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The Effectiveness of Centralized Payment Network Advertisements on Digital Branding during the COVID-19 Crisis

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Abstract: Crises are always challenging for banking systems. In the case of COVID-19, centralized payment networks and FinTech companies' websites have been affected by user behavior globally. As a result, there is ample opportunity for marketing managers and professionals to focus on big data from FinTech websites. This can contribute to a better understanding of the variables impacting their brand name and how to manage risk during crisis periods. This research is divided into three stages. The first stage presents the web analytics and the data retrieved from the FinTech platforms. The second stage illustrates the statistical analysis and the fuzzy cognitive mapping (FCM) performed. In the final stage, an agent-based model is outlined in order to simulate and forecast a company's brand name visibility and user behavior. The results of this study suggest that, during crises, centralized payment networks (CPNs) and FinTech companies with high organic traffic tend to convert new visitors to actual "customers".

Keywords: crowdsourcing; web analytics; fuzzy cognitive mapping; crisis management; innovation; knowledge sharing; customer behavior; advertisement; big data

1. Introduction

Digital Marketing of Centralized Payment Systems and FinTech

Due to e-commerce, digital marketing has grown in popularity. The key factor as to why digital marketing is used by organizations is the fact that it is less expensive and more accessible than traditional marketing [1]. For instance, the price of reaching 2000 consumers via newspaper is approximately $500, whereas the expense of advertisement via digital marketing is approximately $50 [2]. Numerous businesses have expanded through the internet in recent years, not only as a useful way of providing knowledge for advertising but also as a marketing channel to generate profit [3] and increase brand name awareness [4]. Companies build websites to support their activities, such as transactions, but many are uninformed on how effective their websites are in attracting new customers [5]. Digital advertising plays a crucial role in this due to its ability to reach new customers fast and at a low cost [6].

There is a necessity for centralized payment system network companies (CPNs), such as PayPal, to optimize their advertisement campaigns to attract new customers. The consumer–user experience is multidimensional, and involves all consumer's interactions with the website or the mobile application [7]. The user experience has transformed as a result of the digital revolution [8,9]. As a result, conventional marketing practices have been characterized as obsolete for struggling to reflect the challenges of the modern user experience [8]. The authors of this research focus mainly on the impact of digital advertisements on CPNs and FinTech websites' brand names. In contradiction to previous research on the field, which examined the effects in a binary form (such as crisis impact on brand name or crisis impact on digital advertising, which will be discussed in the next section), our study attempts to investigate all of the involved parameters that play a role in corporate brand names. This paper attempts to identify the effects of the COVID-19 crisis on centralized payment network's brand names and how they can be improved with the usage of digital advertisements.

As described in the abstract, after the first stage of big data extraction from CPN websites, the authors proceed to the statistical analysis of these data. The second stage of the methodology includes the statistical analysis and the formulation of a diagnostic model that incorporates these statistics in order to present cause-and-effect situations. The final step is the formulation of an agent-based model to simulate and forecast user behavior for these websites and the impact on their brand name and visibility during the COVID-19 crisis. Furthermore, the contribution of this paper focuses on digital marketing strategies and SEO based on big data and web analytics, in addition to creating an innovative digital marketing strategy based on the findings of the agent-based simulation model.

Predominantly, digital advertisements and web global rank can be influenced by user behavior on CPN and FinTech websites, as evidenced by an examination of the website's analytics data [6,10–12]. The market share of the FinTech industry is growing every year and, according to Statista forecasting, its values of $80 billion in 2017 and $92 billion in 2018 will increase to $188 billion in 2024 [13]. Users of CPN and FinTech websites devote a significant amount of time in order to complete secure transactions. There is a high probability that FinTech companies will take advantage of their popularity in order to better place paid advertisements of their websites on other platforms. An exhaustive analysis of five CPN and FinTech websites was conducted in order to extract behavioral data to assist this research. Web analytics can be defined as the extraction and analysis of a website's structured or unstructured data to optimize digital marketing strategies [5,12]. With the extraction of certain web analytics, such as average time spent on-site and website traffic, the authors were able to investigate the effectiveness of digital advertisements, as well as the future forecasting and simulation of brand name visibility. The websites investigated were Paypal.com [14], Skrill.com [15], Stripe.com [16], Authorize.net [17], and Bluesnap.com [18].

