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The role of digital performance indicators in shaping the promotion strategy of construction services in agribusiness

Abstract. In the context of economic digitalisation, the marketing activities of construction companies oriented towards agribusiness depend on data and analytical tools that enable informed decision-making based on quantitative indicators. The aim of the article was to establish quantitative relationships between the main SEO indicators of websites and the volume of organic traffic, as well as to assess their influence on the development of an effective promotion strategy for construction services aimed at agribusiness enterprises. To achieve this aim, a sample of 17 Ukrainian construction companies specialising in the construction of facilities for the agricultural sector was formed. The data were obtained from the Ahrefs service as of October 2025. The study employed correlation analysis according to the Chaddock scale, single-factor linear regression models, multifactor non-linear regression models with interaction elements, and simulation sensitivity analysis. The results revealed strong positive correlations between organic traffic and key SEO metrics: the number of keywords ranked in positions 1-3 (r = 0.87) and positions 4-10 (r = 0.89), the total number of referring domains (r = 0.91), the number of "dofollow" referring domains (r = 0.91), the number of unique referring IP addresses (r = 0.88), and the number of unique Class C subnets (r = 0.88). Six statistically significant single-factor linear regression models were developed with coefficients of determination R^2 ranging from 0.7427 to 0.8126. Multifactor non-linear models with interaction elements demonstrated higher explanatory power (R^2 up to 0.999). The simulation sensitivity analysis confirmed that the greatest increase in organic traffic is achieved through an increase in the number of keywords in the top 3 positions (+282 visits/month) and through improving the URL rating of web pages (+150-162 visits/month). The practical significance of the study lies in the fact that the obtained results enable construction companies to develop KPI-oriented promotion strategies, optimise the allocation of marketing resources, and improve the effectiveness of interaction with clients in the agricultural sector

Keywords: digital marketing; web analytics; mathematical models; organic traffic; SEO metrics; agricultural enterprises; B2B strategies

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INTRODUCTION

In the context of the digitalisation of the economy, the marketing activities of enterprises are increasingly based on the use of data and analytical tools that enable managerial decisions to be substantiated through quantitative indicators. This is particularly relevant for the market of construction services oriented towards agricultural enterprises, which is characterised by high capital intensity of projects, long decision-making cycles, and a limited number of potential clients. Under such conditions, digital communication channels perform not only an informational function but also become an important element in building trust in the contractor and strengthening its competitive advantages. Scientific research confirms the growing role of digital performance indicators in shaping agribusiness marketing strategies. In their work on SMM strategies for the agricultural sector, S. Koberniuk *et al.* (2025) concluded that content quality, a balance of practical and emotional material, and constant monitoring of ROI are key factors in increasing audience engagement and loyalty in the agricultural sector. Researchers N.B. Zelisko & V.V. Maliuha (2025) analysed the application of marketing tools in the construction industry and found that the integrated use of SMM, SEO and email marketing significantly increases the effectiveness of promoting B2B services in particular. Author I. Yatskevych (2024) described a five-stage model for developing an SMM strategy and emphasised the need to integrate KPIs (reach, engagement, conversion) at each stage to achieve measurable results. Author I. Gushcha (2023) investigated digital technologies in agromarketing and demonstrated that the implementation of the Internet of Things, virtual and augmented reality, as well as data analytics, enables the creation of personalised promotion strategies that directly influence customer loyalty.

D. Nyangoma *et al.* (2024), in their models of strategic digital marketing for agribusiness, demonstrated that a data-driven approach with a focus on ROI and conversion rates is key to enhancing the competitiveness of agricultural companies. Researcher W. Shen (2024), using agricultural machinery manufacturers as an example, demonstrated that the application of artificial neural networks and fuzzy cognitive mapping for traffic analysis enables the optimisation of digital advertising costs and the enhancement of marketing channel effectiveness. In her study of digital marketing for agricultural mechanisation in Africa, A.S. Ajibola (2025) emphasised that KPIs (engagement, conversion to purchases, ROI) are essential for assessing the impact of social media and mobile platforms on the sustainability of small agribusinesses. Authors E.A. Inyommom *et al.* (2025), based on a regression analysis of Nigerian agricultural firms, found that social media marketing, relationship marketing and content marketing collectively explain over 51% of the variation in company performance, with SMM having the strongest influence.

M. Braglia *et al.* (2022) proposed a structured Industry 4.0 approach to KPIs (penetration, recognition, productivity) and demonstrated that systematic monitoring of digital technologies via a metrics matrix is the key to effective digital transformation of production. The authors U.S. Nwabekee *et al.* (2021) demonstrated that integrating digital marketing with financial metrics (ROI, CAC, CLV, ROAS) enables companies in competitive sectors to significantly increase profitability, particularly when organisational barriers between marketing and finance are overcome. In their study of brand awareness and digital marketing in the agricultural sector, M. Sheeraz *et al.* (2023) found that media analytics, web analytics and UTM parameters enable the precise measurement of the impact on brand awareness and organic traffic. According to research into digital marketing strategies in the agri-food sector by N. Kanellos *et al.* (2024), it was found that increased digital marketing effectiveness helps to reduce advertising costs and boost profitability through more efficient use of resources and the optimisation of advertising campaigns.

The specific characteristics of the B2B market for construction services aimed at agricultural enterprises, where organic traffic serves as the primary source of high-quality leads and key SEO indicators (the number of keywords in top positions, backlink profile, URL rating) directly determine promotion effectiveness, remain insufficiently studied. Under conditions of the growing importance of digital marketing, a considerable proportion of agricultural-oriented construction companies utilise websites and other digital tools in a fragmented manner, without a clearly defined system of performance indicators or strategic orientation. In marketing management practice, the evaluation of isolated metrics, such as the number of visits or keyword rankings, predominates without consideration of their combined influence on promotion outcomes. Thus, the absence of empirical studies combining organic traffic analysis with correlation and regression methods specifically for this segment highlighted the need to determine the role of digital performance indicators in shaping the promotion strategy of construction services for agricultural enterprises.

The object of the study was the marketing activities of construction companies providing design and construction services for agricultural enterprises in Ukraine. The subject of the study was the digital performance indicators of the websites of these companies, namely: organic traffic and key SEO metrics, and their impact on the results of promoting construction services in the digital environment. The aim of the article was to determine the role of digital performance indicators in shaping the strategy for promoting construction services for agricultural enterprises based on a correlation and regression analysis of web analytics data from Ukrainian construction companies. To achieve this aim, the article set out to address the following objectives: to analyse the key digital performance indicators of websites belonging to construction companies in the agricultural sector; to assess the strength of the relationship between digital indicators and outcome variables; and to justify the use of digital indicators as a tool for strategic marketing planning.

