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Research article

Web analytics and supply chain transportation firms' financial performance

Nikolaos T. Giannakopoulos[1,*], Damianos P. Sakas[1], Nikos Kanellos[1] and Christos Christopoulos[2]

[1] BICTEVAC LABORATORY-Business Information and Communication Technologies in Value Chains laboratory, Department of Agribusiness and Supply Chain Management, School of Applied Economics and Social Sciences, Agricultural University of Athens, 118 55 Athens, Greece
[2] General Manager, Global Operations Transformation & Excellence, Swissport International Ltd., Zurich, Switzerland

* **Correspondence:** Email: n.giannakopoulos@aua.gr; Tel: +30-694-00-13-673.

Abstract: In the dynamic landscape of today's digitized markets, organizations harness the power of vast and swiftly accessible data to glean invaluable insights. A significant portion of this data emanates from user behavior on business websites. Unraveling the intricacies of this user behavior has become paramount for businesses, serving as the compass guiding the adaptation and evolution of their digital marketing strategies. Embarking on an exploration of this digital frontier, our study delves into the virtual domains of enterprises entrenched in the supply chain sector of the Greek economy. The spotlight falls upon four dominant transportation firms of the Greek supply chain sector, to unravel the relationship between their website activities and the prediction of their stock market prices. Our analytical tools, adorned with sophisticated statistical methodologies, embracing normality tests, correlations, ANOVA, linear regressions and the utilization of regression residual tests were deployed with precision. As the analytical methodology was deployed, a revelation emerged: The digital footprints left by customers on the virtual domains of supply chain firms provided the ability to predict and influence stock prices. Metrics such as bounce rates, the influx of new visitors and the average time on websites emerged as important factors, that could predict the fluctuations in the stock prices of these Greek supply chain firms. Web analytics have been discerned as a determining factor for

predicting the course of transportation firms' stock prices. It serves as a clarion call for global scrutiny, inviting scholars and practitioners alike to scrutinize analogous firms on a global canvas. In this convergence of virtual footprints and financial trajectories lies not just a revelation for today but a harbinger of insights that resonate far beyond the digital borders of the Hellenic transportation sector.

Keywords: supply chain; transportation; financial performance; stock prices; big data; web analytics; digital marketing strategy

JEL Codes: M1, M3, O3

1. Introduction

1.1. Digital marketing, big data and decision-making

A promotional campaign's major aims are to maintain present clients and recruit new ones. Several companies acknowledge the critical impact that big data analytics have in enhancing consumer engagement and promotion (Hassani et al., 2018). Because marketing performance may target every client's demand and preferences and assist in decision-making processes, marketing performance has a direct impact on manufacturing growth. While traditional marketing analytics concentrates on enhancing operational performance elements (client behavior and goods improvement), Big Data Analytics is required to monitor the richness of knowledge and perform analyses in real-time (Sathi, 2014).

Businesses that use Big Data Analysis may constantly observe rivals, study customers, explore the Internet, conduct inexpensive inquiries, develop designs and obtain input. As a result, big data technologies may be viewed as the basis for smart tools that successfully help marketers while reducing the strain of human evaluation (Sharda et al., 2015). In general, improved consumer awareness using big data increases the efficacy of current marketing operations and may contribute to incremental improvements (Story et al., 2011). A corporation must continually rethink marketing efforts and adopt novel approaches by leveraging consumer information gathered from big data (Story et al., 2011). Innovative marketing skills (Barrales-Molina et al., 2014) are important in the setting of marketing analytics as they represent an organization's capacity to participate in market-driven research and then use the information that results to identify and capitalize on prospects, transform its assets and boost its capacity to attain a long-term competitive edge (Vorhies & Morgan, 2005) and outstanding results (Morgan, 2012; Vorhies et al., 2011).

Big data analytics, for instance, may assist marketers in converting "icy" purchases into "hot" deals and understanding customers' propensity to purchase by analyzing customers' browsing activities on web pages (Lilien, 2016). The absence of sufficient IT equipment to assist marketing analytics and corporate analytics management plagues B2B organizations (Leeflang et al., 2014). The issue for marketing departments is getting rid of data in a manner that facilitates corporate utilization and decision-making for strategy whilst decreasing delay (Jabbar et al., 2020).

