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Article

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The influence of websites user engagement on the development of digital competitive advantage and digital brand name in logistics startups

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ABSTRACT

Logistics startups gradually rely on digital marketing strategies to acquire a competitive advantage. The main aim of Logistics startups is to increase their digital brand name and user engagement in order to acquire a competitive advantage. To the completion of this target, various digital marketing strategies could be implemented to ensure a differentiating factor. A three-stage data-driven methodology was adopted to evaluate the contribution between the parameters and to reflect strategies that can be presented to improve the website's user engagement and digital brand name. The first part of the study collects data from nine logistics startups' websites over a period of 180 days. The second part of the study employs Fuzzy Cognitive Mapping (FCM) to develop an exploratory diagnostic model that visually depicts the cause-and-effect relationships between the metrics under consideration. In the last part of the study, a predictive simulation model has been created to present the intercorrelation between the examined metrics and to present possible optimization strategies. According to the findings of this study, Logistics startups' websites must be developed with fewer web pages and need to be focused on the customers' target. Additionally, in contradiction with other industries' websites, logistics startups must maintain a steady flow of digital advertisements to optimize brand name and profit.

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1. Introduction

Investing in logistics start-ups has increased steadily over the last ten years, with a \$3.5 billion increase in 2017 solely (Wyman, 2017). Taking this information into consideration, digital marketing could play a crucial role in the development, establishment, and expansion of logistics startups and in creating a competitive advantage between them (Tajpour & Hosseini, 2021; Moroni, Arruda & Araujo, 2015; Rua & Santos, 2022; Wongsansukcharoen & Thaweepaiboonwong, 2023). More specifically 36% of all startups do not have a website (Shepherd, 2021) and 56.9% of the startups that had a website do not have a marketing department (Campaignmonitor, 2021). This blissful ignorance can also describe why more than 90% of those startups fail in the first year (Shlomo & Maital, 2021). Conventional technology like the World Wide Web, mobile devices, artificial intelligence (AI), and Big

Data record fluctuating client interests and usage habits, accelerating commercial network expansion (Wirtz et al., 2019).

Digitalization and online markets are becoming extremely significant in the logistics operations sector for both enterprises and organizations since they affect traditional frameworks, corporate designs, and sectoral borders (Barrett et al., 2015). Consequently, the main question that startup entrepreneurs attempt to respond to is how the company can survive the first year of operation. A lot of different responses have been given, some of them focus on the entrepreneur's passion, purpose, and philosophy, while others focus on pragmatic solutions such as creating a website and developing a digital marketing strategy (Aminova & Marchi, 2021; Rafiq, Melegati, Khanna, Guerra & Wang, 2021).

The fact that the vast majority of startups fail in the first year of operation (Shlomo & Maital, 2021) provides a fertile ground for research. The main points of the study can be located in the adoption of a Fuzzy cognitive map that helps to a no-cost examination of users' behavior in logistics startup websites as well as the implementation of a predictive simulation for digital marketing campaigns in order to increase brand name and profit and optimize user experience that

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can also be adopted from marketers for free. This is crucial since the vast majority of startups either have budget restrictions or even worse do not have a marketing department (Saura, 2021). Additionally, there is limited relative research on the past that incorporates the digital marketing strategy with the competitive advantage for startups in general (Teixeira et al., 2018).

Negrutiu et al. (2020) highlighted through their research that a digital competitive advantage for logistic firms, in the air forwarding sector, could be obtained from the existence of both sales and dispatch departments. Our paper also studies logistic firms' digital advantage but instead focuses merely on startups and the exploitation of big data. On this basis, Cichosz et al. (2020), researched the enhancement of digital logistics firms' operation efficiency, so as to gain a competitive advantage. Their study indicated that such a factor could be the increasing utilization of IT applications and strategies. To this point, our research aims to explore the potential benefits of big data and logistic startups' user engagement to define such IT applications and strategies capitalization. Zielske et al. (2022) pointed out that fresh logistics startups (with fewer than 5 years of operation), should promote their customers' value to obtain improved financial results. The authors are keen on determining the ways to achieve enhanced customer value and financial results for logistic startups, mainly focusing on improving their digital brand name and their website users' engagement levels. Those facts make this research important since the main goal of startups is to create a brand name as fast as possible in order to exist and flourish; for this purpose, this study provides detailed optimization scenarios.

This research paper focuses on the utilization of digital marketing, big data, and web analytics in achieving a digital competitive advantage for logistic startups in a cost-efficient way since these are valuable tools to reach potential customers and keep the existing ones (Sakas et al., 2022a; Wymbs, 2011; Sakas, Reklitis & Trivellas, 2023). Subsequently, this study is organized as Section 2 illustrates the literature review; Section 3 describes the sample selection and research methodology included in this paper.; Section 4 illustrates the results of the statistical correlation analysis, which is depicted in the FCM and an agent-based model (ABM) has been developed based on the statistical analysis. Finally, Section 5, discusses the results; and Section 6 presents the conclusions, including implications and future research.

2. Literature review and hypotheses development

2.1. Digital marketing in logistics startups

This research paper focuses on digital marketing, big data, and web analytics since are valuable tools to reach potential customers and keep the existing ones (Chaffey & Ellis-Chadwick, 2016; Vogelzang, 2016). In order to obtain more visibility and brand awareness, digital marketing promotes services and goods through smartphone applications and websites (ITIF, 2021). Logistics startups benefit greatly from the development of corporate websites and iOS/Android apps. Digital marketing is described as the implementation of digital technologies to build and maintain integrated and calculable communication that assistances to attract and retain clients while making better relationships with them (Beier, 2016). Marketing managers of logistics companies use digital technology to create a wide range of web advertisements in order to acquire customers' attention and improve brand loyalty (Sakas et al., 2022a; Wymbs, 2011; Tsai et al., 2011; Akkaya, 2021; Ahmed et al., 2015; Nuseir, 2016). Another aspect of digital marketing is social media and its ability to implement easier viral marketing which is one of the most powerful ways of reaching new customers and creating a snowball effect (Petrú, Pavlák & Polák, 2019; Pucciarelli et al., 2017; Wu and Liu, 2021; Choi et al., 2020). A more in depth analysis of the ways to promote the

digital brand name of firms is needed, based on the specific features of logistics startups.

For startups and Small-Medium Enterprises (SMEs) in general, is crucial to attract as fast as possible new customers and build brand awareness to secure their sustainability in a competitive environment (Tardan et al., 2017; Dinesh & Sushil, 2019). For instance, when customers begin to use corporate websites to book a parcel delivery or a collection of a parcel or to track a parcel via an iOS/Android app or computer. This behavior creates various web analytics that can be used by marketers in order to optimize website efficiency and user experience (Sakas et al., 2022b). User experience can be defined as the total impression of a user with a website, in regard to how user-friendly is the corporate website (Saura et al., 2017; Zheng et al., 2015). Two essential factors in this arena are simplicity and speed. People are increasingly searching for websites that are simple, straightforward, and personalized to their preferences and interests and all of those are necessary for the establishment of a positive customer experience (Sakas et al., 2022a; Gardner, 2011; Butkiewicz et al., 2015). It is highlighted by these studies that, increased user engagement of a firms' customers can lead to enhanced levels of brand name and sustainability.

Previous research indicates that when websites load fast, this can boost user experience and increase the brand name (Sakas et al., 2022a). The previous elements in order to be effective must be incorporated into a general digital marketing strategy (Sakas et al., 2022a; Saura et al., 2017; Butkiewicz et al., 2015). The user experience aspect of a marketing strategy can be described as the combination of corporate goals, technical background, and consumer demands (Butkiewicz et al., 2015; Petrescu, Vermeir, Burny & Petrescu-Mag, 2022). In order to utilize those data in the marketing strategy, logistics startups need to collect and analyze data from third-party websites that redirect the customer to their websites, social networks, and other sources to create new personalized services for their clients (Renzi et al., 2015). According to previous research, startups that fail to implement an effective user experience strategy could suffer from low corporate culture as well as fewer sales and failure in the business model (Hokkanen et al., 2016; Jayaram et al., 2015). The implementation of such strategies can lead to the competitive differentiation of SMEs and logistics startups (Jayaram, Manrai & Manrai, 2015; Bruton & Rubanik, 2002; Thomas, 2019). In this direction, our research aims to propose an efficient digital marketing strategy for logistics startups to gain a digital competitive advantage from the analysis of their website user engagement.

2.2. Logistics startups, competitive advantage, and differentiation

Competitive differentiation can be defined as a strategic positioning strategy that a company can use to distinguish its goods and services from those of its competitors (Stubbs, 2014; Fernández, López-López, Jardón & Iglesias-Antelo, 2022). One of the main drawbacks of a company's competitive differentiation is that every company tries to be more innovative or improved than the competitors (Stubbs, 2014; Hausladen & Zipf, 2018). However, competitive differentiation is the outcome of exceeding consumers' expectations (Albert, Merunka & Valette-Florence, 2008). Since the majority of startups fail in the first year of operation (Shlomo & Maital, 2021), the utilization of marketing strategies and technics seems to be a necessity to acquire competitive advantage and differentiation; and there are various examples in different countries (Bruton & Rubanik, 2002; Friar & Meyer, 2003; Potjanajaruwit, 2018). However, for startups in the logistics market, a specific plan based on digital marketing strategies for enhancing their website user engagement is necessary, for them to achieve a digital competitive advantage in their field.

In contradiction with traditional marketing strategies, digital marketing provides a cost-effective solution for startups since, can attract a larger audience, faster, and with less budget (Gulati, 2019; López-

Buenache, Meseguer-Martínez, Ros-Gálvez & Rosa-García, 2022). In digital marketing, competitive differentiation can be achieved by advertising the right product to the right customer at the best time (Albert, Merunka & Valette-Florence, 2008). Competitive differentiation can lead to a competitive advantage. A competitive advantage can be defined as an attribute that allows a business to gain market share and outperform other companies in the same industry (Hagiu & Wright, 2020). At the same time, digital competitive advantage can be described as increased market share in the e-commerce environment, through unique digital improvements of firms' website performance.

In this respect, user experience can play a crucial role in the acquisition of competitive advantage since the user experience strategy can assist a logistics startup in critically considering how its consumers communicate with the corporate website while conducting package tracking (Hokkanen et al., 2016; Väättäjä & Paananen, 2012). More specifically, the correct implementation of a user experience strategy can provide the ability to deliver experiences that the competition can't match and also demonstrates to their consumers that the company concentrates on their needs and satisfaction (Hokkanen et al., 2016; Väättäjä & Paananen, 2012). In this manner, our research aims to provide specific digital marketing processes to increase the user engagement of logistics startups' websites.