MATERIALS AND METHODS

The methodological framework of the study was developed with consideration of the specific characteristics of the construction services market for agricultural enterprises, which is characterised by high-value transactions, long decision-making cycles, and the dominance of B2B communications. Under such conditions, digital promotion channels perform not only an informational function but also a strategic one, fostering trust in the contractor and supporting the customer acquisition process. To achieve the stated aim, the study employed a combination of general scientific and specialised methods. In particular, methods of analysis and synthesis were used to generalise theoretical approaches to evaluating the effectiveness of the digital promotion of services, while the comparative method was applied to compare the levels of digital activity among the analysed companies. The principal tool of quantitative analysis was correlation analysis, which enabled the assessment of the strength and direction of relationships between digital website indicators and the resulting variables. To evaluate linear relationships between variables, a matrix of pairwise Pearson correlation coefficients (r) was calculated, and the interpretation of the strength of relationships was conducted according to the Chaddock scale. Correlation coefficients were determined using the following formula (Illowsky & Dean, 2018):

$$r = \pm\sqrt{R^2}, \tag{1}$$

where, R^2 – the coefficient of determination, which indicates how well the factors explain the outcome, where a value of 0 means that the model explains nothing, while a value of 1 means that the model fully explains the variability of the data (Illowsky & Dean, 2018). Correlation coefficients may vary within the range from -1 to +1 (LibreTexts Ukrayinska, 2025), where values of $|r| > 0.7$ according to the Chaddock scale indicate a strong (close) relationship, $0.3 \leq |r| < 0.7$ indicate a moderate relationship, $0.1 \leq |r| < 0.3$ indicate a weak relationship, and $|r| < 0.1$ indicate a very weak or absent relationship (Tyutchenko, 2022).

To identify causal relationships between the indicators, econometric modelling methods were employed. At the first stage, single-factor linear regression models with separate independent variables were constructed, which made it possible to identify the key influencing factors affecting the resulting indicator and to select statistically significant variables with high coefficients of determination. At the second stage of the study, multifactor non-linear regression models with interaction elements in the form of second-order polynomials without quadratic terms were developed. This approach was chosen in order to account for the synergistic influence of digital indicators on promotion outcomes. Particular attention was devoted to avoiding multicollinearity between independent variables, which was achieved through preliminary analysis of the correlation matrix and the construction of models only with relatively independent factors (Farrar & Glauber, 1967). The adequacy of the constructed models was assessed on the basis of the coefficient of determination R^2, the Fisher criterion, and the level of statistical significance of the regression coefficients (p-value). In addition, average and maximum approximation errors were analysed in order to assess forecasting accuracy.

Sensitivity simulation analysis of multiple regression models was also applied, enabling the assessment of how changes in independent variables (X_n) affect the dependent variable Y_1 (organic traffic). This approach has practical value for marketing applications, as it helps predict the effect of investments in SEO factors for companies operating within the agricultural construction sector. It constituted a logical continuation of the previous regression analysis and was based on the principles of econometrics and scenario modelling. The applied methodological approach made it possible not only to establish statistical relationships between digital website performance indicators and the results of construction service promotion, but also to create a foundation for the practical application of the obtained results within the process of strategic marketing planning for construction companies oriented towards the agricultural sector.

The information base of the study consisted of data from the leading web analytics service Ahrefs (n.d.) and SEO analysis tools (Bek, 2023), reflecting the organic presence of websites in search engines, keyword structure, traffic volume and value, as well as indicators of the external backlink profile. The initial population comprised 32 Ukrainian companies specialising in the construction of facilities for the agricultural sector, selected from search query results across the five most effective search engines: Bing, DuckDuckGo, Yahoo, Ecosia, and Google, which are characterised by relevant, accurate, and unique search outputs (Chertinov, 2025). During the sample formation process, step-by-step data cleaning was conducted: resources not directly belonging to companies (aggregators and advertising platforms), websites displaying signs of fraud or technical threats, and web resources hosted on web studio domains not indexed by analytical services were excluded. In addition, paid advertising indicators were deliberately excluded from the analysis, since only a small proportion of companies used paid traffic acquisition channels, making it impossible to produce representative conclusions. Certain indicators relating to outgoing and backlinks were also excluded because of their low representation within the overall population of analysed websites. Following the completion of the staged data cleaning process, a final sample of 17 companies and a 17 × 17 data matrix containing 17 digital performance indicators were formed.

RESULTS

The construction of facilities for agricultural enterprises (silos, farms, warehouses, etc.) represents a narrow B2B segment with limited search demand. Clients (agricultural producers) search for such services infrequently (seasonally or during investment projects), mainly using local or highly specific queries ("elevator construction", "grain storage construction", "metal structures for farms", etc.). Organic traffic in this sector is consistently lower than in B2C or mass-market B2B segments. Global benchmarks for the construction sector (Kaufman, 2025; Rudan, n.d.) indicated average traffic of approximately 1,000-4,000 sessions per month, primarily characterising large-scale or consumer-oriented companies. According to Ahrefs (n.d.), SEMrush (n.d.), and BrightEdge (n.d.), the volume of organic traffic for professional services in 2024 was generally distributed as follows: small companies generated 1,200-3,500 sessions per month, medium-sized companies 4,000-12,000 sessions per month, and large companies more than 20,000 sessions per month (International Outsourcing Group, n.d.). Reports demonstrated that, globally, the construction sector in the United States and Europe recorded lower average traffic than mass-market industries (e-commerce approximately 20K-200K), but higher traffic than narrow B2B segments in Ukraine (International Outsourcing Group, n.d.). According to B2B statistics for 2025, organic traffic from the first search position generated a 27% CTR on mobile devices (First Page Sage Team, n.d.); the average CTR for keywords ranked in positions 1-3 ranged between 27-32%, whereas for positions 4-10 it declined to 10-15%. This justified the need for a detailed distribution of organic keywords by ranking positions within the data matrix and for subsequent regression analysis in order to accurately determine their influence on organic traffic within the B2B segment (Shum, 2026).

To identify Ukrainian construction companies specialising in the construction of facilities for the agricultural sector, search queries were conducted in five search engines: Bing, DuckDuckGo, Yahoo, Ecosia, and Google (Chertinov, 2025). Each search engine produced search results, from which no fewer than 20 relevant entries were selected. Subsequently, the list of companies was consolidated into a single table with duplicates removed. As a result, a list of 32 companies was obtained (Table 1).

Table 1. Companies specialising in the construction of facilities for agricultural enterprises in the Top 5 organic search results of search engines

No.	Company name	No.	Company name	No.	Company name
1	Lubnymash	12	Platonmax	23	Innovative Technologies Ukraine
2	Pulsar Construction	13	Budmontazh Kolos	24	KMZ
3	Demetra	14	UCG	25	Sokol
4	Eridon Bud	15	Elkos LTD	26	Agrovector
5	Adept Group	16	Invest Bud	27	Grain Capital
6	Finpro Group	17	ServiceStroy	28	Ravaro
7	Neuero Ukraine	18	Neobud-Montazh	29	Delta Engineering
8	Elevator Machinery Plant	19	BOEZ Ukraine	30	Arsenal
9	MUR	20	Ecorembud	31	APK Global
10	Vityaz	21	Bogart Bud	32	TransBud Project
11	Grain Complexes and Systems	22	Rilia Ukraine		

