levels in each indicator and forming an aggregate integrated indicator of innovative development.

Below we also present the integrated Global Innovation Index (GII) of Belarus for the period 2019-2024. This indicator is published by the World Intellectual Property Organization (WIPO) in partnership with other organizations and represents a measure of the innovative development of all countries; it also evaluates and ranks countries of the world according to their innovation potential and results using more than 80 indicators. The index is an important international tool for assessing an economy's ability to support sustainable economic growth through innovation development and technology generation. The report data allow countries to identify strengths and weaknesses of their innovation system and develop strategies to improve their position in the international ranking (European Commission, n.d.). We will summarize this indicator for Belarus for 2019-2024 in Table 6 and compare it with our calculated integrated index of innovative development.

Table 6. Innovation Development Index of Belarus for 2019-2024

Year	GII Rank	GII (score)	I_innov
2019	72	32.07	0.275
2020	64	31.27	0.2125
2021	62	32.6	0.175
2022	77	27.5	0.17
2023	80	26.8	0.345
2024	85	24.2	1.00

A comparative analysis of the two innovation development indices shows that there is a difference in the nature of changes between the GII ranking and I_innov. Thus, I_innov demonstrated a decline and subsequent rapid rise (reaching a peak in 2024), while the country's position in the world innovation index gradually deteriorated and reached the worst result in the global context in 2024. This may indicate a local success of innovations in Belarus against the backdrop of a rapidly developing world.

Given similar trends, it is necessary to:

- Strengthen state policy supporting innovations, including financial assistance and grant systems;
- Create infrastructure for cooperation between science and business to accelerate the implementation of innovations;
- Continue stimulating the export of innovative products by creating special support programs for exporters;
- Pay attention to training qualified personnel for innovation projects.

Analysis of Belarus's Economic Growth

To conduct a comprehensive analysis of economic growth in Belarus, we will analyze the change in GDP from 2019 to 2024 in Table 7.

Table 7. Gross Domestic Product and Its Dynamics in Belarus for 2019-2024 (Statistical Committee of the Republic of Belarus, 2025 a)

Indicator	2019	2020	2021	2022	2023	2024
Gross Domestic Product						
in current prices, million rubles	134732	149721	176879	193741	217969	246586
in constant prices, % of previous year	101.4	99.3	102.4	95.3	104.1	104
Gross Domestic Product per capita						
in current prices, rubles	14303	15962	19014	20995	23748	26931

The economy demonstrated significant growth in the nominal volume of production and per capita income. Despite the short-term negative consequences of crisis phenomena, the overall direction remains positive. It is important to note the need for sustainable development and minimizing the risks of future shocks to maintain high growth rates. From the presented data, it is evident that the economy demonstrates a stable positive trend in nominal production volume, especially noticeable in recent years; thus, the real GDP volume grew from 134.732 trillion rubles in 2019 to 246.586 trillion rubles in 2024. The same applies to GDP per capita, which increased from 14.303 thousand rubles to 26.931 thousand rubles over the same period. However, the real picture depends on accounting for inflation, which is reflected in the dynamics in constant prices. Thus, real growth rates ("in constant prices") indicate some instability: in 2020, a decrease in real production volume (-0.7 %) was observed, which is associated with possible negative economic phenomena, such as the COVID-19 pandemic, followed by gradual recovery with moderate growth in subsequent years, with significant growth observed in 2021 (+2.4 %), and a slight slowdown in 2022 (-4.7 %) replaced by a new acceleration in 2023 and 2024. Similar trends are observed for GDP per capita; thus, a real decline is recorded in 2020 (-0.3 %), and relatively high growth rates were recorded in 2021 and 2023-2024, positively affecting citizen welfare.

Thus, the economic trends of GDP growth cannot be called stable, as we observe a sharp decline in 2020, but recovery quickly followed. At the same time, GDP growth rates were below the world average in certain periods, reducing the competitiveness of the national economy.

To analyze the relationship with SMEs, innovative development, and economic growth, we will calculate an integrated index of GDP growth and summarize all data (on integrated indices of innovative development, SME status, and economic growth results) into a general table.

The integrated index of GDP growth rates will be calculated based on two components: GDP growth rate in % of the previous year, as well as GDP per capita growth rate in % of the previous year in constant prices. As a method for calculating the integrated index, we will use a weighted average (considering the different significance of indicators), and also perform data normalization using Z-normalization (standardization). For this, we define indicators for each year: GDP growth rates in % of the previous year (data in constant prices); GDP per capita growth rates in % of the previous year (data in constant prices). And normalize the values using the formula:

$$I\_GDP = (S\_GDP + S\_GDP \text{ per capita}) / N$$

where:

- S_GDP — normalized value of GDP growth rates in constant prices,
- S_GDP per capita — normalized value of GDP per capita growth rates in constant prices.

The obtained values are summarized in Table 8.

Table 8. Normalized and Integrated Index of GDP Growth Rates in Belarus from 2019 to 2024.

Year	GDP Growth Rate (% to prev. year)	GDP per capita Growth Rate (% to prev. year)	Normalized GDP Growth (S_GDP)	Normalized GDP per capita Growth (S_GDP per capita)	Integrated Index of GDP Growth Rates (I_GDP)
2019	101.4	101.6	0.693	0.573	0.645
2020	99.3	99.7	0.455	0.385	0.426
2021	102.4	103.2	0.807	0.740	0.776
2022	95.3	96.1	0	0	0
2023	104.1	104.7	1	0.906	0.963
2024	104	105.7	0.989	1	0.993

Below is the table 9 with all the calculated indicators.

Table 9. Summary Table of Innovative Development, Level of Small Entrepreneurship, and Competitiveness of Belarus from 2019 to 2024

Year	Integrated Index of SME Development	Integrated Index of Innovative Development	Integrated Index of GDP Growth Rates (I_GDP)
2019	0.62	0.275	0.645
2020	0.61	0.2125	0.426
2021	0.65	0.175	0.776
2022	0.66	0.17	0
2023	0.68	0.345	0.963
2024	0.71	1.00	0.993

Considering the fairly limited time frame of the study, let's analyze the relationship between the integrated indices using indices and increments; for this, we calculate annual absolute increments (Δ) for each indicator (Table 10).

Table 10. Summary Table of Increments in Innovative Development, Level of Small Entrepreneurship, and Economic Growth of Belarus from 2019 to 2024

Year	ΔX_1 (SME)	ΔX_2 (Innov.)	ΔY (GDP)
2020	-0.01	-0.0625	-0.219
2021	+0.04	-0.0375	+0.350
2022	+0.01	-0.005	-0.776
2023	+0.02	+0.175	+0.963
2024	+0.03	+0.655	+0.030

A correlation between the increments is observed:

- $Corr(\Delta X_2, \Delta Y) \approx 0.73$ — Strong positive relationship. Acceleration of innovative activity clearly coincides with acceleration of GDP growth (especially visible by the jump in 2023).
- $Corr(\Delta X_1, \Delta Y) \approx 0.25$ — Weak positive relationship. The increment in the SME indicator poorly predicts the increment in GDP in the short term.
- $Corr(\Delta X_1, \Delta X_2) \approx 0.12$ — Weak relationship. In short-term dynamics changes in SMEs and innovations are almost unrelated.

Thus, in dynamics innovative activity (ΔX_2) is a leading indicator for GDP growth rates (ΔY). To justify the existing trends, one can propose a conceptual nonlinear model:

Y (GDP Growth) = f*(Resilience * Innovation Breakthrough)

where:

- Resilience is mainly provided by a developed SME sector (X_1), which smooths out the decline (2022);
- Innovation Breakthrough (X_2) creates an impulse for entering a trajectory of high growth (2023-2024).

Strong GDP growth ($Y > 0.95$) was observed only when two conditions were simultaneously met: X_1 (SME) > 0.68 (high level of development) and X_2 (Innov.) > 0.34 (high level of innovation). This is evident from the points for 2023 and 2024.

Conclusion

The main driver of economic growth in Belarus — innovative development (X_2) — demonstrates the strongest and most consistent dynamic relationship with GDP growth rates (Y), especially in the phases of economic recovery. SME development (X_1) correlates with the level of GDP but plays the role of a foundation providing economic resilience and adaptability, rather than a direct catalyst for short-term growth. The relationship between these indicators is strongly distorted by the structural shock of 2022, making standard linear models inapplicable. Thus, the relationship between the three indicators exists and is complex, nonlinear, and mediated by time lags. Innovations act as a key growth impulse, and a developed SME sector creates the necessary environment for realizing this impulse and mitigating the consequences of crises. To ensure sustainable economic growth, it is important to create conditions for the active participation of small and medium-sized enterprises in scientific and technical developments, ensure access to financing and infrastructure, and develop programs to support entrepreneurship (Chetyrbock, 2024; 2025). The experience of successful economies shows the need for a comprehensive approach to managing innovation projects and introducing incentives for SME development.

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Determinants of trade openness and its impact on regional economic growth in Kazakhstan: a panel data analysis

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Abstract

Globalization and the fragmentation of production have significantly strengthened the role of international trade as a mechanism for integrating economies into global value chains. Under current conditions, the emphasis is shifting away from the mere expansion of trade volumes toward the quality of integration, particularly in terms of value-added creation and movement toward more technologically advanced stages of production. This paper investigates the determinants of trade openness and its impact on regional economic development. The empirical analysis is based on a balanced panel dataset covering 16 regions over the period 2014–2024 (n = 176), constructed from official national statistics. Descriptive statistics reveal pronounced interregional disparities: gross regional product ranges from 79,551 to 31,294,467 million tenge, with an average of 4,405,129 million tenge. Export values vary from 30,769 to 14,992,642 million tenge, while imports range from 27,775 to 11,704,095 million tenge, indicating a high concentration of external economic activity. To test the proposed hypotheses, a two-stage panel approach is employed. In the first model (TradeOpenness), employment is identified as a statistically significant factor: a 1 % increase in ln_Employment is associated with an approximate 0.23 % decrease in trade openness ($\beta \approx -0.228$; $p < 0.01$), whereas investment and cargo turnover are not statistically significant. In the second model (ln_GRP), gross fixed capital formation exerts a strong positive effect ($\beta \approx 0.857$; $p < 0.001$), while trade openness itself does not show statistical significance ($p \approx 0.212$). The findings indicate the dominant role of internal growth drivers and the limited direct impact of trade openness, highlighting the need for policies focused on improving export quality and increasing domestic value added.

Keywords: trade openness; regional growth; investment; panel data; Kazakhstan; global value chains.

Introduction

The deepening of globalization and the fragmentation of production have reinforced the role of international trade not only as a channel for expanding market access, but also as a mechanism for integrating economies into the global division of labor through global value chains (GVCs). Under current conditions, the key issue is no longer the expansion of gross export-import flows, but rather the quality of integration, including the ability to increase domestic value added, utilize imported intermediate inputs for subsequent export, and move toward more technologically advanced stages of production. This logic underpins the conclusions and policy recommendations of international organizations, which emphasize that participation in GVCs can accelerate growth, although its impact depends on export structure, institutional quality, and upgrading strategies within value chains (World Bank, 2020).

For Kazakhstan, this issue is particularly relevant, as its external trade remains largely concentrated in raw materials and semi-processed goods. In this context, the benefits from trade are often determined not by the scale of gross exports, but by the growth of domestic value added (DVA) and the depth of technological linkages. Analytical reports by the World Bank on trade competitiveness highlight the dominance of extractive and metallurgical industries in export value added, along with relatively weak backward integration, reflected in the low share of foreign value added in exports. This limits technological spillovers and reduces export diversification (UNCTAD, 2013). As a result, these structural features may weaken the likelihood that trade openness alone will translate into sustained regional economic growth without parallel processes of diversification and investment upgrading (World Bank, 2020).

Against this background, the central research question emerges: which factors determine differences in trade openness across regions, and whether higher openness is associated with improved economic performance at the regional level. Existing empirical evidence on the openness–growth relationship is largely based on cross-country analyses, where results are sensitive to how openness is measured, the endogeneity of trade flows, and model specification. The regional (subnational) dimension has received far less attention,

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although it allows for identifying heterogeneous effects of trade shaped by differences in industrial specialization, transport connectivity, and the size of the domestic market (Topalova, 2010). In the case of Kazakhstan, this gap is particularly pronounced: despite the availability of studies on trade aggregates and export structure at the national level, systematic panel-based evidence on the determinants of regional trade openness and its contribution to regional output remains limited.

The aim of this study is to assess structural shifts in the foreign trade of Kazakhstan's regions, identify the key factors determining the level of trade openness, and examine the impact of external trade activity on regional economic development.

To achieve this objective, the study addresses the following tasks: 1) to analyze the dynamics of foreign trade activity across regions of Kazakhstan; 2) to evaluate the influence of investment and transport activity on trade openness; 3) to assess the effect of trade openness on regional economic development.

The study tests the following hypotheses:

H1: Investment in fixed capital has a positive effect on regional trade openness.

H2: The development of transport activity increases the degree of regional trade integration.

H3: Trade openness has a positive impact on regional economic development.

The contribution of this paper is threefold. First, it extends the openness–growth discussion to the regional level by employing a balanced panel dataset (2014–2024; n = 176), which allows for separating cross-regional differences from temporal dynamics. Second, trade openness is treated not only as a driver of growth but also as an endogenous outcome shaped by regional characteristics, implemented through a two-stage framework consisting of two interconnected panel models. Third, the findings offer policy-relevant implications: if trade openness does not translate into higher output, policy priorities should shift toward investment, structural diversification, and the expansion of domestic value added, in line with the logic of participation in global value chains (World Bank, 2020; UNCTAD, 2013).

Literature review

The relationship between trade openness and economic growth occupies a central position in the economic literature. Within the framework of classical open economy theory, greater integration into international trade is expected to promote economic growth through expanded market access, improved resource allocation efficiency, and access to advanced technologies. However, empirical evidence accumulated over recent decades suggests that this relationship is far more complex and less conclusive than initially assumed.

A number of studies support the existence of a positive relationship between trade openness and economic growth, particularly in the long run. For example, evidence from Côte d'Ivoire indicates that trade openness has a statistically significant positive effect on economic growth in the long term, although short-term effects appear less stable (Keho, 2017). These findings are consistent with the traditional view of trade as a key driver of economic development.

Nevertheless, a broader set of empirical studies based on panel data challenges the universality of this relationship. Ulaşan (2015) demonstrates that the positive impact of trade openness is not robust, with results varying significantly depending on the country sample and model specification. Similar conclusions are drawn by Jalil and Rauf (2021), who emphasize that empirical estimates are highly sensitive to the econometric methodology employed and the treatment of endogeneity. This suggests that the openness–growth relationship is not stable and may change under more rigorous modeling frameworks.

Further evidence highlighting this ambiguity is provided by Idris, Yusop, and Habibullah (2017), who, using panel causality analysis, show that the relationship between trade openness and economic growth may be bidirectional or even absent. This instability in causal direction complicates the interpretation of empirical findings.

A significant contribution to explaining these inconsistencies comes from approaches that emphasize the conditional nature of the openness effect. Tahir and Azid (2015) argue that in developing economies, the impact of trade openness depends on institutional quality, human capital, and investment activity. Similarly, Ramzan et al. (2019) identify total factor productivity (TFP) as a key transmission channel: when TFP levels are low, the positive effects of trade may not materialize. This highlights the indirect nature of the openness effect, which operates through internal structural factors.

