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The Contribution of Digital Technology to the Forecasting of Supply Chain Development, in IT Products, Modeling and Simulation of the Problem

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Abstract: Aiming for the forecasting and predictability of their future development, corporations have developed appropriate strategies as a result of the necessity to optimize the distribution networks of new IT products over time. The necessity of diversifying manufacturing was brought on by the fierce competition between businesses and the sophisticated consumer demand trends for personalized items. For businesses looking to create more effective distribution networks for their products, mass adaptability may be advantageous. Fuzzy cognitive mapping (FCM), associations developed from web analytics data, and simulation results based on dynamic and agent-based simulation models work together to practically aid digital marketing experts, decision-makers and analysts in offering answers to their corresponding problems. In order to apply the measures in agent-based modeling, the current work is based on the gathering of web analysis data over a predetermined time period, as well as on identifying the influence correlations between measurements.

Keywords: decision support systems; simulation modeling; fuzzy cognitive maps; digital marketing; web analytics; IT product distribution network; mass customization

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1. Introduction

1.1. The Role of SEO in IT Product Distribution Network Development

Marketing is a sequence of possibilities that increase a company's ability to profit sustainably and grow the company. All cases prove that the marketing space is appropriate to assist the company's growth [1]. Challenger marketing has been characterized as one of the most important sales processes in recent years. According to "The Challenger Sale" [2] and "Challenger Customer" [3], it is widely accepted that defective marketing is a challenging new approach to sales strategy, which digital marketers can use to navigate the disruptive changes in the modern market [4].

George Day, of Wharton University, identified the increasing gap between the accelerating complexity of markets and the ability of most marketing firms to understand and replicate that complexity. In particular, and although the forces of market fragmentation and rapid change are expanding, the use of the internet is the operator of this gap. Digital, or e-marketing, refers to marketing that uses data from electronic devices and channels to achieve its goals.

Specifically, digital marketing data comes from search engines, online advertisements, emails and social media. The role of digital marketing (Digital Marketing) is confirmed in a study by IBM [5], where the following challenges were formulated:

- explosion of data;
- social media;
- proliferation of channels and;

- shifting consumer demographics, which correspond to the developments of the digital market.

Three of these challenges can empower the evolution of digital marketing. In particular, the role of digital marketing in a company's overall strategy extends to the telecommunications sector, as evidenced by the ever-increasing investments of telecommunications companies in digital marketing activities. Along with cost effectiveness and the changing behavior of customers, they favor the results of the investment in digital marketing. One of the advantages that online digital marketing offers is the ability to understand user behavior through web analysis, while defining a multitude of standardized and quantitative metrics. This finding was reported by conclusions and estimates of data analysis of internet user behavior [4,6]. As customers increasingly interact with companies through digital channels, it was established that there was the need to monitor these interactions and measure companies' performance [7] with search engine optimization (SEO), with the aim of achieving high-ranking positions.

However, questions remain as to whether performance measurement and the use of digital metrics in decision making can lead to an improved performance or other business benefits. For this reason, ref. [8] analyzed 99 published papers regarding performance measurement and concluded that more rigorous research methods are associated with a lower probability of the performance measurement having a positive impact. In contrast, various marketing studies [9–14] combined with the use of performance measurement data in business decisions has positive consequences for performance [15,16]. Index research studies show that less information can lead to more accurate, but also more efficient, decision making through the extensive analysis of past data. This follows from the fact that indexical rules can be used for the more effective and safer management of certainty than rules, based on a broader use of information [17–19]. Given this conflicting evidence, this study asserts that measuring a company's performance, or using digital performance metrics, as it pertains to digital marketing does not inherently improve performance. Instead, the benefits that can be obtained are determined by how companies exploit the system with unspecified congestion conditions.

Therefore, this study has three objectives. Primarily, it promotes the theory of corporate performance measurement, advertising how companies can design and implement marketing measurement systems while generating business benefits. Second, although advanced research shows that web analytics are most beneficial to companies that transact online [14,19], in terms of transacting offline, all companies use web analytics metrics in various ways [4]. Therefore, it could be said that web analytics reflect all kinds of buying and selling and can be effective. Finally, new web analytics tools and technologies provide companies with a rapidly increasing amount of digital data about online customer behavior [20–22].

Primarily, a prediction model is proposed that refers to a specific period, which is based on the highest level of adaptability of digital marketing. It concerns the distribution of mobile telecommunication products and presents the optimal ranking of the website produced exclusively by e-marketing, according to modeling with agent-based modeling [23,24]. The ranking position of a website practically helps digital marketers to understand whether their company's new products have a satisfactory level of mobile adaptability. At the same time, they gain an insight into the behavior of the distribution network of the new products. This helps to improve the time perspective that buyers spend on their website or mobile index websites. The results of the study could be very useful for professionals, aiming to understand more the optimal level of adaptability of digital marketing [23,25,26]. In this way, they improve the high-ranking positions of the websites through the correct display of the products of the website offered by digital marketing.

1.2. Hypothesis

The process of creating a predictive model demonstrates the construction of a descriptive model that describes the relationships between factors [25]. The purpose of the current study is to create an FCM-based approach for digital marketing planning. This approach is based on the FCM method that allows for easy integration in different marketing channels and the quantification of the deviation of the relationship between the relevant variables, providing at the same time a systematic analysis to compare different scenarios.

In essence, FCM modeling represents the marketing domain as a connected network, in which nodes represent important concepts (e.g., variables such as frequency of communication with partners) [14,25]. The arcs between the nodes represent causal relationships and the power of causality. The evaluation allows managers to quantify the effect of a change in an independent variable (for example, the number of visits originating via email) on a monitored variable (the total number of visits). The characteristics of a FCM model for strategic planning include the easy incorporation of knowledge by stakeholders and the existence of a systematic propagation algorithm to track the impact of a change in a planning system [27]. The following hypothesis contributes to the understanding of the model:

Hypothesis 1 (H1). *Paid Search affects Global Rank with a positive correlation.*

There is a positive correlation between the Global Rank and Paid Search with ρ df(59) = 0.617 and sig. = 0.001 (2-tailed). This fact practically means that when the measurement of traffic from advertisements with paid search (Paid Search) increases, then the measurement of the position in the global ranking of the website (Global Rank) increases. This means that the position of the world ranking moves away from the first place. Moreover, there is a correlation on the positive axis between the Country Rank and Paid Search with ρ df (59) = 0.733 and sig. = 0.001 (2-tailed). On the contrary, between Category Rank and Paid Search, there is a positive correlation with ρ df(59) = 0.373 and sig. = 0.001 (2-tailed H1 is a logical Pearson correlation on the positive axis, because the probabilities of this correlation are two. In the first case, as the Paid Search metric increases, so does the Rank, which means that the Rank moves away from 1, therefore moving away from the first ranking position. On the contrary, when the Paid Search measurement decreases, the rank also decreases, that is, it will approach the first ranking positions, which is what it is all about. Paid search advertising is expensive for any company, so professionals obtain better results when they do not invest heavily in such advertising methods. Consequently, a low investment in them results in a higher ranking, more readability and more popularity of the company.