Source: compiled by the author

Company No. 26 in Table 1 was excluded from the analysis because the link directed not to the company's website, but to the AgroVector platform containing advertisements for the construction of agricultural facilities. Position No. 29 was excluded from the analysis due to an antivirus warning identifying the site as a scam. Positions No. 31 and No. 32 were removed because the websites were developed on studio domains that are not indexed by Ahrefs (n.d.). Companies No. 8, No. 15, No. 21, and No. 23 were excluded from the analysis due to an insufficient number of indexed indicators, as well as having a zero domain rating and no Ahrefs rank assigned (Ahrefs, n.d.). In addition, companies No. 5, No. 14, No. 18, No. 19, No. 20, No. 28, and No. 30 were excluded because of the absence of data on organic traffic. From the dataset obtained through the Ahrefs analytics service (Bek, 2023), indicators related to paid advertising were excluded, since only 3 out of the 32 companies (9.4%) used such services: BOEZ Ukraine (No. 19), KMZ (No. 24), and Grain Capital (No. 27). Indicators relating to the uniqueness of outgoing domains, outgoing links, and backlinks were also excluded from the analysis due to their limited coverage, representing only 25% of the total number of analysed construction companies (8 out of 32). As a result of the step-by-step data cleaning process, a final sample of 17 companies and a 17 × 17 data matrix were formed, including 17 digital performance indicators (Table 2).

Table 2. Analysis of the main performance indicators of the websites of Ukrainian companies in the construction sector for agricultural enterprises (beginning)

No.	Target	Rating		Organic							
				Keywords					51+	Traffic	Value
		URL	Domain	Total	Top 3	4-10	11-20	21-50			
		X_1	X_2	X_4	X_5	X_6	X_7	X_8	X_9	Y_1	Y_2
1	lubnymash.com/	8	8	31	3	18	1	4	5	207	21.27
2	pulsar-construction.ukr/uk	0	15	17	4	4	0	6	3	67	3.25
3	demetra.ua/	5	16	72	7	35	4	17	9	179	13.72
4	www.eridonbud.com/	5	2.6	12	1	4	0	4	3	56	0.05
5	finpro.group/uk	0	10	19	2	2	2	8	5	18	0.09
6	neuero-ukraina.com.ua/	7	1.1	23	3	6	4	7	3	59	5.62
7	mur.vn.ua/	4.5	3	14	1	4	0	5	4	33	0
8	mzv.com.ua/	13	20	70	4	25	10	16	15	75	9.45
9	gcs.com.ua/	5	2.8	9	0	3	1	4	1	16	4.65
10	platonmax.com.ua/	0	0	15	1	7	2	3	2	10	2.14
11	bmkolos.com/	6	3.6	21	2	12	2	4	1	22	3.74
12	invest-bud.com.ua/	0	0	25	2	6	1	9	7	7	1
13	servicestroy.com.ua/	8	18	63	5	26	6	13	13	109	13.76
14	rielaukr.com.ua/	7	0	25	3	9	5	5	3	41	7.13
15	kmzindustries.ua/	4.9	32	138	20	63	16	24	15	327	45.94
16	zeosokol.com.ua/uk	0	0.8	13	2	3	1	6	1	26	4.09
17	zeo.ua/	6	30	61	5	22	11	17	6	79	9.57

Source: compiled by the author using data from Ahrefs (n.d.)

In the study, the indicator of Organic Traffic was used as the dependent variable Y_1, representing the estimated monthly number of website visits generated through organic search (Ahrefs, n.d.). Additionally, Y_2 was calculated as the monetary value of organic traffic (Organic Value), reflecting the equivalent cost of such traffic if acquired through paid advertising (USD/month) (Ahrefs, n.d.). The independent variables X_1-X_{17} consisted of key SEO metrics characterising the backlink profile and organic ranking of websites (Bek, 2023): X_1 – the strength rating of a specific URL page (URL Rating) on a scale from 0 to 100; X_2 – the strength rating of the entire domain (Domain Rating) on a scale from 0 to 100; X_3 – the overall domain ranking (Ahrefs Rank) among all websites in the Ahrefs database, where a lower value indicates a stronger domain; X_4 – the total number of organic keywords (Organic Keywords Total) for which the website ranks within the top 100 results; X_5 – the number of keywords ranked in positions 1-3; X_6 – the number of keywords ranked in positions 4-10; X_7 – the number of keywords ranked in positions 11-20; X_8 – the number of keywords ranked in positions 21-50; X_9 – the number of keywords ranked in positions 51-100; X_{10} – the total number of referring domains (Referring Domains Total); X_{11} – the number of referring domains with "dofollow" links, which transfer "link equity" and authority from the donor site to the recipient; X_{12} – the number of referring domains with "nofollow" links, which do not transfer authority or link equity; X_{13} – the total number of unique IP addresses from which backlinks originate (Referring IPs); X_{14} – the number of unique Class C subnets (Referring Subnets); X_{15} – the total number of backlinks (Backlinks Total); X_{16} – the number of "dofollow" backlinks, which transfer search authority and ranking value from the donor website to the target website, directly influencing rankings; and X_{17} – the number of "nofollow" backlinks, which do not transfer search authority but may generate direct traffic (Table 2 and Table 3). All data were obtained from the Ahrefs service (n.d.) as of October 2025.

Table 3. Analysis of the main performance indicators of the websites of Ukrainian companies in the construction sector for agricultural enterprises (conclusion)

No.	Target	Ahrefs Rank	Referring					Backlinks		
			Domains			IPs				
			All	Followed	Not followed	IPs	Sub nets	All	Followed	Not followed
		X_3	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}
1	lubnymash.com/	19739586	148	105	44	121	107	2,289	2,122	167
2	pulsar-construction.ukr/uk	10759264	13	12	1	13	13	54	50	4
3	demetra.ua/	9902041	111	81	31	103	91	369	281	88
4	www.eridonbud.com	40920917	57	46	11	41	40	85	48	37
5	finpro.group/uk	17127335	3	3	0	3	3	3	3	0
6	neuero-ukraina.com.ua/	56175383	19	2	17	18	18	41	3	38
7	mur.vn.ua/	38046653	47	17	31	45	43	169	56	113
8	mzv.com.ua/	7478921	71	45	28	77	70	1,400	1,175	225
9	gcs.com.ua/	39166039	67	47	20	63	59	149	113	36
10	platonmax.com.ua/	0	0	0	0	0	0	0	0	0
11	bmkolos.com/	34444817	46	29	18	40	38	1,883	38	1,845
12	invest-bud.com.ua/	0	16	0	16	15	15	20	0	20
13	servicestroy.com.ua/	8624514	145	109	37	152	130	990	582	408
14	rielaukr.com.ua/	0	1	0	1	1	1	1	0	1
15	kmzindustries.ua/	2873777	363	310	59	332	278	1,178	967	211
16	zeosokol.com.ua/uk	61285701	6	6	0	2	2	13	13	0
17	zeo.ua/	3505420	136	90	53	138	127	2,205	1,039	1,166

Source: compiled by the author using data from Ahrefs (n.d.)

For the agricultural construction B2B sector in Ukraine, the actual figures for organic traffic proved to be 12 times lower than global indicators, with a typical range for small and medium-sized enterprises of 7-327 organic visits per month, highlighting the need for stimulation and clear expansion of traffic generation efforts. Using Formula 1, the author calculated Pearson correlation coefficients (r) between the website performance indicators of construction companies and constructed a matrix of pairwise coefficients (Table 4 and Table 5), in which changes in cell background colour were used to highlight indicators demonstrating strong relationships between variables.