2.3. Big data of logistics startups

From social sciences and business studies (Salganik, 2019; Erevelles, Fukawa & Swayne, 2016) to psychology (Harlow & Oswald, 2016) and healthcare (Andreu-Perez, Poon, Merrifield, Wong & Yang, 2015), big data analysis is becoming increasingly popular. There are various definitions and attempts to describe big data. Big data could be defined as vast amounts of complicated, and unstructured information that require complex techniques and methods to acquire, store, distribute, manage, and analyze this information (Favaretto, De Clercq, Schneble & Elger, 2020). Given the fact that most startups collapse in the first year of operation (Shlomo & Maital, 2021) and have been reluctant to adopt the new technology of big data analytics, exposing them to the risk of being left behind (Coleman et al., 2016). Startups and SMEs face various challenges in implementing big data and analytics. The most profound is:

- Lack of understanding (Beaver et al., 2010; Sendra-Pons et al., 2022). A clear example is that 36% of all startups don't have a website (Shepherd, 2021). That highlights the ignorance of using big data.
- Lack of expertise. The vast majority of startups don't have a dedicated digital marketing department (Campaignmonitor, 2021). That leads to fewer sales which leads to less profit.
- Lack of organizational models (Beaver et al., 2010; Turienzo et al., 2023). Many startups and SMEs do not have a clear organizational structure which leads to confusion. The main prerequisite for a successful implementation of a big data analytics strategy is an appropriate management structure (McAfee & Brynjolfsson, 2012).

The implementation of big data analytics seems to be a necessity for the vitality of startups. The above challenges have led to the increasing demand of effective context for logistic startups that are able to provide them a digital competitive advantage in their market. Some of the big data analytics and techniques are text analytics, video analytics, social media analytics, and predictive analytics (Gunasekaran et al., 2017; Gandomi & Haider, 2015; Shah et al., 2018). Predictive analytics can be applied to almost any discipline (Schulte-Althoff, Fürstenau & Lee, 2021; Neubert, 2018; Sodero, Jin & Barratt, 2019; Waller & Fawcett, 2013). Predictive analytics refers to a group of techniques that forecast future results based on historical data

(Gandomi & Haider, 2015). Text analytics refers to the extraction technics that can be used to obtain data from a text, such as from financial websites, and social networks (Hu & Liu, 2012; Chung, 2014). Generally, big data analytics could potentially assist logistics startups to achieve a digital competitive advantage, if adopted properly, through analytical modeling of the firms' environment and its strategic processes.

A range of methodologies and techniques are used in video analytics to extract, gather and analyze useful data from video content (Gandomi & Haider, 2015; Jiang, Ananthanarayanan, Bodik, Sen & Stoica, 2018). Those techniques can be applied in stored videos, such as YouTube videos, or in real-time videos, such as political speeches (Walsh, O'Brien & Slattery, 2019; Beraldo & Milan, 2019). Finally, the extraction and interpretation of data from social media platforms are defined as social media analytics (Moe & Schweidel, 2017). The extraction and interpretation of data from social media platforms are defined as social media analytics. Social media is a general term applied to various mobile applications (Android/iOS) and websites that allows the creation and sharing of content by users (Lee, 2018). A mere focus is put on the experience and engagement of website users, thus it indicates a path for developing effective digital marketing strategies for achieving a digital competitive advantage for firms.

The examination of big data analytics provides valuable insight into the users' experience in a logistics website (Sakas & Reklitis, 2021a; Sakas et al., 2022a; Sakas et al., 2023). The abundance of big data generated by a variety of websites and social media has been a great source of knowledge for user experience strategists. By evaluating these huge amounts of data, developers may offer more efficient solutions to their clients (Park, 2019). The most significant benefit of utilizing Big Data for user experience is that it encompasses all aspects of data supplied by visitors (Palomino et al., 2021). For instance, it is useful to know the average time that a visitor spends on their website as well as how many web pages are accessed until they find the resolution (Palomino et al., 2021; Merendino et al., 2018). The usage of big data and web analytics is beneficial since those data contain useful information gathered without any possible cognitive biases (Chitkara & Mahmood, 2020). The above examples of Big Data capitalization highlight the importance of their role in achieving a digital competitive advantage over firms' antagonists.

2.4. KPIs, web analytics, and user engagement in logistics startups

Web analytics plays a crucial role in startups' and SMEs' success since a website's traffic performance can be extracted and get measured in order to optimize digital marketing strategy (Chitkara & Mahmood, 2020; Moral, Gonzalez & Plaza, 2014). Additionally, the analysis and implementation of web analytics have a positive impact on startups' digital advertisement campaigns because the correct (available) customer can be reached at the correct time (Chitkara & Mahmood, 2020; Moral, Gonzalez & Plaza, 2014). The web analytics that is extracted from logistics startups' websites and used in quantitative form can be described as key performance indicators (KPIs) (Järvinen, Tollinen, Karjaluoto & Jayawardhena, 2012; Saura, Palos-Sánchez & Cerdá Suárez, 2017; Chaffey & Patron, 2012).

A key performance indicator (KPI) can be defined as a performance measurement that assesses a company's growth in specific activities that it manages (Saura, Palos-Sánchez & Cerdá Suárez, 2017). Web analytics KPIs are often used to evaluate various objective targets with the performance of a website (Saura, 2021). There are two types of web analytics KPIs, behavioral, such as average visit duration, and the technical, such as fully loaded time (Sakas et al., 2022b). The user's behavior and activity are extracted in quantitative form. For instance, has been gathered metrics such as organic traffic, average visits duration, pages per visit, paid traffic, user engagement, and global rank.

The user's behavior on a website is described as User Engagement (Sakas et al., 2022b). "User engagement" relates to the comprehension of the person's feelings, that is, the user's emotions in specific situations like love and death, as well as the comprehension of the person's "cognitive engagement," which explains regular occurrences (Bobek, Zaff, Li & Lerner, 2009). The user engagement metric is made from several behavioral metrics, including "Average Time on Site", "Pages/Vitis", "Total Visitors" and "Bounce Rate" (Drivas, Kouis, Kyriaki-Manessi & Giannakopoulou, 2022; Saura, Palos-Sánchez & Cerdá Suárez, 2017). On the other hand, the technical programming factor of a startup such as a website's loading time can provide valuable insights for sales (Kaur, Kaur & Kaur, 2016). According to previous research, a customer will not wait for a webpage to load for 45 s to buy a product despite how good the product offered by this website (Kaur, Kaur & Kaur, 2016; Sakas et al., 2022b).

Moreover, regarding the measurement of digital competitive advantage, specific website metrics have been chosen as KPIs that can present the efficiency of a company's digital performance. These metrics are the global rank and organic traffic variables, which shows a firm's website rank and the amount of traffic that visits its website through search engines. The enormous amount of digital marketing campaigns, combined with a lack of understanding of web metrics, makes it difficult for KPIs to meet the necessary criteria (Kirsh & Joy, 2020). This research investigates the Web analytics KPIs presented in Table 1.

2.5. Research approach

In order to proceed to further analysis of how logistic startups can achieve a competitive advantage from their website usage, a review of relevant empirical studies needs to be referred to. E-commerce industries have proven to be benefited from low supplier power, thus

highlighting the sector's path for acquiring a competitive advantage over firms' competition (Purbasari et al., 2020). By investing in relationships with their suppliers and keeping supplier costs low, logistic startups can achieve a competitive advantage. Moreover, Negrutiu et al. (2020) state that startups in the freight forwarding sector could capitalize on new technologies and sustainable retail activities to improve customers' utility and experience in order to achieve a competitive advantage in digital commerce. Our study also seeks to investigate the utilization of e-commerce and new technologies through big data analytics to improve logistics startups users engagement, thus gaining them a competitive advantage in the digital world.

Regarding logistic startups' financial approach, an improvement could be noted by adopting innovative financial methods like blockchain finance and thus, according to Korpysa et al. (2021), an increased corporate performance could be set leading to a competitive advantage for the firm in the market sector. Moreover, Zielske and Held (2022) found that the usage of various innovative agile methods of process management contributed to enhanced connection with the customer by decreasing corporate response time to market. This means that new firms operating in the logistics sector should seek customers engagement to achieve a competitive advantage. The methodological framework adopted by the authors aims to provide sufficient insights to logistics firms and especially startups to achieve such an advantage.

Additional related research examined the marketing content of various organizations and discovered that using emotions in advertisements can lead to an improvement in brand equity and competitive advantage (Hutchins & Xiomara, 2018). Other studies highlight the necessity of the analysis and the implementation of big data in the corporate marketing strategy in order to acquire an advantage (Sun, Hall & Cegielski, 2020) and a link found between correctly placed advertisements with the forecast purchase intention that leads to gain market share (Lin, Paragas & Bautista, 2016; Grewal, Bart, Spann & Zubcsek, 2016; Vázquez-Martínez, Morales-Mediano & Leal-Rodríguez, 2021). A connection between the effect of advertisements of firms and big data utilization is the basis of our study, hence the authors propose a plethora of procedures based on logistics startups' digital marketing initiatives to enhance their brand equity.

To acquire digital competitive advantage and differentiation, social media marketers benefit from the opportunity to gather, analyze and use, social media big data and web analytics (Dwivedi et al., 2021). This study from Dwivedi et al. (2021), opens the way for our research methodology that is based on exploiting web analytical data from logistics startups' websites. Hence, having analyzed the above relevant studies the authors were mainly focused on exploring the characteristics that synthesize a digital competitive advantage for startups in the logistic sector, by providing a handful of intel to support the enhancement of the startups' financial performance.

2.6. Research hypotheses

Logistics startups operate in a competitive environment, and they must discover and analyze all those factors that affect their profitability, and brand name. In order to accomplish higher levels of brand name, startups have to take into consideration the KPIs that affect the user engagement of their websites with the visitors. Some of the main KPIs that affect user engagement are Bounce Rate, Average Time on Site, Pages per Visit, and the total visitors. It is extremely crucial for startups to understand the effectiveness of their organic traffic, as this parameter has a significant impact on user engagement, as well as the inverse.

This study attempts to address this field by investigating the factors that affect user engagement, as well as the web analytics that affects the brand name and the profit. The findings of this study could produce useful suggestions on the effectiveness of logistics startups' website activities. The findings could allow:

Table 1
Presentation of the extracted Web analytics KPI's.

Web Analytics KPIs	Description of the Web Analytics KPIs
Global Rank	This KPI generated from the platform's total traffic. The smaller the number of global rank, the greater the websites fame and brand name. (Drivas, Kouis, Kyriaki-Manessi & Giannakopoulou, 2022; Attentioninsight, 2021).
Organic Traffic	Organic traffic relates to users who enters on the website via an unpaid search engine (Baye, De los Santos & Wildenbeest, 2016a, 2016b).
Bounce Rate	Bounce rate generated when a visitor accesses a website and then instantly leaves without watching anything else in this the website. Low numbers of bounce rate indicate that the webpage is much more productive (Wang, Li, Cai & Liu, 2021; Dolma, Kalani, Agrawal & Basu, 2021).
Average Time on Site	This KPI calculates the average time a visitor spends on a website in seconds (Semrush, 2022).
Pages per Visit	When visitors access a website, they visit a number of pages, the total amount of pages that accessed per visitor is calculated by the KPI named "Pages per visits" (Plaza, 2011).
Paid Traffic	The KPI Paid Traffic is produced exclusively through paid ways. When a person clicks an advertisement in google search redirects to the company's website (Fossen & Schweidel, 2019).
Total Visitors	The KPI Total Visitors refers to the total amount of user accessed a website per day. This amount is generated while each user's IP address is counted via a cookie (Parmenter, 2015).
Social Traffic	The KPI "Social traffic" refers to traffic that generated from social media platforms (Facebook, Instagram, Twitter) to the logistics website's (Drivas, Kouis, Kyriaki-Manessi & Giannakopoulou, 2022; Fossen & Schweidel, 2019).
Gross Profit	This KPI monitors the gross profit performance provided by the companies (Cascade, 2021).