Hypothesis 2 (H2). *Display Ads affects Country Rank with a positive correlation.*

The correlation is positive between the Rank and Display Ads. When the Global Rank moves away from unity, then Display Ads increase with ρ df(59) = 0.519 and sig. = 0.001 (2-tailed) as between the Country Rank with ρ df(59) = 0.687 and sig. = 0.001 (2-tailed) and between the Category Rank with ρ df(59) = 0.141 and sig. = 0.001 (2-tailed). In conclusion, the H2 correlation is a logical correlation on the positive axis, as companies spend more on video display advertising, resulting in a decrease in their equity, which implies a decrease in the value of their products. Companies should not invest large amounts of money in advertisements that do not have a large impact on their customers, showing little importance in such advertisements. At the same time, they save money for the optimization of other parts (e.g., hardware). In this way, they increase the value of the customer while at the same time their website is in higher-ranking positions.

Hypothesis 3 (H3). *Direct affects Global Rank with a negative correlation.*

The results show that there is a negative correlation between the Direct metric and Rank. When the Direct metric increases, then the Global Rank metric decreases with ρ df(59) = −0.106 and sig. = 0.001 (2-tailed), which means it is close to 1, i.e., a higher-ranking position globally. Additionally, between the Direct and Country Rank there is a negative correlation with ρ df(59) = −0.214 and sig. = 0.001 (2-tailed). Between the Direct and Category Rank there is a weak-small negative correlation with ρ df(59) = −0.113 and sig. = 0.001 (2-tailed). H3 is a negative Pearson correlation, which has a positive impact on website ranking. Direct traffic is mostly about users who tend to visit a particular website. Therefore, it is reasonable that an increase in the Direct metric would decrease the Rank so that it approaches 1, meaning a higher-ranking position for the site.

Hypothesis 4 (H4). *Social affects Global Rank with a negative correlation.*

Between Rank and Social there is a negative correlation, while between Global Rank and Social, there is a weak negative correlation that is almost neutral with df (59) = −0.028 and sig. = 0.001 (2-tailed). That is, as the visits on social media increase, the position in the global ranking is in higher positions worldwide. The same happens with Country Rank with ρ df (59) = −0.100 and sig. = 0.001 (2-tailed), while with Category Rank, there is a negative correlation with ρ df (59) = −0.147 and sig. = 0.001 (2-tailed). H4 is a logical negative correlation. With the Social metric at high values, customer trust is enhanced, resulting in the optimization of the site's ranking position.

Hypothesis 5 (H5). *Email affects Global Rank with a positive correlation.*

The correlation between Rank and Email is positive. Between Global Rank and Email, there is a positive relationship as df (59) = 0.477 and sig. = 0.001 (2-tailed), i.e., the higher the email visits, the lower the site is in the global ranking. The same correlation occurs between Country Rank with ρ df (59) = 0.501 and sig. = 0.001 (2-tailed) and Category Rank with ρ df (59) = 0.507 and sig. = 0.001 (2-tailed). The results for correlation H5 showed that it is a positive Pearson correlation because the probabilities of this correlation are two. In the first, as the Email metric increases, so does the Rank, which means that the Rank metric moves away from unity, thus moving away from the first ranking position. On the contrary, when the Email metric decreases, the Rank also decreases, that means it will approach the first ranking positions.

Hypothesis 6 (H6). *Organic Search affects Global Rank with a positive correlation.*

A positive relationship was found between Organic Search and Rank. When the Organic Search metric increases, then the Global Rank metric increases with ρ df (59) = 0.061 and sig. = 0.001 (2-tailed), which means that it does not approach 1, i.e., in a higher-ranking position globally. Moreover, between Organic Search and Country Rank, there is a positive correlation with ρ df (59) = 0.174 and sig. = 0.001 (2-tailed). Between the metric Organic Search and Category Rank, there is a weak-small positive correlation with ρ df (59) = 0.050 and sig. = 0.001 (2-tailed). H6 is a positive Pearson correlation, which is about direct traffic, i.e., visits that come through unpaid search engine results. Unpaid traffic when there is a small percentage, lowers the Rank values, i.e., closer to higher popularity positions. H7 shows a negative correlation between Referrals and Rank. When the Referrals metric increases, then the Global Rank metric decreases with ρ df (59) = −0.131 and sig. = 0.001 (2-tailed), which means that it approaches unity, i.e., in a higher-ranking position globally. Moreover, between Referrals and Country Rank, there is a negative correlation with ρ df (59) = −0.223 and sig. = 0.001 (2-tailed). Between the referrals metric and the Category Rank metric, there is a weak negative correlation with ρ df (59) = −0.059 and sig. = 0.001 (2-tailed). H7 is a negative correlation, which is about link traffic, and shows the strong relationship between affiliates and partners. That is, an increase in the visits that come through links, increases the site's ranking position, as it approaches higher positions of popularity. In conclusion, the Direct, Social and Referrals metrics have a positive impact on the ranking of a website, since as these metrics increase, the rank decreases and approaches unity, meaning the first ranking positions. On the contrary, Paid Search, Display, Email and Organic Search have negative effects and especially when the Rank metric increases, they move away from 1. Therefore, an increase in the Direct, Social and Referrals metrics and a decrease in Paid Search, Display Ads, Email and Organic Search, to increase the ranking of the website.

In Figure 1, through the modeling approach using FCM, the extracted correlations between the ten-hypothesis testing-driven web analysis metrics and the results of the six different sites, which were also used previously, are listed.

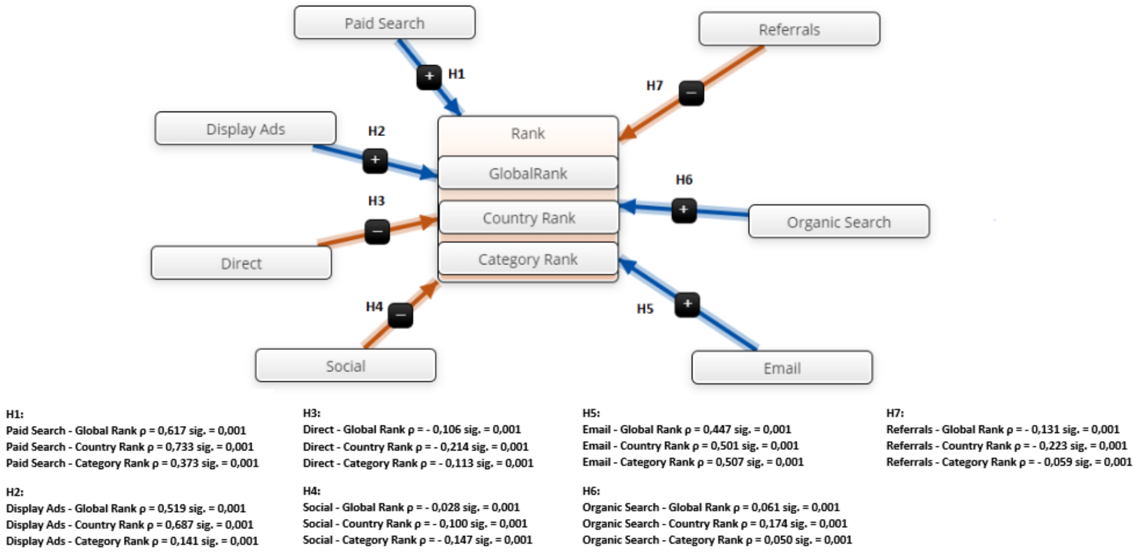

Figure 1. Descriptive representation of the correlations obtained between the ten-web analytics metrics through FCM.