Table 4. Correlation between the website performance indicators of construction companies (beginning)

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	1,0									
X_2	0.31	1.0								
X_3	-0.05	-0.48	1.0							
X_4	0.38	0.85	-0.48	1.0						
X_5	0.15	0.75	-0.37	0.92	1.0					
X_6	0.38	0.79	-0.45	0.98	0.92	1.0				
X_7	0.46	0.82	-0.45	0.90	0.80	0.84	1.0			
X_8	0.30	0.88	-0.45	0.94	0.83	0.88	0.88	1.0		
X_9	0.48	0.74	-0.53	0.86	0.69	0.80	0.75	0.85	1.0	
X_{10}	0.34	0.76	-0.29	0.88	0.87	0.91	0.74	0.75	0.68	1.0

Table 4, Continued

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_{11}	0.28	0.75	-0.29	0.88	0.90	0.91	0.74	0.74	0.66	0.99
X_{12}	0.53	0.72	-0.24	0.75	0.62	0.76	0.66	0.69	0.63	0.86
X_{13}	0.37	0.80	-0.32	0.90	0.87	0.92	0.78	0.78	0.71	1.00
X_{14}	0.38	0.80	-0.31	0.89	0.86	0.92	0.78	0.78	0.71	0.99
X_{15}	0.57	0.56	-0.22	0.44	0.29	0.48	0.47	0.36	0.34	0.55
X_{16}	0.57	0.56	-0.29	0.51	0.37	0.54	0.46	0.40	0.51	0.62
X_{17}	0.27	0.26	-0.02	0.13	0.04	0.16	0.23	0.12	-0.04	0.17
Y_1	0.32	0.67	-0.29	0.83	0.87	0.89	0.62	0.68	0.63	0.91
Y_2	0.31	0.64	-0.29	0.82	0.88	0.85	0.74	0.63	0.61	0.92

Source: calculated by the author

Table 5. Correlation between the website performance indicators of construction companies (conclusion)

	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	Y_1	Y_2
X_{11}	1.0								
X_{12}	0.80	1.0							
X_{13}	0.99	0.88	1.0						
X_{14}	0.98	0.89	1.0	1.0					
X_{15}	0.49	0.72	0.55	0.57	1.0				
X_{16}	0.57	0.73	0.61	0.62	0.81	1.0			
X_{17}	0.13	0.33	0.19	0.20	0.70	0.15	1.0		
Y_1	0.91	0.74	0.88	0.88	0.46	0.65	0.03	1.0	
Y_2	0.93	0.70	0.90	0.89	0.49	0.63	0.06	0.88	1.0

Source: calculated by the author

All correlation coefficients with Y_1 were positive, indicating a direct relationship, except for X_3, where the negative sign was expected, since a lower rank corresponds to a stronger website. The values were rounded to two decimal places for ease of interpretation. The highest correlation coefficients with Y_1 were observed for X_4 (0.83), X_5 (0.87), X_6 (0.89), X_{10} (0.91), X_{11} (0.91), X_{12} (0.74), X_{13} (0.88), and X_{14} (0.88), which justified the subsequent selection of variables (X_5, X_6, X_{10}, X_{11}, X_{13}, X_{14}) for single-factor regressions with $r > 0.7$ and $R^2 > 0.7$.

Six simple linear regression equations were identified, representing single-factor models with separate independent variables X_5, X_6, X_{10}, X_{11}, X_{13}, and X_{14} and the dependent variable Y_1. These models demonstrated a linear relationship and were statistically significant with a high level of probability at coefficients of determination $R^2 > 0.7$: $R^2 = 0.7427$ for Formula 2, $R^2 = 0.7915$ for Formula 3, $R^2 = 0.8126$ for Formula 4, $R^2 = 0.8096$ for Formula 5, $R^2 = 0.7712$ for Formula 6, and $R^2 = 0.7581$ for Formula 7.

$$Y_1 = 15.658 + 16.376 \times X_5. \tag{2}$$
$$Y_1 = 8.4065 + 4.7714 \times X_6. \tag{3}$$
$$Y_1 = 16.158 + 0.8507 \times X_{10}. \tag{4}$$
$$Y_1 = 26.201 + 1.0046 \times X_{11}. \tag{5}$$
$$Y_1 = 17.719 + 0.8913 \times X_{13}. \tag{6}$$
$$Y_1 = 14.627 + 1.0502 \times X_{14}. \tag{7}$$

The positive sign of the coefficients associated with the independent variables confirmed a direct relationship (Beyer, 2023), whereby an increase in the independent variable X_n correspondingly resulted in an increase in the dependent variable Y_1, as illustrated in the graphs (Fig. 1). The magnitude of the coefficient associated with the independent variable indicated the strength of the factor's influence on the outcome.