Marketeers to extract, analyze and use web analytics and big data which could be beneficial to reorganize and reform the company's marketing plan. Startups can benefit from the correct implementation of a digital marketing strategy because through advertisements and campaigns, startups can reach potential customers faster (Ghasemaghaei and Calic, 2020; Tardan, Shihab & Yudhoatmojo, 2017; Shlomo & Maital, 2021).

Website developers to gain a comprehensive knowledge of the effects of their website's user engagement on brand name and sales in order to create a better website that fits the purpose. For instance, it's unimportant how good and innovative are the selling products if the website needs 45 s to load a page. Additionally, through the knowledge acquired from web analytics and big data, they could more actively contribute to the company's operations and strategies.

Decision-makers take into consideration the added value of those analytics and incorporate them into sales and marketing strategies to optimize profit and create future digital investments (Mariani & Fosso Wamba, 2020).

As a result, five hypotheses have been developed in order to broaden the knowledge about the importance of the implementation of web analytics and its effects on a brand name, profit, and user engagement.

Hypothesis 1. (H1). The "Organic Traffic" of Logistic Startups websites affects the "Global Rank" variable of Logistic Startups websites through their "Total Visitors" metric.

This hypothesis focuses on determining whether "Organic Traffic" and "Total Visitors" as parameters of User Engagement impact the "Global Rank" in order to find potential intercorrelations between the examined web analytics. Furthermore, the purpose of this hypothesis is to identify if only those two parameters of user engagement affect the total rank without taking into consideration other engagement parameters.

Hypothesis 2. (H2). The "Paid Traffic" of Logistic Startups websites affects the "Global Rank" variable of Logistic Startups websites through their "Search Traffic" metric.

This hypothesis focuses on determining whether "Global Rank" is affected by the intercorrelation of "Search Traffic" from social media and "Paid Traffic". This hypothesis is important because will produce interesting results on digital advertising in logistics startups. It is essential for startups; especially the ones with a limited budget; to identify if there is a necessity to place paid advertisements to search engines or social media and up to what extent and if this advertisement will result in better website ranking and brand name consequently.

Hypothesis 3. (H3). The "Pages per Visits" metric of Logistic Startups websites affects the "Global Rank" of Logistic Startups websites through their "Average Time on Site" metric.

This hypothesis attempts to identify whether the "Global Rank" is affected by the intercorrelation of two User engagements' parameters, the "Pages per Visits" and "Average Time on Site". It is crucial for startups to identify what is the main User engagement parameter that plays a crucial role in the digital brand name (Global Rank).

Hypothesis 4. (H4). The "Bounce Rate" of Logistic Startups websites affects the "User engagement" variable of Logistic Startups websites through their "Organic Traffic" metric.

According to previous research, "User Engagement" can be defined as the total of all behavioral metrics on a webpage such as Average Time on Site, Total Visitors, Pages per Visits. This hypothesis attempts to identify what are the implications when a user leaving from a startup website ("Bounce Rate") and what are the effects on "User Engagement" and "Organic Traffic" metrics.

Hypothesis 5. (H5). The "User Engagement" of Logistic Startups websites affects the "Gross Profit" variable of Logistic Startups websites through their "Global Rank" metric.

This hypothesis is if the total "Gross Profit" is affected by fluctuations of the "User Engagement" and "Global Rank" metrics and to what extent. This hypothesis attempts to identify also it is beneficial for a startup to invest in a creation of a better website with an emphasis on the development of the user engagement parameters. The following Fig. 1 illustrates the conceptual framework of the examined hypothesis.

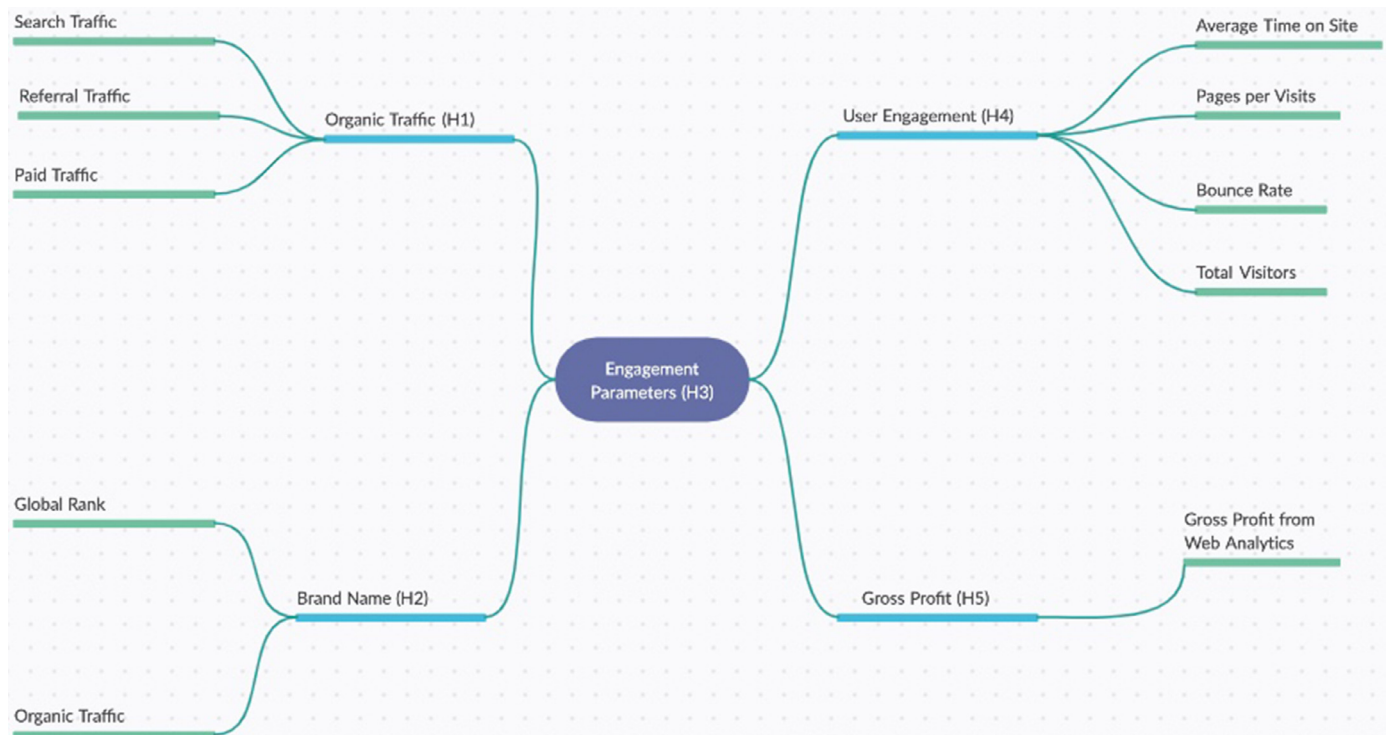


Fig. 1. Conceptual framework of the involved metrics that lead to the formulation of the examined hypothesis.

3. Methodology

This research paper attempts to implement a methodological approach for establishing a holistic framework for logistics startup marketing departments regarding the benefits of advertising on search engines. In this respect, data has been gathered from the nine biggest logistics startups (Seedtable, 2023; Explodingtopics, 2022); based on size and profit; and analyzed with the assistance of analytical tools. This allowed us to identify the potential relationship between the examined metrics gathered from the logistics startups' websites.

Furthermore, an exploratory model has been implemented in order to measure the important correlations of web analytics using Fuzzy Cognitive Mapping (FCM) (Kireev, Rogachev & Yurin, 2019). From there, we moved on to the creation of an agent-based simulation and prediction model which used the above statistical analysis results to analyze the effect of the aforementioned metrics and predict the behavior of the users on the websites for the next 180 days. As a result, the first step of the methodology is primarily directed to advise logistics startups marketing managers about significant behavioral Web analytic metrics that have a significant impact on their brand name and profitability. As a result, following data collection, we analyzed their integration with the study's selected KPIs.

The second step of the methodology concentrated on the historical values of the examined metrics and their statistical analysis, where variabilities in the web analytic metrics of startups websites seem to create interesting predictions for fluctuations in startups' user engagement, profit, and global rankings. This could also be determined using FCM that can provide accurate guidelines for startups' digital advertisements related to a particular decision-making process. The methodology's final step was to create and run the predictive model with the web analytics' intercorrelations extracted from SPSS. Finally, this research attempts to discover plausible relationships between logistics startups' websites' organic traffic, user engagement metrics, profit, and ranking web analytic metrics.

3.1. Sample selection and data retrieval

At this point, the authors conducted a daily, 6-month longitudinal study to better understand the users' behavior on a logistics startup's website (Zhu, Dong & Luo, 2021) after assessing the subject several times throughout the period. Consequently, two of the main characteristics of the empirical research are the "recreation" of the study and the "generalization" of the finding on a larger scale (Hubbard & Lindsay, 2002; Zhu, Dong & Luo, 2021). In this study, the authors extracted big data from 9 logistics startups of 2022 (Seedtable, 2023; Explodingtopics, 2022); based on size and profit; with the assistance of the web analytics tools Alexa and SEMRush which satisfies this characteristic, since other researchers can follow the same process and extract the same data. Additionally, empirical research has been used since is a reliable method of investigation that eliminates the

possibility of data misinterpretation and isolates any possible cognitive bias which is crucial for big data studies (Zhu, Dong & Luo, 2021). At this point in the research, we gathered web analytics data from nine logistics startups' websites. Web analytics data gathered from all those websites relates to metrics from website users and their behavior in the webpage such as pages per visit and average time on site. To accomplish this, the authors, used decision support systems as well as two platforms that extract these analytics, SEMrush, and Alexa. Those data have been observed and extracted daily for a period of 180 consequent days, which allows a more accurate analysis of the examined metrics.