Hypothesis 7 (H7). *Referrals affect Global Rank with a negative correlation.*

For the Category Rank metric, there is a weak negative correlation with ρ df (59) = −0.059 and sig. = 0.001 (2-tailed). H7 is a negative correlation, which is about link traffic, and shows the strong relationship between affiliates and partners. That is, an increase in the visits that come through links increases the site's ranking position, as it approaches higher positions of popularity. In conclusion, the Direct, Social and Referrals metrics have a positive impact on the ranking of a website, since as these metrics increase, the Rank decreases and approaches unity, meaning the first ranking positions. On the contrary, Paid Search, Display, Email and Organic Search have negative effects and especially when the Rank metric increases, they move away from 1. Therefore, an increase in the Direct, Social and Referrals metrics and a decrease in Paid Search, Display Ads, Email and Organic Search increases the ranking of the website.

1.3. Methodology

SimilarWeb's Application Programming Interface (API) was used to collect the above web analytics data. Visits are the basic unit behind SimilarWeb's information and most of its metrics. The data was collected over a period of 60 days from six leading sectors of mobile telecommunications companies. The domains made available to SimilarWeb's platform for web analytics metrics mining are: samsung.com, apple.com, huawei.com, xiaomi.com, vivo.com and lg.com.

The specific period was derived from the data preparation and testing process [28], after observing data overload after the recovered 60 daytime period of the web mining process. The process of collecting and mining web analytics metrics from the companies' websites were used to identify the following metrics: Global Rank, Country Rank, Category Rank, Paid Search, Display Ads, Direct, Social, Email, Organic Search and Referrals. SimilarWeb does not update its metrics daily and displays them in comparison to the last three months. Despite this, all measurements for the web analysis were collected daily to gain a deeper understanding of the range of variation. However, with the prolonged renewal of SimilarWeb metrics the range of fluctuations differed only monthly and that, to a large extent, compared to previous results. This difference arises due to the different stimuli of digital marketing users, as well as the values of the positions of the global ranking, the ranking based on the visits of the most attractive country and the ranking based on the category of the website.

The estimation of the possible relationships based on the seven hypotheses results from the Pearson p coefficient. With this method, the possible linear correlations between the web analysis data extracted in the considered time range of 60 days (N) are calculated.

2. Materials and Methods

Digital Marketing Web Measurements and Analytics

For digital marketing web analytics, web analytics metrics (Web Analysis, WA) are leveraged. Web analytics metrics refer to a tool that collects data regarding the source of website traffic (e.g., email, search engines, display ads, social links), navigation paths and visitor behavior while browsing on the internet [22]. Essentially, web analytics data are used to understand the behavior of online customers and to measure their responses to digital marketing stimuli. In addition, they optimize digital marketing elements and actions that encourage their behavior, which benefits each company [22]. Although web analytics metrics are limited to the digital environment, their use is an important developmental step toward measurable marketing [29]. As the evolution of the digital world expands through the increased consumption of digital media and the integration of the online and offline world, the share of marketing actions covered by web analytics is increasing. Many offline marketing activities are already included in the digital elements that can be detected by web analytics. For example, quick response (QR) codes, embedded in print and outdoor media, and augmented reality applications, which are used in product demonstrations and product trade exhibitions [4]. Additionally, companies can pause offline campaigns to increase total visits to digital channels and measure their impact on customer behavior through their website. It is concluded that companies' ability to achieve web analytics to improve marketing performance remains limited. The web analysis metrics data that will be considered for the development of this study are detailed in Table 1 using SimilarWeb.

Table 1. Description of the web analytics metrics considered for the role of digital marketing in new product distribution.

Web Analytics Metrics (WA Metrics)	Description of the WA Metrics
Global Rank	This factor is a method of ranking the traffic of a website compared to all the countries of the world.
Country Rank	It determines the most responsive country traffic ranking of the company's website compared to competing companies.
Category Rank	It presents the degree of traffic compared to other websites according to its main category.
Direct	This factor is about direct traffic, which usually comes from people who are aware of or are inclined towards a particular website. This metric is used to assess the strength of a company's brand. Direct traffic differs from traffic, which represents the total number of users who entered a URL directly into a browser or saved bookmarks or links outside the browser (e.g., Word, PDF, etc.)
Email	Shows traffic coming from email customers. A website that receives a high volume of email traffic is likely to have a large loyal customer base through a proprietary mailing list.
Referrals	It represents the traffic of a web page that is transferred directly through a link. This type of traffic consists of communication through affiliates, partners and traffic through direct purchases from sales or promotional media. A website that receives a lot of traffic in this way is likely to have strong affiliates or significant news coverage.

Table 1. *Cont.*

Web Analytics Metrics (WA Metrics)	Description of the WA Metrics
Social	The Social metric reflects the traffic which is sent through social media sites, such as Facebook or Reddit. It includes direct purchase through other platforms, such as Facebook. Social media visits are considered to easily influence public opinion. A website that generates high and consistent traffic from those means is quite likely to have a loyal community of users.
Organic Search	This factor is based on traffic through unpaid results on search engines, such as Google or Bing. When Organic Search is at a high percentage, it optimizes the top ranks of search results. These visits usually gather high-interest users, with particularly notable participation rates compared to the average visits and are classified as direct traffic.
Paid Search	It is a factor directly related to the traffic which is sent by ads with a paid search to a search engine. A site that collects visits from paying is the advertising budget which is spent on increasing brand awareness. Paid search campaigns have the potential to drive higher conversion rates as they target users with high purchase intent. They can also demonstrate the potential of advertisers and optimize a campaign's Key Performance Indicators (KPIs). Its utility is to monitor the list of paid keywords and search ads, with the goal of understanding those words that users focus on to find products.
Display Ads	Finally, the Display Ads factor refers to traffic sent from display and video ads through well-known ad-serving platforms, such as GDN and Doubleclick. A large percentage of this source means increasing brand readability and audience engagement.