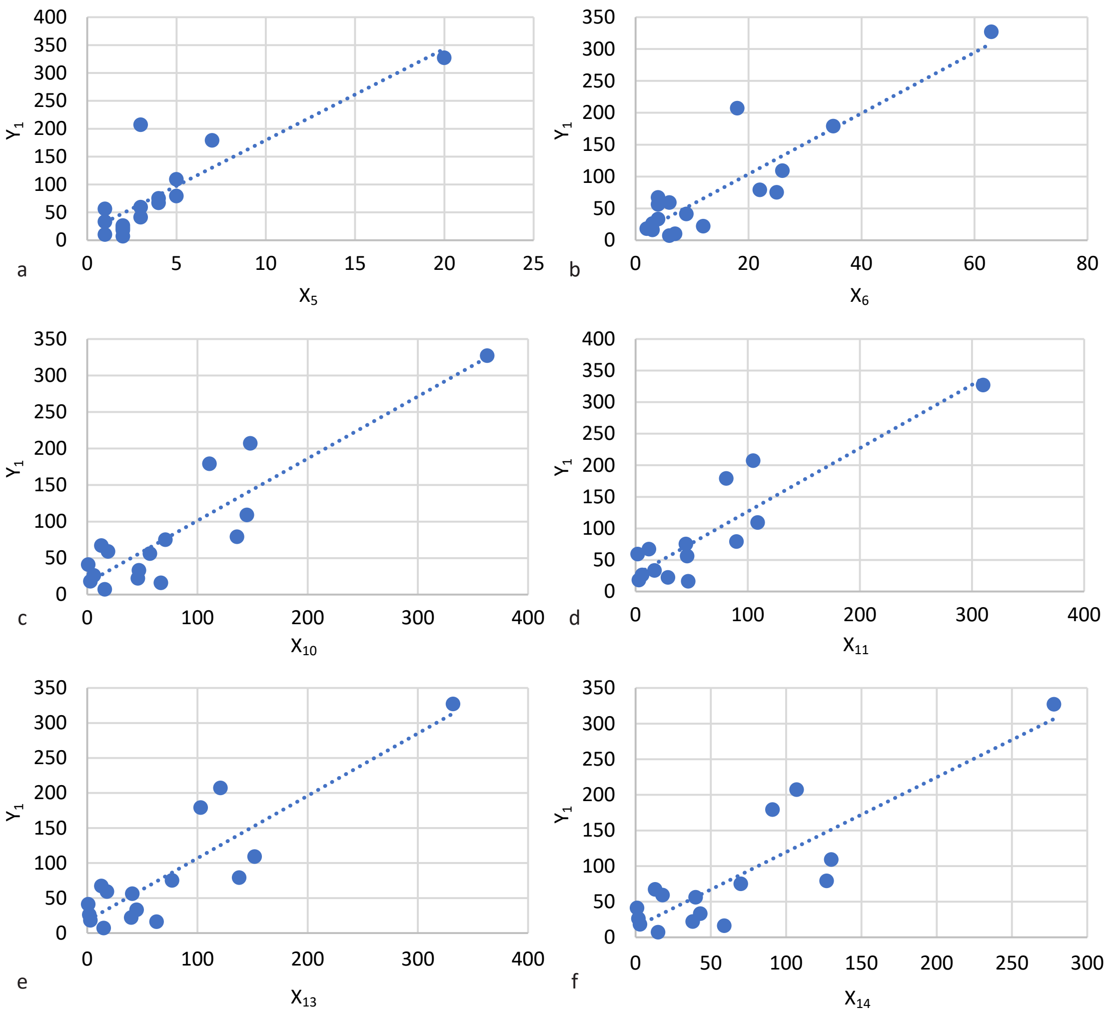

Figure 1. Scatter plots with regression lines for single-factor models of the dependence of organic traffic (Y_1) on key SEO indicators (X_5, X_6, X_{10}, X_{11}, X_{13}, X_{14})

Source: compiled by the author

Figure 1 presents scatter plots with linear regression lines for six single-factor models that proved to be statistically significant with coefficients of determination $R^2 > 0.7$. The points on the plots correspond to empirical observations, the straight line represents the constructed linear regression model, and the equations together with the R^2 values are provided directly in Formulas 2-7. Each diagram illustrates the relationship between organic traffic (Y_1, visits/month) and the corresponding independent variable for the 17 analysed companies, where:

a) the diagram with the steepest regression slope (coefficient 16.376) demonstrates the strongest influence: an increase of one keyword in the top-3 positions increases organic traffic by an average of 16.376 visits. The points are densely concentrated around the line, and the model explains 74.27% of the variability between X_5 and Y_1;

b) the second strongest factor of influence (coefficient 4.7714), where an increase of one keyword in positions 4-10 results in an average traffic increase of 4.771 visits. The model explains 79.15% of the variability between X_6 and Y_1;

c) the diagram illustrating the influence of the total number of referring domains with a coefficient of 0.8507. This model demonstrated the highest explanatory power, accounting for 81.26% of the variability between X_{10} and Y_1, although with a relatively limited influence on organic traffic;

d) the diagram illustrating the influence of "dofollow" referring domains on organic traffic, with a modest coefficient of 1.0046 and an explanatory power of 80.96%. The regression line has a moderate slope but a high density of data points;

e) the diagram illustrating the influence of the diversity of referring IP addresses, with a modest coefficient of 0.8913 and explanatory power of 77.12%;

f) the diagram illustrating the influence of the diversity of Class C subnets, with a modest coefficient of 1.0502 and explanatory power of 75.81%.

All graphs demonstrate a clear positive linear trend without pronounced non-linear deviations or outliers, confirming the adequacy of applying simple linear models for these factors.

The six identified models demonstrated good explanatory power, where between 74.27% and 81.26% of the variation in the dependent variable Y_1 was explained by variability in factors X_5, X_6, X_{10}, X_{11}, X_{13}, and X_{14}. The remaining variation in Y_1, ranging from 25.73% to 18.74%, was attributed to other factors not included in the models and to random influences. These equations described a strong direct linear relationship between the variables, representing a strong result for simple regression models, and may therefore be used to forecast Y_1 with relatively high accuracy. The influence of the independent variables on the dependent variable Y_2 was not investigated due to the strong direct linear relationship with the dependent variable Y_1, where the correlation coefficient $r = 0.88 > 0.7$. Since part of the variation remained unexplained, the study additionally considered extending the model with supplementary factors through the application of multifactor regression analysis.

A prerequisite for constructing the multifactor regression model was the avoidance of multicollinearity, whereby the independent variables had to remain relatively independent from one another in order to prevent instability of regression coefficients, reduce standard errors, increase the reliability of forecasts, and improve the assessment of the influence of individual factors (Farrar & Glauber, 1967). Combinations of independent variables with weak inter-factor relationships between X_n variables were identified, and equations of multiple non-linear regressions with interaction elements were developed in the form of second-order polynomial models without quadratic terms, depending on combinations of independent variables.

Equation No. 7 for the combination of independent variables X_1-X_3-X_5-X_9-X_{15}:

$$\begin{gathered}Y_1=-713.336-677.512\times X_1+7.01\times10^{-5}\times X_3+\\+682.908\times X_5+128.841\times X_9-3.679\times X_{15}+\\+6.85\times10^{-6}\times X_1\times X_3+219.359\times X_1\times\\\times X_5-26.914\times X_1\times X_9+0.018\times X_1\times X_{15}-\\-3.9\times10^{-5}\times X_3\times X_5-5\times10^{-7}\times X_3\times X_9+\\+9.02\times10^{-8}\times X_3\times X_{15}-108.622\times X_5\times\\\times X_9+0.439\times X_9\times X_{15}.\end{gathered} \tag{8}$$

The equation contains both linear terms (X_1, X_3, X_5, X_9, X_{15}), and bilinear products of individual factors ($X_1 \times X_3$, $X_1 \times X_5$, $X_1 \times X_9$, $X_1 \times X_{15}$, $X_3 \times X_5$, $X_3 \times X_9$, $X_3 \times X_{15}$, $X_5 \times X_9$, $X_9 \times X_{15}$), incorporating 5 independent variables and 9 interaction terms, giving a total of 14 regressors and a constant term. The model explains 99.5% of the variation in the dependent variable Y_1 (coefficient of determination $R^2 = 0.995$). The Fisher criterion $F = 0.054 \approx 0.05$ lies on the threshold of significance, under which the model is formally insignificant; however, due to the exceptionally high coefficient of determination, it possesses substantial practical value. The average approximation error amounted to 2.2%, while the maximum error was 11.2%, indicating high forecasting accuracy across the entire sample.

The significance level of the observed result (p-value) in the statistical hypothesis testing proved to be less than 0.05 for each independent variable and interaction term, except for the term $X_1 \times X_{15}$, for which p-value = 0.099 > 0.05, and $X_3 \times X_9$, for which p-value = 0.153 > 0.1. The p-value indicates the probability of obtaining an extreme value of the statistic under the assumption that the null hypothesis is true. Thus, when $p < 0.05$, there is strong evidence against the null hypothesis in favour of the alternative hypothesis, meaning that the factor influences the dependent variable Y_1; when $p > 0.1$, the data are consistent with the null hypothesis; and when $0.05 < p < 0.1$, a borderline case with weak evidence against the null hypothesis is observed, under which the null hypothesis is formally not rejected.