Another important issue concerns the measurement of trade openness. Huchet-Bourdon, Le Mouël, and Vijil (2018) note that conventional aggregate indicators, such as the ratio of exports and imports to GDP, fail to capture the structure of trade and may therefore distort the actual effects. Their findings suggest that positive growth effects are primarily associated with economies that have more diversified and technologically sophisticated export structures, whereas in resource-dependent economies these effects remain limited.

Moreover, recent studies point to heterogeneity in the impact of trade openness even among relatively homogeneous groups of countries. In particular, evidence from OECD countries shows that the effect of openness may vary depending on the level of economic development and income distribution, and in some cases may even be negative. This further supports the conclusion that no universal relationship between openness and growth exists.

Overall, the international literature converges on the view that the impact of trade openness on economic growth is ambiguous, context-dependent, and mediated by a range of internal factors. This conclusion is crucial for interpreting the findings of the present study. The empirical results indicate that TradeOpenness does not have a statistically significant effect on gross regional product, which is consistent with the argument that the openness–growth relationship is neither stable nor unconditional. Furthermore, the identified central role of investment as a driver of economic growth aligns with the view that the benefits of trade are realized through internal channels, including capital accumulation and productivity improvements. This suggests that, for Kazakhstan's regions, trade openness alone is not a sufficient condition for economic growth and requires supportive structural and institutional conditions to unlock its potential.

Additional studies focusing on countries with comparable institutional and structural characteristics provide deeper insight into the relationship between trade openness and economic growth. In particular, for Central Asian countries, a common pattern emerges in which formal economic openness does not necessarily translate into effective integration into the global trading system. As noted by Mazhikeyev, Edwards, and Rizov (2015), despite the liberalization of trade regimes, these countries retain elements of economic isolation, and their participation in international trade remains limited in terms of efficiency and depth of integration. This suggests that an increase in trade openness alone does not guarantee higher economic returns from external economic activity.

Similar conclusions are observed in studies of resource-dependent economies. Evidence from Azerbaijan indicates that trade openness does not exert a stable positive effect on economic growth, whereas internal development factors, including investment and economic structure, play a decisive role (Seyfullayev, 2022). This finding is particularly relevant for Kazakhstan, where extractive industries dominate and dependence on external markets remains high.

Studies specifically focused on Kazakhstan are also of particular importance. Khan et al. (2018) identify the existence of a long-term relationship between trade openness and economic growth, but emphasize the ambiguity of causal linkages. This indicates that the impact of openness on economic development is not direct and may be mediated by other macroeconomic factors. Thus, even at the national level, there is no clear empirical evidence supporting the dominant role of trade as a driver of growth.

Recent research increasingly highlights the conditional nature of the impact of trade openness. Nguyen and Nguyen (2025) demonstrate that the effect of openness on economic growth depends significantly on institutional and structural characteristics, including governance quality, the level of information and communication technologies, human capital, and resource endowment. In the absence of these conditions, the impact of trade may be limited or statistically insignificant.

This perspective is consistent with other empirical studies emphasizing the role of internal factors as key transmission channels of the openness effect. In particular, the impact of trade on economic growth may operate through improvements in total factor productivity, human capital accumulation, and technological development (Ramzan et al., 2019; Fatima et al., 2020). In developing economies, where these channels are insufficiently developed, the positive effects of openness may not fully materialize.

Furthermore, evidence from Central Asian countries suggests that economic growth is driven primarily by internal factors, including technological progress and digitalization, which reduces the role of trade openness as an independent growth driver (Kurmanov et al., 2025). This reinforces the argument that in transition and resource-based economies, structural transformation and investment activity are of primary importance.

Taken together, these studies provide a theoretical and empirical foundation for interpreting the results of the present research. Contrary to the classical view of a direct and positive relationship between trade openness and economic growth, contemporary evidence points to a more complex, mediated, and context-dependent relationship. This helps explain the finding of this study that trade openness does not have a statistically significant impact on gross regional product.

Thus, it can be concluded that, for the regions of Kazakhstan, trade openness alone is not a sufficient condition for economic growth. Its effects are realized through a system of internal factors, including investment, technological development, and structural characteristics of the economy, highlighting the need to shift economic policy from the quantitative expansion of trade toward improving its quality and deepening integration into global value chains.

Data and Methodology

This study employs an econometric approach to analyze the factors determining trade openness across the regions of the Republic of Kazakhstan, as well as to assess the impact of external trade activity on their economic development. The methodological framework is based on panel data analysis, which allows for capturing both cross-regional heterogeneity and temporal dynamics of the indicators.

The empirical basis consists of panel data covering 16 regions of the Republic of Kazakhstan over the period 2014–2024 (176 observations). The selected time frame is determined by the availability of consistent and comparable regional statistics on foreign trade.

The data are sourced from the Bureau of National Statistics of the Republic of Kazakhstan. To ensure the comparability of the panel dataset, several regions were excluded from the analysis due to limited data availability for earlier years. Specifically, the regions of Zhetysu, South Kazakhstan, Ulytau, Abai, as well as the city of Shymkent, were not included, as their statistical records are available only from 2018 onward, which prevents the construction of a balanced panel for the full study period.

In addition, due to administrative-territorial changes in the Republic of Kazakhstan, statistical data for the South Kazakhstan and Turkestan regions were aggregated and treated as a single territorial unit. This adjustment was necessary to maintain consistency in time series and preserve the integrity of the panel structure. To ensure comparability, export and import values originally reported in foreign currency were converted into tenge using the average annual official exchange rate.

Within the study, the following dependent variables are defined: ln(GRP), the natural logarithm of gross regional product, used as an indicator of regional economic development, and TradeOpenness, a measure of trade openness calculated as the ratio of total exports and imports to gross regional product:

$$\text{TradeOpennessit} = \frac{Export_{it} + Import_{it}}{GRP_{it}} \tag{1}$$

The independent variables are specified as logarithmic transformations of the following macroeconomic indicators: ln_GFCF, the logarithm of gross fixed capital formation; ln_Cargo, the logarithm of cargo turnover; and ln_Employment, the logarithm of employment.

The use of logarithmic transformation is motivated by the need to reduce the variability of the data and to allow the estimated coefficients to be interpreted in terms of elasticities.

To achieve the research objectives and test the proposed hypotheses, a two-stage econometric framework is employed, based on the estimation of two interconnected panel models. This approach enables a sequential analysis of both the determinants of regional trade structure and its impact on economic development.

The first model is designed to identify the factors determining the level of trade openness across regions. In this specification, trade openness is treated as an outcome of internal economic conditions, including investment activity, the development of transport infrastructure, and the scale of employment. Accordingly, the first model addresses the question of which factors explain differences in trade integration across regions of Kazakhstan. The econometric specification of the model is as follows:

$$\text{TradeOpennessit} = \beta 0 + \beta 1 ln(\text{GFCFit}) + \beta 2 ln(\text{Cargoit}) + \beta 3 ln(\text{Employmentit}) + \mu\text{i} + \varepsilon\text{it} \tag{2}$$

where:

TradeOpenness_it denotes the level of trade openness of region *i* at time *t*;

GFCF_it represents investment in fixed capital;

Cargo_it refers to cargo turnover;

Employment_it indicates employment;

μ_i captures region-specific fixed effects reflecting time-invariant characteristics;

ε_it is the error term.

The selection of explanatory variables is grounded in the economic logic of trade activity formation. Investment in fixed capital reflects the production capacity of a region and creates conditions for expanding external economic activity. Cargo turnover is used as a proxy for the level of development of transport and logistics infrastructure, which directly affects the intensity of trade flows. Employment characterizes the scale of economic activity and the size of the domestic market, which may either stimulate or reduce reliance on external trade.

The second model aims to assess the impact of trade openness on regional economic development. In this specification, trade openness is treated as an explanatory variable, allowing its contribution to gross regional product to be evaluated. Accordingly, the second model addresses whether the level of trade openness influences the economic development of Kazakhstan's regions. The econometric specification of the model is as follows:

$$\ln(GRPit) = \beta0 + \beta1TradeOpennessit + \beta2\ln(GFCFit) + \beta3\ln(Employmentit) + \mu i + \varepsilon it \qquad (3)$$

where:

GRP_it denotes the gross regional product, while the remaining variables correspond to those defined in the previous model.

The inclusion of the trade openness variable allows testing the hypothesis regarding its effect on economic growth. According to open economy theory, a higher degree of integration into international trade should promote growth through expanded market access, improved efficiency, and access to advanced technologies. At the same time, investment serves as a key driver of economic growth, reflecting capital accumulation and the expansion of productive capacity, while employment is included as a control variable capturing the scale of regional economic activity.

For clarity, the sequence of methods and stages of the empirical analysis is illustrated in Figure 1.

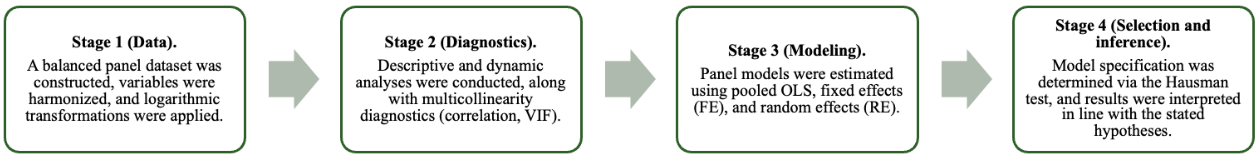

Figure 1. Conceptual framework of the empirical analysis

The established methodological framework provides a basis for proceeding to the interpretation of the empirical results obtained from the estimated models.

Results and Discussion

The study employs a balanced panel dataset covering 16 regions of the Republic of Kazakhstan over the period 2014–2024. The constructed dataset allows for capturing both cross-regional differences and the temporal dynamics of key economic indicators, which is essential for analyzing processes of trade integration. Table 1 presents the descriptive statistics of the variables used, enabling an assessment of their distribution, variability, and general patterns of regional development.

Table 1 –Descriptive statistics of variables

Indicator	GRP (mln tenge)	GFCF (mln tenge)	Cargo (mln t-km)	Employment (thousand persons)	Export (mln tenge)	Import (mln tenge)
Mean	4 405 129	693 810	24 937	511	1 390 781	919 799
Median	3 051 730	508 124	24 042	424	798 446	396 967
Standard deviation	4 236 935	645 403	10 854	214	2 184 817	1 704 927
Minimum	79 551	116 943	5 646	249	30 769	27 775
Maximum	31 294 467	4 328 236	53 698	1 083	14 992 642	11 704 095
Observations	176	176	176	176	176	176
Note: compiled and calculated by the authors using RStudio based on the original dataset						

The average value of gross regional product (GRP) amounts to 4,405,129 million tenge, with a median of 3,051,730 million tenge, indicating a pronounced right-skewed distribution. The gap between the minimum (79,551 million tenge) and maximum values (31,294,467 million tenge) confirms a very high level of interregional disparity in economic development.

A similar pattern is observed for gross fixed capital formation: while the mean is 693,810 million tenge, the median is considerably lower at 508,124 million tenge, and the range spans from 116,943 to 4,328,236 million tenge. This suggests a strong concentration of investment activity in a limited number of regions. External trade indicators exhibit even greater heterogeneity: average exports amount to 1,390,781 million tenge, with a maximum of 14,992,642 million tenge, while imports range from 27,775 to 11,704,095 million tenge.

The high standard deviation values—4,236,935 million tenge for GRP, 2,184,817 million tenge for exports, and 1,704,927 million tenge for imports—indicate substantial variability and further confirm significant regional disparities. In contrast, employment shows a relatively narrower dispersion (with an average of 511 thousand persons and a range from 249 to 1,083 thousand), reflecting greater stability of demographic factors compared to economic indicators.

Overall, the quantitative characteristics of the dataset clearly point to structural heterogeneity in Kazakhstan's regional economy, a high concentration of economic activity, and considerable differences in investment and trade performance across regions. These features justify the application of panel data models that account for region-specific effects.

Table 2 — Variables and their economic justification

Variable	Description	Justification
TradeOpenness	Ratio of exports and imports to GRP	Captures the degree of regional integration into international trade and external markets
ln(GRP)	Natural logarithm of gross regional product	Serves as an indicator of regional economic development
ln(GFCF)	Natural logarithm of gross fixed capital formation	Reflects investment activity and capital accumulation as key drivers of growth
ln(Cargo)	Natural logarithm of cargo turnover	Acts as a proxy for the development of transport and logistics infrastructure
ln(Employment)	Natural logarithm of employment	Controls for the scale of economic activity and labor resources

The key indicator in this study is trade openness (TradeOpenness), which reflects the degree of regional integration into international trade. This measure is calculated as the ratio of total exports and imports to gross regional product (Equation 1), ensuring comparability across regions with different economic scales. Figures 2 and 3 illustrate the average level and distribution of TradeOpenness across regions, allowing for the identification of key trends and differences in external trade activity.

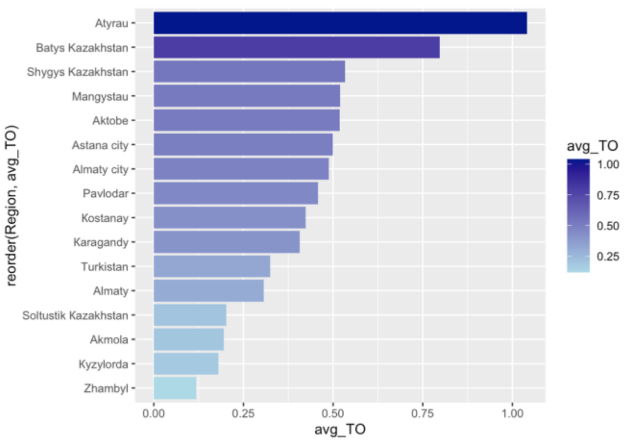

Figure 1. Average level of trade openness across regions

Note: compiled by the authors using RStudio based on data from the Bureau of National Statistics of the Republic of Kazakhstan.

The results presented in Figures 1 and 2 indicate a pronounced interregional disparity in the level of trade openness across Kazakhstan. In particular, resource-oriented regions such as Atyrau and West Kazakhstan occupy leading positions, with values significantly exceeding the regional average. This is consistent with their strong involvement in export-oriented activities, primarily in the extractive sectors of the economy.

At the same time, several regions, including Zhambyl, Kyzylorda, and Akmola, exhibit considerably lower levels of TradeOpenness, indicating a stronger orientation toward the domestic market and limited participation in external economic activities. Overall, these patterns point to a persistent structural heterogeneity within the regional economy.

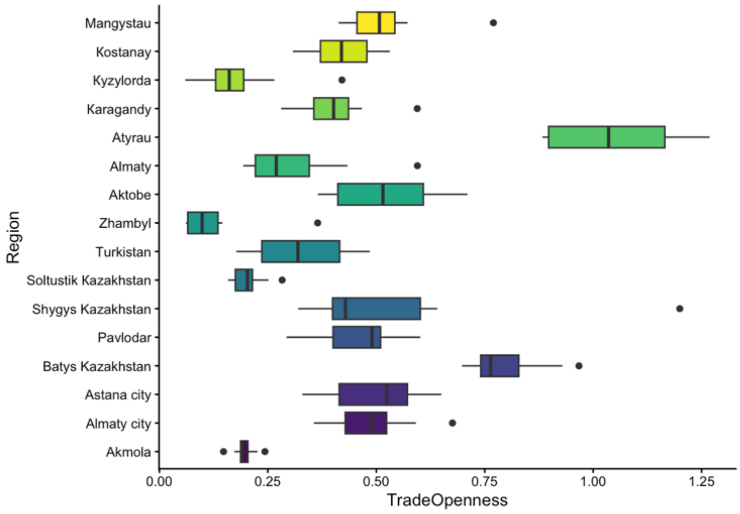

Figure 2. Variability of trade openness across regions

Note: compiled by the authors using RStudio based on data from the Bureau of National Statistics of the Republic of Kazakhstan

Furthermore, the analysis of the distribution of the indicator (Figure 2) shows that differences are observed not only in the levels, but also in the variability of trade activity. In some regions, significant fluctuations and outliers are evident, which are likely associated with dependence on external market conditions and the volatility of export flows.