The study by Järvinen and Karjaluoto [4] confirms that web analytics do not inherently improve the marketing space. Due to these findings, more emphasis will be placed on the use of this data. At the same time, the future challenge of achieving a clear understanding of customers and marketing performance will be highlighted. In particular, the level of the ranking of the website concerning each company, and the origin of the traffic (e.g., social media, email, paid advertisements, etc.) will be analyzed. These metrics help digital marketers and decision makers to make informed decisions going forward to:

- Understand metrics and their impact on the digital marketing practices they use;
- To define a strategic model for the collection of data about the origin of the users' visit to their company's websites;
- Understand the potential interactions they may have by studying these metrics;
- Improve analytical skills and take advantage of the results of web analytics data to understand more general user behavior;
- To design, implement, evaluate and improve the performance measurement system, regarding the advertised methods of digital marketing, that will offer to their future users.

3. Results

Hypothesis Trials and Results

By examining the possible interdependencies between the above web analytics metrics, digital marketers will take the most decisive steps. This way they will understand the area (e.g., social media marketing, email marketing, etc.) they need to invest in the marketing space (paid ads, email, etc.) in order for their company to rank higher in the global ranking, in the ranking based on visits to the country with the most attraction and in the ranking based on the category of the website. For example, the level of sales of mobile products could be a critical element in how to attract more customers using marketing. However, the question is whether and how the level of adaptability of the level of digital marketing affects the ranking positions that the website receives. It is assumed that the lower the interaction of users in the digital stimuli of e-marketing, the lower the positions in the global ranking, in the ranking based on visits to the most attractive country and in the ranking based on the category of the website. The higher the interaction, the more the total number of visits to the website, which is based on paid or unpaid results in search engines and, by extension, higher-ranking positions. Next, and in the context of citing a descriptive modeling technique, the construction of the prediction model is analyzed.

In Table 2, the Pearson ρ correlations are presented regarding the examined websites, which present their services through the means of communication. In addition, descriptive statistics, such as means, modes of operation, standard deviations and minimum and maximum values, are included, which will be important for the modeling process with an ABM (agent-based modeling) system.

Table 2. The Pearson ρ coefficient between the web analytics metrics namely: Global Rank, Country Rank, Category Rank, Direct, Social, Email, Organic Search, Paid Search, Referrals and Display Ads.

	Global Rank	Country Rank	Category Rank	Direct	Social	Email	Organic Search	Paid Search	Referrals	Display Ads	Global Rank
Global Rank	-										
Country Rank	0.925 **	-									
Category Rank	0.866 **	0.697 **	-								
Direct	−0.106	−0.214 **	−0.113	-							
Social	−0.028	−0.100	−0.147 *	0.056	-						
Email	0.447 **	0.501 **	0.507 **	−0.344 **	−0.358 **	-					
Organic Search	0.061	0.174 **	0.050	−0.336 **	−0.706 **	0.674 **	-				
Paid Search	0.617 **	0.733 **	0.373 *	−0.510 **	−0.336 **	0.559 **	0.670 **	-			
Referrals	−0.131 *	−0.223 **	−0.059	−0.077	0.671 **	−0.601 **	−0.900 **	−0.577 **	-		
Display Ads	0.519 **	0.687 **	0.141 *	−0.281 **	−0.147 *	0.339 **	0.507 **	0.903 **	−0.535 **	-	
Global Rank: Mean: 2158.63115, Mode: 485.5000, Std. Deviation: 3878.320695, Minimum: 55.0, Maximum: 14.716.000											
Country Rank: Mean: 1121.47814, Mode: 82.00000, Std. Deviation: 1821.260859, Minimum: 58.0, Maximum: 6527.000											
Category Rank: Mean: 16.47541, Mode: 6.0000, Std. Deviation: 37.161155, Minimum: 1.000, Maximum: 155.000											
Direct: Mean: 31.17344, Mode: 29.87000, Std. Deviation: 10.155552, Minimum: 17.190, Maximum: 51.450											
Social: Mean: 3.10281, Mode: 2.93000, Std. Deviation: 1.458156, Minimum: 0.860, Maximum: 6.010											
Email: Mean: 1.2821, Mode: 1.1100, Std. Deviation: 0.49280, Minimum: 0.67, Maximum: 2.58											
Organic Search: Mean: 45.24325, Mode: 45.53000, Std. Deviation: 19.536547, Minimum: 6.400, Maximum: 71.530											
Paid Search: Mean: 3.55801, Mode: 3.31000, Std. Deviation: 2.438169, Minimum: 0.080, Maximum: 8.700											
Referrals: Mean: 14.15533, Mode: 4.28000, Std. Deviation: 2.098487, Minimum: 2.790, Maximum: 61.900											
Display Ads: Mean: 1.77623, Mode: 1.105000, Std. Deviation: 1.466863, Minimum: 0.010, Maximum: 6.250											

* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed). N = 60; Degree of Freedom = df: 59.

In Figure 1, from the collection of Big Data data and the Pearson analysis that was performed, the extracted correlations between the ten web analytics metrics based on the hypothesis tests and the results of the six different sites is represented through the fuzzy cognitive mapping descriptive modeling approach.

Big Data analysis, using the Pearson p coefficient and web analytics metrics, shows the correlations between the variables affecting the problem. These correlations are presented by creating the fuzzy cognitive map of Figure 1.

Regarding the examination of scenario H1, it is evident from Table 2 that the variable Paid Search has a positive correlation with the variables Global Rank, Country Rank and Category Rank with weights of 0.617, 0.733 and 0.373, respectively. These findings show that traffic related to paid search ads in search engines has a positive impact on the traffic factors of both the global ranking and the website's country and the main ranking category, respectively.

Regarding the examination of scenario H2 from Table 2, it appears that the variable Display Ads has a positive correlation with the variables Global Rank, Country Rank and Category Rank with weights of 0.519, 0.687 and 0.141 respectively. These findings show that traffic sent from display and video ads through well-known ad-serving platforms has a positive impact on traffic factors for both the website's global and country rankings, as well as its primary ranking category, respectively.

Regarding the examination of scenario H3, it is evident from Table 2 that the variable Direct has a negative correlation with the variables Global Rank, Country Rank and Category Rank with weights of −0.106, −0.214 and −0.113, respectively. These findings show that direct traffic coming from people who know or tend to a particular site has a negative impact on the direct traffic factors in both the global ranking, the site's country and the main ranking category, respectively.

Regarding the examination of scenario H4 from Table 2 it appears that the variable Social has a negative correlation with the variables Global Rank, Country Rank and Category Rank with weights of −0.028, −0.100 and −0.147, respectively. These findings show that traffic sent through social media sites has a negative impact on traffic factors in both the global ranking, the site's country and the main ranking category, respectively.

Regarding the examination of scenario H5, it is evident from Table 2 that the variable Email has a positive correlation with the variables Global Rank, Country Rank and Category Rank with weights of 0.447, 0.501 and 0.507 respectively. These findings show that traffic originating from email clients has a positive impact on the traffic factors of both the website's global and country rankings, as well as the main ranking category, respectively.