Since the effect size of factor $X_3 \times X_9$ proved to be extremely small and influenced the dependent variable only within the seventh decimal place, and considering its consistency with the null hypothesis, it was decided to disregard this factor. Given the small effect size, factor $X_1 \times X_{15}$, which demonstrated weak inconsistency with the null hypothesis, was also disregarded. As a result, an equation with 12 regressors and a constant term was obtained in the following form:

$$\begin{gathered} Y_1 = -713.336 - 677.512 \times X_1 + 7.01 \times \\ \times 10^{-5} \times X_3 + 682.908 \times X_5 + 128.841 \times X_9 - \\ -3.679 \times X_{15} + 6.85 \times 10^{-6} \times X_1 \times X_3 + 219.359 \times \\ \times X_1 \times X_5 - 26.914 \times X_1 \times X_9 - 3.9 \times 10^{-5} \times \\ \times X_3 \times X_5 + 9.02 \times 10^{-8} \times X_3 \times X_{15} - 108.622 \times \\ \times X_5 \times X_9 + 0.439 \times X_9 \times X_{15} \end{gathered} \quad . (9)$$

Equation No. 8 for a combination of independent variables X_1-X_4-X_{15}:

$$\begin{gathered} Y_1 = -75.484 + 17.74 \times X_1 + 8.802 \times X_4 - 0.287 \times \\ \times X_{15} - 1.211 \times X_1 \times X_4 + 0.045 \times X_1 \times X_{15}. \end{gathered} \quad (10)$$

The equation contains both linear terms (X_1, X_4, X_{15}), and bilinear products of individual factors ($X_1 \times X_4$, $X_1 \times X_{15}$), including 3 independent variables and 2 interaction terms, giving a total of 5 regressors and a constant term. The model explains 97.0% of the variation in the dependent variable Y_1 (coefficient of determination $R^2 = 0.97$), which confirmed the excellent fit of the model to the data and its high quality. The Fisher criterion $F = 5.43 \times 10^{-6} < 0.05$ demonstrated that the model is statistically significant at any conventional level and confirmed that the regressors collectively explain Y_1 substantially better than the simple mean value. The average approximation error was determined at 16.1% and is considered acceptable; however, the maximum error reached 38.5%, which is associated with outliers and with the fact that, at these points, the values of the factors extend beyond the typical data range. The significance level of the observed result (p-value) in the statistical hypothesis testing proved to be less than 0.05 for each independent variable and interaction term, indicating a low probability of obtaining extreme statistic values under a true null hypothesis and providing strong evidence in favour of the alternative hypothesis, whereby each factor and interaction contributes substantially.

Equation No. 9 for the combination of independent variables X_1-X_3-X_7-X_{12}-X_{17}:

$$\begin{gathered} Y_1 = =64.101 + 1.1 \times X^{17} + 1.86 \times 10^{-7} \times \\ \times X_1 \times X_3 + 0.975 \times X_1 \times X_{12} - 0.181 \times X_{\_1} \times X_{17} - \\ -1.96 \times 10^{-7} \times X_3 \times X_{12} + 0.05 \times X_{\_7} \times X_{12} - \\ -0.024 \times X_7 \times X_{17}. \end{gathered} \quad (11)$$

The dependence of Y_1 on the factors is described exclusively through one linear term (X_{17}) and six bilinear interaction terms ($X_1 \times X_3$, $X_1 \times X_{12}$, $X_1 \times X_{17}$, $X_3 \times X_{12}$, $X_7 \times X_{12}$, $X_7 \times X_{17}$). The model assumes that the influence of most factors manifests only in combination with others and explains 99.9% of the variation in the dependent variable Y_1 (coefficient of determination $R^2 = 0.999$), which demonstrated the excellent fit of the model to the data and its high quality. The Fisher criterion $F = 7.18 \times 10^{-4} < 0.05$ showed that the model is statistically significant at any conventional level and confirmed that the regressors collectively explain Y_1 substantially better than the simple mean value. The average approximation error was determined at 1.0%, while the maximum error was 3.2%, indicating high forecasting accuracy across the entire sample and demonstrating an almost perfect fit of the model to the data within the sample range. The significance level of the observed result (p-value) in the statistical hypothesis testing proved to be less than 0.05 for the independent variable (X_{17}) and the six interaction terms, indicating strong evidence in favour of the alternative hypothesis, where the factor and each interaction are statistically significant and make a substantial contribution.

High values of the coefficient of determination in the multifactor models confirmed the appropriateness of a comprehensive approach to shaping a digital promotion strategy based on the interaction of several key indicators rather than the isolated management of individual metrics. To assess the marginal effect of each independent variable on Y_1 through "what-if" simulation analysis, the interactions of factors in the non-linear models were taken into account, making it possible to obtain average values of traffic growth resulting from a unit change in Xn. The research was conducted on a sample of 17 companies using actual data from Tables 2 and 3 within the original Equations No. 7, 8, and 9. Actual values of the independent variables (Xn) for each of the 17 websites were separately substituted into each second-order polynomial equation, enabling the determination of baseline (initial) theoretical values of Y_1 for each equation. Subsequently, each independent variable Xn was increased by one unit ($\Delta Xn = +1$), while all other variables remained unchanged. For each such iteration, a new predicted value of Y_1 was recalculated, and this procedure was repeated for all Xn variables in Equations No. 7, 8, and 9 and for each of the 17 websites. For every variable Xn, website, and equation, the absolute increase ΔY_1 was calculated using the following Formula 12:

$$\Delta Y_1 = (\text{predicted } Y_1 =) - (\text{baseline } Y_1). \quad (12)$$

The absolute increase ΔY_1 represents a quantitative measure of influence, indicating traffic growth when the value is positive and traffic decline when the value is negative. Calculations according to Formula 12 were performed separately in order to account for variation between websites. For each Xn variable, the average value of the increase ΔY_1 for the sample of 17 websites was aggregated, producing a generalised effect (Table 6), where each value is accompanied by the symbols "+" for direct influence and "–" for inverse influence.

Table 6. Average increase in organic traffic resulting from a one-unit increase in one of the independent variables of the model

Equation	Average increase in Organic Traffic (ΔY_1), visits/month resulting from a one-unit increase in the independent variable								
	X_1+1	X_3+1	X_4+1	X_5+1	X_7+1	X_9+1	$X_{12}+1$	$X_{15}+1$	$X_{17}+1$
Equation 7 (F. 8)	+161.8	$+6.1\times10^{-6}$		+282		-142.6		+0.7	
Equation 7 (F. 9)	+150.2	$+8.9\times10^{-6}$		+282		-132.2		+0.7	
Equation 8 (F. 10)	+1.6		+3.1					-0.1	
Equation 9 (F. 11)	-21.6	-3.4×10^{-6}			-5		+0.7		+0.2

Source: calculated by the author

Table 6 contains cells with missing data. This is due to the absence of the corresponding independent variables Xn in Equations 7, 8 and 9 (see Formulas 8, 9, 10, and 11). The simulation analysis additionally highlighted the necessity of a comprehensive approach to the group of variables: increasing X_5 (the number of keywords ranked in Top-3 positions) and X_1 (the URL Rating of a specific page) in order to achieve maximum traffic growth; reducing X_9 (the number of keywords ranked in positions 51-100), since growth in this variable has a negative effect; disregarding X_3 (the overall domain rank within the Ahrefs database) because of its lack of substantial influence and the negative nature of the relationship; and secondary efforts directed towards increasing X_4 (the total number of organic keywords), X_{12} (the number of referring domains with "nofollow" links), X_{15} (the total number of backlinks), X_{17} (the number of "nofollow" backlinks), as well as reducing X_7 (keywords ranked in positions 11-20), in order to support the overall effectiveness of the profile.