In the context of the proposed hypotheses, these findings suggest that the level of trade openness is shaped by the structural characteristics of regions, including their sectoral specialization and the presence of export-oriented industries.

Results of the panel regression analysis.

At the first stage of the empirical analysis, the relationships between the key variables of the model are examined. This step allows for a preliminary assessment of the direction and strength of associations, as well as the identification of potential multicollinearity issues that may affect the robustness of subsequent regression estimates.

Given that the study employs two interconnected models, the correlation analysis includes all main variables, covering indicators of economic development, trade openness, and factors reflecting regional production activity (Table 3).

Table 3 — Correlation matrix of variables

Variables	ln_GRP	TradeOpenness	ln_GFCF	ln_Cargo	ln_Employment
ln_GRP	1.000	0.500	0.858	—	0.309
TradeOpenness	0.500	1.000	0.584	0.058	-0.223
ln_GFCF	0.858	0.584	1.000	0.330	0.086
ln_Cargo	—	0.058	0.330	1.000	0.002
ln_Employment	0.309	-0.223	0.086	0.002	1.000
Note: compiled and calculated by the authors using RStudio based on the original dataset					

The results of the correlation analysis indicate the presence of economically meaningful relationships among the variables under consideration. The strongest positive correlation is observed between gross regional product and gross fixed capital formation (0.858), confirming the central role of capital accumulation in driving regional economic growth (Figure 3).

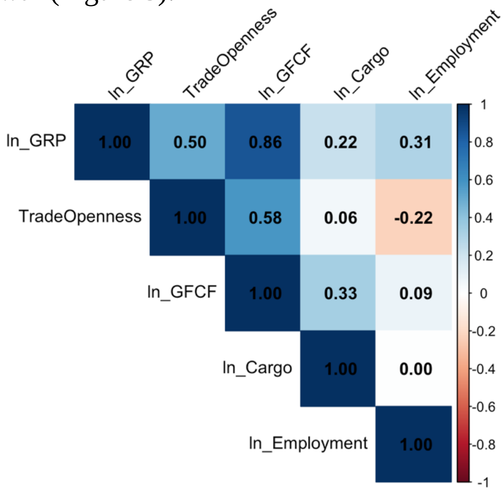

Figure 3. Correlation matrix of variables

Note: compiled by the authors using RStudio

The relationship between trade openness and the level of economic development is moderate (0.5), indicating the importance of external economic activity, but not allowing it to be considered as the sole or dominant driver of growth. This indirectly suggests that the effect of openness operates through more complex channels, including investment and the structural characteristics of regional economies.

Particular attention should be given to the moderate positive correlation between TradeOpenness and investment (0.584), which may reflect a mutually reinforcing relationship: on the one hand, openness facilitates capital inflows, while on the other hand, investment creates the foundation for expanding external trade activity.

At the same time, the relationships among the explanatory variables remain low (with a maximum of 0.33), indicating their relative independence and supporting the validity of including these factors in the regression models.

In the context of the proposed hypotheses, these findings suggest that investment activity serves as a key driver of economic growth, whereas trade openness plays a complementary rather than a decisive role, shaping the conditions for further regional development.

To more rigorously test for multicollinearity, the variance inflation factor (VIF) was calculated for all explanatory variables. Unlike correlation analysis, this measure provides a quantitative assessment of the degree of linear dependence among the factors within the model.

Table 4 — Multicollinearity test (VIF)

Переменные	Model 1	Model 2
ln_GFCF	1.13	1.64
ln_Cargo	1.12	—
ln_Employment	1.01	1.14
TradeOpenness	—	1.71

As shown in Table 4, the calculated VIF values range from 1 to 2, which is well below the commonly accepted critical thresholds (5–10). This indicates the absence of multicollinearity and confirms the correctness of the model specification. Accordingly, the included variables do not duplicate each other and allow for obtaining stable and interpretable regression coefficient estimates. This ensures the reliability of subsequent estimations and enables progression to the key stage of the study, namely the estimation of panel models. It is at this stage that the main research question can be addressed: which factors determine regional trade integration and whether it contributes to economic growth.

Tables 5 and 6 present the results of the panel regression estimations obtained using least squares methods adapted to panel data structures (pooled OLS, fixed effects, and random effects specifications).

Table 5 — Estimation results of Model 1 and Hausman test

Variables	Coefficient	Std. Error	t-statistic	p-value
ln_GFCF	0.025	0.0239	1.0457	0.2973
ln_Cargo	0.026	0.0556	0.4716	0.6379
ln_Employment	-0.228***	0.0857	-2.6617	0.0086
Model statistics	Value	χ^2	p-value	Model choice
R^2	0.053	106.5	<0.001	Fixed Effects
F-statistic	2.919			
Prob (F-stat)	0.0359			
Note: dependent variable — TradeOpenness *** indicates statistical significance at the 1 % level. Calculated by the authors using RStudio based on the study data.				

The econometric specification of the model is as follows:

$$TradeOpennessit = -0.834 + 0.025ln(GFCFit) + 0.026ln(Cargoit) - 0.228ln(Employmentit) + \mu i + \varepsilon it$$

The results indicate that employment is the only statistically significant factor in the model. The coefficient on ln_Employment is negative and significant at the 1 % level (β = −0.228), suggesting that a 1 % increase in employment is associated with an approximate 0.23 % decrease in trade openness.

From an economic perspective, regions with higher levels of employment tend to have more developed domestic markets and a lower dependence on external economic relations. In such regions, economic activity is primarily oriented toward domestic demand, which reduces the relative importance of foreign trade.

At the same time, investment (ln_GFCF) and cargo turnover (ln_Cargo) do not have a statistically significant effect on TradeOpenness. This may indicate that the presence of infrastructure and investment activity alone does not ensure regional integration into international trade in the absence of appropriate export specialization.

The low value of the coefficient of determination ($R^2 = 0.053$) suggests that the model explains only a small share of the variation in trade openness. This implies the presence of additional factors, such as institutional or sectoral characteristics, that are not captured in the model. The results of the Hausman test (p-value < 0.001) support the preference for the fixed effects specification, indicating the presence of unobserved region-specific characteristics affecting trade activity.

As for the results of the second model (Table 6), the estimated coefficients provide further insight into the factors determining regional economic development. The estimated equation is as follows:

$$ln(GRPit) = 1.286 + 0.173TradeOpennessit + 0.857\,ln(GFCFit) - 0.003\,ln(Employmentit) + \mu i + \varepsilon it$$

The results indicate that investment in fixed capital is the key driver of economic growth. The coefficient on ln_GFCF is positive and statistically significant at the 1 % level (β = 0.857), implying that a 1 % increase in investment is associated with an approximate 0.86 % increase in gross regional product. This finding is fully consistent with economic theory and confirms the role of capital accumulation as a primary engine of growth.

Table 6 — Estimation results of Model 2 and Hausman test

Variables	Coefficient	Std. Error	t-statistic	p-value
TradeOpenness	0.173	0.1377	1.33	0.2120
ln_GFCF	0.857***	0.0385	22.2510	<0.001
ln_Employment	-0.003	0.1467	-0.0195	0.9845
Model statistics	Value	χ^2	p-value	Model choice
R^2	0.764	апр.74	0.192	Random Effects
F-statistic	169.357			
Prob (F-stat)	<0.001			
Note: dependent variable — ln_GRP (regional economic development) *** indicates statistical significance at the 1 % level. Calculated by the authors using RStudio based on the study data.				

At the same time, the TradeOpenness variable does not demonstrate statistical significance (p-value = 0.212), despite having a positive coefficient. This indicates that, during the period under study, trade openness does not have a direct effect on regional economic growth. Its impact is likely indirect and operates through investment or structural transformations of the economy. Employment (ln_Employment) also does not have a significant effect on GRP, which may reflect differences in labor productivity and suggests that quantitative increases in employment do not necessarily translate into higher economic efficiency. The model exhibits strong explanatory power ($R^2 = 0.764$), indicating that the included variables account for a substantial share of the variation in gross regional product. The results of the F-test ($F = 169.357$; p-value < 0.001) confirm the overall statistical significance of the model.

According to the Hausman test results (p-value = 0.192), there are no systematic differences between fixed and random effects estimators, which justifies the use of the random effects specification. Overall, the results of the second model suggest that regional economic growth in Kazakhstan is primarily driven by internal factors, particularly investment activity, while the effect of trade openness remains statistically insignificant.

Based on the econometric findings, the proposed research hypotheses can be evaluated.

The first hypothesis, stating that investment activity has a positive impact on regional economic development, is fully supported. The coefficient on ln_GFCF is positive and statistically significant at a high level, confirming the key role of investment in shaping gross regional product.

The second hypothesis, which assumes a positive effect of trade openness on economic growth, is not supported. Despite the positive sign of the coefficient, the TradeOpenness variable is not statistically significant, indicating the absence of a direct impact of foreign trade on regional economic performance.

The third hypothesis, concerning the influence of production-related factors on trade openness, receives partial support. In particular, employment shows a statistically significant but negative effect on TradeOpenness, while investment and cargo turnover do not exhibit significant effects. This suggests a more complex nature of trade openness formation, driven by the structural characteristics of regional economies.

The results presented in Table 7 summarize the findings of the econometric analysis and provide an overall assessment of the degree to which the proposed hypotheses are supported.

Table 7 — Summary of hypothesis testing results

Hypothesis	Hypothesis description	Result	Interpretation
H1 (Model 2)	Investment (ln_GFCF) has a positive effect on economic development (ln_GRP)	Confirmed	The coefficient is positive and statistically significant, confirming the key role of investment as a driver of economic growth
H2 (Model 2)	Trade openness (TradeOpenness) has a positive effect on economic growth	Not confirmed	Despite the positive sign, the coefficient is statistically insignificant, indicating the absence of a direct effect of foreign trade on economic development
H3 (Model 1)	Production activity factors influence the level of trade openness	Partially confirmed	Employment has a significant negative effect, while investment and cargo turnover do not demonstrate statistical significance

Thus, the findings indicate the ambiguous impact of foreign trade and confirm the dominant role of internal factors, particularly investment activity.

Conclusion

The conducted study has identified key patterns in the formation of trade openness and economic development across the regions of Kazakhstan in the context of their integration into global economic processes.

The results show that the regional economy is characterized by a high degree of heterogeneity, reflected both in the level of trade activity and in the scale of economic development. Trade openness is largely concentrated in resource-oriented regions, which reflects the existing model of Kazakhstan's participation in international trade.

The econometric analysis confirms that investment in fixed capital is the primary driver of economic growth, while the effect of trade openness is statistically insignificant. This finding suggests that participation in foreign trade alone does not ensure sustainable economic growth and requires additional conditions, such as the development of processing industries and the expansion of value added.

At the same time, the analysis of the determinants of trade openness indicates that its formation is driven less by investment and infrastructure and more by the structural characteristics of regional economies, including sectoral specialization and orientation toward domestic or external markets.

From a policy perspective, these findings highlight the need to shift from the quantitative expansion of foreign trade toward improving its qualitative aspects. This involves deeper integration into global value chains, the development of export-oriented processing industries, and the promotion of investments aimed at enhancing the technological level of production.

Overall, the study confirms that sustainable regional economic development in Kazakhstan is primarily driven by internal factors, while trade openness plays a complementary role and requires institutional and structural strengthening to fully realize its potential.

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Digital financial inclusion and poverty reduction in Kazakhstan

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Abstract

Digital financial inclusion serves as a key mechanism for enhancing accessibility of financial services and fostering inclusive and sustainable economic growth. The accelerated expansion of financial technologies including digital banking, electronic payments and online platforms has opened new prospects for improved financial availability, especially for disadvantaged and underserved populations. Simultaneously, the degree of contribution the digital financial inclusion exerts on poverty mitigation remains a critical challenge for both scholars and policymakers. The present study aims to evaluate the poverty-reducing impacts of digital financial inclusion in Kazakhstan. To do that, the research focuses on examining both short-run dynamics and long-term relationships between poverty level and digital financial inclusion. To proxy digital financial inclusion, a composite index was designed combining internet users with automated teller machines based on principal component analysis. The empirical study utilizes Autoregressive Distributed Lag approach to examine both short-run dynamics and long-term associations between variables. The results of cointegration testing validate the presence of stable equilibrium relationships among variables in the long run. Estimated parameters reveal that digital financial inclusion exerts a strong long-term negative impact on poverty level. The findings of empirical analysis underscore the importance of digital financial inclusion in alleviating poverty, suggesting that enhanced digital financial infrastructure substantially contributes to inclusive economic progress. By assessing the association between digital financial technologies and poverty indicators, the study contributes to the current literature in the context of developing countries. Research results generate several policy implications for expanding financial inclusion and developing digital financial ecosystems to support long-term poverty reduction.

Keywords: digital financial inclusion, poverty reduction, internet users, automated teller machines, ARDL approach, short-run dynamics, long-term relationships.

Introduction

Poverty reduction continues to be one of the principal objectives of long-term economic development in developing economies. Despite considerable improvements in alleviating poverty levels in many countries, comparative poverty and income differences remain a key challenge for policymakers. In this regard, enhanced access to basic financial services has been acknowledged as a core mechanism for fostering all-inclusive development and mitigating poverty (Ozili, 2018; Khan,2024). Financial inclusion allows households and businesses to afford fundamental financial services including loans, payments, investments and insurance, enabling them to cope with financial risks, balance consumption and participate in profit-making activities. Consequently, expansion of available financial services is increasingly recognized as a significant tool for achieving Sustainable Development Goals, connected to poverty alleviation and inclusive development (Sahay et al.,2015).

Over the past decades, rapid technological progress has revolutionized traditional financial service channels and gave rise to digital financial inclusion. It refers to the provision of financial services through advanced technologies including digital banking, online payment systems, digital platforms and wallets. Thus, digital financial inclusion enables individuals and entrepreneurs to get facilitated access to core financial services, particularly those who are economically disadvantaged and formerly excluded from formal financial services (Sun, 2018). By decreasing operational costs, mitigating spatial barriers, and strengthening accessibility, digital financial services integrate vulnerable groups into the institutional financial system (Al Khub et al.,2024).

Increasing body of literature underscores the importance of digital financial inclusion in reducing poverty and income disparities. Improved financial access allows households to save money, get secure loans, engage in efficient economic activities, reinforcing earning opportunities and reducing susceptibility to economic risks (Fouejieu et al., 2020). Moreover, financial inclusion strengthens financial resilience and social support by incorporating earlier excluded groups into regulated financial markets (Khan, 2024). Many

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empirical studies have revealed that enhanced financial access plays a substantial role in poverty mitigation and fosters economic well-being in developing countries.