The research paper is structured as follows. Section 1 presents the literature review. Section 2 discusses the sample selection of web analytics and the methodological approach used in this study. Section 3 presents the results of the statistical analysis including regression and correlation analysis illustrated on a fuzzy cognitive map (FCM), and the agent-based model development based on the statistical analysis from the sample and the exploratory representation. Section 4 explains, describes, and discusses the results. Section 5 illustrates the study's conclusions, directions for future research, and potential research implications.

2. Literature Review

2.1. Passive Crowdsourcing Participatory Culture and Mind Sharing

Crowdsourcing and crowdfunding practices could play a crucial role in CPNs and FinTech advertisements by reaching all players, such as investors and technicians [19,20]. Howe and Robinson invented the term crowdsourcing to describe an internet corporate model that relies on the collaborative force of many globally connected users that participate in a project through an open call [21]. As a logical consequence, crowdsourcing, better described as "knowledge of the crowds" [22,23], incorporates two main web users: the requesters and the employee participants [24]. Participation and mind sharing are both key elements of crowdsourcing tasks. Mind sharing refers to the use of crowd knowledge, and emphasis is given to the diversity of opinions [25,26]. A significant advantage of focusing on crowdsourced knowledge is the strategic optimization of decision-making processes, for example in efficacy and objectiveness [25–28]. It is vital to establish participation or a "participatory culture" to accomplish mind sharing.

The participatory culture encourages users to behave as entrepreneurs and main contributors and not simply as customers [29]. Crowdsourcing and crowdfunding can be fruitful and beneficial for the community with the application of the mentality of participatory culture [30]. Since the purpose of crowdsourcing is to collect ideas and provide solutions [31], participatory culture is necessary since the user takes on a role in the crowd and adds value to it [32]. The two critical elements are implicit participation and explicit participation [33]. Explicit participation is perceived as an actual act that is created by motivation [33]. For example, a participant uploads a response to a question. Implicit participation, on the other hand, does not necessarily involve intentional action [33–35].

According to previous studies, there are a lot of types of crowdsourcing, including direct crowdsourcing, collaborative crowdsourcing, passive crowdsourcing, and crowdfunding (which is considered a type of crowdsourcing since the platform delivers financial benefit by facilitating transactions among companies and members of the crowd) [31,36]. The crowd's everyday internet activity produces a massive amount of user-generated data. The gathering of publicly available data without a specific request is referred to as passive crowdsourcing [37,38]. Governments are inquiring about behavioral data from internet platforms to gain a deeper knowledge of public opinion [39] and passive crowdsourcing in various fields such as European research projects [39] and environmental sciences [39]. Passive crowdsourcing encounters difficulties in terms of quality and ambiguity of the outcomes. A significant barrier, for instance, is how to filter worthless and malicious content [40]. This research is based on passive crowdsourcing and implicit participation.

2.2. Crisis and Risk Management

Many previous studies present different strategies in order to expand the company's reputation and minimize risk in the supply chain and FinTech [41,42]. This study is focused on the correlation between crisis and risk management in centralized payment networks and FinTech. Risk management, in a general context, refers to a company's organized activities that are aimed at risk control [43]. Risk management is crucial in crisis periods, especially in a pandemic period [44]. Specific guidelines must be followed in order for a risk management strategy to be successful. The PACED set of guidelines is mainly used by organizations since they promote the successful implementation of the risk management strategy [45]. Except for PACED, other guidelines are commonly used and the main points in all are the same; the core elements include identification, assessment, treatment, monitoring, and reporting [46].

Supply chains serve as a connecting platform for goods and services to move from suppliers to distribution companies to end customers [47]. Consequently, in a broader sense, CPN and FinTech companies, such as PayPal, fit that purpose. A small disturbance in the supply chain could lead to financial disaster for the companies involved [48]. In a highly volatile and challenging environment, low-risk supply chains seem to be the main strategy to ensure uninterrupted and profitable business operations [48]. In FinTech and CPN companies, various strategies have been promoted in order to ensure that in challenging periods the supply chain will remain productive and beneficial [42,49]. The analysis of big data and the implementation of artificial intelligence in risk management strategies can play a significant role in the vitality of a company [42].