During this research, the following sections have been used to present its findings: In the introductory section, a cohesive elaboration of the major topics discussed are given, followed by the Materials and Methods part, where the methodological framework and information regarding the sample's collection are provided. Hence, in the Results section, the statistical analyses that were deployed are presented. Lastly, in the Discussion and Conclusions sections, the theoretical and practical outcomes from the utilization of web analytics in transportation supply chain firms' financial performance are presented.

1.2. Website analytics and firms' promotion

Analysis of web company performance metrics (KPIs) is an excellent area to start when developing an organization's digital environment as an interface with business objectives and client orientation. Nowadays, every smart company strategy includes a social media marketing campaign. The relevance of social propagation is expanding at an accelerated rate, as is the requirement for enterprises to obtain and maintain market knowledge. The details that follow are the primary web analytic data required for a thorough and successful study:

1. Website traffic in aggregate (Overall traffic).
2. The bounce rate. A "bounce" or departure occurs when an individual visits an internet site and leaves without viewing another page. The bounce rate is a proportion of these sessions compared to the overall traffic on the web page. This score is crucial since it indicates if the website has any unresolved accessibility difficulties.
3. Sources of web page arrival. Many new visitors will locate a web page via hyperlinks instead of typing in the URL. The major sources of traffic typically divide into four distinct groups:

- Search engines
- Links from other websites
- Email campaign visits
- Social media connections;

4. Workstation vs. mobile visitors. It ought to come as an unsurprising fact that numerous online consumers have completely accepted mobile traffic. It eclipsed conventional PC traffic, indicating that firms must have web pages that provide a good mobile presence.
5. New and returning visitors.

Organizations generally desire users to return to their sites. These people are known as "returning visitors", which are very crucial for the performance of the companies, as well as the main customer base of the enterprises.

To evaluate and comprehend information, businesses must be provided with the necessary resources and capabilities (Wu et al., 2014). Management personnel can gain extra dividends/benefits with enhanced preciseness that have previously evaded them by combining machine learning and cognitive analytics approaches into conventional demand forecasting techniques. Big data and data analytics from social media provide the opportunity for businesses in the B2B industry to tackle two critical aspects of an organization, notably marketing and operations, in a manner that may help a firm accomplish its sustainability objectives (Sivarajah et al., 2020).

1.3. Big data and supply chain management

The definition of the supply chain is the coordination of important company procedures via the final customer to the initial vendors supplying goods, services and data that add value to clients, as well as additional partners (Lambert et al., 1998). Content, knowledge and financial activities are all critical components of supply chain activities (Tang & Musa, 2011). As a result, there is more than a growing amount of effort put forth on integrating analytics into supply chain firms' performance (Waller & Fawcett, 2013). Material transportation concerns emerge due to supply and demand cooperation issues or disruptions in regular operations (Kleindorfer & Saad, 2005). The hazards associated with the transfer of data include difficulties like data precision, security of data systems and interruption, trademarks and data outsourcing (Tang & Musa, 2011).

The demand-based prediction uses sophisticated methods for data mining to discover indicators of clients' demand (Chase Jr, 2013), which uses big data to analyze the performance of advertising campaigns by recognizing trends in customer behavior. Demand-driven logistics systems are motivated by the desire to provide greater worth to their customers (Zokaei & Hines, 2007). Businesses might profit from data collected by their suppliers in addition to incorporating inner company tracking applications and collecting data on customer purchasing patterns and technological advances (Barbosa et al., 2018). For an efficient inventory management approach, reliable predictions and the proper arrangement of predicting operations are critical (Kumar et al., 2020a).

1.4. Literature review and research objectives

The purpose of using big data analytics is to get knowledge via either human evaluation or computer intelligence for improved decision-making. A firm should aim to engage consumers to gain access to substantial customer information to better promote their services (Erevelles et al., 2016). As stated by Hedin et al. (2014), data originating from organizations' transactions is gathered, analyzed and transformed into knowledge that aids decision-making. According to Tan et al. (2013), essential variables influencing strategic advertising choices may be constantly monitored by analyzing information from website data.