Digital technologies further enhance finance-growth relationships by enlarging financial affordability to underserved and marginalized groups. Through digital banking and electronic payments households in isolated and provincial areas can get formal financial services without attending physical banking branches. This decreases financial exclusion, generates new business and investment opportunities (Aracil et al.,2022; Wang&Luo, 2022). Accordingly, digital financial inclusion has been widely approved as a strategic government tool for alleviating poverty and supporting inclusiveness of economic growth.

However, the association between digital financial inclusion and poverty remains exposed to continuing discussion in the existing literature. Some researchers argue that financial technologies mitigate poverty by facilitating credit accessibility and enhancing resource distribution, while others imply that benefits of digital technologies may be unequally shared across different income levels (Fouejieu et al., 2020). To be precise, recent findings indicate that financial technological progress may worsen income gap if digital technologies are predominantly accessible to upper-income groups with better technological framework and financial education (Wong et al.,2023). Thus, the influence of digital financial inclusion on poverty reduction may differ among countries due to institutional quality, digital infrastructure, and country-specific characteristics.

Despite an increasing amount of research examines the relationship between poverty and financial inclusion, evidence-based findings on digital financial inclusion stay relatively limited, especially in developing economies. Most previous research primarily focus on large emerging regions such as Africa and Asia, while insufficient attention has been paid to Central Asian region. Interpreting the role of digital financial inclusion in developing economies is significantly important, considering their persistent financial transformation and expanding digital diffusion. Against this context, this study evaluates the influence of digital financial inclusion on poverty alleviation in Kazakhstan. To do that, this research aims to examine both short-run dynamics and long-term relationships between poverty level and digital financial inclusion controlling for economic factors such as exports of goods and services, inflation and gross capital formation. Having considered theoretical frameworks and empirical findings, it is hypothesized that digital financial inclusion exerts significant negative impact on poverty level and its effect may vary across short-run and long-term dynamics. To investigate the DFI-poverty nexus, a composite DFI index is constructed applying principal component analysis integrating indicators such as internet users and ATMs. The quantitative analysis estimates both short-run trends and persistent long-term relationships based on Autoregressive Distributed Lag (ARDL) approach. By assessing the association between digital financial technologies and poverty indicators, the study adds to the current literature on financial inclusion and inclusive economic growth in developing countries. Research findings are assumed to provide critical insights for policymakers intending to enhance digital financial inclusion and long-term poverty alleviation.

Literature review

Poverty reduction continues to be a primary goal of development strategies, and extensive research highlights that expanding access to basic financial services improves household living standards and alleviates poverty. Access to deposits, transactions, and loans are enhanced by financial inclusion, thereby facilitating consumption balancing, uncertainty management and earning opportunities. Cross-national evidence supports the poverty mitigation effect of financial inclusion. For instance, Tran and Le (2021) design a composite financial inclusion index based on principal component analysis (PCA) using a panel of European countries and found that improved financial inclusion is connected to reduced poverty across different poverty thresholds. In a similar manner, Nsiah et al. (2021) indicate that financial inclusion in Sub-Saharan Africa alleviates poverty only after attaining the cutoff point, reflecting non-linear nexus between finance and poverty. This suggests that inefficient financial systems may not inherently generate poverty mitigation benefits.

With accelerated adoption of ICT, the emphasis has been placed on digital financial inclusion (DFI) rather than traditional financial inclusion. The DFI refers to the use of digital pathways and technological advancements to broaden financial access, reduce intermediation costs, and resolve geographic barriers. Emerging empirical literature reveals that digital financial inclusion can enhance poverty mitigation by strengthening service delivery, decreasing operational transaction costs and enabling new channels for financial engagement. Kumari and Giri (2025) generated DFI index through PCA across Asian economies and found positive relationship between DFI and poverty reduction in the long run, recoding reverse causality between the two. These results imply that digital pathways can reinforce the spillover effect via enhanced availability of financial services and involvement in market activities.

Empirical results from China offer most comprehensive findings on the connection between DFI and poverty applying both large scale and micro-level household data. Xie (2023) provides regional evidence concluding that DFI substantially mitigates poverty rates even after considering the effects of income inequality, sectoral structure and financial investment in agricultural, educational and open-economy policies. At the micro level, Dong et al. (2024) argue that digital financial inclusion advances noticeably alleviate household poverty by functioning through local enterprise activities. The authors also found that these effects are more pronounced within rural households. Consistent with these results, Tao et al. (2023) clearly concentrate on relative poverty, revealing that digital financial inclusion reduces the likelihood of entering comparative poverty by diminishing formal loan constraints, supporting engagement in high-risk financial investments and promoting small-scale rural entrepreneurship. Within a similar research lines, Wang and Fu (2021) state that DFI alleviates exposure to poverty within rural communities and both the extent and intensity of DFI usage are important. Importantly, their indirect effect analysis underscores agricultural outputs, non-farm employment and entrepreneurship as core mechanisms.

Moreover, empirical evidence from South Asia and Africa also validates that DFI can strengthen social welfare effects, even though the outcome may vary across different fintech tools. Onyejiaku et al. (2024) examining African developing economies based on ARDL approach, found that automated cash machines, digital wallet transactions and broader financial development lead to poverty reduction measured by consumer consumption. While digital payments exhibit negative association with poverty alleviation reflecting that cost, service charge and usage behavior may generate differential welfare outcomes. Similarly, Kelikume (2021) indicates that mobile coverage and internet adoption are correlated with poverty mitigation in Africa highlighting the connection between digital diffusion, financial inclusion and shadow economy. Islam et al. (2025) analyzed disadvantaged populations in Bangladesh using logistic statistical model and variable reduction method and found that enhanced access to digital financial services results in reduced poverty, especially through income generation and non-food spending pathways. Consistent with these results, Hussain and Dikko (2024) provide empirical evidence from north-western Nigeria implying that both traditional and digital financial inclusion promote alleviation of poverty through job opportunities, increased consumer capacity, and enhanced wellbeing, emphasizing entrepreneurial activities as the main transitional outcome.

Large bodies of literature also highlight that socio-economic and institutional conditions influence the magnitude and direction of DFI's poverty-related outcomes. Joseph (2025) offers panel evidence based on IV method, implying that financial inclusion eradicates extreme poverty and the impact is much more significant when combined with digital network systems and financial awareness programs. This corresponds with wider perspectives that ICT infrastructure and capability barriers can restrict poverty reducing potential of digital financial inclusion. Based on systematic literature review, Amarasooriya (2025) argues that digital instruments including digital banking, wallets and platforms support economic stability, enterprise development behavior and living standards among vulnerable groups. The research also emphasized research limitations regarding cross-border cash inflows, ecological consequences, digital technology risks and cyber protection. Moreover, Tay et al. (2022) suggest that even though digital financial inclusion is predominantly enhanced to achieve SDGs, especially poverty reduction goals, differences by gender, economic status and geographic location persist, implying that uneven access to digital tools, internet availability and digital skills may exacerbate inclusive effects of digital finance.

Another line of research connects poverty to financial inclusion with overall macroeconomic stability and income distribution frameworks. Khan (2024) states that financial inclusion alleviates poverty and income gap, thereby strengthening financial resilience. The author also highlights that inflation increases poverty and income disparities. In a related manner, Kumari et al. (2025) demonstrate that gender-specific digital financial inclusion and female empowerment substantially facilitate poverty mitigation in Asian countries, implying that allocation effects of digital finance may rely on gender divide in access and enabling mechanisms. Overall, prior literature indicates that digital financial inclusion contributes to poverty reduction through several important pathways such as improved access to credit, promotion of entrepreneurship, output growth and strengthened household stability. The effects vary in scale and direction across different settings, tools and communities (Tao et al.,2023; Tay et al., 2022; Onyejiaku et al.,2024). Importantly, many empirical studies focus on China, Africa and other multi-country samples, while Central Asia remains insufficiently investigated. This research gap is especially meaningful for Kazakhstan, which is characterized by rapid expansion of digital transaction systems and fintech startups, but questions related to poverty-reducing impacts of digital financial inclusion in Kazakhstan remain underexamined. Following earlier research, the current study aims to investigate the relationship between DFI and poverty in Kazakhstan as a noteworthy case from developing economy context.

Methodology

Estimation approach

The study uses the Autoregressive Distributed Lag (ARDL) estimation to investigate the connection between digital financial inclusion and poverty. This framework, designed by Pesaran, Shin and Smith (2001), is broadly utilized in evidence-based macroeconomic analyses to evaluate both short-term and long-term interactions.

The ARDL approach has numerous strengths, that make it appropriate for this study. First, it can be employed when variables follow an order of integration (I (0) and I (1)), given that none is integrated of order I (2). This feature enables the ARDL to be more adaptable compared to other conventional cointegration methods. Second, the ARDL technique works effectively in small datasets, which is relevant for research based on annual economic data with restricted sample observations. Third, this approach allows the assessment of both short-term fluctuations and long-run stable equilibriums in an integrated approach via the Error correction model (ECM). Moreover, the ARDL is characterized by procedures that test bounds and presence of long-run connections between variables without the necessity of identical order of integration. Considering these methodological advantages, ARDL is recognized as a suitable framework for examining the effect of digital financial inclusion on poverty alleviation.

DFI index design

In order to quantify the level of digital financial inclusion, a composite index was built based on Principal component analysis (PCA). This method is used in empirical studies to aggregate several related indicators into a single unified index while simplifying dimensions and keeping maximum information content of the initial variables.

The DFI index was constructed based on two essential indicators related to availability of digital financial services:

– -the number of individuals using the internet (% of population), indicating the extent of digital connection and potential availability of digital financial services.

– -the number of ATMs per 100,000 adults, reflecting the maturity of financial structures and banking facilities

These variables cover reinforcing dimensions of digital financial access. While internet diffusion represents the technological settings that enhance digital financial inclusion, ATM reflects the availability of fundamental financial services.

Model specification

To examine the factors influencing poverty, the long-run model formulated as follows:

$$\boldsymbol{lnpoverty_t=\beta_0+\beta_1 DFI_t+\beta_2 gfcf_t+\beta_3 lnexports_t+\beta_4 inflation_t+\varepsilon_t}$$

where:

- $lnpoverty_t$ — the log of poverty;

-DFI_t — digital financial inclusion index;

-$gfcf_t$ — gross fixed capital formation;

-$lnexports_t$ — the log of exports of goods and services;

-$inflation_t$ — inflation rate;

-ε_t — error term.

To consider temporal adjustments, the ARDL error correction model specification is constructed in the following manner:

$$\Delta ln(poverty_t) = \alpha_0 + \sum_{\{i=1\}_i} \alpha_i \Delta ln\left(poverty_{\{t-i\}}\right) + \sum_{\{j=0\}_j} \beta j X_{\{t-j\}} + \lambda ECT_{\{t-1\}} + u_t$$

where λECT_{t-1} indicates error correction term, representing the adjustment coefficient towards the steady state after short-term shocks. The error correction term exhibited a negative and statistically significant coefficient, validating the existence of long-term relationship between variables.

Diagnostic tests

To check for credibility of empirical results, numerous assessment tests are conducted. The Breusch-Godfrey is used to detect serial autocorrelation in the residuals of the model, while Breusch-Pagan test is performed to evaluate heteroskedasticity. The Ramsey RESET test is carried out to verify model correctness. Moreover, variance inflation factors (VIFs) are utilized to assess multicollinearity among independent variables. These validation tests enable the confirmation of the model and verify that the fitted connections between digital financial inclusion and poverty are statistically reliable and consistent.

Data and variables

The empirical evaluation relies on annual national accounts data across the period between 2004 and 2024. Observational dataset involves core economic indicators that represent both financial inclusion and macroeconomic settings affecting poverty trends. The data were extracted from World Development Indicators database which offers standardized international metrics for macroeconomic and financial parameters.

The poverty rate is the main predicted variable, indicating the share of population below the societal poverty threshold. To normalize variance and decrease heteroskedasticity the poverty was converted to natural log form.

Digital financial inclusion index, designed by principal component analysis, is the main independent variable. The index integrates two metrics reflecting availability of both digital and traditional financial instruments: internet coverage and the number of automated teller machines (ATMs). This combined indicator enables us to generate a more comprehensive assessment of digital financial inclusion covering both digital penetration and financial infrastructure.

Multiple control variables are incorporated into the model to adjust for macro-financial factors that may affect poverty. Investment activities are proxied by gross fixed capital formation, implying that greater the investment levels higher the employment opportunities. As a result, expansion of entrepreneurship and overall economic activities may lead to poverty reduction.

The exports of goods and services reflecting the effects of trade openness are also expressed in natural log form. Increased exports can foster economic engagement and increase household earnings with the help of workforce expansion and output growth.

Lastly, inflation is included in the model as a control for macroeconomic stability. Increasing inflation may decrease consumer purchasing power, especially for poor households, thereby increasing poverty levels.

Results and discussion

Table 1 demonstrates summary statistics of all variables applied in the baseline model estimation. It reports descriptive data including min, max, mean and standard deviation poverty, digital financial inclusion, gross capital formation, inflation and exports of goods and services across the chosen period.

Table 1. Descriptive statistics

Variable	Mean	Std.dev.	Min	Max
Lnpoverty	2.532	0.362	2.092	3.459
Dfi	0	1.391	-2.6	1.488
Gcf	27.536	3.001	22.998	35.527
Lnexports	3.688	0.204	3.35	4.046
Inflation	8.841	3.487	5.196	17.14
Note –compiled by the authors				

As can be seen from Table 1, the average value of lnpoverty is 2.532 implying moderate variability during the observed sample period. The digital financial inclusion index has a zero-mean suggesting the standardized and scaled form of the index. Exports and gross capital formation also exhibit moderate dispersion, while inflation shows widest distribution within the variables.

To analyze the temporal dynamics of variables, the time series trends were explored. Figure 1 shows visual depiction of all variables over the examined period.

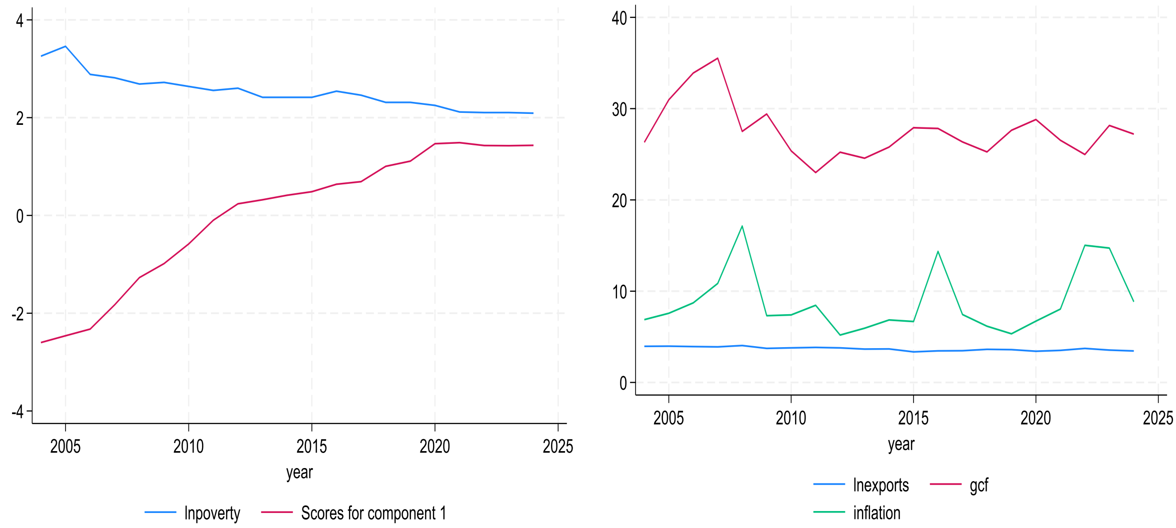

Figure 1. Time series dynamics of variables

Note — compiled by the authors

Figure 1 shows that poverty demonstrates slow downward trend during the observed period, while digital financial inclusion exhibits gradual upward increase, confirming the rapid expansion of digital financial instruments. Gross capital formation varies slightly, while inflation displays greater instability across the study period. Exports demonstrate consistent patterns with small variations. Overall, graphical representation offers initial insights into evolving behavior of variables before model estimation.