2.3. Innovative Crisis Effects Analysis

One of the most significant parts of corporate survival has been the development of crisis management. Following major crises have been identified amongst the most fruitful periods for an upsurge in innovation. A decrease in the quantity of innovation performed by tech startups does not always reflect a decrease in economic growth [50]. The lengthy consequences of such disturbance are determined not just by its volume influence, but also by the value improvement that it could cause. But real financial effects of the disturbance are partly determined by the capacity of innovation to migrate throughout various companies. Overall, a crisis phase could be used to shift innovation processes to more efficient organizational structures and meaningful initiatives [51].

In the aftermath of a crisis, there is a huge and continuous reduction in emerging enterprises, and great technical breakthroughs are made by both stalwarts and startups. These included the beginnings of FinTech, cloud storage/computing, knowledge sharing, along with substantial developments in artificial intelligence, which fueled a surge in innovative initiatives [52]. In this path, the adoption and analysis of crowdsourced-obtained data regarding customers' onsite behavior can be an innovative leap forward. During a crisis period, organizations, especially those counting on customers' service usage frequency, need access to customers' behavioral data. These data refer to web analytic metrics, acquired via crowdsourcing platforms, providing valuable intelligence to FinTech organizations. Such information could be harvested in terms of timely assessment of crises' effects on centralized payment network organizations' website customers.

2.4. Big Data, and Web Analytics of Passive Crowdsourcing and FinTech

According to previous research, competitive advantage can be accomplished by analyzing and utilizing big data [53]. "Big data" is a large amount of unstructured information [12]. Marketeers, to gain knowledge from these massive amounts of information must structure and process those data [12]. A wide range of industries could gain useful insights from the use of big data such as government agencies, FinTech, and crowdfunding [54]. Web analytics is a type of passive crowdsourcing that incorporates the big data generated by web users throughout their normal web research [3,4,55]. This process can be elucidated as the gathering and evaluating user's activity on a company's website, for businesses to acquire a wider knowledge of the interactions that occur between web users and corporate web pages [56,57]. This process can be applied in social media marketing research to produce useful results for web developers and marketers [58]. The use and research of big data support innovation in the CPN and FinTech industry by making the procedures more interactive, platforms better to use, and promotes innovative business models [59,60].

Web analytics are extracted from corporate websites and transformed and processed in quantitative form, widely known as key performance indicators (KPIs) [61,62]. When users access a website in order to make a payment, various KPIs are produced. Those KPIs are divided into two categories: technical KPIs, such as fully loaded time for webpage size, and some behavioral KPIs, which include traffic, bounce rate, and average visits duration. In this research, the authors attempt to study the behavioral KPI's. Search engine marketing (SEM) encompasses every aspect of extracting search engines results encouraging the digital marketing strategy. The abundance of digital marketing campaigns and the poor knowledge of web metrics create challenges for KPIs to meet essential requirements [3,63] and for marketers to integrate web analytics metrics with the optimal outcome for the organization's KPIs [3,64]. In this research, the authors propose and investigate the KPIs listed in Table 1.

As can be distinguished from previous research [3,4,6], the importance of various web analytic metrics to firms' digital marketing and advertising campaigns' efficiency has been proven significant. The referred researches focus mainly on crowdsourcing organizations, air forwarder businesses, airline firms, and cryptocurrency trade organizations. Therefore, a research gap is spotted regarding the digital advertising efficiency of CPN organizations, via crowdsourced web analytic metrics utilization. In order to extract valid insights for CPNs' advertising performance, the impact of user engagement metrics (bounce rate, average time on site, average pages per visit, etc.) and website traffic type (branded or non-branded) to the main digital advertisement measurement variables of organic traffic and global rank [6].

Table 1. Illustration of the extracted KPIs.

Web Analytics	Description of the Web Analytics
Global Rank	This figure is derived from the visibility of the website and the overall traffic. The lower the figure of global rank means higher in popularity [11,65].
Organic Traffic	Organic traffic refers to visitors who arrive on a webpage as from unpaid search such as google search [4,66].
Branded Traffic	The traffic generated from users who have typed the company's brand name in their web searches is referred to as branded traffic [67].
Non-Branded Traffic	The traffic that generated from users who have not typed the corporate brand name in their searches [67].
Bounce Rate	Bounce rate is generated when a user visits a webpage and then leaves immediately without viewing any other webpage on the website. With lower bounce rates meaning that the website is more efficient [68,69].
Average Time on Site	This web analytic measures the average estimated time in seconds a user stays on a website [68].
Average Pages per Site	When a user enters a website, they access a lot of web pages, the metric Average Pages per Site counts how many web pages have been viewed per visitor [70].