The logistics startups web analytics that gathered from SEMrush and Alexa are: Wolt, Urbantz, Sennder, Paack, Lalamove, Byrd, FourKites, Centrica, Cargo.one. Since the focus is located on the user experience, the authors extracted the behavioral big data (average time on site, pages per visit) from the two web analytics platforms in order to assess the experience without making a questionnaire and asking questions that might lead to various opinions and consequently to biased results (Power, Cyphert & Roth, 2019). As Table 2 illustrates, we gathered behavioral data for 4.717.930 visitors in total over a six-month period for 9 logistics startup websites. Some other behavioral KPIs that were used for this purpose were "organic traffic", "bounce rate", "average time on site" and "pages per visit". Those data were gathered for every company daily from the web analytics platforms and after six months we initiate the statistical analysis process followed by the creation of a fuzzy cognitive map and agent-based model.

3.2. Diagnostic and exploratory model development

The gathering of web analytics from the startup's webpages, followed by statistical analysis, revealed the presence of correlations between the extracted data. An FCM is a macro-scale analysis model that has been developed to illustrate the power of the correlations, which could be used in the development of an effective marketing strategy as well as on the decision-making process (Salmeron, 2009). The primary goal of developing the FCM is to create a visual illustration of the positive or negative intercorrelations, as well as the cause-and-effect relationships between the web analytics that are under consideration (Salmeron, 2009). By illustrating the correlation between the metrics, FCM offers the ability of a macro perspective on the development of a better digital marketing strategy.

3.3. Adoption of an agent-based model

After conducting a macro-scale analysis which depicted an overall description of the study, a micro-scale analysis was also required in order to provide a complete picture of the situation. ABM could indeed produce an effective simulation by displaying the dynamic relationships between key variables (Giabbanelli, Gray & Aminpour,

Table 2
Descriptive Statistics of the 9 logistics startups companies' websites, during six months.

	Mean	Min	Max	Std. Deviation
Logistics Startup's Organic Traffic	286,053.37	2621	1,917,808	581,396.62
Logistics Startup's Paid Traffic	61,434.42	0.00	746,343	159,267.07
Logistics Startup's Average Time on Site	1098.64	2.00	3683.00	998.57
Logistics Startup's Bounce Rate	0.545	0.076	0.889	0.191
Logistics Startup's Pages/Visit	3.028	1.110	10.245	2.003
Logistics Startup's Total Visits	1,007,893.01	1559.00	4,717,930.00	1,372,863.01
Logistics Startup's Global Rank	237,118.25	5671.19	648,538.87	184,626.53
Logistics Startup's User Engagement	104,404,650,028.76	4231.89	665,427,256,800.00	179,098,783,737.02
Logistics Startup's Profit Logistics Startup's Social Traffic	6.869 23,430.92	.38 0.00	18.85 153,764.00	6.812 43,064.64

N = 180 observation days for 9 logistics startups websites.
The Pearson's Coefficients for the (H1) are shown in Table 3.

Table 3
Coefficients between the examined metrics for H1.

Correlations	Global Rank	Visitors	Organic traffic
Global rank	1		
Visitors	-0.501**	1	
Organic traffic	-0.584**	.945**	1

** Correlation is significant at the 0.01 level (1-tailed).

Table 5
Coefficients between the examined metrics for H2.

Correlations	Global Rank	Paid Traffic	Social traffic
Global Rank	1		
Paid Traffic	-0.475**	1	
Social Traffic	-0.624**	.724**	1

** Correlation is significant at the 0.01 level (1-tailed).

2017). ABM offers the options to estimate the influence of logistics startups websites' user engagement parameters such as average time on site, and pages per visit on their global rank and profit, during a 180-day duration.

An ABM works from the interaction of various characters (agents) which are characterized by specific characteristics and run inside the system elicited from predefined "if-then" rules (Barbati, Bruno & Genovese, 2012). Various previous research that implemented relevant methodological approaches has adopted this method, especially in the digital marketing field (Kavak, Padilla, Lynch & Diallo, 2018). The implementation of ABM is advantageous for marketing managers as the simulation that is produced, promotes the improvement of the existing marketing plans (Zhang & Vorobeychik, 2019; Kavak, Padilla, Lynch & Diallo, 2018). In general, an Agent-based model monitors organic traffic and then produces with the assistance of the statistical analysis behavioral data of the user's activity on the website (Sakas & Reklitis, 2021a).

4. Results

4.1. Statistical analysis

This chapter exhibits the outcomes of the data collection platforms. IBM SPSS Statistics 23 was utilized for the statistical analysis of this article. The findings in question are made up of raw data (gathered from nine logistics startups webpages), as shown in Table 1, which have been examined using statistical analysis software. After the data gathering of the logistics websites, the extracted data from every category was merged in order to conduct a per sector data analysis. Table 2 displays the descriptive statistics for the collected web analytics metrics, more specifically, the standard deviation, min, max, and mean. These values are the outcome of web analytics metrics during a 180-day duration. For instance, the "Logistics Startup's Pages/Visit" means, is the mean of all nine startups' webpages over 180 days.

Regarding the (H1) on the Table 3, a significant positive correlation with $\rho = 0.945 **$ was found between Visitors and Organic traffic, indicating that when the Organic traffic reach higher levels more users access the websites. Additionally, significant negative correlations have been found between the Global Rank and the Organic traffic with $\rho = -.584 **$ and between the Global Rank and Visitors with $\rho = -.501 **$. When Organic traffic and Visitors reach higher levels the Global rank takes lower prices. This is a good sign since lower levels of global ranks provide a better brand name to the company. For instance, when the global rank is 2 (lower level) is better than a company with a global rank of 15 (higher level). The Regression for the (H1) is illustrated in Table 4. Regression analyses are

Table 4
Regression for H1.

Variables	Standardized Coefficient	R ²	F	p Value
Constant (Organic Traffic)	-	.909	255.089	.812
Global Rank	-0.148			.760
Visitors	.871			<0.001

The Pearson's Coefficients for the (H2) are illustrated in Table 5.

statistically significant, with p values of less than 5%. The model is not significant and with every 1% rise of Global Rank and total Visitors, organic traffic decreases by 14,8% and increases by 87.1% respectively.

As for the (H2) on the Table 5, a significant positive correlation with $\rho = 0.724 **$ was found between Paid Traffic and Social traffic, showing that, when an advertisement is placed on a search engine benefits the company not only with visitors that access the webpage through the advertisement but also with more visitors from the website's social networks. Moreover, a significant negative correlation has been found among the Global Rank and the Paid traffic with $\rho = -.475 **$. That practical means, the paid advertisements provide a beneficial result to the company's brand name through climbing the site on higher levels, for instance from 12th place to 11th. Finally, a significant positive correlation with $\rho = 0.624 **$ was found between Global rank and social traffic, showing that, when an advertisement is placed on a social media website profits the company's brand name. The Regression for the (H2) is illustrated in Table 6. Regression analyses are statistically significant, with p values of less than 5%. The model is significant and with every 1% rise of Paid Traffic and Social Traffic, Global Rank decreases by 4,9% and by 58.9% respectively.

In regard to the third hypothesis (H3) on the Table 7, a significant positive correlation with $\rho = -0.370 **$ was found between Global rank and Average Time on Site, representing that company's brand name can benefit if the user stays more time on the website. Additionally, non-significant correlations have been found between the Global Rank and the Pages per Visits with $\rho = -.046$ and between the Average Time on Site and Pages per Visits with $\rho = 0.054$. That practically means, it's unimportant for the company's brand name how many web pages will be viewed per visitor on the website. The Regression for the (H3) is illustrated in Table 8. Regression analyses are statistically significant, with p values of less than 5%. The model is not statistically significant and by every 1% rise of Average Time on Site and Pages per Visits, Global Rank increases by 37.4% and decreases by 6.6% respectively.

Regarding the, the (H4) on the Table 9, a significant positive correlation with $\rho = 0.694 **$ was found between Organic traffic and User Engagement, meaning that when a visitor has a positive feeling while browsing on a website will access it again. Additionally, non-significant correlations have been found between the Bounce Rate and the Organic traffic with $\rho = 0.030$, and between the User Engagement and Bounce Rate with $\rho = -0.107$. When a user doesn't find the content attractive or doesn't feel good on the webpage (user engagement) will leave from the webpage (Bounce Rate), which illustrates the user's expected behavior. The Regression for the (H4) is illustrated in Table 10. The model is not significant and with

Table 6
Regression for H2.

Variables	Standardized Coefficient	R ²	F	p Value
Constant (Global Rank)	-	.391	16.338	<0.001
Paid Traffic	-0.049			.760
Social Traffic	-0.589			<0.001

The Pearson's Coefficients for the (H3) are displayed in Table 7.

Table 7
Coefficients between the examined metrics for H3.

Correlations	Global Rank	Pagers per Visits	Average Time on Site
Global Rank	1		
Pagers per Visits	-0.046	1	
Average Time on Site	-0.370**	.054	1

** Correlation is significant at the 0.01 level (1-tailed).

Table 8
Regression for H3.

Variables	Standardized Coefficient	R ²	F	p Value
Constant (Global Rank)	-	.141	4.201	<0.001
Average Time on Site	.374			.006
Pages per Visits	-0.066			.614

The Pearson's Coefficients for the (H4) are illustrated in Table 9.

every 1% rise of Organic Traffic and Bounce Rate, User Engagement increases by 69.8% and decreases by 12.7% respectively.

As for the final Hypothesis (H5) on the Table 11, a significant negative correlation with $\rho = -.381^{**}$ was found between User Engagement and Global Rank, meaning that when a user has a positive feeling for the logistics startup website, will access it again and this behavior contributes to better Global rank levels which directly contribute to the brand name. Additionally, a significant negative correlation with $\rho = -.433^{**}$ was found between User Engagement and Profit. That interestingly illustrates, when a user spends more time on a website or browses into different pages on the website has fewer possibilities to financially contribute, buy a product or a service. Practically means, that the websites need to be more technically effective, easy to use, and goal-oriented (to sales or services) instead of amusing the customers. Finally, a non-significant correlation had been found between the Global rank and the Gross Profit. The Regression for the (H5) is illustrated in Table 12. The model is significant and with every 1% rise of Global Rank and Gross Profit, User Engagement decreases by 38.3% and increases by 43.5% respectively. The Durbin-Watson test, according to Savin and White (1977), is the most common way to assess the assumption of independence. The test statistic has a value between 0 and 4, and lower values suggest that consecutive residuals are positively connected. The Durbin-Watson test was applied for all hypotheses to assess for linear regression dependence. The Durbin-Watson test for the first hypothesis is 2189. The Durbin-Watson test for the H2 is 1038, the H3 is 1072, and the H4 is 1994. Finally, the Durbin-Watson test for H5 is 1484. The hypotheses H2 and H3 are close to 1000 which means that although the hypothesis is accepted, generalizations must be made with caution.

Table 9
Coefficients between the examined metrics for H4.

Correlations	User Engagement	Bounce Rate	Organic traffic
User Engagement	1		
Bounce Rate	-0.107	1	
Organic traffic	.694**	.030	1

** Correlation is significant at the 0.01 level (1-tailed).

Table 10
Regression for H4.