The results of the conducted study provided construction companies specialising in the construction of facilities for the agricultural sector with a specific, data-oriented toolkit for transitioning from intuitive or fragmented digital marketing towards a KPI-oriented strategy. The practical application of the results involves the clear prioritisation of SEO investments aimed at ensuring the fastest possible traffic growth without the need for additional content. The highest priorities are keywords ranked in the Top-3 positions (X_5) and positions 4-10 (X_6), which exert the most substantial influence on organic traffic. To increase the number of such keywords, construction companies are advised to systematically develop a content strategy focused on "long-tail" queries reflecting the specific characteristics of the agricultural sector. Parallel priority should be given to backlink profiles (X_{10}, X_{11}, X_{13}, X_{14}). Domain authority should be strengthened through the acquisition of high-quality "dofollow" links from industry-related resources. To achieve this, construction companies may conduct regular informational and outreach activities on agricultural portals, farmers' forums, industry media, and the websites of equipment suppliers. Another parallel priority is the URL Rating of a specific page (X_1). To improve this indicator, construction companies should focus on optimising the internal structure of their websites by improving the technical performance of each page (speed, mobile optimisation, internal linking). Such a comprehensive approach enables not only the forecasting of traffic growth but also the optimisation of marketing expenditure, ensuring maximum return on investment in digital promotion.

From a strategic perspective, the results of the study enable construction companies to develop an annual KPI-oriented promotion programme in which organic traffic becomes the key measurable performance indicator. The use of empirical models makes scenario forecasting possible, allowing companies to estimate potential lead growth and conversions even before implementation measures begin, as well as to promptly adjust strategy based on the results of monthly monitoring. The implementation of the proposed recommendations is intended to contribute to reducing customer acquisition costs, increasing trust among agricultural producers, and ensuring a long-term competitive advantage within the market for construction services in agribusiness.

DISCUSSION

According to B2B statistics from 2025, 61% of marketers prioritised SEO and organic traffic as the main focus of inbound marketing, which delivered a high ROI through personalised content and highlighted the importance of digital metrics (First Page Sage Team, n.d.); 57% of companies believed that SEO generated more leads than any other channel, with 76% of web traffic coming from search engines (Shum, 2026); 68% of companies reported that organic traffic from search engines was their primary source of high-quality leads, whilst 54% of marketers planned to increase investment in SEO precisely because of the higher ROI compared to paid advertising, which is particularly important for sector-specific markets such as construction services for the agricultural sector (Bateman, 2025). 73% of B2B buyers considered SEO and organic search to be one of the most important sources of information during the supplier research phase, and companies that invested in quality content and SEO generated 55% more leads than those relying primarily on paid advertising (PBJ Marketing, n.d.). According to digital marketing data for the agricultural sector, agricultural companies that invested in SEO and content marketing received a steady stream of high-quality leads through organic search, as farmers and agribusinesses actively used online channels to search for service providers, equipment and solutions, making digital metrics key to building trust and competitive advantages in the B2B segment (Dombrowski, 2025). The effectiveness of promotion in segmented industries, such as construction for the agricultural sector, depended to a large extent on a comprehensive approach to content, technical optimisation and the quality of the backlink profile, which allowed for a steady flow of organic traffic even in the face of limited search demand and high customer acquisition costs (Romain, 2024), whilst strategic flexibility in shaping marketing strategies enabled companies to adapt effectively to changes in demand and the competitive environment, which was particularly important for sector-specific markets such as the construction of facilities for agricultural enterprises, where the long deal cycle required a rapid response to digital opportunities and precise measurement of effectiveness (Norouzi, 2025).

The agricultural sector, farmers and agricultural producers increasingly sought out suppliers of services, equipment and solutions via social media and search engines, where brands that actively published useful content and optimised their profiles for key search terms significantly increased their visibility and trust among their target audience, making digital performance metrics critically important for construction companies focused on agribusiness (Baranowska, 2025), whilst agricultural companies that integrated SEO, content marketing and digital advertising with a clear focus on measurable KPIs (organic traffic, conversion, lead quality), achieved a significantly higher ROI than those relying solely on traditional channels or fragmented digital tools, which is particularly important for the B2B services segment, such as the construction of facilities for agribusinesses (Rhea + Kaiser, n.d.). In the agricultural sector, even with zero search volume for key queries, a comprehensive content marketing strategy, SEO optimisation and targeted information and awareness-raising efforts enabled significant growth in organic traffic and high-quality leads, demonstrating the potential of digital performance metrics for sector-specific construction companies operating with limited search demand in the agricultural segment (Sandyriev, 2025).

A review of the literature on digital marketing in agribusiness revealed significant academic interest in the role of digital performance metrics in shaping promotional strategies. Researchers S. Wang & R. Meng (2024) developed the "Zebra" optimiser model with a weighted random forest algorithm (ZO-WRF) to forecast marketing channels for agricultural products in Leshan and confirmed that machine learning based on social data achieves 95% accuracy in predicting media marketing effectiveness, significantly outperforming traditional methods. The issue of using digital performance indicators was addressed in studies by S. Hasnain & A. Kazmi (2015) on digital marketing, brand management and service promotion. Despite a significant body of scholarly work, most studies have focused on general agromarketing strategies, whilst the works of A. Mostova (2022) and Z. Lu (2023) focused on consumer markets, whilst the research by S. Hasnain & A. Kazmi (2015) concentrated on specific online communication tools.

The analysed studies confirmed that digital performance indicators form the strategic foundation for developing a marketing strategy in agribusiness. Researchers D. Nyangoma *et al.* (2024) highlighted the shift from an intuitive to a "data-driven" approach, where KPIs (reach, engagement, conversion, ROI) have become an essential tool for optimising resources and enhancing competitiveness. In particular, researchers S. Koberniuk *et al.* (2025) and I. Yatskevych (2024) emphasised the need to monitor digital metrics in SMM strategies. Researchers I. Gushcha (2023) and M. Sheeraz *et al.* (2023) focused on the role of data analytics and brand awareness. Author W. Shen (2024) investigated the power of machine learning predictions. Researcher A.S. Ajibola (2025) focused on KPIs for technology adoption among smallholder farmers. Researchers M. Braglia *et al.* (2022) focused on a structured Industry 4.0 KPI system. Authors U.S. Nwabekee *et al.* (2021) paid particular attention to the integration of digital marketing with financial metrics. The authors' findings were fully consistent with this paradigm, empirically confirming the strong influence of SEO metrics on organic traffic in the B2B segment.