Expanding our research's results, another variable is being added to specify insights for CPN firms by focusing on digital advertising efficacy during the COVID-19 crisis period. This will enable the proposition of an optimized digital advertisement campaign approach, regarding examination and optimization of selected digital marketing KPIs/web analytic metrics. These metrics (organic traffic and global rank), as mentioned before, provide a clear image of digital marketing and advertisement progress [6], and the selected period of measurement and examination set during the COVID-19 crisis could form an analytical methodological framework for CPN firms to consult.

Thus, we predominantly swift our focus to CPN companies' organic traffic and global rank variation, which depicts digital advertising efficiency, during the COVID-19 crisis. To do so, through our research, the main difference discerning the situation before COVID-19 and after should be discrete and inarguably proven. For a more appropriate description of a company's digital performance, the capitalization of the following KPIs must be evaluated by comparing to each other every 30 days.

3. Materials and Methods

3.1. Problem Formulation and Research Hypotheses

The ongoing COVID-19 pandemic has had a variety of effects on global supply chains. Many of these changes are still unknown since customers' behavior is constantly changing in response to the crisis's dynamic nature. During the early stages of the pandemic, the COVID-19 crisis grew almost linearly, as evidenced by the increasing number of COVID-19 cases. Customers' increased risk perception regarding the pandemic led them to e-commerce solutions, a move that is expected to trigger increased use of e-payment services.

Three fundamental questions arose as a result of this situation. Firstly, what was the effect of the crisis on the centralized payment networks websites' traffic, and how much was this traffic affected by the organizations' brand name? Secondly, in which way did customers change their engagement behavior with the centralized payment networks websites' content during the crisis? Finally, how did the crisis-induced online customers' behavior alternations impact the centralized payment networks' digital brand name?

The above questions aim at a single objective goal, namely to provide an adequate answer to whether web analytic metrics, with close relation to significant digital marketing KPIs, can be utilized to enhance CPNs advertising campaigns' efficiency. Paper's goal could be achieved by examining both digital advertising and marketing factors' impact from user engagement metrics' variation during the COVID-19 crisis. For digital marketing and advertising representative factors, organic traffic and global ranking metrics were chosen. Provided a rise of organic traffic metric, as well as, an enhancement (decrease) of global ranking metric emerges during the COVID-19 crisis, the implementation of website analytics, such as user engagement metrics, to assess and optimize CPN firms' digital advertising campaigns could be proven to be crucial and essential.

To provide answers to our questions, we will use passive crowdsourcing data from centralized payment networks websites, focusing on specific KPIs related to website traffic, user engagement, and site's ranking in the search engine. The results will allow centralized payment networks' managers to plan efficient marketing plans while operating in crisis environments and will provide them with valuable information to answer questions such as:

- Is online advertisement a good option during a crisis, or will the traffic attracted by brand name not justify the investment?
- Is search engine optimization of the network's website an effective way to use resources during a crisis, or will customers increase their focus on offline consumption choices?
- Should an organization allocate resources in brand empowerment through digital marketing, or the is significance of the brand's name dwindling during a pandemic crisis?

To provide answers to these research questions, we developed five hypotheses:

Hypothesis 1 (H1). *The rise of confirmed cases during the beginning of the COVID-19 crisis significantly affected the Organic Traffic of Centralized Payment Network websites.*

The number of daily new infections is the main communication tool that governments have used as a "pandemic severity metric". People's risk perception regarding the COVID-19 hazard changes as the crisis escalates and affects their consuming behavior by leading them to e-commerce solutions that are supported by remote payment networks. With Hypothesis 1, we want to clarify the cause-effect connection between the crisis escalation and the rise of centralized payment network websites' traffic. Results regarding this research question will lead to suggestions concerning resources allocation targeting effective crisis marketing strategies.