Variables	Standardized Coefficient	R ²	F	p Value
Constant (User Engagement)	-	.498	25.336	.051
Organic Traffic	.698			<0.001
Bounce Rate	-0.127			.205

The Pearson's Coefficients for the (H5) are illustrated in Table 11.

Table 11
Coefficients between the examined metrics for H5.

Correlations	User Engagement	Global Rank	Gross Profit
User Engagement	1		
Global Rank	-0.381**	1	
Gross Profit	-0.433**	.006	1

** Correlation is significant at the 0.01 level (1-tailed).

Additionally, the connection between the independent and the dependent variables is characterized as an nth-degree polynomial in x in polynomial regression. The fitting of a nonlinear connection between the value of x and the conditional mean of y is described by polynomial regression. It was typically equivalent to the least-squares approach. According to the Gauss Markov Theorem, reduces the variance of the coefficients (Lindgren et al., 2011). This is a form of Linear Regression in which the dependent and independent variables have a curvilinear connection, and the data is fitted with a polynomial equation (Boryga & Graboś, 2009). In this case, the dependence between input and output variables can be described by a higher degree polynomial.

4.2. Fuzzy cognitive map formation

The statistical correlations discovered in Section 3.1 were used to construct the FCM. Figure 2 illustrates the FCM model that has been developed with the assistance of a Mental Modeler. Blue lines represent positive correlations and red lines the negative ones. The thickness of a line represents how strong the correlation is. The plus sign indicates a positive connection between the two measurements, whereas the minus sign indicates a negative correlation. This approach was utilized in this article since it has been widely included in previous research on Search Engine Optimization (SEO) and Search Engine Marketing (SEM) (Giabbanelli, Gray & Aminpour, 2017; Sakas et al., 2022b). For instance, as indicated in Fig. 2, User Engagement can be increased by a rise of organic traffic and can decrease by the percentage of the users that exit the page (bounce rate).

4.2.1. Adoption of fuzzy cognitive map scenarios to analyze the data

Following the creation of the FCM model, 5 scenarios were conducted to evaluate the projected discrepancies in the KPIs of logistics startups' websites throughout various stages of the human interaction with the website. The hyperbolic tangent function was adopted for all cases since provides the ability to illustrate values that can be negative and fall inside the range (-1, 1) (Kokkinos, Lakioti, Papa-georgiou, Moustakas & Karayannis, 2018). Figures 3,4 and 5 illustrate three optimization scenarios. Fig. 3 illustrates, after a lot of trials, the User Engagements optimization scenario for the logistics startups industry according to the extracted web analytics and the statistical analysis. To achieve 10% better user engagement and 10% more visitors, startups need to reduce the Pages per Visits metric by 36% and this can be accomplished by creating a website with fewer pages and easy to use. Additionally, an expected increase by 8% in Average Time on Site can be observed as well as an increase in the Bounce Rate by 20%. Interestingly, a decrease in the "Gross Profit" by 5% is expected and will be explained in the next section.

Table 12
Regression for H5.

Variables	Standardized Coefficient	R ²	F	p Value
Constant (User Engagement)	-	.334	12.796	.005
Global Rank	-0.383			.002
Gross Profit	.435			<0.001

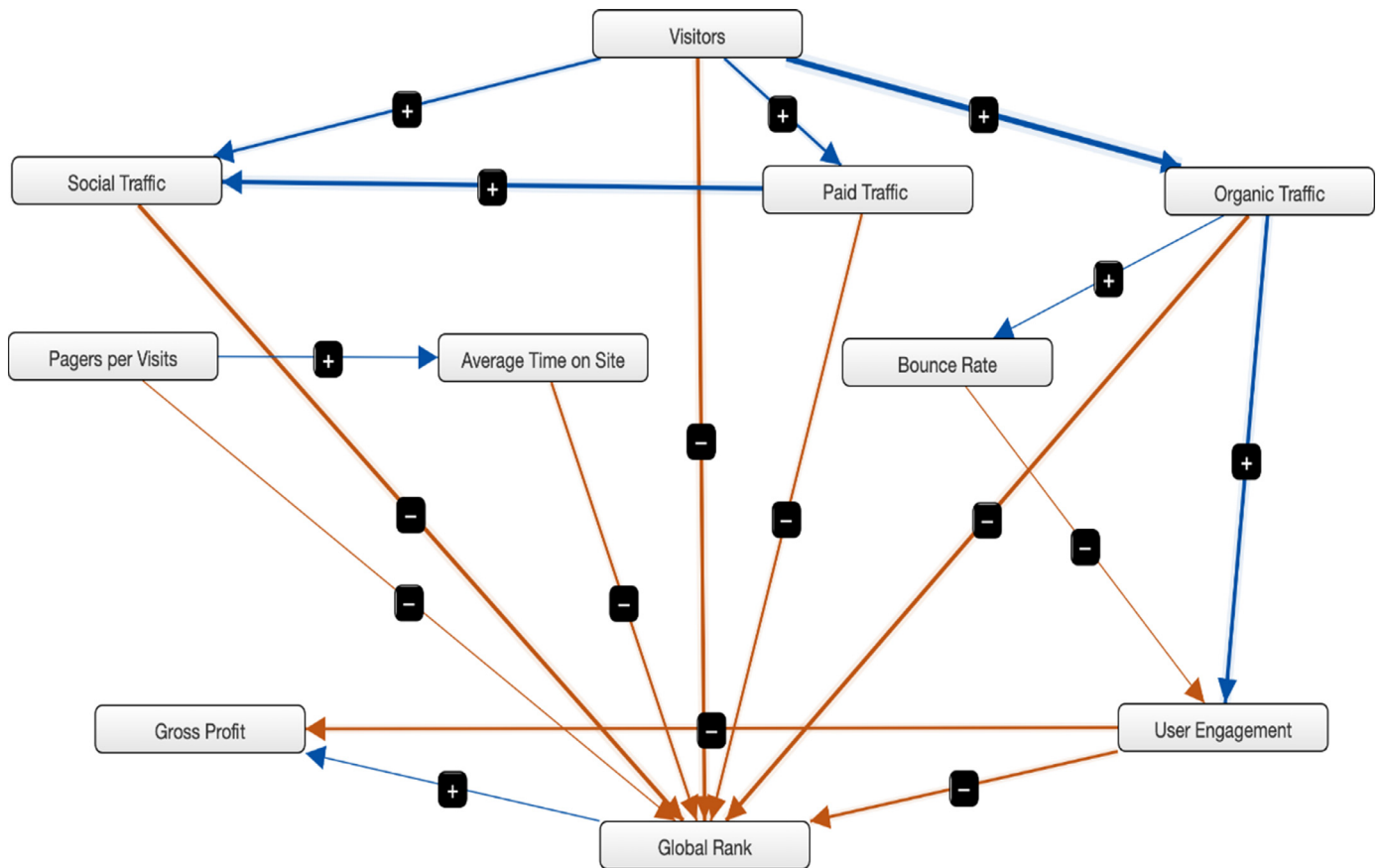


Fig. 2. Fuzzy Cognitive Map illustrates the correlations between the examined metrics (mentalmodeler.com, accessed on 14 December 2022).

Figure 4 illustrates a website development optimization scenario. More specifically, examined what will happen if the website developers manage to develop a user-friendly website, with less information, that reduces the Average Time on Site by 25% and increase Organic Traffic by 5%. The bounce rate will increase by 15% which is expected

since when more visitors access the website increase the possibility of exiting. Also, a decrease in Pages per Visit by 9% can be observed. This scenario aligns with previous research (Krrabaj, Baxhaku & Sadrijaj, 2017; Pakkala, Presser & Christensen, 2012), it illustrates that the Google algorithm takes into consideration the total Pages

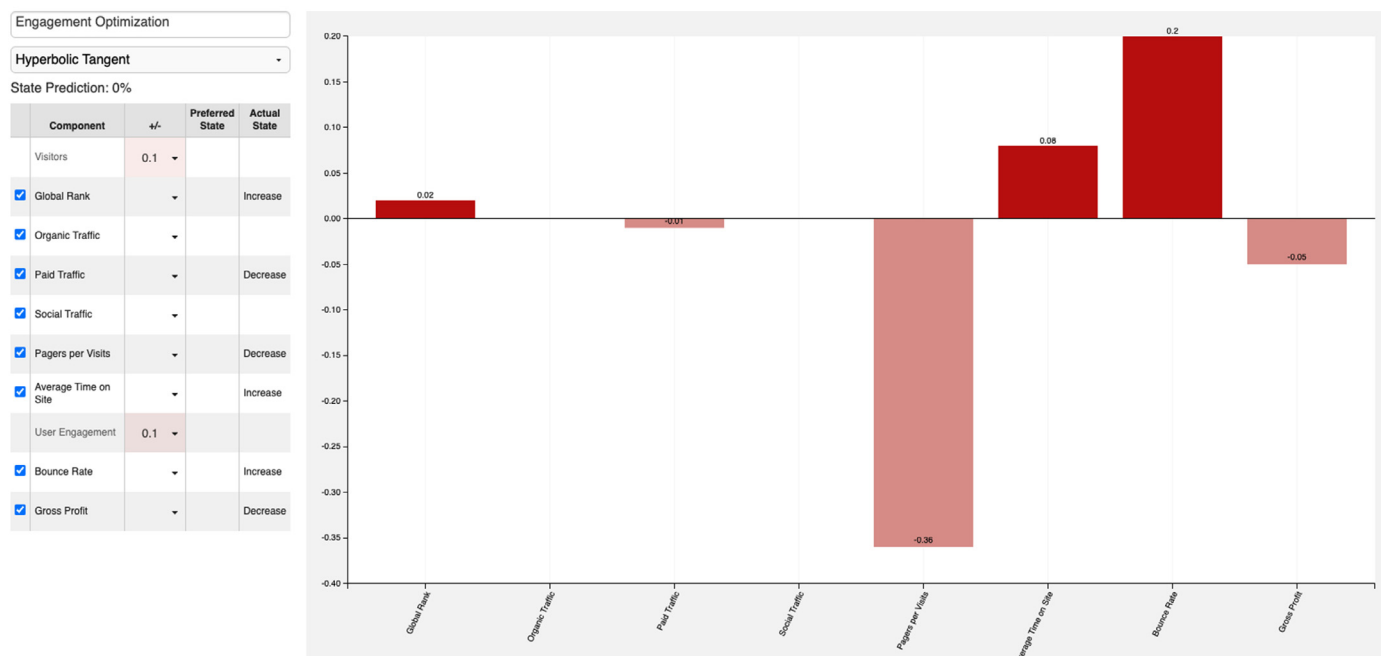


Fig. 3. Engagement Optimization Scenario (mentalmodeler.com screenshot).