Table 2 below demonstrates correlation matrices between variables. The correlation analysis gives initial evidence of the size and direction of the relationships between dependent and independent variables.

Table 2. Pairwise correlations

Variables	lnpoverty	dfi	gcf	Lnexports	inflation
lnpoverty	1				
dfi	-0.940 (0.000)	1			
gcf	0.403 (0.070)	-0.509 (0.018)	1		
lnexports	0.731 (0.000)	-0.8 (0.000)	0.233 (0.310)	1	
inflation	-0.134 (0.562)	0.019 (0.934)	0.142 (0.539)	0.164 (0.479)	1
Note –complied by the author based on correlation analysis results					

The correlation results from Table 2 reflect statistically significant and negative association between poverty and digital financial inclusion, implying that high levels of DFI lead to reduced levels of poverty. Exports of goods and services positively correlate with poverty, while gross capital formation displays moderate positive connection. Even though inflation negatively correlates with poverty levels, it exhibits weak associations with both dependent and independent variables. Generally, the correlation coefficients do not reveal sever multicollinearity within independent variables.

To visualize the association between digital financial inclusion and poverty level the scatter plot was generated. The figure below depicts the relationship between lnpoverty, and digital financial inclusion index obtained using PCA.

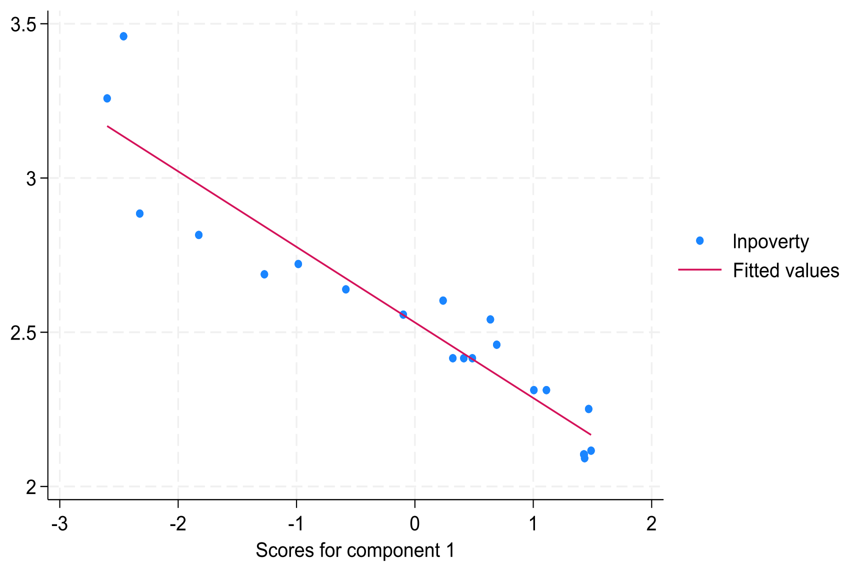

Figure 2. The relationship between poverty and digital financial inclusion

Note — compiled by the authors

Figure 2 illustrates pronounced negative correlation between DFI and poverty indicators. Greater digital financial inclusion is tied to reduced poverty levels, revealing that enhanced digital financial services substantially contribute to poverty alleviation. This graphical trend aligns with the results of correlation analysis reported above.

Prior to model estimation, variables were tested for stationarity relying on Augmented Dickey-Fuller unit root examination. This assessment test was utilized to identify the degree of variables' integration and verify the absence of second-order integration among variables. The ADF unit root test results are reported in Table 3.

Table 3. Augmented Dickey-Fuller unit root test results

Variable	Level ADF statistic	p-value	First Difference ADF	p-value	Integration order
Lnpoverty	-1.76	0.4	-6.5***	0.0000	I(1)
Dfi	-2.944**	0.04	-	-	I(0)
Gfcf	-2.324	0.1644	-4.951***	0.0000	I(1)
Lnexports	-1.728	0.4166	-5.743***	0.0000	I(1)
inflation	-3.251***	0.01	-	-	I(0)
*Note–compiled by the authors based on ADF results, ***p<0.01,**p<0.05,*p<0.1*					

As is noticed from Table 3, digital financial inclusion and inflation display level stationarity, while poverty, gross capital formation and exports achieve stationarity at first difference. Thus, variables exhibit integration orders of I (0) and I (1). Since variables demonstrate different orders of integration, the ARDL is the proper approach to investigate both short term and long-term associations between variables.

Based on unit root test results, the prevalence of long-term linkage between variables was explored applying ARDL bounds testing method. This approach enables us to conduct a cointegration test irrespective of integration orders of variables. Cointegration test outcomes are presented in Table 4 below.

Table 4. ARDL bounds test for cointegration

Test statistic			Value	
F-statistic			6.265	
t-statistic			-4.228	
Significance level	**I(0) lower bound (F)**	**I(1) upper bound (F)**	**I(0) lower bound (t)**	**I(1) upper bound (t)**
10 %	3.050	4.548	-2.542	-3.674
5 %	3.924	5.732	-2.984	-4.219
1 %	6.374	8.998	-3.959	-5.427
Note –complied by the author based on ARDL bounds test results				

As given in Table 4, the obtained F-statistic (6.265) is above the upper critical threshold at 5 % and 10 % levels. This rejects the null hypothesis indicating the absence of cointegration. Thus, these findings validate the presence of steady-state relationship between variables in the long run. Considering the existence of cointegration, the ARDL error correction approach is applied to estimate both short-run and long-run trends of the model.

Having confirmed the cointegration by ARDL bounds test, the long-term and shot run relationships between poverty and digital financial inclusion are examined utilizing the error correction method. Derived coefficients of ARDL estimation for both long-run and short-term dynamics are given in Table 5.

Table 5. ARDL estimation results

Variables	Long-run	Short run
Dfi	-0.348*** (-7.69)	0.254 (1.44)
Gcf	-0.035** (-2.31)	0.043*** (3.22)
Lnexports	-0.681** (-2.38)	0.614** (2.45)
Inflation	0.002 (0.26)	-
ECT	-	-1.089*** (-4.23)
Constant	-	6.488*** (4.20)
Note –compiled by the authors based on ARDL estimation results ****p<0.01, **p<0.05, *p<0.1, t-statistics are given in parentheses*		

The results in Table 5 demonstrate that digital financial inclusion exhibits negative and strongly significant influence on poverty level in the long run, implying that enhanced availability of digital financial services are associated with reduced poverty. The DFI coefficient implies that when DFI increases by one unit poverty decreases by 34.8 %. Similarly, both gross capital formation and exports of goods and services also display negative and statistically significant long-term impact on poverty, indicating that increased levels of investment and exports of goods and services facilitate poverty mitigation. In contrast, inflation does not exert statistically significant effect on poverty in the long term. The coefficient of error correction term has negative sign and is statistically significant at 1 % level, validating stable and steady-state equilibrium linkage between variables in the long run. The magnitude of ECT reveals that variations from equilibrium are adjusted at a rapid pace.

The short-run dynamics of the model indicate that changes in exports and gross capital formation positively and significantly influence poverty, while digital financial inclusion does not have significant effect on poverty in the short run. This implies that poverty-reducing effects of DFI are more prominent in the long run than in the short run.

To confirm the credibility of estimated results several diagnostic tests were performed. These evaluation tests address some econometric issues including autocorrelation, heteroskedasticity, potential model misspecification and multicollinearity between independent variables. Table 6 below presents the results of diagnostic tests.

Table 6. Diagnostic tests of the ARDL model

Test	statistic	p-value	conclusion
Breusch–Godfrey LM test (Autocorrelation)	$\chi^2(1) = 0.822$	0.3646	No serial correlation
Breusch–Pagan test (Heteroskedasticity)	$\chi^2(1) = 0.88$	0.3495	Homoskedasticity
Ramsey RESET test (Model specification)	$F(3,8) = 4.18$	0.05	No model misspecification
Variance Inflation Factor (Multicollinearity)	Mean VIF = 3.28	-	No serious multicollinearity
Note –complied by the author based on correlation analysis results			

The results in Table 6 reveal that designed ARDL model fulfills the main requirements of econometric assumptions. The Breusch-Godfrey test validates that residuals show no serial correlations, while the Breusch-Pagan test validates the absence of residual heteroskedasticity. Moreover, the Ramsey RESET confirms that model form does not demonstrate misspecification, implying that the model is appropriately formulated. The values of variance inflation factors show that multicollinearity is not a critical issue, since the mean VIF is well below the acceptable threshold. Overall, the findings of empirical analysis confirm that the fitted model is robust and reliable.

Research results reveal that digital financial inclusion has a major long-term impact in reducing poverty. The statistically significant negative coefficient of DFI reflects that increased accessibility of digital financial services leads to poverty mitigation by enhancing financial inclusion and encouraging economic engagement. These findings validate research hypotheses. First, digital financial inclusion exhibits substantial negative long-term impact on poverty, confirming its poverty-alleviating function. Second, results imply that poverty-reducing effect of digital financial inclusion differs across short-run and long-run dynamics, reflecting that poverty reduction benefits of DFI appear over time in the long-run. These findings are also in line with prior research underscoring the poverty mitigating role of digital financial inclusion (Lee et al., 2022; Kumari&Giri,2025). Gross capital formation and exports also exhibit sustained long-run outcomes in reducing poverty, implying that investment flows and trade operations can strengthen market opportunities and revenue creation. While inflation does not show evidence of significant influence on poverty alleviation in the long run.

The negative and economically meaningful coefficient of error correction term confirms the presence of stable equilibrium in the long-term relationship between variables. The size of ECT coefficient indicates that variations from equilibrium are steadily adjusted over time. However, in the short run, digital financial inclusion does not have significant impact on poverty, suggesting that its poverty-reducing effects emerge over time rather than demonstrating immediate outcomes. Overall, empirical evidence underscores the importance of organizational and regulatory aspects in determining the long-term association between digital financial inclusion and poverty mitigation.

Analytical results provide numerous policy recommendations. First, policymakers should predominantly focus on strengthening digital finance frameworks to broaden the availability of digital financial services, especially among vulnerable and disadvantaged groups. Enhancing online payments, digital banking systems, and fintech evolutions can foster financial inclusion and economic involvement. Second, improved financial education and digital competence increase the effectiveness of digital financial services' use. Instructional initiatives and awareness programs enhance assurance of digital financial landscape and promote digital readiness. Third, enabling regulatory environments is vital to encourage fintech innovations leading to stable financial systems. Well defined rules and cooperation between fintech companies and financial service providers support sustainable progress of digital financial systems. Finally, government strategies aimed at increasing investments and exports can enhance financial inclusion by generating economic prospects and facilitating sustainable poverty alleviation.

Conclusion

This study examined the connection between digital financial inclusion and poverty level based on ARDL estimation framework. The results of ARDL bounds test confirmed the equilibrium relationship between variables in the long run and revealed that digital financial inclusion exhibits statistically significant poverty-reducing impact in the long run. These findings indicate that enhanced digital financial inclusion substantially alleviate poverty levels by expanding access to formal financial services and strengthening economic empowerment.

Moreover, gross capital formation and exports of goods and services were also found to significantly mitigate poverty levels in the long run. This indicates that increasing investment channels and trade operations provide wider economic opportunities and profit-making activities. In contrast, inflation does not demonstrate significant impact on poverty level. In general, research findings highlight the importance of developing digital network systems and encourage financial inclusion to support sustainable long-term economic growth. Advancing digital financial instruments, improving financial awareness, and generating supportive institutional regulations expand financial inclusion and increase economic engagement of marginalized and underserved populations. Overall, digital financial inclusion can be recognized as a key strategic tool for alleviating poverty and achieving inclusive economic growth in the long run.

Despite its contributions this study has several limitations. The empirical analysis examines Kazakhstan as a country-level case and uses macroeconomic indicators, which may not completely describe individual household access to digital financial services. Further investigation could extend the analysis to household-level data or comparisons across countries to reveal deeper understanding of the association between digital financial inclusion and poverty alleviation.

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A systematic review of the impact of artificial intelligence in the hospitality industry

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Abstract
Purpose: The purpose of this review is to assess the impact of artificial intelligence (AI) on the hospitality industry, focusing on how AI technologies are transforming customer experiences, operational processes, and decision-making within the sector. With AI becoming an integral part of modern business, this review aims to consolidate existing research on the integration of AI tools such as chatbots, robotic assistants, predictive analytics, and personalization systems in hospitality settings.
Design/methodology/approach: The methodology involves a systematic review of peer-reviewed journal articles, industry reports, and case studies published over the last decade. The collected data were analyzed to identify key trends, challenges, and benefits associated with AI implementation in hospitality. The article examines various articles by different criteria such as by year, by author, organization, countries, by document type and by field of knowledge.
Findings: The findings indicate that AI significantly enhances customer service efficiency, personalizes guest experiences, and optimizes pricing and inventory management. For example, AI-driven chatbots have improved response times and reduced staffing costs, while predictive analytics has allowed hotels to tailor offers based on guest preferences and behavior patterns. However, challenges such as high initial costs, data privacy concerns, and the need for employee retraining remain significant barriers to widespread adoption.
Originality: We confirm that we are the original creators of this research and that no part of this work has been previously published or submitted for publication in any other venue.

Keywords: artificial intelligence, impact, hospitality industry, systematic literature review, innovation, chat-bot, customer experience

Introduction

The hospitality industry is currently undergoing a major transformation as artificial intelligence (AI) and robotics become increasingly integrated into daily operations and customer service. Traditionally, hospitality has been known for its personal and high-contact interactions with guests. However, the industry is now working to find the right balance between maintaining this human-centered service and benefiting from the efficiency and innovation that technology can provide. Broad overviews and sector-focused studies also document this transition (Iberamia, 2016; Bhushan, 2021; Citak et al., 2021; Dangwal et al., 2023; Jabeen et al., 2022; Nannelli et al., 2023; Samala et al., 2022; Smrutirekha et al., 2023).

The COVID-19 pandemic played a significant role in accelerating this shift toward digital solutions. Hotels and tourism businesses were forced to adopt new technologies to improve safety, streamline operations, and create more personalized experiences for guests (Bauer, 2023). Related research has examined pandemic-driven automation, biosecurity, hygiene, and post-COVID recovery (Afaq & Gaur, 2021; Ivanov, Webster, Stoilova, & Slobodskoy, 2022; Marques et al., 2022; Perić & Vitezić, 2021; Pillai et al., 2021; Van et al., 2020; Vuong & Tung, 2021; Zeng et al., 2020).