Hypothesis 2 (H2). *The impact of the COVID-19 crisis' confirmed cases on Centralized Payment Network Websites' Global Rank is significant.*

There are many indicators to measure a pandemic's spread to the public. However, the COVID-19 pandemic's escalation is usually indicated by reporting the number of daily new infection cases. The general public's perception of COVID-19 risk is expected to increase as this indicator rises. Hypothesis 2 attempts to explain the impact of this phenomenon on the search engine rankings of centralized payment network websites. The findings for Hypothesis 2 will help organizations plan effective marketing strategies during crisis periods by highlighting the main interactions between crisis variables and e-branding rankings.

Hypothesis 3 (H3). *User Engagement metrics cause a significant effect on Centralized Payment Network Websites' Global Rank.*

User engagement metrics is a helpful indicator that shows how much online users interact with a website. During the COVID-19 crisis, user engagement-related KPIs are expected to show increased engagement as online customers seek more information regarding the problems caused by the crisis to e-commerce and online payments. Outcomes from Hypothesis 3 will help organizations plan effective marketing strategies by predicting customer behavior during a novel crisis.

Hypothesis 4 (H4). *The impact caused on Centralized Payment Network Websites' Organic Traffic by User Engagement metrics is significant.*

The pandemic crisis led to supply chain irregularities triggering modifications to consumers' behavioral patterns. Consumers' adaptation to the COVID-19 crisis by adopting e-commerce solutions is well documented. However, their interaction with the websites' content has still not been thoroughly studied. Results related to Hypotheses 4 will allow us to highlight the correlational connections between users' engagement metrics and the organic traffic KPI of centralized payment networks websites, leading to conclusions regarding cost-efficient e-branding strategies.

Hypothesis 5 (H5). *Organic Traffic of Centralized Payment Network websites is significantly affected by Branded and Non-Branded Traffic.*

Consumers' risk perception is reported to be highly affected by trust. A well-established brand is more likely to attract visitors to the company's website compared to non-branded options. However, in crises, people adapt to the new dynamic environment by implementing new consuming habits. Hypothesis 5 will attempt to clarify the extent that brand name affects organic traffic of centralized payment network websites. Results regarding this research question will help centralized payment organizations clarify whether e-brand empowerment is an effective marketing strategy during a novel crisis.

3.2. Sample Selection and Collection

The sample collected for research purposes has been composed of the top five payment networks' websites that are based on central authorities (e.g., financial institutions, banks, etc.), based on website services' user interface, security protocols, and transactions performed, all of which promote security and confidentiality [71]. Data collection occurred through harvesting of crowdsourced data via specific website service providers in a period of time from 180 days to 2 years. The gathered data illustrate time-variated websites users' onsite behavior and are commonly known as Web Analytics. The collected web analytic metrics of the sample originated from the following websites: Paypal, Skrill, Stripe, Bluesnap, and AuthorizeNet.

With the observation and collection period reaching up to 720 days, we gathered daily analytic metrics of website users' behavior after attentive elaboration. As far as the COVID-19 confirmed cases are concerned, we addressed the European Center for Disease Prevention and Control (ECDC) archives and collected daily registered cases from 23 January 2020 until 2 December 2021. The obtained data refer to important business' digital marketing KPIs, where most of these data correspond to a unique KPI. In other words, each metric matches with a specific variable appeared in Table 1. They are quantitative raw data, that present the historical trajectory of the selected metrics. The source of the data originates from a decision support platform based on the Internet (www.semrush.com; accessed on 10 January 2022), where access can be granted only through payment via that platform. After obtaining the above datasets, we developed an extensive analysis, aiming to provide centralized payment networks with a handful of insights regarding the effectiveness of their advertisement to their digital branding, during potential crises, such as the COVID-19 pandemic.

4. Model Formulation

4.1. Diagnostic Model Deployment

Due to the rapid growth of WEB applications in organizations and businesses, the use of web technologies has also increased, a fact that will enhance strategic decision-making skills [72]. FCM is a parameterized form of concept mapping where static models representing knowledge can be developed by defining the basic characteristics of a system such as system variables, positive or negative correlations between variables, and the degree of correlation that a variable can have in another. FCM analytical mechanisms are based on the structure of concept maps and are carried out using graphs and graph-based analyzes between the variables contained in a model. These models can be used to model a system affected by many variables, where the attempt is made to map the correlations between the variables and to map the system [73]. Big data mining provides bulky data that needs to be analyzed in order to turn it into information for businesses and organizations. Using FCMs, data can be converted into information by drawing complete conclusions from the data received from the web. Misinterpretation of web data could lead to erroneous conclusions about the analysis of information, resulting in a negative impact on the development strategies of the organization or business. For proper data analysis, researchers recommend the use of FCM-based web analytics data.