It is not obvious whether corporate analytics could be applied to enhance decisions regarding implementation and company competition and/or performance (Chen et al., 2015; Germann et al., 2013; Wedel & Kannan, 2016). As a result, further study with greater examination is required (Sharma et al. (2014). Even though multiple marketing activities connected with data analytics have been incorporated (e.g., keeping customers, client segmentation), according to Amado et al., (2018), a handful seem very pertinent to the subjects that were disclosed, while those that showed up subsequently demonstrate a fragile connection than the significance of the specific big data term.

According to Cao et al. (2019), the application of marketing analytics could result in enhanced advertising decision-making and enhanced performance. Despite the difficulty of assessing the relationship between the application of marketing analytics, advertising and long-term competitive advantage, they highlight the need to successfully utilize marketing analytics. According to Fan et al. (2015), the application of a marketing model to direct study on big data handling for developing smart marketing is suggested. Chen et al. (2015), investigated the effect of corporate intelligence on supply chain management, focusing on technological reliability, managerial and support for teams, anticipated advantages, pressure from rivals and corporate preparation.

Supply chain and big data connection benefits both commercial concerns and the long-term sustainability of the economy. Hung et al. (2020), suggested that the utilization of big data analytics for engaging clients may greatly boost their acceptance ratio to a marketing effort. Association analysis may thus be expanded to more complex areas like supply chain firms' financial performance. Website analytics (website visitors and behavioral metrics) were mostly used for managing risks (DuHadway et al., 2019). Sena & Ozdemir (2020) discovered that supply chain firms could profit from their collaborators' dedication to big data analytics (BDA), as far as technical effectiveness and advancement.

Getting past inventory information in addition to real-time data usually involves gaining admission to a webpage while gathering data. Although the data is acquired in real-time, it can be hard to acquire all of the data as we want to investigate in a short amount of time. The purpose of a stock investing agency is to assess if the price of a specific commodity is increasing or declining and to maximize revenue by purchasing and trading at appropriate prices. Stock price forecasting employs trends derived from massive amounts of past stock data and other big data. According to Jeon et al. (2018), stock prices display comparable trends, and many of the Big Data Analysis factors they employed to evaluate their trajectory had little or no impact on them.

Troisi et al. (2020), study demonstrates that B2B advertising techniques can profit from a based-on-data mentality in generating numerous (financial, knowledge-based and advertising) benefits throughout the supply chain and in improving client interactions. Financial performance is frequently employed as an indicator for evaluating an organization's competitive edge (Kaufman, 2015). Numerous researches have emphasized the capacity of Big Data Analysis tools to improve firm financial performance (Wamba et al., 2017; Mikalef et al., 2019). As stated by Fagan (2014), website big data can offer clearer and concrete data to supply chain firms' investors.

Regarding the sustainability and performance of supply chain firms, many factors have been analyzed, mostly related to their internal management perspective (Trivellas et al., 2020), their customer relationship management (Tseng & Liao, 2015) and diversified firm practices (Verma & Kumar, 2017). Moreover, Kumar et al. (2023) studied the various subfactors of supply chain firms' sustainability that affect their risk management procedure, while Raj et al. (2023), connected supply chain firms' big data with their sustainability and performance enhancement initiatives. For further enhancement of supply chain firms' operations in crisis periods (COVID-19), various strategies have been elaborated that focus on supplier relationships (Kumar et al., 2022; Zaridis et al., 2020), customer relationships (Jha et al., 2021), human resourcing (Akhil et al., 2023) and stock-inventory categorization activities (Sachan et al., 2023).

More specifically, referring to the financial performance of supply chain firms, Kumaer et al. (2020b), indicated the added value of consumers' behavioral metrics for supply chain firms' performance, while supply chain SMEs' sustainability and profitability could be enhanced through the implementation of environmental practices (Ghadge et al., 2017). Research related to supply chain firms' financial performance by Gangaraju et al. (2023), showed that customers' involvement in firms' operations leads to increased profitability and agility. Chowdhury et al. (2018) highlighted the role of intellectual capabilities of firms' staff to their financial performance, especially on return on assets (ROA), and return on equity and asset turnover (ATO).