Regarding the examination of scenario H6 from Table 2 it appears that the variable Paid Search has a positive correlation with the variables Global Rank, Country Rank and Category Rank with weights of 0.061, 0.174 and 0.050, respectively. These findings show that traffic through unpaid search engine results has a positive impact on traffic factors in both the global ranking and the site's country and main ranking category, respectively.

Finally, and regarding the examination of scenario H7, it is evident from Table 2 that the variable Paid Search has a positive correlation with the variables Global Rank, Country Rank and Category Rank with weights of −0.131, −0.223 and −0.059, respectively. These findings show that traffic consisting of affiliates and traffic through direct purchases from sales or promotional media has a negative impact on traffic factors in both global ranking, site country and primary category ranking, respectively.

4. Discussion

In this segment, the arrangement of agent-based modeling (ABM) is demonstrated. For ABM sending, the energetic relationship and subordinate and free variables' coefficients are utilized. This leads to a potential forecast demonstrating the effectiveness by improving its consistency [27]. The most objective of the model's arrangement is the examination of supply chain websites' worldwide rank and natural activity factors amid supply chain improvement forms. Within the ABM strategy, a gathering of operators (guests) intercommunicates with each other and gives profitable intel for the organizations' decision-making forms [30]. Operators are teaching to comply with indicated commands, set by parameters such as supply chain day-by-day cases, normal pages per visit, normal time on location, etc., and different administrators, such as 'if', etc.

Using Fuzzy Logic Cognitive Mapping (FCM), a quantitative model is being created, which is used to map the relationship between the factors of the problem and to assign the weights between the independent and dependent variables to each of the components of the factors considered.

Logistics refers to activities required to move and position inventory throughout a supply chain [31] and usually faces multi-objective problems [32]. The optimization of the content of the web pages, regarding logistics companies is about the top ranking of the search engines. Search engines use the same content search terms, according to the SEO command core. Browsing the web affects search and so does e-branding.

Through the modeling process, it was concluded that the higher level of marketing metrics, derived from advertising through direct social media traffic and a link, implies an increase in the distribution network of its new products. In contrast, marketing spent on email, video display, paid ads and non-search ads has a negative impact.

The goal is to understand the period of these 60 days, when higher metrics are obtained in visits through direct traffic, through social media and via links. Once this understanding becomes possible, decision makers will be able to:

- Realize why, over the given period, the above web analytics metrics have resulted in a higher global ranking and a ranking based on traffic of the most popular country and the company's category.
- Understand the impact of visits coming from direct traffic, email, a link, social media, paid or unpaid results, as well as video display ads, thereby determining their influence on global ranking, country ranking with most visits and ranking based on the site's category during the 60 daytime period in which the web analytics metrics data was collected.
- Combine the results, aiming to be informed about the performance, based on digital marketing data, which indicate in a certain period the correct promotion of mobile products. Considering the maximum engagement of the users, in terms of the origin of their visits to the website, the global ranking, the ranking in the most attractive country and the ranking position, according to the category of the website, which implies the improvement of digital marketing and network distribution of the company's new products.

Based on the above results, analysts can predict which are the best advertising media and which may have higher web analytics metrics in terms of website ranking.

Potentially, it could prove particularly useful to achieve digital marketing optimization and act as a supporting tool for personalization in the process of a reliable strategy for developing a new distribution network for new mobile telecommunications products.

The period when the content of the website receives the highest positions in the global ranking, ranking in the country with the most visits and ranking based on the category of the website, which are derived from the interaction of users with the digital marketing implemented by the company, the process is adopted of ABM (agent-based modeling).

Agent-based modeling is a computer simulation consisting of multiple agents that are autonomous decision makers (e.g., users). Agents receive specific rules for interacting with other agents or other entities within a system, and consequently, through such rules and interactions, more entanglements occur [33]. The agent system modeling strategy provides the advantage for decision advisors to:

- Use the capabilities of customer web analytics data as a company 'face', that is, to understand the utility of web analytics data as a quantitative process that describes user behavior on websites containing the company's products.
- Understand the term organization and the role of digital marketing in terms of business processes in their services, but also in terms of how users interact with them. In particular, how each visitor generates different numerical values regarding the origin of their visit, which may be from a direct visit, paid advertisement, unpaid advertisement, display ad, social media, link or from email.
- They rely on the flexibility of agent system modeling to build their own model, combining entities based on past user behavior data, to enable them to solve emerging issues. Agent system modeling is flexible and variable in the process of adding new measures to a particular agent model, rather than explaining the relationships of the new measures through structured differential equations, a situation also supported by other research approaches [34].

By adopting the agent-based model, aggregated quantitative user behavior data are suitable for extracting the real situation, as well as for integrating data-driven practices and studies with social analytics datasets [33]. The process of extracting behavioral analytics through web analytics tools helps focus on building a model based on real data.

That is, building the model and agents with the stored behavior analysis datasets and then using the model to gain understanding through iteration of all viable decisions to optimize the metrics under consideration. Next, the process of agent-based modeling and the available web analysis components used for its construction using AnyLogic PLE is presented and described.

In the below Figure 2, in gray (PotentialVisitors), all potential visitors to the website are represented. The data in question is a springboard for the model-building process, which has already been mentioned as a common feature (e.g., marketing) [35] in agent system-based modeling.

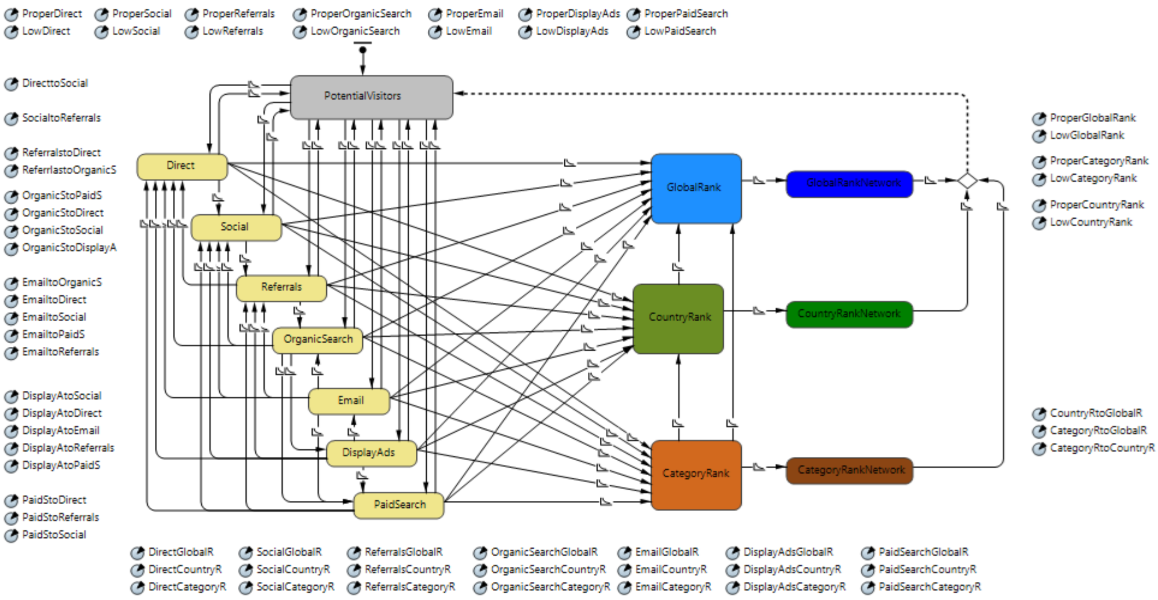

Figure 2. Agent-based modeling (ABM), where the influence of the Social, Direct, Referrals, Email, Display Ads, Organic Search and Paid Search metrics on the Global Rank Network, Country Rank Network and Category Rank metrics is examined.