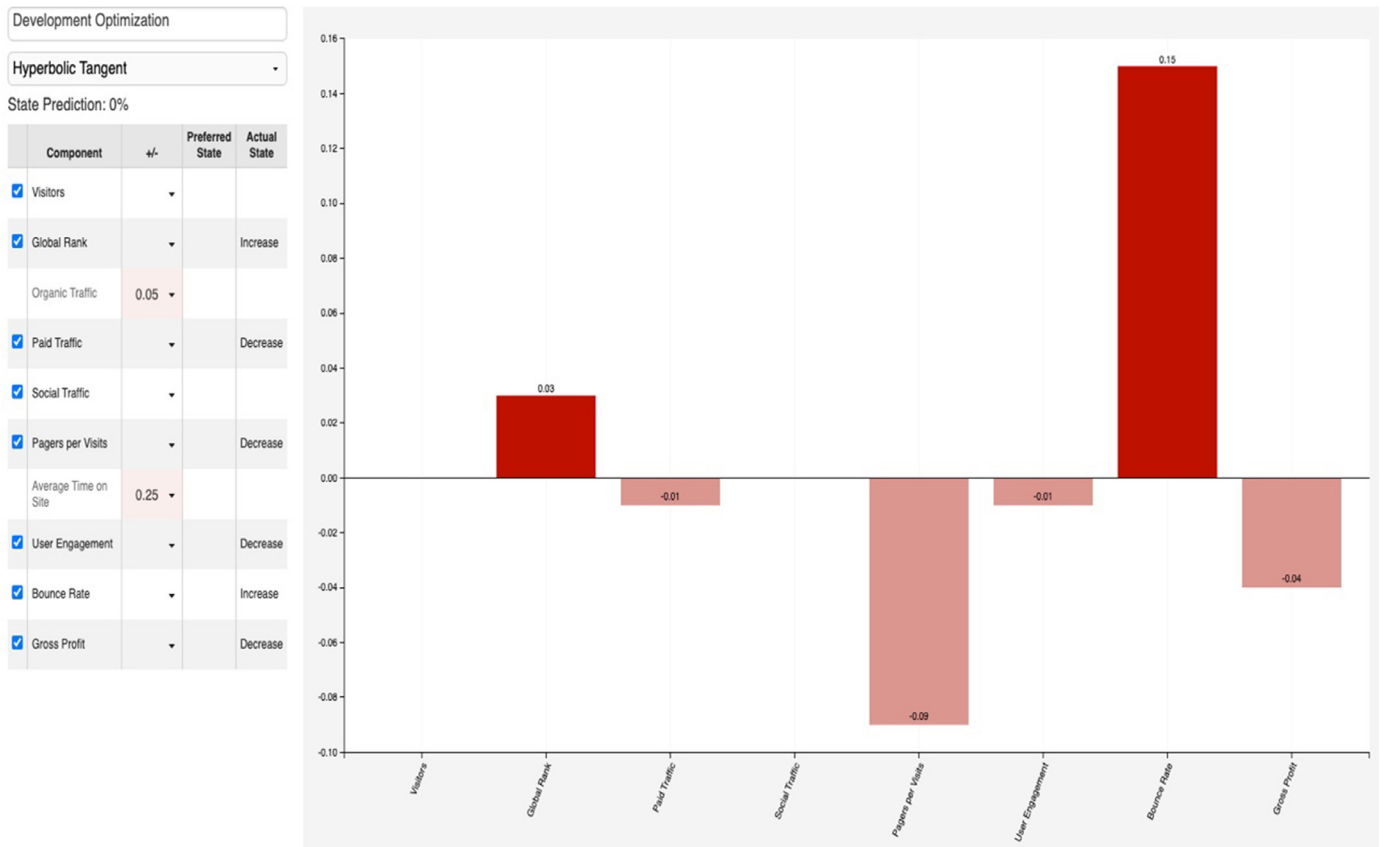


Fig. 4. Website Development Optimization Scenario (mentalmodeler.com screenshot).

per Visit when constructing the rankings. Developers should consider it while developing a logistics startups’ website since there is no need to make it complicated.

Finally, Fig. 5 illustrates a Profit Optimization Scenario. More specifically, examined how the logistics startups will gain 5% more gross profit. According to this scenario, in order to accomplish this goal, startups need to place advertisements in search engines and social media by 7% and 4% accordingly. Additionally, increases in user engagement can be observed by 2% as well as in brand name by 15%.

4.3. Adoption of agent-based model

ABMs provide double attention to the user behavior inside the platform as well as the system operations overall (Barbati, Bruno & Genovese, 2012; Bonabeau, 2002). The Agent-Based Model depicted in Fig. 6 is built up of unique features that interact inside a “cause-and-effect” system to provide an outflow of correlations (Aguilar, 2005). The application of ABM provides the ability for the monitoring of both user behavioral data (User engagement) and their effects on the examined website (Global rank, profit) (Barbati,

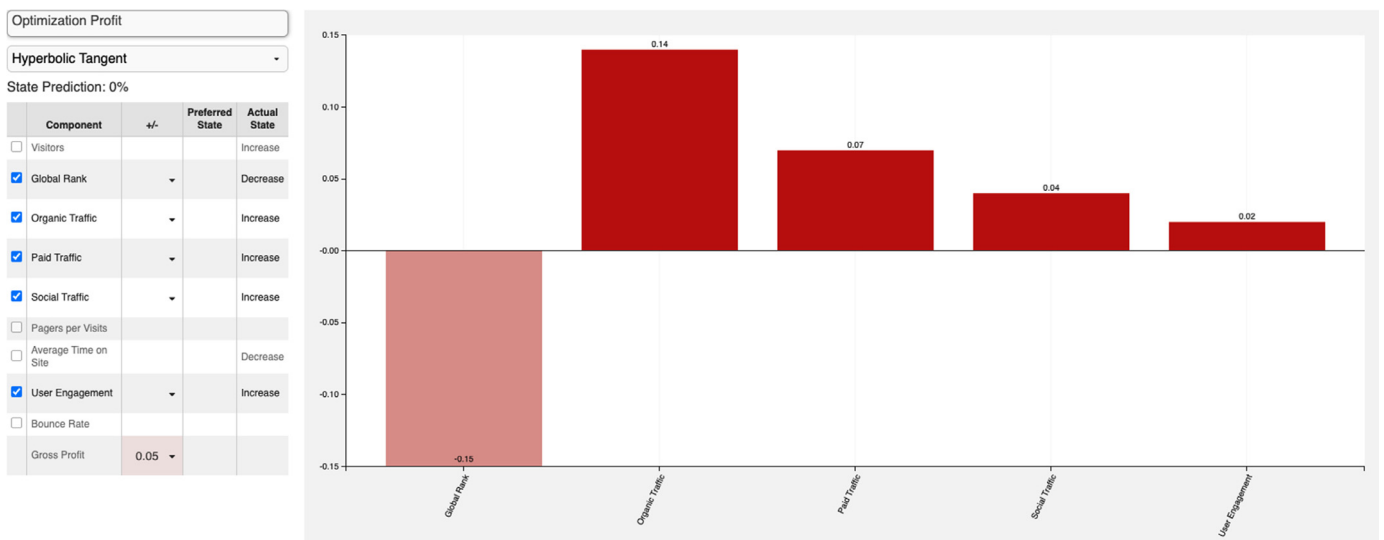


Fig. 5. Profit Optimization Scenario (mentalmodeler.com Screenshot).

Bruno & Genovese, 2012). As a consequence, various findings of the correlations from these interactions are produced. Because ABM emphasizes the presence and discovery of connections between distinct system elements, this developmental method prioritizes the identification of conditions that impact the agents' behavior inside the model (Sakas & Reklitis, 2021a). As a result, the adoption

of Agent-Based Models enables businesses to completely understand the insights supplied by data in terms of user interaction with their websites as well as opportunities for expansion (Giabbanelli, Gray & Aminpour, 2017). The system Anylogic 8.7.9 with the computer language "Java" has been used to create the entire model.

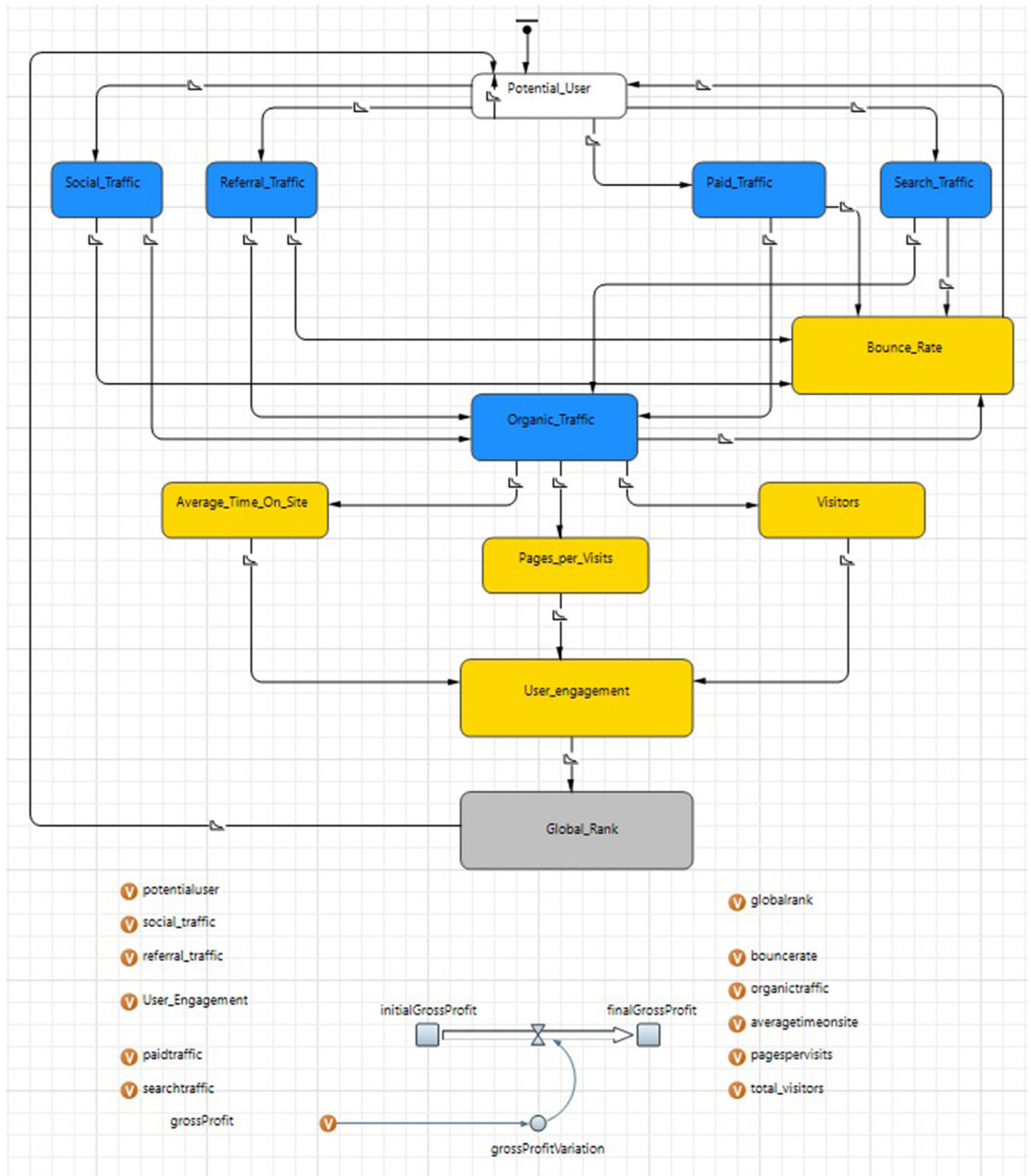


Fig. 6. ABM for the optimization of logistics startups' User Engagement, Global Rank, and gross profit through Digital Marketing and SEO.