Business benefits can be of many kinds, such as financial, operational, internal environment, etc., but in this case, we will deal with finance (Sakas et al. 2023c). The authors are interested in the financial progress and development of companies, as expressed through their stock prices and not their gross profit (Sakas et al., 2023), and the impact of their Web Analytics on them. In particular, throughout the literature, such a research focus is missing, meaning that not all the aspects of supply chain firms' financial performance have been analyzed. Therefore, we conclude the research objectives with the following research hypothesis:

Hypothesis 1 (H1): "*There exists a strong relationship between the use of web analytics and supply chain firms' stock price variation*".

2. Materials and methods

Marketing intelligence refers to developing insights from data to make marketing decisions. Data mining techniques can help achieve such a goal by extracting or detecting patterns or predicting customer behavior from large databases. Common data mining methods include correlation mining, classification, clustering and regression (Ngai et al., 2009). As far as the present work is concerned, the main interest is focused on the influence of big data on the financial results of companies operating in the supply chain sector. Thus, the authors opted to follow the research methodology presented below, to extract valuable insights into supply chain firms' financial performance through big data analysis.

In the first part of the methodological context, the collection of the required data took place. This took place through the observation and daily collection of the web analytic metrics of the supply chain firms' websites, as well as their stock price values. To perform this step an appropriate DSS platform that enables the collection of web analytic data was utilized. Next, based on the selected web analytic metrics of the supply chain firms, and their stock price values that refer to the same period, we proceeded to calculate the basic descriptive statistics of the variables and the creation of 4 linear regression models, for each firm. The linear regression models of each firm's stock price (dependent variables) aim to examine whether their website analytical data can explain the stock price's variation. Such an outcome would later assist in the verification or not of the paper's research hypotheses.

At last, the final part of the methodology refers to the validation of the linear regressions' outcomes. To do so, the capitalization of applied statistical tests for this validation occurred, such as the application of homoscedasticity and autocorrelation tests was performed. This last stage of the context, will validate the regression results and contribute to the verification of the paper's research hypotheses.

2.1. Data origin, selection and retrieval

In this research, the authors selected the 4 leading companies in the sector of supply chain transportation services in Greece (handling, warehousing, sales forecasting, etc.), which are listed on the Athens Stock Exchange Center. These are the ELGEKA Group, the Foodlink (FDL) Group, the Piraeus Port Authority (OLP) and the Thessaloniki Port Authority (OLTH). The above companies were chosen based on their size (turnover and number of employees). It can easily be concluded that the impact of big data on the marketing of supply chain products and services is of utmost importance and is connected to their profitability. Here, the profitability of these companies is represented by their stock market price and its variation over 6 months. Accordingly, in this period of 6 months, analytical data were obtained from the websites of the selected firms, that represent visitor behavior metrics (e.g., new visitors, pages per visit, average visit duration and bounce rate). To do so, the website platform Decision Support System (DSS) of Semrush (2023) was utilized as the required website analytical data to be collected.

3. Results

3.1. Descriptive statistics

At this point in the research, and having referred to the study's sample, the examination of the sample's variables will be performed in terms of their descriptive statistics. The descriptive statistic measures selected for the research are the mean, standard deviation, range kurtosis, skewness (Table 1) and the normality of the variables. The first three aim at understanding the measures of position and dispersion, mainly the share price of each company, to gain insights into the progress of the companies. The next two, including the normality tests, aim at examining the normality of the variables' distribution. Finally, for all the companies in the sample, the results of the Shapiro-Wilks Normal distribution tests are presented in Table 2. We notice that the stock prices of the study's firms follow the Normal distribution (significance level > a = 0.05).

Table 1. Descriptive statistics of the stock prices of the 5 Greek supply chain firms.

	Mean	Range	Std. Deviation	Skewness	Kurtosis
ELGEKA Group	0.352	0.115	0.047	1.128	−0.378
FDL Group	0.498	0.201	0.080	−0.312	−1.628
OLP	19.214	6.498	2.960	0.145	−1.823
OLTH	22.974	6.620	2.948	0.798	−1.827

Table 2. Normality tests of Greek supply chain firms' stock prices.