The calculated parameters (ProperDirect, ProperSocial, ProperReferrals, ProperOrganicSearch, ProperEmail, ProperDisplayAds and PaidSearchP) relate to the way potential users visit the website, influencing the parameters (Direct, Social, Referrals, OrganicSearch, Email, DisplayAds and PaidSearch, respectively) with the color yellow, through triangular distributions (triangular) with the numerical values minimum, maximum and mode for each pool, respectively. In this way, the model distributes the population of agents, i.e., the users of the website, based on the origin of the traffic, based on the statistical correlations.

The parameters (*LowDirect*, *LowSocial*, *LowReferrals*, *LowOrganicSearch*, *LowEmail*, *LowDisplayAds* and *LowPaidSearch*) work as "if–then" rules, which reinforce the practice of specialization of the models and their theoretical background [33–37]. Practically, the norm is realized through the continuous distribution (lognormal), which is limited on the lower side, with the numerical values of mean, std. deviation and minimum. The waveforms of the lognormal distribution show the most failures, which are most often due to the weakness of the project, wrong start, capacity operation or wrong construction [36]. Due to the Pearson coefficients of the web analytics metrics (Table 1), it becomes impossible to ignore the influences between the metrics Direct, Social, Referrals, Organic Search, Email, Display Ads and Paid Search, and consequently, the parameters are created: *DirecttoSocial*, *SocialtoReferrals*, *ReferralstoDirect*, *ReferralstoOrganicS*, *OrganicStoPaidS*, *OrganicStoDirect*, *OrganicStoSocial*, *OrganicStoDisplayA*, *EmailtoOrganicS*, *EmailtoDirect*, *EmailtoSocial*, *EmailtoPaidS*, *EmailtoReferrals*, *DisplayAtoSocial*, *DisplayAtoDirect*, *DisplayAtoEmail*, *DisplayAtoReferrals*, *DisplayAtoPaidS*, *PaidStoDirect*, *PaidStoReferrals* and *PaidStoSocial* among *Direct*, *Social*, *Referrals*, *OrganicSearch*, *Email*, *DisplayAds* and *PaidSearch* in order to display all associations.

In particular, the influence appears in the naming of the parameters. In particular, the DirecttoSocial parameter shows the influence that the Direct metric has on the Social metric.

The parameters represent the influence through Poisson distributions with λ values, which will produce different values during the modeling process.

Pearson coefficients, according to the above, show that the Direct, Social, Referrals Organic Search, Email, Display Ads and Paid Search metrics influence the Global Rank, Country Rank and Category Rank metrics, which prompt the creation of parameters between them. Therefore, the addition of 21 additional parameters follows, as the Direct, Social, Referrals OrganicSearch, Email, DisplayAds and PaidSearch parameters (highlighted in yellow), affect the GlobalRank, CountryRank and CategoryRank parameters (highlighted in blue, olive, and coral, respectively.

The generated parameters (*DirectGlobalR*, *DirectCountryR*, *DirectCategoryR*, *SocialGlobalR*, *SocialCountryR*, *SocialCategoryR*, *ReferralsGlobalR*, *ReferralsCountryR*, *ReferralsCategoryR*, *OrganicSearchGlobalR*, *OrganicSearchCountryR*, *OrganicSearchCategoryR*, *EmailGlobalR*, *EmailCountryR*, *EmailCategoryR*, *DisplayAdsGlobalR*, *DisplayAdsCountryR*, *DisplayAdsCategoryR*, *PaidSearchGlobalR*, *PaidSearchCountryR* and *PaidSearchCategoryR*), are set under Poisson distributions through λ values.

More specifically, it lists the extent to which advertising through direct traffic, social media, links, unpaid searches, email, video views and paid searches affects the global ranking, top country visit ranking and ranking based on category. In this way, these parameters, in turn, affect in their own way the transition process of the population of agents in each of the classification types.

Influence is shown due to Pearson coefficients between Country Rank and Global Rank metrics, as well as Category Rank with Global Rank and Country Rank. Therefore, parameters (CountryRtoGlobalR, CategoryRtoGlobalR and CategoryRtoCountryR) were created to illustrate the influence between them. The parameters distribute the values of the coefficients through Poisson distributions with values of λ.

The parameters (ProperGlobalRank, ProperCountryRank and ProperCategoryRank) affect the transition of the agents to the next parameters (GlobalRankNetwork, CategoryRankNetwork and CountryRankNetwork), through triangular distributions (triangular) with the numerical values minimum, maximum and mode for each pool, respectively. In this way, they affect the transition process of the agent population in each reservoir in a different way.

In contrast, the parameters LowGlobalRank, LowCountryRank and LowCategoryRank function as an "if–then" rule, which reinforces the practice that specifies their practical and theoretical background [36–39], through the lognormal distribution with the numerical values of mean, std. deviation and minimum.

The LowGlobalRank, LowCountryRank, and LowCategoryRank parameters are associated with a branch that represents the branching point and connection to the first pool (PotentialVisitors). The given branch was used to create the state transition and execute a common action. The control performed within the branch reflects the ranking errors, which are returned as quantitative results to the first pool, aiming to continuously change the population of user agents.

The GlobalRankNetwork pool (highlighted in blue) shows the site's global ranking, the CategoryRankNetwork pool (highlighted in green) looks at the website's category-based ranking and the CountryRankNetwork pool (highlighted in brown) shows the website's ranking in the country with the most traffic on the website.

The difference between the GlobalRank, CountryRank and CategoryRank parameters is the influence that the GlobalRankNetwork, CategoryRankNetwork and CountryRankNetwork parameters have on the mobile product distribution network.

The role of digital marketing in decision making is reasonable in terms of the influence of rankings to improve the distribution of new mobile products through the website.

After considering the parameters and the types of probability distributions (triangular, Poisson and lognormal), defined in each parameter, it is observed that several transitions are made that are triggered by the conditions of the parameters to distribute the population of agents in each pool accordingly.

Figure 3 shows the simulation results through a time graph of the GlobalRankNetwork, CountryRankNetwork, CategoryRankNetwork, Direct, Social, Referrals, OrganicSearch, Email, DisplayAds and PaidSearch parameters, where the vertical axis depicts the percentage of traffic on a scale of 0–100 that they receive the pools and the horizontal axis of days on a scale of 1–60. Web analysis measurements were considered.