Today, AI is used in many areas of hospitality. For example, automated check-in systems allow guests to access their rooms quickly without waiting in line, while robotic concierges can assist with information and simple tasks. In addition, intelligent chatbots provide round-the-clock customer support, helping hotels respond to guest requests faster and more efficiently (Blöcher & Alt, 2021; Huang, 2021). These technologies not only streamline service delivery but also address persistent challenges such as labor shortages and increasing service expectations (Rasheed, 2023). Despite the obvious benefits of automation, researchers emphasize the importance of maintaining emotional intelligence and human empathy when interacting with guests, as their loss can lead to a weakening of personal connection (Yeh, 2020). Research also covers robot hotels, intelligent rooms, digital service systems, and technology-based responses to labor shortages (Bowen

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& Morosan, 2018; Gupta et al., 2022; Lai & Hung, 2018; Leonidis et al., 2013; Morosan & Bowen, 2022; Mustafa, 2022; Nam et al., 2021; Reis et al., 2020; Singh et al., 2023; Verma et al., 2021).

However, despite a significant increase in the number of scientific papers devoted to the implementation of artificial intelligence in the hospitality industry, existing studies are fragmented. Most focus either on individual technologies or the short-term effects of their application, with insufficient attention paid to the integration of bibliometric and systematic approaches. This gap highlights the need for a comprehensive summary of global scientific trends to more accurately understand the current state of research and identify promising areas. The fragmented evidence base has therefore prompted systematic, bibliometric, and conceptual reviews (Doborjeh et al., 2022; Hossain et al., 2022; Kumar Singh et al., 2022; Mariani & Wirtz, 2023; Osei et al., 2020; Saydam et al., 2022; Sharma, K., Dhir, & Ongsakul, 2022; Singh, Tyagi, Singh, et al., 2022; Yang & Chew, 2021).

The purpose of this study is to analyze the development of scientific research on the application of artificial intelligence in the hospitality industry. Specifically, the work aims to identify key research trends, the most influential authors, leading academic institutions, and key thematic clusters. Furthermore, special attention is paid to identifying the conceptual and methodological approaches that shape the current academic agenda in this field.

To achieve this goal, the following research questions were formulated:

1. What are the main thematic areas and trends characterizing research of AI implementation in the hospitality industry?

2. Which countries, authors, and academic organizations are making the greatest contribution to the development of this field?

3. What research gaps exist, and what promising areas can be proposed for future research?

The conceptual framework of this study is based on a model of technological innovation adoption, which emphasizes the relationship between the efficiency achieved through the use of AI, customer satisfaction, and the interaction between employees and intelligent technologies in the service sector. Technology-adoption studies examine guest attitudes, organizational intention, perceived value, repurchase intention, and service-robot acceptance (Alma Çallı et al., 2023; Ayyildiz et al., 2022; Binesh & Baloglu, 2023; Ho et al., 2022; Huang, 2022; Ivanov et al., 2018; Lei et al., 2023; Lv, Luo, Liang, et al., 2022; Meidute-Kavaliauskiene et al., 2021; Nazir et al., 2023; Nozawa et al., 2022).

In recent years, the hospitality industry has been undergoing rapid digital transformation, driven by both technological advances and the need for post-pandemic recovery. Despite the existence of several review studies on the application of AI in the hospitality industry, a comprehensive analysis based on systematization and bibliometric processing of the data remains lacking. Therefore, conducting a structured literature review appears relevant and necessary to consolidate disparate scientific findings and form a holistic understanding of the development of this field. Studies of digital transformation further address software, digital marketing, competitiveness, business performance, big data, information architecture, and hotel technologies (Helgemeir & Cenzano, 2019; Ispahi, 2023; Kapoor & Kapoor, 2021; Kumar et al., 2023; Sharma, K., Jain, & Dhir, 2022; Sharma, M., Bathla, Kaushik, et al., 2023; Singh & Munjal, 2021; Stylos & Zwiegelaar, 2019; Sultanow et al., 2021; Voronova et al., 2020).

The scientific novelty of this study lies in the integration of a systematic literature review, conducted using the PRISMA methodology, with bibliometric visualization tools. This approach allows for a more in-depth and comprehensive analysis of the evolution of scientific research related to the application of AI in the hospitality industry.

At the same time, several limitations of the study should be considered. In particular, the analysis is based exclusively on publications indexed in Scopus, which may lead to the exclusion of relevant works presented in other scientific databases. Second, only English-language publications were considered, which may restrict the diversity of perspectives represented in the review. Finally, bibliometric visualization conducted through VOSviewer involves a degree of interpretation, which may influence how the results are understood.

Background

Artificial intelligence (AI) has become an important driver of change in the hospitality industry, influencing how businesses interact with customers, manage operations, and use data to support decision-making. Over the past decade, academic research has increasingly examined how AI technologies — such as service robots, chatbots, and predictive analytics — are being integrated into tourism and hospitality services (Ivanov & Webster, 2020; Huang et al., 2022). The application landscape also includes food-and-beverage automation, process automation, robotics, the metaverse, and AI-enabled resource management (Dani et al., 2022; Goyal & Singh, 2021; Ivanov, Webster, & Berezina, 2022; Khaliq et al., 2022; Nair et al., 2023; Rosete et al., 2020; Ruel & Njoku, 2020; Singh & Chaudhary, 2023).

Many scholars highlight the potential of AI to improve operational efficiency, enhance service personalization, and strengthen customer engagement (Goel et al., 2022). For instance, AI-powered chatbots can respond to guest inquiries in real time, while predictive analytics helps hotels forecast demand and adjust pricing strategies more effectively. Furthermore, robotic technologies can support service delivery by performing routine operations, ensuring greater service consistency and helping to reduce operating costs (Kim et al., 2022; Yordanova, 2023). As a result, their implementation allows hospitality businesses to more effectively adapt to changing customer expectations, especially in the post-COVID-19 period. Empirical work additionally addresses customer analytics, demand forecasting, decision support, loyalty, emotion recognition, and online-review analysis (Akdim, 2021; Al-Hyari et al., 2023; Buckley et al., 2014; Caicedo-Torres & Payares, 2016; Chen, 2017; Chen et al., 2021; Claveria et al., 2015; C.-Sánchez et al., 2022; González-Rodríguez et al., 2020; Hajek & Sahut, 2022).

However, despite these advantages and the growing interest in the use of artificial intelligence, a number of unsolved problems and research gaps remain in this field. In particular, much existing work focuses primarily on the technological potential of AI systems, while the managerial, ethical, and cultural aspects that significantly influence the success of their implementation in the hotel industry remain understudied. Issues such as employee adaptation, data privacy, and human–robot interaction require deeper exploration (Herrera et al., 2023; Rawal et al., 2023). Furthermore, previous reviews have primarily been narrative rather than systematic, lacking comprehensive bibliometric mapping of research trends and collaboration networks. Human-centered research examines employee outcomes, technological competencies, career concerns, job displacement, and workforce readiness (Alipour et al., 2021; Bhargava et al., 2021; Ersoy & Ehtiyar, 2023; Hopf et al., 2018; Hsu & Tseng, 2022; Kong et al., 2021; Lestari et al., 2022; Lestari et al., 2021; Li et al., 2019; Yeh et al., 2020).

This background thus establishes the need for a systematic review and bibliometric analysis that synthesizes existing studies, identifies dominant themes, and highlights gaps in AI research within hospitality.

In the context of Central Asia, and particularly Kazakhstan, the integration of AI technologies into hospitality and tourism management is still at an early stage. Local studies mainly address digitalization and smart tourism, yet there remains a lack of bibliometric synthesis reflecting regional trends. Incorporating Kazakhstan's perspective is important for understanding how global AI developments align with emerging markets and post-Soviet innovation systems (Lv, H., Shi, S., & Gursoy, D., 2022). Contextual applications span halal tourism, GIS, smart and green hospitality, health tourism, eco-friendly technologies, and social-media safety analysis (Battour et al., 2022; Chaudhuri & Ray, 2018; Tan & Wright, 2022; Wang et al., 2022; Xess et al., 2021; Zeng et al., 2023).

This study, which combines quantitative mapping and qualitative interpretation, aims to develop a more holistic understanding of how artificial intelligence is transforming the hospitality industry and to identify areas requiring further research.

Methodology

This study uses a combined methodological approach, including a systematic literature review and bibliometric analysis, to examine the development dynamics, scope, and thematic structure of research on the application of artificial intelligence in the hospitality industry. The methodology employed complies with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, ensuring the transparency and reproducibility of the research process.

3.1 Database Selection and Search Strategy

Scopus was chosen as the primary data source due to its broad coverage of high-quality peer-reviewed scientific publications and its suitability for bibliometric analysis. Furthermore, Scopus integrates effectively with visualization tools such as VOSviewer, facilitating the visual presentation and analysis of scientific data (Pranckutė, 2021).

The study`s timeframe spans from January 2010 to February 2024, allowing us to trace the evolution of scientific trends both before and after the COVID-19 pandemic. Publications were searched in February 2024 using keywords included in titles, abstracts, and author keywords, such as “artificial intelligence” AND “hospitality industry” OR “tourism” OR “robotics”.

To ensure the quality and relevance of the selected sources, the following inclusion criteria were established:

- Publications between 2010 and 2024;
- Articles in peer-reviewed journals, conference proceedings, and review papers;
- Publications in English;
- Studies specifically focused on the application of AI in hospitality and tourism.

Exclusion criteria included:

- Non-scientific materials (editorials, book reviews, short communications);
- Publications unrelated to AI or devoted to other fields;
- Duplicate records resulting from overlapping search queries.

3.2 Selection and Screening Process

The initial search in the Scopus database identified 421 publications. During the pre-processing stage, 170 duplicate records were identified and removed, leaving 251 unique studies for further analysis.

The next step involved a detailed analysis of titles, abstracts, and author keywords to assess the relevance of the publications to the study objectives. Following this stage, 96 studies that did not meet the established relevance criteria were excluded from the sample. The main reasons for exclusion included the absence of a clear focus on the hospitality or tourism sector, limited relevance to artificial intelligence applications, or a primary focus on other industries.

Following this stage, 155 publications remained and were considered suitable for further analysis. These studies directly addressed the use and role of artificial intelligence in hospitality and tourism and therefore formed the final dataset for the bibliometric and qualitative analysis.

A summary of the selection procedure is presented in Table 1 (Summary of the PRISMA Study Selection Process).

3.3 Bibliometric and Visualization Analysis

The bibliometric data from the 155 selected publications were exported from the Scopus database in CSV format and analyzed using VOSviewer (version 1.6.19). This software was used to visualize relationships within the dataset, including co-authorship networks, keyword co-occurrence patterns, and citation links among publications.

The analysis focused primarily on identifying relationships based on co-occurrence and citation, with author keywords and countries serving as the primary units of analysis. The study utilized a full-count method, in which each element occurrence and each relationship were weighted equally, reflecting their cumulative presence in the analyzed dataset.

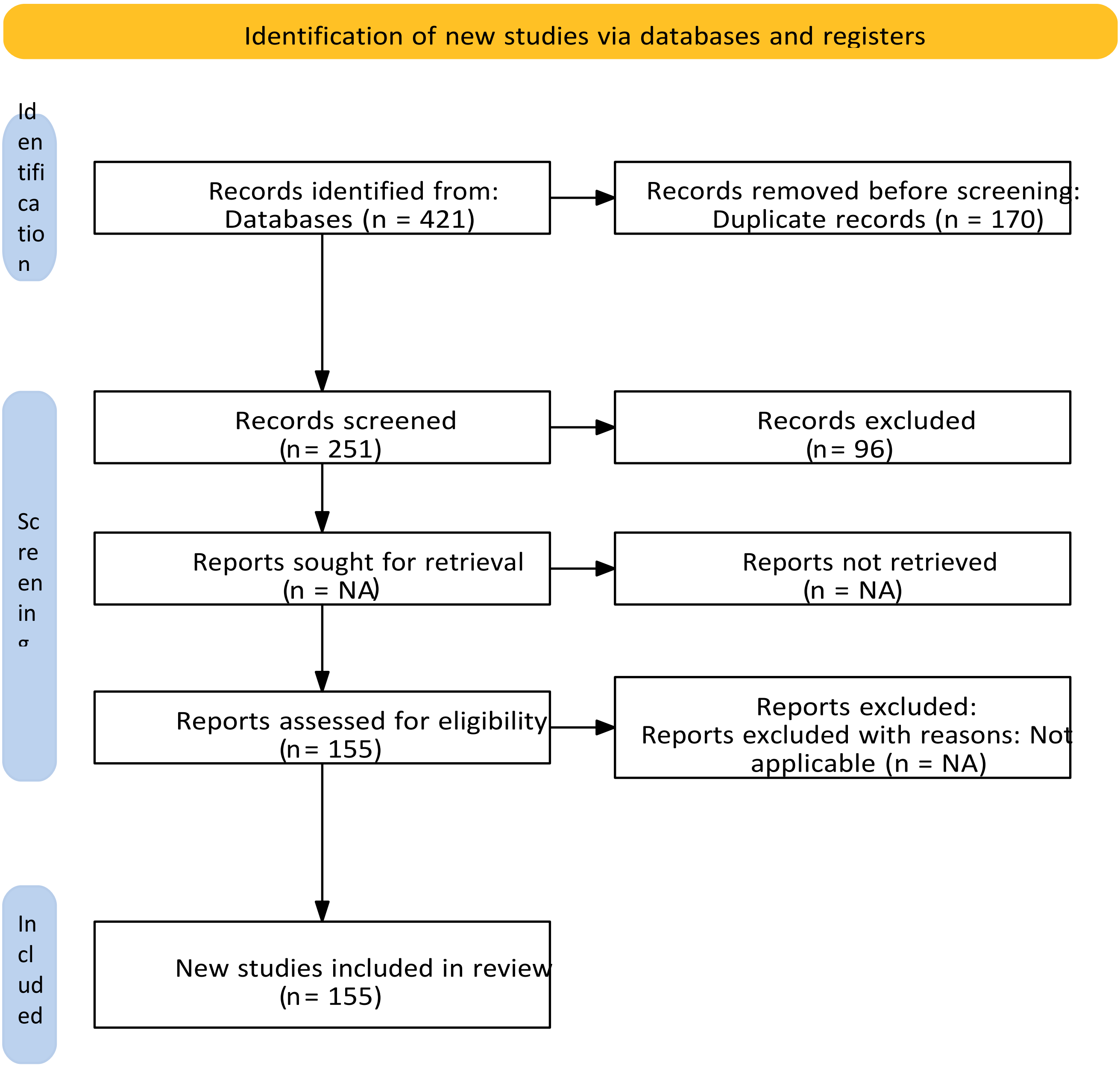
To enhance the relevance of the results, a minimum threshold of at least five occurrences for each keyword was established. This allowed us to focus on the most frequently used terms in the scientific literature. Additionally, a normalized association strength method was used to standardize the relationships between elements, which, in turn, facilitated their comparison and enabled a clearer identification of clusters and structural relationships within the network. Taken together, these parameters allowed us to identify key thematic areas and uncover key research patterns in the field.

3.4 Limitations of the Methodology

Despite the use of a systematic approach, this study has several limitations. First, the analysis is based exclusively on publications indexed in Scopus and presented in English, which may exclude relevant studies published in other languages or included in alternative scientific databases.

Second, while bibliometric tools such as VOSviewer provide meaningful quantitative metrics reflecting the relationships between scientific publications, they do not allow for a full assessment of the qualitative depth of content and methodological rigor of individual studies. For this reason, the findings should be interpreted with caution. These limitations are acknowledged in the conclusion, where the need for complementary qualitative approaches is also discussed in order to achieve a more comprehensive understanding of AI research in the hospitality industry.