The ABM visualizes the impact of display advertisements on visitors and their interactions with the logistics startups' websites. The circular blocks depict the agent's initial status before any move. Movements among the blocks are depicted with the arrows on the ABM, and such movements come from changes to the required circumstances dictated on the bottom of the picture in Fig. 3. The Poisson distribution has been adopted for this study for two main reasons (Consul & Jain, 1973). The specified variables for the ABM were implemented with the Poisson distribution and are the outputs of the statistical analysis illustrated in Section 4.1. Additionally, the findings from the statistical correlations illustrated above are applied in the ABM for the agents to travel from block to block.

The model on the Fig. 6, initially depicts potential users in the upper center block, who are separated into two groups. Users that accessed the logistics startups' websites through a paid advertisement are divided into "Paid Traffic" (e.g., google ads.) and "Social Traffic" (social media advertisements, e.g. Facebook ads.). On the other hand, a website can generate users directly from a search engines search depicted as "Search Traffic" and from "Referral Traffic" which are users that entered a website through a link from another website. Next, all those types of traffics constitute the general "Organic traffic" of the web page. On the top right-hand side "Bounce rate" can be identified. "Bounce rate" is the percentage of the visitors that exit from the website without searching anything else. After a user enters the website ("Organic Traffic") produce some behavioral analytics are divided into "Average Time on Site", "Pages/Visits" and "Total Visitors". All those parameters are constituting the "User Engagement" parameter above. Continuously, the model agents move to the next block and produce the "Global Rank" before they exit the website. Finally, inside the "Global Rank" block runs the procedure of "Gross Profit" with a triangular calculation method (Anylogic, 2022). Those variables are the outcome of the statistical analysis of the web analytics and the behavior of the users in the websites. The Agent-based model produces an agent population distribution (Fig. 7a and b) and two time charts (Fig. 8a and b) that present the fluctuations in logistics websites' User engagement parameters in correlation to web ranking and profit as a result of changes in paid and nonpaid traffic.

Figure 7(a) and (b) depict the execution of the ABM model shown in Fig. 6. The study explores the movement of the users in the Agent-based model for 180 days period. The agents embody the potential users moving through the model until they access the ending block named "User engagement" and provide an outcome for the parameters "User Engagement" and the variables "Global rank" and "Gross Profit" in Fig. 7. The gray agents represent the users that access the website through a paid traffic source, blue agents represent the user that generated from a search traffic source. The red dots are the users that left from the website (bounce rate). The yellow agents illustrate users that contribute to user engagement, the light blue agents illustrate the users that contribute to the Global Rank and the green agents embody the users of the webpage that contribute to the increase or decrease of profit. This logical, since, once the paid advertisement campaign was launched, the website's Global Rank increased, and consumers reached the startup's website directly, as the corporate brand name grew.

Figure 8a and b illustrate the results of the predictive model. According to Anylogic the chart "displays the history of contribution of several data items into a total during the latest time horizon as stacked areas" (Anylogic, 2022). The values of the simulation results are indicated on the vertical axis. The horizontal axis depicts the period over which the simulation takes place (180 days) for the logistics startups' websites. Figure 8a illustrates the placement of an advertisement in social media at the time "0". We can observe that the social traffic from the advertisement increased as well as the general organic traffic of the website. When the advertisement stopped on the day "5", the social traffic and organic traffic dropped. Additionally, on day "8"

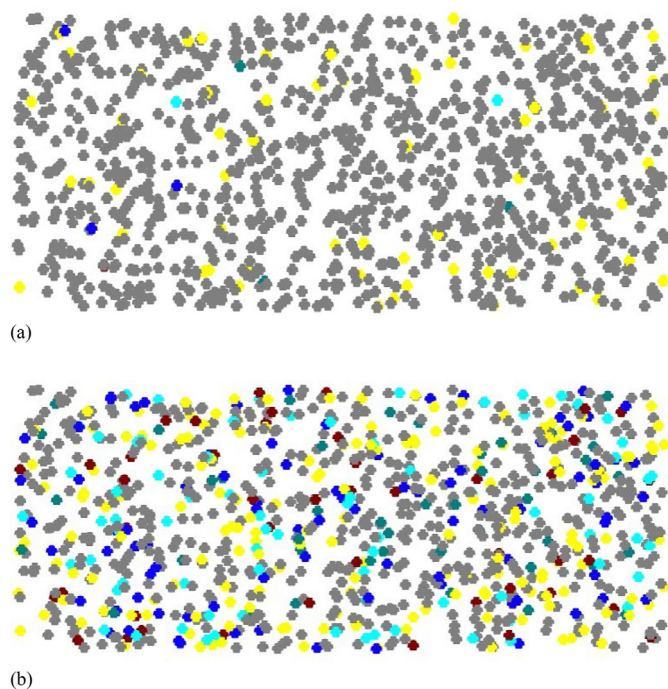


Fig. 7. (a) Experiment's population allocation with 1000 agents for a period of 180 days. Day 12. (b) Population allocation with 1000 agents for 180 days. Day 54.

the second placement of a search engine advertisement took place and remained until the end of the simulation. As can be observed, to maintain good visibility and high organic traffic, logistics startups' websites need to keep a steady stream of advertisements and keep them going in order to be effective in contrast to the FinTech industry websites (Bapat, 2018; Tien, Cheng & Pei-Ling, 2018).

Figure 8b illustrates the results of the main examined metrics after the placement on an advertisement in the day "0". There is a sudden spike in global rank that remained until the day "120" which decreases. A decrease in global rank is beneficial since a website ranking in 10th place is better than a website ranking in 100th place. Additionally, an increase in user engagement can be observed after day "8" on the model and correlates with a placed advertisement in social media as can be observed in Fig. 8a. As can be observed on the day "120" with the sudden drop of Global Rank, a brand name has been created. Finally, there is no correlation between Engagement and the Brand name with the profitability.

Marketers and developers need to create easy-to-use and dedicated to the result websites in order to enhance engagement. For instance, the customer must have easy access to tracking numbers or booking parcels for delivery, which will lead to the creation of brand loyalty (Zheng, Cheung, Lee & Liang, 2015). This is crucial because the needs of logistics websites customers are diametrically opposite from other websites such as online clothing stores. For instance, in online clothing stores, such as Zara and Mango, the importance is located on creating different and strong emotions to maximize the user experience, which will lead to a sale (Goldsmith & Flynn, 2004). Consequently, it is crucial for a logistics startup website to place paid advertisements both on google and social media regularly to maintain high levels of visibility.

5. Discussion

The purpose of this research is to develop an effective "modus operandi" to investigate the influence of brand name and user engagement on profit and vice versa to identify options that can be used to optimize the digital marketing and advertising strategy.

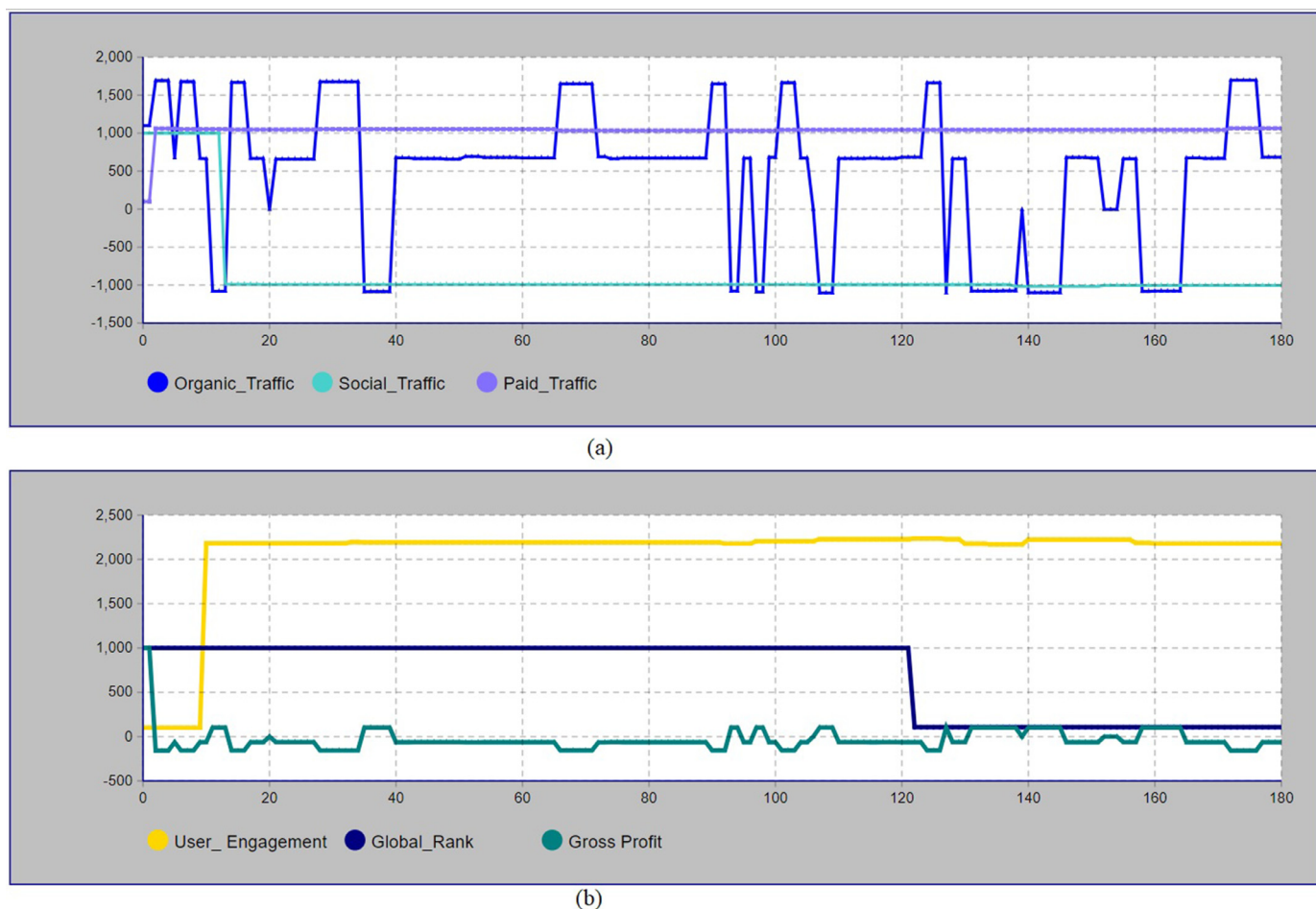


Fig. 8. (a). The time chart presents the history of the contribution of the parameters: Organic traffic, Social traffic, Paid traffic from the time that placed an advertisement for 180 days. (b). The time chart presents the history of the contribution of the parameters: Global rank, User Engagement, and Gross Profit from the time that placed an advertisement for 180 days.