Despite a shared methodological framework, the studies differ significantly in subject matter and approach. The studies by M. Sheeraz *et al.* (2023) and E.A. Inyommom *et al.* (2025) focused on general digital strategies (SMM, content marketing, "big data") in the agri-food industry or at the level of end consumers/smallholder farmers. The authors D. Nyangoma *et al.* (2024) proposed conceptual models, whilst the researchers M. Braglia *et al.* (2022) focused on universal Industry 4.0 KPI frameworks. The authors S. Wang & R. Meng (2024) paid particular attention to predictive ML models. In contrast, the author's work was purely empirical and econometric: it was based on a correlation and regression analysis of real-world data from Ahrefs (n.d.) for 17 Ukrainian construction companies and proposed specific quantitative models of the impact of SEO metrics on organic traffic specifically within the B2B segment of construction services. Thus, whilst most of the literature addressed the question "which tools and models to use", this study answers the question "which specific SEO metrics have the greatest impact on results and how to optimise them quantitatively".

The analysed works highlighted additional aspects that significantly broaden the understanding of the role of digital performance indicators in shaping the strategy for promoting construction services in agribusiness. In particular, the works of A.S. Ajibola (2025) and D. Nyangoma *et al.* (2024) highlighted the specific characteristics of developing countries, resource constraints and the need to personalise strategies. Meanwhile, I. Yatskevych (2024), S. Koberniuk *et al.* (2025), and N.B. Zelisko & V.V. Maliuha (2025) highlighted the synergy of various digital channels (SMM, SEO, content marketing) to achieve a cumulative effect.

In turn, the author's work organically complemented this body of research, adding an empirical dimension specifically to the B2B segment of construction services: the high capital intensity of projects, the lengthy decision-making cycle, limited search demand, and the synergistic influence of SEO factors. Thus, the body of analysed sources formed a solid theoretical and methodological foundation, against which this study demonstrated scientific novelty – the quantitative verification of the role of digital performance indicators for the strategic planning of construction services promotion in agribusiness, using Ukrainian companies as a case study. The results obtained not only confirmed the general trends in the literature but also offered practical tools for construction companies operating in the agricultural sector, facilitating the transition from descriptive recommendations to predictive KPI-oriented strategies.

CONCLUSIONS

As a result of the conducted study, the decisive role of digital performance indicators in shaping the promotion strategy of construction services for agricultural enterprises was confirmed. The analysis demonstrated that, within a B2B market characterised by high-value contracts and long decision-making cycles, the website of a construction company serves as a key instrument of communication, trust formation, and support for the customer acquisition process. The correlation analysis confirmed the existence of strong direct relationships between the majority of digital website performance indicators and the resulting variables characterising the level of their presence within the digital environment. High values of correlation coefficients according to the Chaddock scale demonstrated that organic visibility in search engines, the structure and quality of keywords, as well as the characteristics of the backlink profile, exert a systematic influence on the effectiveness of the digital promotion of construction companies operating within the agricultural sector.

The constructed single-factor linear regression models confirmed the statistically significant influence of individual digital indicators on the resulting variable Y_1 (organic traffic), with coefficients of determination exceeding 0.7, indicating the high explanatory power of the models. This provided grounds for asserting that individual SEO indicators may be used as reliable measures of the effectiveness of construction service promotion strategies within the digital environment. The results of the multifactor regression analysis and sensitivity simulation analysis demonstrated the existence of a synergistic effect between digital performance indicators, whereby their combined influence substantially exceeded the influence of each individual factor. In particular, the greatest average increase in organic traffic resulting from a unit increase in the independent variables was observed for X_5 (the number of keywords ranked in positions 1-3) and X_6 (the number of keywords ranked in positions 4-10), which was confirmed by high positive coefficients. This indicated the priority of focusing specifically on these variables in order to achieve rapid and substantial traffic growth.

A secondary but still important direction identified in the study was work on variables X_{10} (the total number of referring domains), X_{11} (the number of referring domains with "dofollow" links), X_{13} (the total number of unique referring IP addresses), and X_{14} (the number of unique Class C subnets), where comprehensive optimisation of these factors would strengthen domain authority and improve positioning within search engines. The obtained results made it possible to consider digital website performance indicators not only as tools for the operational control of marketing activities, but also as elements of strategic planning. Accordingly, for construction companies working with agricultural enterprises, systematic management of organic visibility, keyword structure, and the quality of digital content may serve as the foundation of a long-term competitive advantage in the market. Prospects for further research include expanding the sample of enterprises, analysing the dynamics of digital indicators over time, and incorporating additional factors into the models that characterise user behaviour and content quality. This would allow for a deeper understanding of the mechanisms through which digital indicators influence the strategic promotion of construction services within the agricultural sector and would improve the accuracy of forecasting marketing performance outcomes.

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Роль цифрових показників ефективності формування стратегії просування будівельних послуг в агробізнесі

Анотація. В умовах цифровізації економіки маркетингова діяльність будівельних компаній, орієнтованих на агробізнес, залежить від даних та аналітичних інструментів, які дозволяють приймати обґрунтовані рішення на основі кількісних показників. Метою статті було встановити кількісні залежності між основними SEO-показниками веб-сайтів та обсягом органічного трафіку, а також оцінити їх вплив на формування ефективної стратегії просування будівельних послуг для підприємств агробізнесу. Для досягнення мети сформовано вибірку із 17 українських будівельних компаній, що спеціалізуються на будівництві об'єктів для аграрного сектору. Дані отримано з сервісу Ahrefs станом на жовтень 2025 року. Використано кореляційний аналіз за шкалою Чеддока, однофакторні лінійні регресійні моделі, багатофакторні нелінійні регресійні моделі з елементами взаємодії, а також симуляційний аналіз чутливості. У результаті дослідження виявлено сильні прямі кореляційні зв'язки між органічним трафіком та ключовими SEO-метриками: кількістю ключових слів у позиціях 1-3 ($r = 0,87$) і у позиціях 4-10 ($r = 0,89$), загальною кількістю реферальних доменів ($r = 0,91$), кількістю «dofollow» – реферальних доменів ($r = 0,91$), кількістю унікальних IP-адрес рефererів ($r = 0,88$) та кількістю унікальних підмереж класу C ($r = 0,88$). Побудовано шість статистично значущих однофакторних лінійних регресійних моделей з коефіцієнтами детермінації R^2 від 0,7427 до 0,8126. Багатофакторні нелінійні моделі з елементами взаємодії показали вищу пояснювальну здатність (R^2 до 0,999). Симуляційний аналіз чутливості підтвердив, що найбільший приріст органічного трафіку забезпечує збільшення кількості ключових слів у топ-3 (+282 відвідування/місяць) та підвищення рейтингу сили URL-сторінки (+150-162 відвідування/місяць). Практичне значення дослідження полягає в тому, що отримані результати дозволяють будівельним компаніям формувати KPI-орієнтовані стратегії просування, оптимізувати розподіл маркетингових ресурсів та підвищувати ефективність взаємодії з клієнтами в аграрному секторі

Ключові слова: цифровий маркетинг; веб-аналітика; математичні моделі; органічний трафік; SEO-метрики; сільськогосподарські підприємства; B2B-стратегії