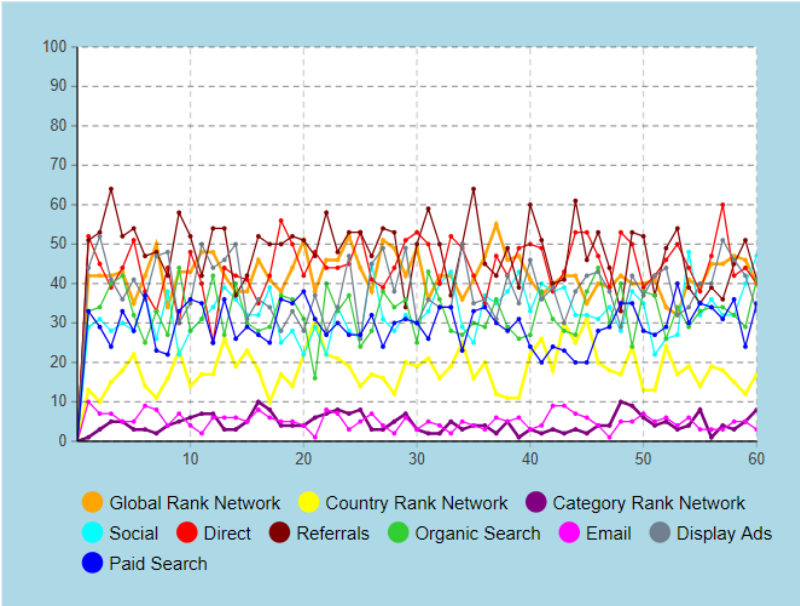

Figure 3. Time stack chart showing the values received by the parameters (GlobalRankNetwork, CountryRankNetwork, CategoryRankNetwork, Direct, Social, Referrals, OrganicSearch, Email, DisplayAds and PaidSearch) over the 60 day measurement period.

Figure 4 shows through a time stack diagram the values of the reservoirs as in the previous figure, with the difference that the vertical axis shows the percentages (0–100%) of the reservoirs and the horizontal axis starts from day zero, i.e., its values range from 0–60.

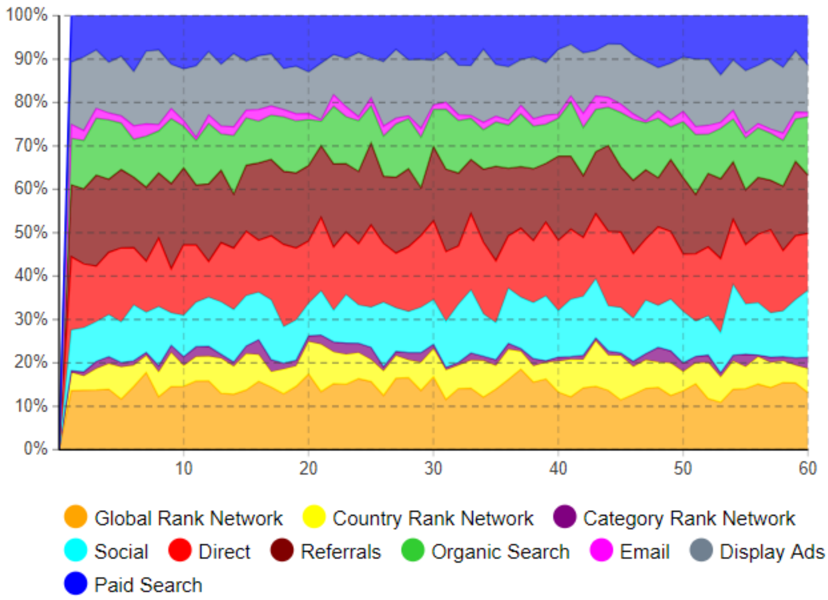

Figure 4. Expanded time stack chart showing the values received by the parameters (GlobalRankNetwork, CountryRankNetwork, CategoryRankNetwork, Direct, Social, Referrals, OrganicSearch, Email, DisplayAds and PaidSearch) over the 60 day measurement period.

A pie chart is used in Figure 5, where the percentage comparison of the GlobalRankNetwork, CountryRankNetwork and CategoryRankNetwork metrics on the last day of data collection are represented.

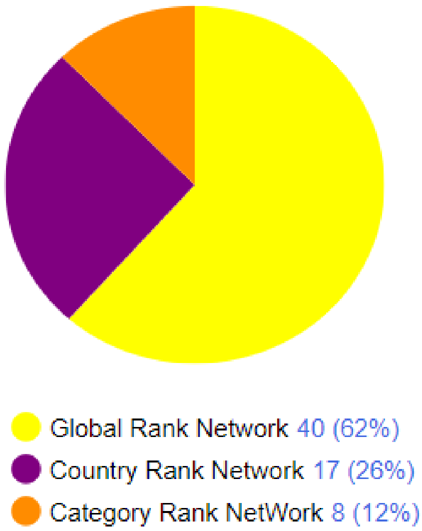

Figure 5. Pie chart showing the values obtained by the reservoirs (GlobalRNetwork CountryRNetwork and CategoryRNetwork) on the sixtieth day of measurement.

The pools pictured are as follows:

- orange color: GlobalRankNetwork;
- yellow color: CountryRankNetwork;
- purple color: CategoryRankNetwork;
- blue color: Social;
- red color: Direct;
- burgundy color: Referrals;
- green color: OrganicSearch;
- pink color: Email;
- gray color: DisplayAds;
- blue color: PaidSearch.

In the span of the 60 days that web analytics data were collected from six popular mobile company websites, fluctuations were observed across all types of agents. By adjusting the parameters of the model under consideration, as well as the values of the probability distribution for the distribution of the agents, it is observed that the values of the graph refer to the values received by the parameters GlobalRankNetwork, CountryRankNetwork, CategoryRankNetwork, Direct, Social, Referrals, OrganicSearch, Email, DisplayAds and PaidSearch.

By verifying the results based on the model of FCM because of web analysis metrics (Figure 1) with high percentages coming from advertisements through direct traffic, social media and links give high percentages in the ranking of the website.

As was mentioned previously, high values in these metrics indicate that companies have strong subsidiaries, a strong brand, high influence in public opinion and high direct sales. However, high rates were also observed in marketing from random (non-paid) search engine results, which means there is a lot of user interest in the company's products.

High quantitative values showed ads coming from paid results, which is interpreted as the readability of the company logo. High percentages from video ad views highlight the value of the customer as the face of the company. In contrast, low rates were seen in email advertisements, which is interpreted as a non-loyal customer base of the companies.

In practice decision makers have further advantages by exploiting the results in question. Initially, they can estimate the engagement of visitors to the content of websites, while the lowest and highest values of rankings correlate and influence the lowest and highest values of web analytics metrics to develop a new distribution network for mobile telecommunication products.

In addition, they can detect the content of the websites extracted at certain time intervals, the highest percentages of the global ranking, the ranking in the country with the most attraction and the ranking based on the category of the website, because of digital marketing.