Table 1. Summary of the PRISMA Study Selection Process



Results

The thematic review articulates its findings through nine analytical dimensions that collectively offer a detailed understanding of artificial intelligence research in the hospitality industry. The key aspects include publication trends over time, the contribution of leading organizations and authors, citation patterns, geographical research distribution, main thematic areas and their interdisciplinary links, sources of research funding, keyword co-occurrence and thematic clusters visualized with VOSviewer, author collaboration networks, and interpretive insights into emerging research trends.

This comprehensive, multidimensional approach allows for an in-depth exploration of how AI-related studies have developed across regions and over time, highlighting increasing interdisciplinarity in the field. This review goes beyond simply counting the number of scientific papers. Using a combination of publication statistics (bibliometrics) and semantic content analysis (concept analysis), we uncover the underlying structure of research in the field of artificial intelligence for the hospitality industry. We identify key areas in which this research is developing. Concept-mapping methods have also been applied to organize knowledge in the hospitality sector (Fornells et al., 2015).

To identify key themes, we used VOSviewer. It groups keywords based on how frequently they appear together. We established that a word or phrase must appear at least five times to be included in the analysis. A normalization method was used to assess the strength of relationships between words. Initially, the program identified five topic groups. These groups were then reviewed and slightly adjusted manually to ensure their logical consistency. The result was clearly defined thematic areas reflecting the main research directions in this literature.

4.1 Publication Trends by Year

The analysis shows that interest in the application of AI in hospitality has been steadily growing over the past decade. From 2010 to 2016, the number of publications was small and mostly theoretical or exploratory, consistent with the initial stage of development of this field.

However, since 2017, there has been a rapid increase in the number of studies. This suggests that scholars increasingly recognize the potential of AI to transform the hotel industry and customer service. A particularly noticeable surge occurred after 2020, largely due to the COVID-19 pandemic, which accelerated the adoption of digital and contactless technologies in the industry.

This trend indicates that AI is now viewed as an important strategic tool for maintaining competitiveness and ensuring the sustainability of the hotel industry. The steady annual growth in the number of publications also demonstrates that AI research has evolved from a niche topic to a recognized field within tourism and hospitality management research (Fig. 1).

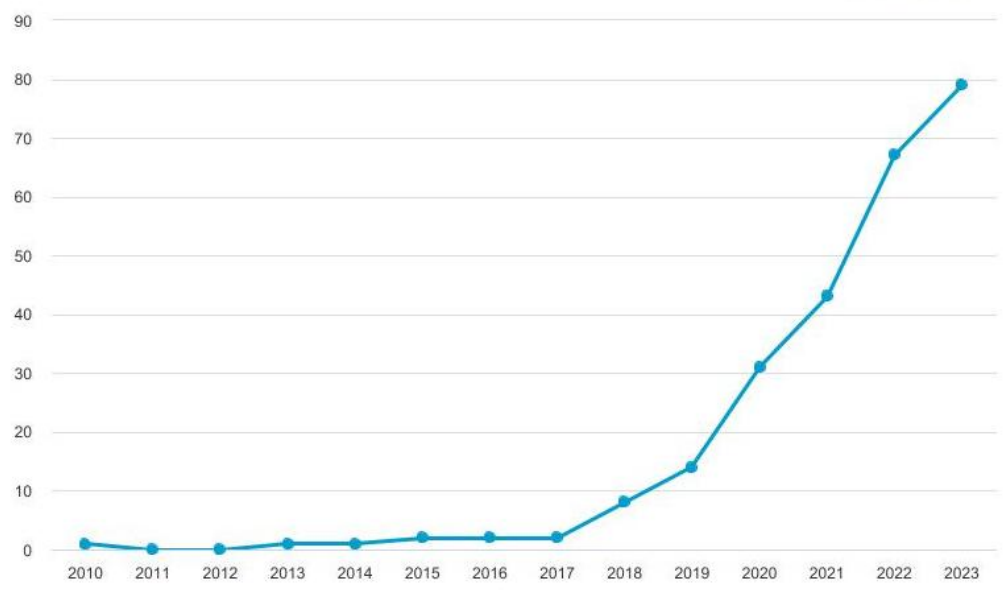


Figure 1. Documents by year

4.2 Centers of Excellence in AI Research in Hospitality and Their Productivity

The analysis shows that cutting-edge research in artificial intelligence for the hospitality industry is concentrated in a small number of reputable academic centers, primarily located in technologically advanced countries. Notable among these are the Hong Kong Polytechnic University, Cornell University, and the University of Surrey, which have made significant contributions to the theoretical and empirical foundations of this field (Sharma, S., Rawal, Y. S., Soni, H., & Batabyal, D., 2023).

A key factor in the success of these universities is their commitment to an interdisciplinary approach. Collaboration between specialists in hospitality management, computer science, and data analytics enables comprehensive research into the application of AI in the service sector and the development of innovative solutions.

The success of these leading institutions is supported by factors such as research funding, access to cutting-edge technologies, strong academic ties, and partnerships with industry representatives. However, there is limited participation from institutions in developing regions, highlighting the need for greater global engagement. Expanding the geographic scope of participants can bring new perspectives, research contexts, and methodological approaches, contributing to a more inclusive and globally relevant understanding of the role of AI in the hospitality industry (Fig. 2).

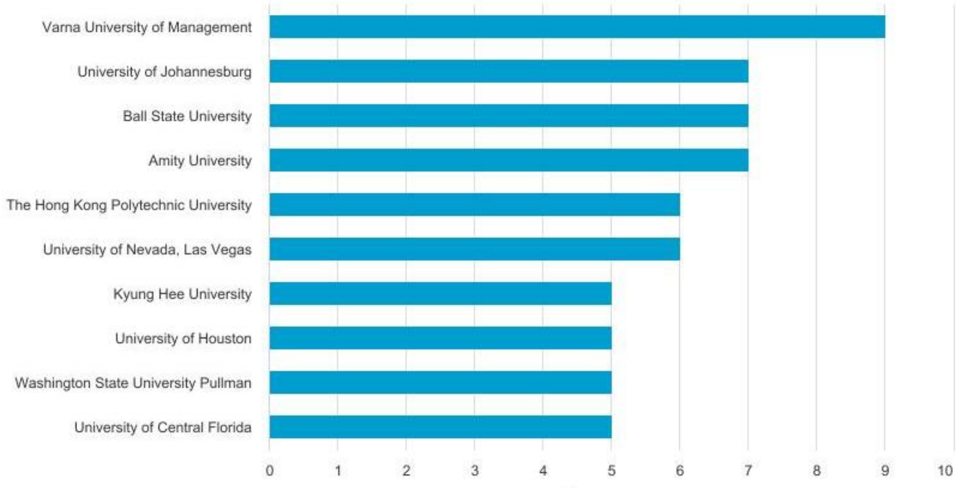


Figure 2. Documents on organizations

4.3 Influential Figures and Academic Networks in AI for Hospitality

The analysis revealed that several prominent scholars have played a decisive role in shaping the field of AI research in the hospitality industry. Among the most significant are Stanislav Ivanov, Craig Webster, Dogan Gursoy, and Oh Haemun Chi (Chi, O. H., Denton, G., & Gursoy, D., 2020). Their research has provided valuable insights into service automation, robotics implementation, and consumer perceptions of AI technologies in the hotel industry (Lu, L., Cai, R., & Gursoy, D., 2019). The contributions of Ivanov and Webster also include analyses of demographic change and robot-based tourism futures (Webster & Ivanov, 2020a; Webster & Ivanov, 2020b).

A citation network analysis reveals close academic ties between these researchers, indicating active collaboration and ongoing exchange of ideas within the academic community. These interconnected networks contribute to the progressive development and refinement of theoretical concepts related to the integration of AI in hospitality.

Furthermore, the presence of cross-references between works on hospitality and marketing demonstrates the growing interdisciplinary nature of this field. The high citation rate of these authors indicates that the research has reached a more advanced stage of conceptual development and is moving toward the formation of a well-established theoretical framework. This growing body of research lays a solid foundation for future research on the role of artificial intelligence in the hospitality sector (Fig. 3).

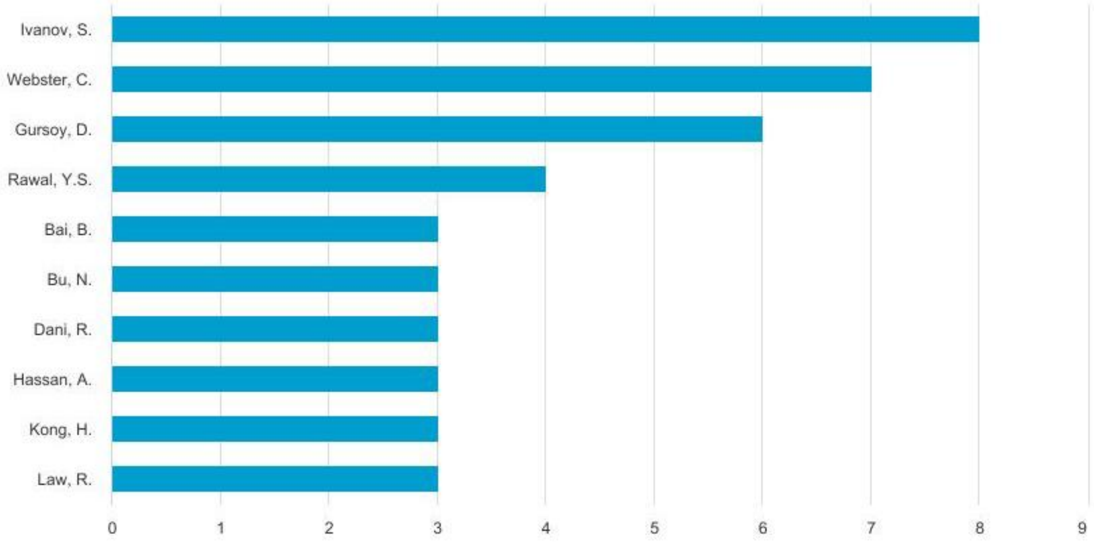


Figure 3. Documents by authors

4.4 Geographic Distribution of Research

An examination of the geographic distribution of scientific publications on artificial intelligence in the hospitality industry reveals a distinct concentration in East Asia, North America, and Western Europe. These regions boast both high levels of technological development and mature hospitality sectors. The leading author countries are China and the United States, followed by South Korea, the United Kingdom, and Australia. The significant presence of these countries is due to their developed research infrastructure, access to financial resources, and early adoption of AI technologies in the service sector, including hospitality and tourism, which contribute to a favorable environment for technological innovation and academic research.

At the same time, research from emerging economies, particularly Central Asia, remains relatively limited. This imbalance highlights the need for more contextualized research that takes into account the specific cultural, infrastructural, and socioeconomic factors influencing AI implementation in various regional hospitality contexts. Expanding the geographic scope of research will allow for a more comprehensive understanding of the impact of artificial intelligence on tourism and hospitality across diverse regional and cultural environments (Fig. 4).

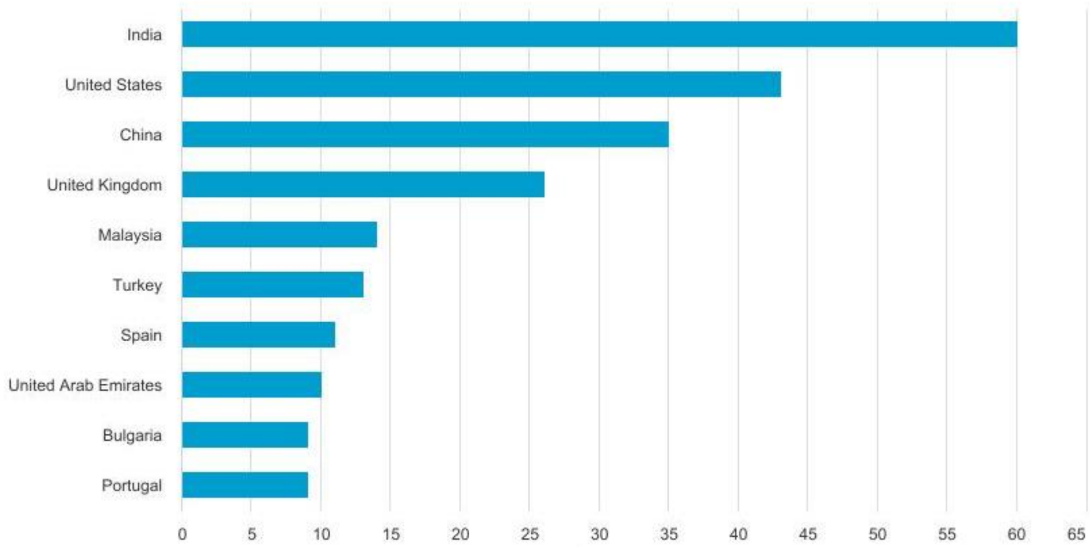


Figure 4. Documents by countries

4.5 Key Areas and Interdisciplinary Links

Research in artificial intelligence for the hospitality industry is characterized by an interdisciplinary approach. Experts from disciplines such as management, computer science, psychology, and data analysis contribute to this field. This diversity of specialists reflects the complex nature of AI implementation in the service sector. Thematic mapping revealed three main research areas. The first area focuses on technological innovation and automation, studying the integration of AI technologies into the operational activities of hospitality businesses. The second area centers on customer experience and satisfaction, exploring how AI-based services influence guest perceptions and service quality. The third theme addresses human–AI interaction and ethical considerations, including issues related to trust, acceptance, and the role of human employees in increasingly automated service environments. The interdisciplinary scope extends to indoor environmental quality, Industry 5.0, education, healthcare, sensory systems, blockchain, e-learning, and smart landscapes (Bangwal et al., 2023; Chourasia et al., 2023; Guo, 2021; Hacikara, 2023; Ilapakurti et al., 2018; Jahan, 2021; Liu, 2023; Patzer et al., 2018; Puri et al., 2023; Tien et al., 2021).

The relationships between these themes suggest that hospitality research is gradually moving beyond purely operational concerns. Instead, scholars are increasingly adopting broader perspectives that also consider behavioral, ethical, and managerial dimensions of AI adoption. Behavioral and ethical research additionally considers empathy, vocal warmth, cuteness, social presence, resistance, and acceptance in human-robot encounters (De Kervenoael et al., 2020; Huang & Sénécal, 2023; Pelau et al., 2021; Pitardi et al., 2022; Rauf et al., 2022; Singh et al., 2021; Vitezić & Perić, 2021; Wang et al., 2023; Zhong et al., 2020; Zulfakar et al., 2023).

In addition, the presence of interdisciplinary links with fields such as marketing and human resource management indicates that artificial intelligence is being studied not only as a technological innovation but also as a driver of organizational change and evolving service cultures within hospitality businesses (Fig. 5). Organizational implications include recruitment, digital human-resource management, emotional intelligence, fairness, transparency, and AI-enabled surveillance (Dominique-Ferreira et al., 2022; Johnson et al., 2020; Prentice, 2023; Sharma, S., Rawal, Pal, & Dani, 2022; Zhao et al., 2023).