	Shapiro-Wilks stat.	Significance
ELGEKA Group	0.821	0.091
FDL Group	0.929	0.569
OLP	0.836	0.120
OLTH	0.811	0.073

3.2. Statistical analysis

In this part of the research, we will examine the impact of each independent variable on the stock price of the sample's firms, and extract insights regarding the utilization of website data in corporate financial performance. Thus, the existence of a possible linear relationship between dependent (stock price) and independent variables will be tested, followed by the proper residual tests, i.e., normality, autocorrelation and homoscedasticity. In this context, we assist in the extraction of potential information regarding the contribution of website data to firms' financial performance. Table 3 presents the regression model of the sample firms. Here, for the companies of ELGEKA Group and OLP, the R^2 is at 100%, indicating that the independent variables explain the variability of the dependent variable (full adjustment). Also, these regressions have a small standard error and the models are confirmed overall, as the significance levels of the F statistic are less than a = 0.01. The values of the D-W statistics show that there is evidence of negative autocorrelation of the regression residuals.

In the linear regression model of the FDL Group, the R^2 is 84.9%, lower than the other firms. The model is not confirmed overall, and the ANOVA shows that the significance level is greater than a = 0.05. Also, from the D-W statistic, we discern that there is a negative autocorrelation of the regression residuals, so the residuals are characterized by negative autocorrelation. Furthermore, we observe that all independent variables fully explain the stock price of OLTH, with significance levels < 0.01 and an excellent level of determination coefficient $R^2 = 1.000$. In Table 4–7, we have the independent variables of the stock price regression (ELGEKA Group, FLD Group, OLP and OLTH). For the ELGEKA Group, we see that all variables are statistically significant in terms of their impact on the dependent variable (Sig. < a = 0.05).

Table 3. Linear regression models of the Greek supply chain firms.

	R^2	Std. Error	F-statistic	Significance	D-W Statistic
ELGEKA Group	1.000	0.000046	1282360.841	0.001**	2.492
FDL Group	0.849	0.06974	1.407	0.553	2.558
OLP	1.000	-	-	0.000**	0.280
OLTH	0.881	1.3154	11.055	0.041*	2.555

Note: * and ** indicate statistical significance at the 95% and 99% levels accordingly.

Table 4. ELGEKA group's independent variables impact.

Variables	Coefficients	Std. Error	t-statistic	Significance
Constant	0.682	0.000	3112.016	0.000**
New Visitors	0.007	0.000	723.447	0.001**
Pages per Visit	0.000	0.000	−1409.337	0.000**
Average Visit Duration	0.014	0.000	508.074	0.001**
Bounce Rate	−0.250	0.000	−1799.295	0.000**

Note: ** indicate statistical significance at the 99% level.

Table 5. FDL group's independent variables impact.

Variables	Coefficients	Std. Error	t-statistic	Significance
Constant	1.372	0.415	3.304	0.187
New Visitors	−000.8	0.000	−0.109	0.931
Pages per Visit	0.000	0.000	−2.113	0.281
Average Visit Duration	−0.023	0.033	−0.698	0.612
Bounce Rate	−0.419	0.295	−1.421	0.390

For the FDL Group, we can observe that the independent variables are not statistically significant with a = 0.05 level of significance (Sig. > a = 0.05). Thus, based on the above, it is proven that the independent variables do not affect significantly the stock price of the specific company.

Table 6. OLP's independent variables impact.

Variables	Coefficients	Std. Error	t-statistic	Significance
Constant	−396.512	0.000	-	0.000**
New Visitors	−0.002	0.000	-	0.000**
Pages per Visit	0.004	0.000	-	0.000**
Average Visit Duration	0.106	0.000	-	0.000**
Bounce Rate	−4.529	0.000	-	0.000**

Note: ** indicates statistical significance at the 99% level.

In Table 7, we see that one of the two independent variables (Average Visit Duration), selected by the Enter method in the statistical package used, is below the level of statistical significance a = 0.05 (Sig. = 0.044), while, New Customers are not statistically significant in terms of the firm's stock price, with a significance level much greater than a = 0.05.