Decision makers will be able to take advantage of the lower ranking values on both websites (understanding the role of digital marketing of the website that caused technical problems in a certain period, with the low level of email ads and a high percentage through video views) which has already mentioned, has the consequence of negative effects, focusing on avoiding any future implementations on their websites.

Further research and application are estimated to be required using the proposed web analytics mining methodology, the use of descriptive cognitive mapping and agent system modeling in order to apply it to other marketing domains (e.g., Business2Business Marketing). Therefore, other scientists with similar cases are studying similar problems, using modeling and simulation [27,30,31,39].

5. Conclusions

This study focuses on examining the impact of digital marketing through direct traffic, email, social networking sites, unpaid results, paid searches, as well as video display ads through well-known platforms with global ranking, ranking in countries with more traffic and ranking based on category.

Moreover, in quoting a proposal regarding the focus of the methodology as a practical tool for evaluation by decision makers and consultants, so that they can understand the role and influence of digital marketing in the set of cases under consideration. By examining the influence in question, consultants will be able to make new solutions to develop a new, renewed and improved distribution network for new mobile products, which will be based on promotion through digital marketing.

The correlations of statistics, as well as modeling and simulation results with the agent system, will provide remarkable solutions to the issues of consultants and decision makers of mobile companies.

Decision makers will be able to study and compare the rates of traffic through direct traffic, email, links, social media, unpaid and non-results and video display ads, and succeed in building a sophisticated network distribution of new mobile products, where it will help to increase the overall ranking of the site.

Decision makers, in finding new ways to optimize digital marketing, will be able to suggest and adopt the parameters that contributed to the emergence of the high percentages of the web analytics metrics discussed earlier, focusing too on specific time periods.

In this way, the instability and complexity will keep expanding, and in a few cases, the number of web investigation estimations will be bigger than the populace beneath thought, and thus will speak to unsatisfactory values within the examination control panels, causing perplexity within the securing handle choices.

On this, the proposal derived from the above measurements analyzes and concludes a methodology that will initially explain and define the measurements of web analysis to eliminate any misconceptions of their usefulness. Furthermore, adopting a descriptive modeling approach through FCM, to make the impact of web analysis metrics more noticeable and understandable, is suggested.

In the event that choice producers wish to extend the large number of web analytics measurements and the potential for interdependencies between them, FCM, as a clear and energetic modeling strategy, provides the adaptability to advance and expand mapping, while parameterizing the key execution markers of computerized showcasing.

Moreover, by applying statistical analysis with Pearson correlations using web analysis metrics, it was possible to understand the web analysis metrics and extract their values, as well as decipher −1 or +1 correlations between Pearson's test means and using FCM, the numeric values [−1, +1] were applied. This study enables decision makers to develop and implement new ways of promoting through digital marketing that will:

- determine the performance metrics of digital marketing efforts and communication channels, which in turn will generate the user behavior data that drives the metrics;
- understand the correlations between metrics and ways to influence user behavior (e.g., social media platform);
- leave behind previous marketing performance measurement methods that suffer from small numbers of customers or user samples, which give time-consuming data collection and are more static, instead of dynamic, propositions of valid approval for digital marketing optimization.

Recreation of the energetic commitment of specialist-based modeling, within the period of enormously created web analytics behavioral datasets, is picking up increasing acknowledgment.

Data-driven mindsets of building simulation models with an agent system can usher in a new era of predictive modeling that will be a highly sophisticated process technology for all organizational and decision-making members.

This paper attempts to contribute to the process of building simulation models based on data, but also to the perspective of the quantitative creation of a model, not only the behavior and actions of agents within a system, by:

- utilizing the extricated modeling information;
- enhancing the validity and reliability of the proposed model based on real data;
- characterizing as the center, the beginning state of extricating conceivable relationships between the factors that characterized the behavior of the specialists, but moreover, of the net investigation measurements, communicating information analysis to the agents, stores and parameters within the reenactment demonstrate;
- verifying that the proposed model did not lead to large differences in the interactions between the agents' behavior and the transitions and descriptive statistics with the proposed extracted correlations.

The existing study was based on the overall research project of strategic website optimization through web analytics data of online user behavior.

Because of this, the field of mobile company websites and user behavior data analysis, generated from the origin of their visits, based on digital marketing metrics, was examined. Below in Tables 3 and 4 are represented the descriptive statistics from the metrics used for the study.

Table 3. Descriptive statistics for web analysis metrics.

	Global_Rank	**Country_Rank**	**Category_Rank**	**Total_Visits**	**Avg_Visit_Duration**
Mean	2158.63115	1121.47814	16.47541	688,556,639.34426	2.724997
Median	485.5000	82.00000	6.0000	260,600,000.00000	3.24000
Std. Deviation	3878.320695	1821.260859	37.161155	855,576,621.725807	0.72840444
Minimum	55.000	58.000	1.000	5,560,000.000	1.260
Maximum	14,716.000	6527.000	155.000	2,733,000,000.00	4.44

Decision makers and consultants can use this type of agent system modeling to deal with types of approach complexity and uncertainty.

They can focus on the highest values of the specific days produced by the simulation engine, looking for the digital marketing role over the 60 day period or the divergence from its previous published role, to optimize the metrics of site rankings.

Optimization methodology will be able to face the difficulties of forecasting models, as through tests, in a risk-free environment, with the numerical values of the highest rates in a prolonged period more than that of the 60 days that the model was run in this research.

Table 4. Summary descriptive statistics for web analysis metrics.

	Global_Rank	Country_Rank	Category_Rank	Total_Visits	Avg_Visit_Duration
Mean	2158.63115	1121.47814	16.47541	688,556,639.34426	2.724997
Median	485.5000	82.00000	6.0000	260,600,000.00000	3.24000
Std. Deviation	3878.320695	1821.260859	37.161155	855,576,621.725807	0.72840444
Minimum	55.000	58.000	1.000	5,560,000.000	1.260
Maximum	14,716.000	6527.000	155.000	2,733,000,000.00	4.44
	Pages_per_Visit	**Bounce_Rate**	**Direct_Traffic**	**Mail_Traffic**	**Referral_Traffic**
Mean	2.84708	60.54443	31.17344	1.2821	14.15533
Median	2.64500	61.51500	29.87000	1.1100	4.28000
Std. Deviation	0.638824	4.971571	10.155552	0.49280	2.098487
Minimum	2.010	50.860	17.190	0.67	2.790
Maximum	4.110	71.120	51.450	2.58	61.900
	Social_Traffic	**Organic_Traffic**	**Paid_Traffic**	**Display_Traffic**	
Mean	3.10281	45.24325	3.55801	1.77623	
Median	2.93000	45.53000	3.31000	1.10500	
Std. Deviation	1.458156	19.536547	2.438169	1.466863	
Minimum	0.860	6.400	0.080	0.010	
Maximum	6.010	71.530	8.700	6.250	

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