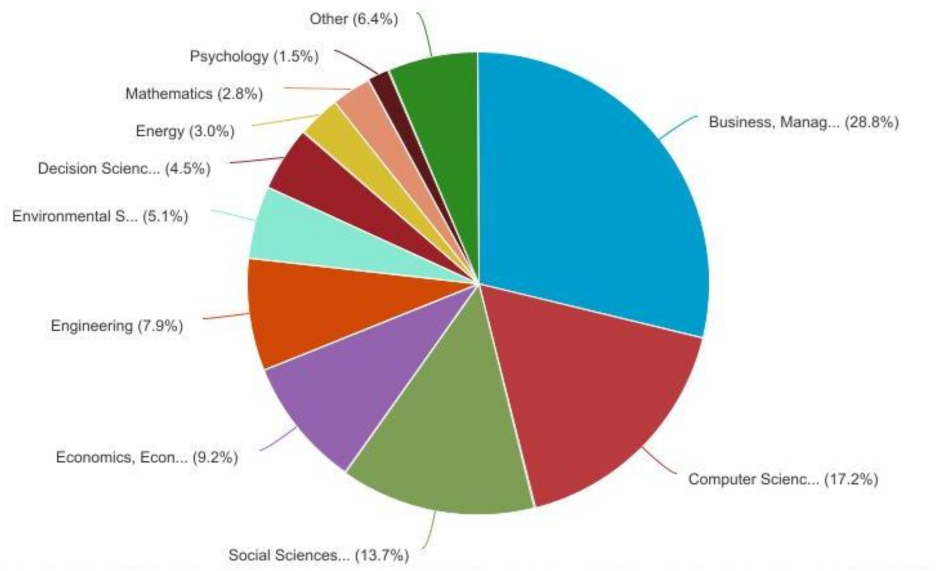


Figure 5. Documents on the field of knowledge

4.6 Funding Sources

The analysis indicates that many studies in this research area do not clearly report their funding sources, which makes it difficult to identify broader patterns of financial support within the field. Among the publications that do disclose funding information, most are supported by national science foundations, university research councils, or government innovation programs. Such funding is particularly common in countries like China, the United States, and South Korea.

These funding bodies often prioritize research initiatives related to digital transformation and smart tourism, reflecting national strategies aimed at encouraging the adoption of artificial intelligence within the service sector, including hospitality and tourism (Wong, I. A., Huang, J., Lin, Z. C. J., & Jiao, H., 2022).

At the same time, the analysis shows relatively limited involvement from industry-funded research. This suggests a potential gap between academic studies and practical implementation within the hospitality industry. Strengthening collaboration between academic institutions and industry partners could help address this gap by increasing the practical relevance of future research and facilitating the translation of theoretical findings into real-world applications (Fig. 6).

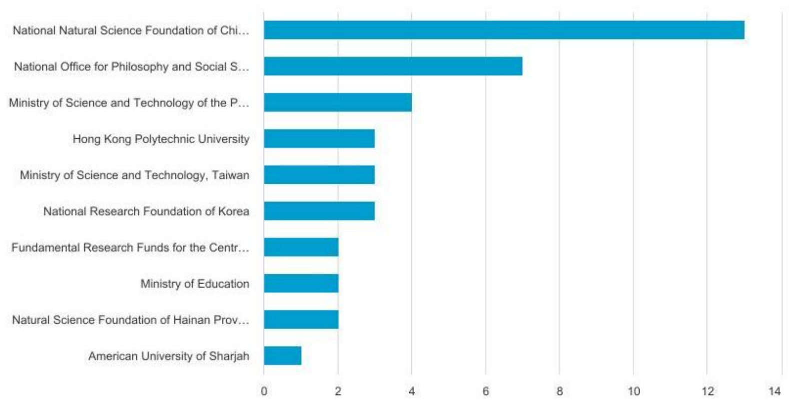


Figure 6. Documents on the funding sponsor

4.7 Keyword Co-occurrence and Thematic Clusters (VOSviewer)

The keyword co-occurrence analysis conducted with VOSviewer helps reveal the main conceptual connections within the research on artificial intelligence in the hospitality industry. The most frequently appearing keywords include "artificial intelligence," "service automation," "chatbots," "customer satisfaction," and "robotics." These terms highlight both the technological aspects of AI implementation and its influence on guest experience within hospitality services. These clusters are reflected in studies of customer-robot interaction, automated review management, ChatGPT, explainable machine learning, voice assistants, and service recovery (Huang et al., 2021; Katsiuba et al., 2022; Kaur et al., 2023; Koc et al., 2023; Lee et al., 2021; Lee et al., 2022; Limna & Kraiwanit, 2023; Liu & Xu, 2023; Lv et al., 2021; Rasheed, Chen, Khizar, & Safeer, 2023; Rasheed, He, Khizar, & Abbas, 2023; Ruiz-Equihua et al., 2023; Sharma et al., 2021; Xu & Liu, 2022).

Contemporary AI publications increasingly incorporate new keywords such as "ethics", "privacy", "sustainability", and "human-AI collaboration". This demonstrates that research is moving beyond purely technical issues to encompass the broader social, ethical, and governance implications of AI. An analysis of thematic clusters revealed three main themes: AI-enabled personalization, operational optimization, and human adaptability. Taken together, these themes demonstrate the evolution of research toward a more holistic understanding of the role of AI in hospitality. The keyword structure also reflects the growing conceptual maturity and interdisciplinary nature of the field, as scholars increasingly explore not only technological breakthroughs but also the organizational and societal challenges associated with AI integration (Fig. 7).

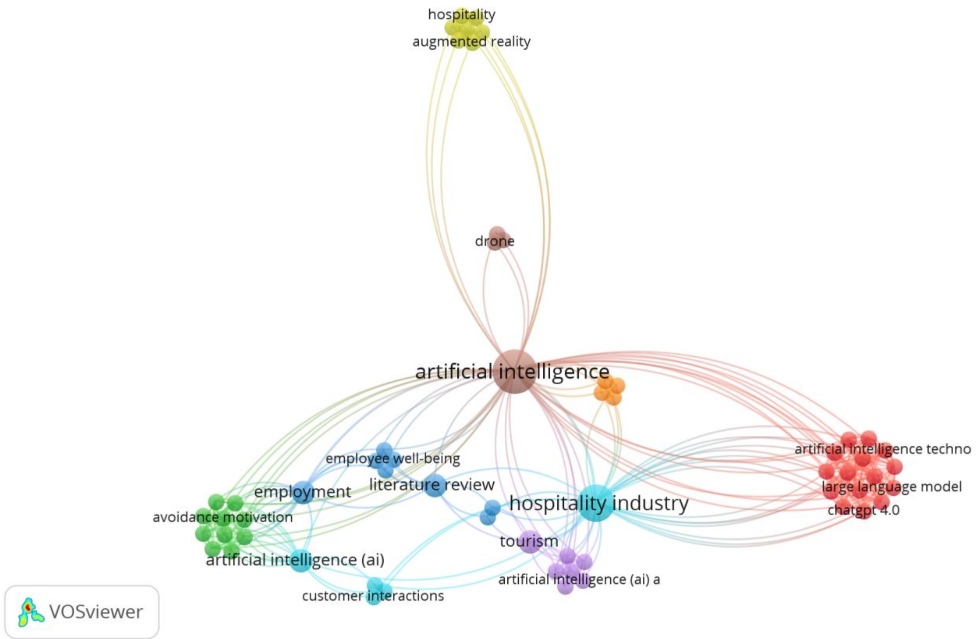


Figure 7. Thematic Clusters in Artificial Intelligence Applications within Hospitality

4.8 Development of Collaborative Research Efforts

The analysis demonstrates a clear trend toward increased research collaboration in the field of artificial intelligence applications in the hospitality industry. Recently, co-authorship models have become international, and interactions between institutions have become closer. This demonstrates a growing trend for researchers from different countries and academic networks to collaborate on AI-related issues in the hospitality and tourism sectors.

The collaborative network is formed around several interconnected clusters of researchers, particularly from Asia and Europe. These clusters represent dynamic research communities that play a key role in advancing the field and shaping current academic debates.

The high degree of network connectivity also indicates the presence of effective global knowledge transfer mechanisms. Through such collaborations, researchers are able to more effectively exchange ideas, methodologies, and findings.

However, the study also found that partnerships with researchers from developing regions remain underdeveloped. Expanding these connections could be key to addressing existing knowledge gaps, integrating more diverse research perspectives, and fostering a more inclusive global vision of AI in the hospitality industry (Fig. 8).

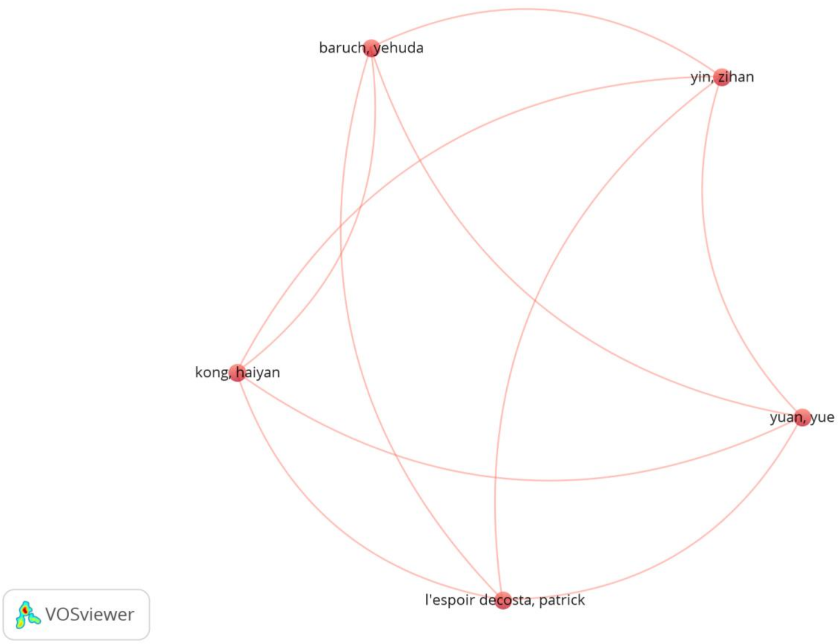


Figure 8. Collaboration Network of Key Authors in AI and Hospitality Research

4.9 Analysis of Results and Future Directions

A general overview of AI research in the hospitality industry demonstrates rapid growth in both volume and depth. There is a clear shift from purely technological developments to more comprehensive studies encompassing human-AI interaction, ethical aspects, and management challenges. This underscores the recognition that successful AI implementation requires considering not only technical capabilities but also human factors and organizational processes.

An important trend has been the strengthening of interdisciplinary collaboration between specialists from computer science, tourism, marketing, and management. This approach allows for a deeper understanding of the impact of AI on service quality and customer experience.

Modern research has also begun to address broader topics such as sustainable development and psychological well-being, signaling a shift toward a human-centered research agenda. Bibliometric analysis shows that the field has moved from descriptive case studies to conceptual and analytical models, demonstrating its academic maturity.

Data visualization revealed a diversity of AI applications in the hospitality industry, from customer interaction to decision support. The authors` collaborative networks confirm the global nature of the research and identify key players.

These findings help identify both existing knowledge gaps and emerging trends, forming a foundation for future research. Strengthening interdisciplinary collaboration and exploring understudied areas will be particularly important for the further development of the field.

Discussion and Conclusion

This study confirms the dynamic development of AI research in the hospitality industry. This progress is driven by technological advances and evolving consumer demands. Bibliometric analysis identified five key thematic areas demonstrating the impact of AI on hospitality operations. These themes range from customer engagement and service automation to broader issues such as ethics and sustainability.

The analysis of publication trends shows a clear increase in research output beginning around 2018, with an even sharper rise after the COVID-19 pandemic. This pattern supports earlier findings by Stanislav Ivanov and Craig Webster (2020), as well as Dogan Gursoy and colleagues (2022), who identified the pandemic as a major driver of digital transformation in hospitality (Webster, C., & Ivanov, S. 2020). During this period, the industry increasingly relied on technological solutions to improve operational efficiency and maintain safety standards. In contrast to previous narrative reviews, the present study applies a systematic bibliometric approach to map the development of the field and reveal the relationships between technological, managerial, and human-centered aspects of AI adoption (Chi, O. H., Gursoy, D., & Chi, C. G., 2022).

The thematic clustering also suggests that research on AI in hospitality has evolved over time. Earlier studies focused primarily on operational efficiency and technological implementation. Recently, the focus of AI research has shifted toward human-AI interaction, employee adoption, and ethical issues. This shift is consistent with the assertion by Rawal et al. (2023) that successful AI adoption requires not only technological capabilities but also workforce readiness and consumer trust. Our study advances this idea by quantifying the prevalence and interrelationships of these topics in the global academic literature, offering a clearer understanding of their manifestations (Rawal, Y. S., Soni, H., Dani, R., & Bagchi, P., 2023).

Another important finding concerns the geographic imbalance in research. Developed countries, particularly the United States and China, dominate publications and funding. Meanwhile, the contribution of developing countries remains limited, although there has been gradual growth, particularly in applied AI research in tourism and hospitality. This imbalance highlights the need for further research on regional differences in AI adoption, innovation potential, and industry readiness.

Methodologically, this study contributes to the literature by combining a systematic review with bibliometric analysis. Rather than simply summarizing existing work, it maps the relationships between topics, authors, and institutions. Co-occurrences and citation network analysis provide a structured overview of the collaboration patterns and intellectual foundations shaping AI research in the hotel sector.

Practical Relevance

From a management perspective, the findings demonstrate that the implementation of artificial intelligence can significantly improve not only service quality and personalized customer engagement, but also strategic planning and long-term sustainability in hospitality organizations. AI technologies enable companies to analyze vast amounts of data, anticipate customer needs, and more effectively optimize work processes. Practical applications include revenue simulation, e-procurement, purchase-duration prediction, digital feedback systems, booking-cancellation models, robot-hotel review analysis, and technology amenities (Jie Seah et al., 2019; Li et al., 2023; Luo et al., 2021; Mathew & Abdulla, 2022; Mathew & Abdulla, 2021; Narayan et al., 2022; Rakesh et al., 2022; Ramnarayan et al., 2022; Zhang et al., 2023).

Furthermore, the bibliometric data collected during this study can help hospitality executives and other industry stakeholders better navigate current research developments. By identifying leading research centers, key research areas, and emerging topics, organizations can compare best practices and anticipate the skills and competencies required in an increasingly AI-centric service environment.

Limitations and Prospects for Further Research

Despite its comprehensive approach, this study has several limitations. First, the analysis was limited to publications indexed in Scopus and written in English, potentially excluding relevant studies published in other languages or indexed in alternative databases.

Future studies could address this limitation by incorporating additional databases, such as the Web of Science and regional academic repositories, to obtain a more comprehensive view of global research. Furthermore, while bibliometric analysis provides valuable quantitative data, qualitative methods — such as interviews, surveys, or case studies — could provide a deeper understanding of the human, organizational, and ethical aspects of AI implementations in hospitality.

Conclusion

In conclusion, artificial intelligence is rapidly transforming the global hospitality industry, enabling improved operational efficiency, data-driven personalization, and contactless service. The results of this bibliometric review contribute to a clearer understanding of how AI has evolved both as a research topic and as a practical tool in hospitality and tourism

By identifying key thematic areas, research gaps, and models of academic collaboration, this study provides a structured overview of the development of AI-related research in the hospitality industry. These findings may be useful for both future academic research and the practical implementation of AI technologies.

Overall, this research contributes to the scientific understanding of AI in hospitality by systematically examining the relationships between technological, managerial, and human-centered dimensions of AI adoption. Unlike earlier descriptive reviews, the present study combines bibliometric evidence with interpretive analysis, demonstrating how the research focus has gradually shifted from operational efficiency toward broader considerations such as human interaction, ethics, and sustainable AI integration within the hospitality industry.

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