Throughout this study, some interesting findings, that were extracted from the results section, need to be highlighted. It has been found that, throughout the simulation, logistic startups' website social and paid traffic is following organic traffic's variation during the first days of advertisements' placement with a small lag of response. Furthermore, users' engagement seems to increase with the increase of the organic traffic of logistic startup websites with a small-time delay, underlining their connection, and finally, their gross profit is strongly affected by the variation of user engagement and global rank (brand name) metrics, also with a small-time delay.

More specifically, this study highlights that it is beneficial for a logistic startup to create a good brand name (Nasiopoulos et al., 2021), which can be accomplished by gathering more visitors on the website from an organic source (google search or direct access) (H1). For logistic startups to maintain and develop a brand name and loyalty, a steady stream of advertisements is needed both in social media and search engines, in contradiction with other industries such as clothing stores and tourism that can create advertisements seasonally (H2) (Zheng et al., 2015; Fitz-Gibbon, 1990; Palos-Sanchez, Saura, Velicia-Martin & Cepeda-Carrion, 2021; Ramón Cardona, Martorell Cunill, Prado Román & Serra-Cantalops, 2021; Solakis, Peña-Vinces & Lopez-Bonilla, 2022). Marketers and developers are urged to create easy-to-use and dedicated-to-the-result websites in order to enhance engagement. For instance, the customer must have easy access to tracking numbers or booking parcels for delivery, which will lead to the creation of brand loyalty (H3) (Zheng et al., 2015). Consequently, it is crucial for a logistics startup website to place paid

advertisements both on Google and social media regularly to maintain high levels of visibility.

In contradiction with other sectors' websites, for instance, online clothing stores, which are dedicated to the users' experience and focused on how to keep the customer on their website as much as possible (H4) (Zheng et al., 2015), logistics startups must emphasize on solving the customers' problems fast and satisfy their need for easier to use and user-friendly websites. Additionally, brand name and profit can be enhanced by increasing the organic traffic of logistic startups' websites. In a similar logic, paid advertising can boost various kinds of traffic data that can increase startup websites' user engagement (H5) (Sakas et al., 2022c; Pucciarelli et al., 2017). The shift in logistic startups' focus to increase website users' engagement and overall traffic can really provide a digital competitive advantage in their sector since it has been found that user engagement and brand name (like global rank) metrics can increase their gross profit.

The results of our research are aligned with the existing literature and provide further insights regarding its differentiation, while highlighting new approaches. Byun et al. (2020) research utilized big data from mobile applications of logistics startups to enhance users' engagement, aiming to improve mobile app usability and logistics startups' brand name. The present study utilized big data analytics from logistics startups' websites, regardless of the device used (mobile or desktop), and also indicated that through improving the engagement of their website users, these startups can enhance their brand name and their profitability. It has been stated that logistics startups are discerned by innovation and efficient models that

promote sustainability and profitability (Oliveira-Dias et al., 2022), mainly due to higher levels of IT innovation applications. The findings of our research are aligned with these statements, and furthermore, it provides a potential framework, through big data and IT applications, for logistics startups to enhance their profitability levels through higher brand name recognition. Moreover, based on big data originating from website customers, Huang and Wang (2022) found that the decision-making process of logistics startups can be optimized significantly. Throughout our paper, it becomes clear that apart from the optimization of logistics startups' decision-making, other advantages arise from the utilization of a context based on improving website user engagement, such as the promotion of their brand name, that can potentially establish a digital competitive advantage in the field.

6. Conclusions

This research collected and analyzed nine logistics startups' website data, resulting in the identification of intriguing insights that marketing managers, advertisers, and decision-makers may utilize in order to optimize their digital marketing and advertising strategy. The research concentrated on improving logistics startups' brand name, user engagement, and profit with the assistance of digital advertising and organic traffic. In general, the research accomplished the following objectives: (1) a better understanding of the big data and web analytics metrics and their usefulness for developers and marketers, (2) the detection of existing correlation between the metrics under consideration, (3) the implementation of these findings to better understand consumers' behavior in the context of digital marketing and digital advertising.

6.1. Theoretical implications

Decision support systems and simulation models enable continuous monitoring of customers' digital behavior across real-time market data, with the goal of eliminating digital marketing inefficiencies and improving user engagement. For instance, digital marketing metrics (global ranking and gross profit) have a beneficial impact on traffic-related Key Performance Indicators (organic and paid traffic) and behavioral-related KPI metrics (pages per visit). In this logic, marketing efforts should be directed toward paid ads and targeting specific keywords in order to improve profit and brand recognition; which will lead eventually to the sustainability of a startup company since the vast majority of them fail in the first year of operation (Shlomo & Maital, 2021). Furthermore, resources need to be allocated to producing unique content in order to increase user engagement (Byun et al., 2020). Big data-powered trigger-based customer journeys help businesses to foresee potential developments and concentrate on delivering exceptional digital experiences (Terragni & Hassani, 2019). Additionally, in contrast to other industries, which can create advertisements seasonally (Zheng et al., 2015; Fitz-Gibbon, 1990), logistic startups require a consistent stream of advertisements in both social media and search engines in order to maintain and develop a digital brand name and customer loyalty.

Digital advertising campaigns; as a part of a general digital marketing strategy, are centered on boosting logistics startups' websites visibility, resulting in higher corporate profit. Paid marketing messages, such as banner ads, are an essential aspect of digital advertising; and this research focused specifically on paid ads from search engines as well as from social media and their effects on startups' websites user engagement. Additionally, the findings of this study highlight the necessity of monitoring and analyzing the web analytic metrics for the optimization of corporate brand name through the global rank metric (Sakas & Reklitis, 2021a; Drivas, Kouis, Kyriaki-Manessi & Giannakopoulou, 2022).

Finally, we suggest that in order to establish their company in the market, startup marketing managers should monitor changes in their web pages' organic traffic and global rankings in relation to user engagement metrics and profit. As a consequence, decision-makers will have a better view of advertising campaigns for their products, and services. The current study's findings lend credibility to various big data research on the digital marketing process of logistic startups. Behl et al. (2019) have published a study expressing the valuable potential of big data on marketing capacities in favor of startups. The authors emphasize the startups' ignorance of big data capabilities, which reduces the effectiveness of a big data-driven digital marketing approach in startups. Furthermore, the current study aligns with the Cavicchioli and Kocollari (2021) and Roumeliotis et al. (2022) studies, in which important key marketing metrics are investigated, resulting in efficient digital marketing strategies, such as increased lead generation and conversion rates. Finally, this study highlights that customers' behavioral web and social analytics, on the other hand, can provide added value to startups' digital marketing strategies.

6.2. Practical implications

The findings of the present research highlight the necessity of logistics startups to devote more resources in understanding the behavioral patterns of digital customers using big data analytics. By doing so, logistics startups can be able to follow existing trends and identify the aspects that significantly influence customers' online purchase behavior based on their web and social media engagement (Negedu & Isik, 2020). The integration of behavioral analytics into concrete digital advertising strategies is a tough assignment that involves numerous components, including the behavioral KPIs (Saura, Palos-Sánchez & Cerdá Suárez, 2017).

More specifically, marketers and decision-makers must extract, evaluate, and utilize web analytics and big data to restructure the startup's marketing strategy. Startups may advantage from the proper execution of digital marketing strategy since advertising and campaigns allow them to contact potential clients more quickly (Tardan, Shihab & Yudhoatmojo, 2017; Shlomo & Maital, 2021; Mariani & Fosso Wamba, 2020).

Additionally, in order to construct a user-friendly website that suits their business purpose, website developers need to obtain a thorough understanding of the implications of their website's user engagement on gross profit and digital brand name. Furthermore, with the knowledge gained from big data, they could contribute to a greater degree to the startups' operations. Finally, we suggest that in order to establish their company in the market, startup marketing managers should monitor changes in their web pages' organic traffic and global rankings in relation to user engagement metrics and profit. As a consequence, decision-makers will have a better view of advertising campaigns for their products, and services.

6.3. Future research and research limitations

The vitality of a startup is based on reaching new consumers and maintaining the existing ones. The first parameter can be accomplished with digital advertising; the second one is the adoption of a well-designed and user-friendly website. In order to develop an effective website, the user engagement analytics must be examined in correlation to the technical parameters of a website (Sakas et al., 2022b). Since technical parameters examination are crucial for identifying a company's website usability; their investigation in correlation to behavioral analytics can provide valuable insights to marketers. It could be interesting for instance, to identify the effects of a slow-loading startup's webpage on the purchase rate or the correlation between the total webpage size with the total parcel search time as studied before in the agri-logistics sector (Sakas & Reklitis, 2021b). Additionally, it would be beneficial to examine the effects of

the logistics startups' social media on the overall user experience and interactivity of their websites.

Moreover, since a correctly placed advertisement is crucial for maximizing market share (Lin, Paragas & Bautista, 2016; Grewal, Bart, Spann & Zubcsek, 2016) and the usage of emotions in ads promotes the brand name (Hutchins & Xiomara, 2018), it could be beneficial to examine the effectiveness of the advertisement with the assistance of neuromarketing tools. For instance, it could be beneficial to examine where the customers focus on a website in order to make it easy to use and user-friendly as studied in other industries' websites and social media (González-Mena et al., 2022). Additionally, it could be examined if a well-designed logistics startup website can reduce customers' frustration and anger while searching for a parcel with the assistance of an EEG. Eye-tracking could be used to identify where the customer looks frequently to place the advertisements and EEG could be used to illustrate a consumer's emotional reaction to a specific advertisement (Vences, Díaz-Campo & Rosales, 2020).

Finally, the first limitation relies on the quantity of the examined websites. More websites could be examined to acquire better insights into the sector. Secondly, the data gathered from the "SEMrush" data extraction webpage. More, behavioral data could be beneficial in order to examine the logistics startups' user engagement in depth. Additionally, social analytics can be extracted and analyzed in correlation to behavioral and technical factors in order to get a holistic approach to the logistics startups' digital entities. Further research can be held with the assistance of interviews and questionnaires for a more holistic qualitative and quantitative approach (Reklitis et al., 2017; Looor-Zambrano, Santos-Roldán & Palacios-Florencio, 2022). Finally, the research is limited to the logistics startups sector, further research to other startup sectors could be beneficial. The interviewees' opinions extracted from questionnaires in relation to their actual behavior on a website as extracted from web and social analytics could provide valuable insights to marketers, managers, and startup owners.

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