Table 7. OLTH's independent variables impact.

Variables	Coefficients	Std. Error	t-statistic	Significance
Constant	15.246	5.310	2.871	0.064
New Visitors	−0.001	0.000	−0.002	0.999
Average Visit Duration	0.289	0.093	3.088	0.044*

Note: * indicates statistical significance at the 95% level.

The next step is to check the unstandardized residuals of the statistically significant regressions (ELGEKA Group, OLP, OLTH). In Table 8, we can discern how the unstandardized residuals of these regressions follow the normal distribution (Sig. or significance level > a = 0.05 not rejecting the initial hypothesis of normality of the Shapiro-Wilks test). Thus, it can be claimed that the unstandardized residuals of the regressions follow the normal distribution.

Table 8. Normality test for linear regressions' residuals.

	Shapiro-Wilks stat	Significance
ELGEKA Group	0.914	0.462
OLP	0.935	0.522
OLTH	0.954	0.775

In Table 9, the test for the existence of autocorrelation of the unstandardized residuals of the regressions (ELGEKA Group, OLP, OLTH) is displayed, where we see that the values of the Ljung-Box statistic, for 4-time lags, give significance levels greater than a = 0.05. This means that we do not reject the initial hypothesis of independence of the residuals' distribution, and thus the absence of autocorrelation in the unstandardized regression residuals.

Table 9. Autocorrelations test for linear regressions' residuals.

Lags	Autocorrelation	Part. Autocorrelation	Ljung-Box stat	Significance
ELGEKA Group				
1	−0.506	−0.506	2.462	0.117
2	0.022	−0.315	2.468	0.291
3	−0.074	−0.327	2.556	0.465
4	0.131	−0.133	2.968	0.563
OLP				
1	−0.312	−0.295	2.466	0.205
2	0.069	−0.132	2.955	0.563
3	−0.103	−0.106	3.103	0.699
4	0.022	−0.086	3.388	0.921
OLTH				
1	−0.337	−0.337	1.092	0.296
2	−0.083	−0.221	1.174	0.556
3	−0.276	−0.457	2.396	0.494
4	0.201	−0.193	3.365	0.499

Finally, from White's homoskedasticity test for the companies with statistically significant ANOVA values (ELGEKA Group, OLP, OLTH), it emerged that: LM = 5.011, 4.095 and 0.633 < $\chi^2_{5,\,0.05}$ = 11.07, 10.897 and 7.815 (confidence interval a = 0.05), therefore the null hypothesis of homoscedasticity of the residuals is not rejected, which are now characterized by homoscedasticity, as shown in Table 10.

Table 10. Homoskedasticity test for linear regressions' residuals.

	White statistic (LM)	$\chi^2_{5,\,0,05}$
ELGEKA Group	5.011	11.070
OLP	4.095	10.897
OLTH	0.633	7.815

4. Discussion and findings

After the analysis of the results of the statistical analysis, the summary of the results mentioned before takes place. The research hypothesis (H1), suggesting that there exists a strong relationship between the use of web analytics and supply chain firms' stock price variation, has been verified for 3 out of the 4 firms of the sample. The H1 hypothesis is verified since those 3 firms' linear regression models (ELGEKA Group, OLP and OLTH) had p-values lower than the a = 0.05 level of significance. This means that these regression models are significant, while most of their independent variables (web analytics) had a significant impact (p-values < a = 0.05) on the stock price (dependent variable) of these firms. Therefore, for the 4 biggest transportation supply chain firms of the Greek sector, it can be discerned that their website visitors' activity can have an important impact on the variation of their stock price.

From this point forward, the web analytic metrics of the supply chain firms' websites that were found to have a significant impact on their stock price are new visitors, pages per visit, average visit duration and bounce rate. More specifically, visitors, pages per visit, average visit duration and bounce rate affect the stock price of ELGEKA Group and OLP, while OLTH's stock price is connected only to average visit duration. An increase in the number of new visitors, pages per visit and average visit duration of supply chain firms' websites increases the value of their stock price, while a decrease in the bounce rate metric leads also to an increase in the stock price's value. Hence, an observation and analysis of the specific metrics of supply chain firms' websites could indicate potential topics for optimizing the financial performance of supply chain firms.

Utilization of web analytic data from corporate websites remains at an early stage, despite the abundance of daily-produced data. Such data could indicate a path for improving SEO and SEM strategies for firms in the supply chain sector, across the world. In the present study, it can be discerned that for supply chain firms to increase their stock price value, they should focus mostly on improving website visitors' time spent on their web page, and on decreasing their abandonment rate (bounce rate).

There are also some limitations when using web analytics. As with most quantitative information, any conclusions about human behavior based on web analytics should be considered working hypotheses until a more experimental approach can be taken. In addition, web analytics may indicate user behavior, but they do not reveal what motivates users in their choices on the website. Also, web analytics treats people in an impersonal transaction, aggregating individuality and not providing information about the needs of website visitors.

Marketing research has provided many interesting results that have not been adequately applied. When estimates are prepared to support managers in marketing mix decisions, they cover not only the statistical errors of bias but also yield optimized models. Hence, companies can have good decision-making ability (Kaur & Arora, 2015). Hajli et al. (2020), showed that Big Data Analysis enables B2B companies to gain customer agility, and Hung et al. (2020), indicate how big data analytics can improve supply chain finance and the effectiveness of marketing campaigns. In general, Zheng et al. (2020), Sivarajah et al. (2020), Hajli et al. (2020) and Hung et al. (2020), recognize that web analytics could play a key role in achieving sustainable growth and enabling innovation in business environment.

5. Conclusions

In this section of the paper, we intend to highlight the major outcomes of the study, while also indicating the theoretical and practical implications of the research. We discerned the role of specific web analytic metrics of transportation firms' websites, in the Greek supply chain sector, (average visit duration, pages per visit and bounce rate) in determining and predicting the stock price value. A strong causal relationship arose, for 3 of the 4 selected firms of the study, between their stock price value and their average visit duration, pages per visit and bounce rate. More specifically, an increase in transportation firms' stock price value, in the Greek supply chain sector, and thus, financial performance, could be accomplished from the development of digital marketing strategies and campaigns, based on increasing the time duration that their visitors/customers spend in their websites, while also decreasing their abandonment rate.

Our paper's outcomes are aligned with multiple relevant studies in the literature. These refer to the studies of Chen et al. (2015); Germann et al. (2013); Wedel & Kannan (2016); Sharma et al. (2014); Cao et al. (2019); Hung et al. (2020); Jansen (2009); Troisi et al. (2020); Sena & Ozdemir (2020); Jeon et al. (2018); Wamba et al. (2017); Mikalef et al. (2019) and Fagan (2014). The referred research highlights the importance and contribution of big data and web analytic data to the financial and non-financial performance of businesses, and supply chain firms. In contradiction with relevant studies, our research's results state that big data can adequately explain the stock price performance of transportation companies, due to the high volatility of the latter. Hence, we note that web analytic metrics of supply chain firms are capable of predicting and influencing the trajectory of their stock price value, and their financial performance.

Transportation firms, and generally businesses in the supply chain sector, should explore their website data and compare it with other inputs from the various business functions to coordinate the supply chain processes enhancing their financial performance, by utilizing specialized methodological skills (e.g., big data analysis). Based on the web analytic data to indicate the course of supply chain firms' stock price, more investment should be directed to these operations (analysis of website visitors' behavior) (Raguseo et al., 2020) to enhance corporate knowledge over their stock price value's variation. Therefore, the focus of firms should not be turned to the collection of a plethora of data. Instead, supply chain firms should opt to gather website visitors' behavioral data (visit duration, pages per visit, bounce rate, number of new/returning visitors) that could also assist in the optimization of their digital marketing strategies (Sakas et al., 2023a; Sakas et al., 2023b; Sakas et al., 2023d).

The limitations of the present research lie in the selected web analytic metrics used, referring only to website visitors' behavioral patterns, as well as the amount of transportation firms, in the supply chain sector, selected for the study. For future research, more web analytic metrics could be collected for elaboration, while more firms from other sectors could constitute new studies. On the same page, the analysis of other countries' transportation sectors should be performed to achieve a holistic approach to the subject.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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