The development of FCM will help organizations to implement effective advertising strategies [74], with the aim of developing digital brand name. For this analysis, we will use the data collected from web analysis platforms [75]. Using FCM, we will develop simulation scenarios based on positive and negative interactions that are statistically significant. The FCM will be developed between the variables related to the daily case values of COVID-19 and the performance indicators of KPI's websites selected for the purpose of this study. We focus on providing SCRM information related to strategies for developing the digital brand name, which occurs in times of crisis such as the COVID-19 pandemic [76].

From the previous stages of analysis, data were extracted that are related to five selected globally active organisms, for a period of 24 months, during the existence of COVID-19. The data obtained refer to eight variables representing the branch organization of the central payment system websites. The Cronbach alpha method was applied to these data for their reliability and the relationships between the variables related to the KPI variables and the COVID-19 crisis were established [77].

The data obtained were further processed through the Pearson correlation coefficient test with a total of 15 statistically significant correlations. Twelve strong correlation characteristics are presented at the level of statistical significance 0.01. These results highlight the dynamic characteristics of digital branding during a crisis, such as the COVID-19 pandemic.

Through the variation of the statistical analysis variables, a causal link was established between the variables with high Pearson correlations ($r > 0.8$). The strong correlations and variables associated with web analytics are based on research findings on consumer behavior, which report consumer behavioral adjustments that respond to external stimuli (such as a new crisis).

The research findings using web analytics show strong correlations between the variables related to the COVID-19 crisis and digital branding [78]. Also important is the element that highlights the behavioral adjustments of consumers that respond to external stimuli such as a new crisis. Using this data, we developed an FCM to present all of the interactions between the COVID-19-related variables and the KPIs studied in our research (Figure 1). The dynamic environment of the FCM provides a wide range of possibilities for evaluating and reporting results in relation to our study, as this technique can simulate the interaction results between the KPI and COVID-19 variables (Figure 2) with stable correlations and provide us with the information we need in relation to decision making.

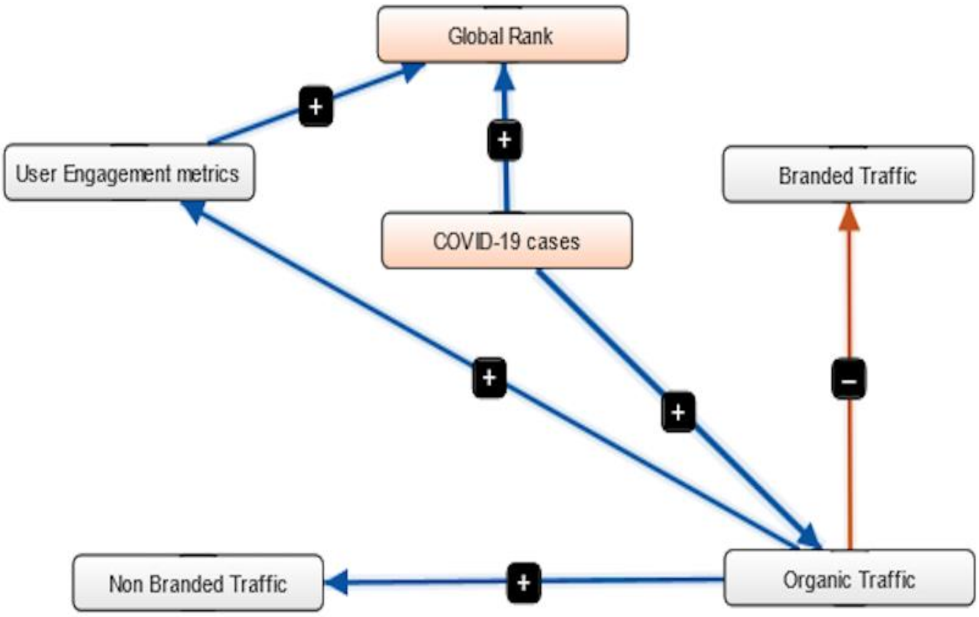


Figure 1. Correlations between variables with FCM.

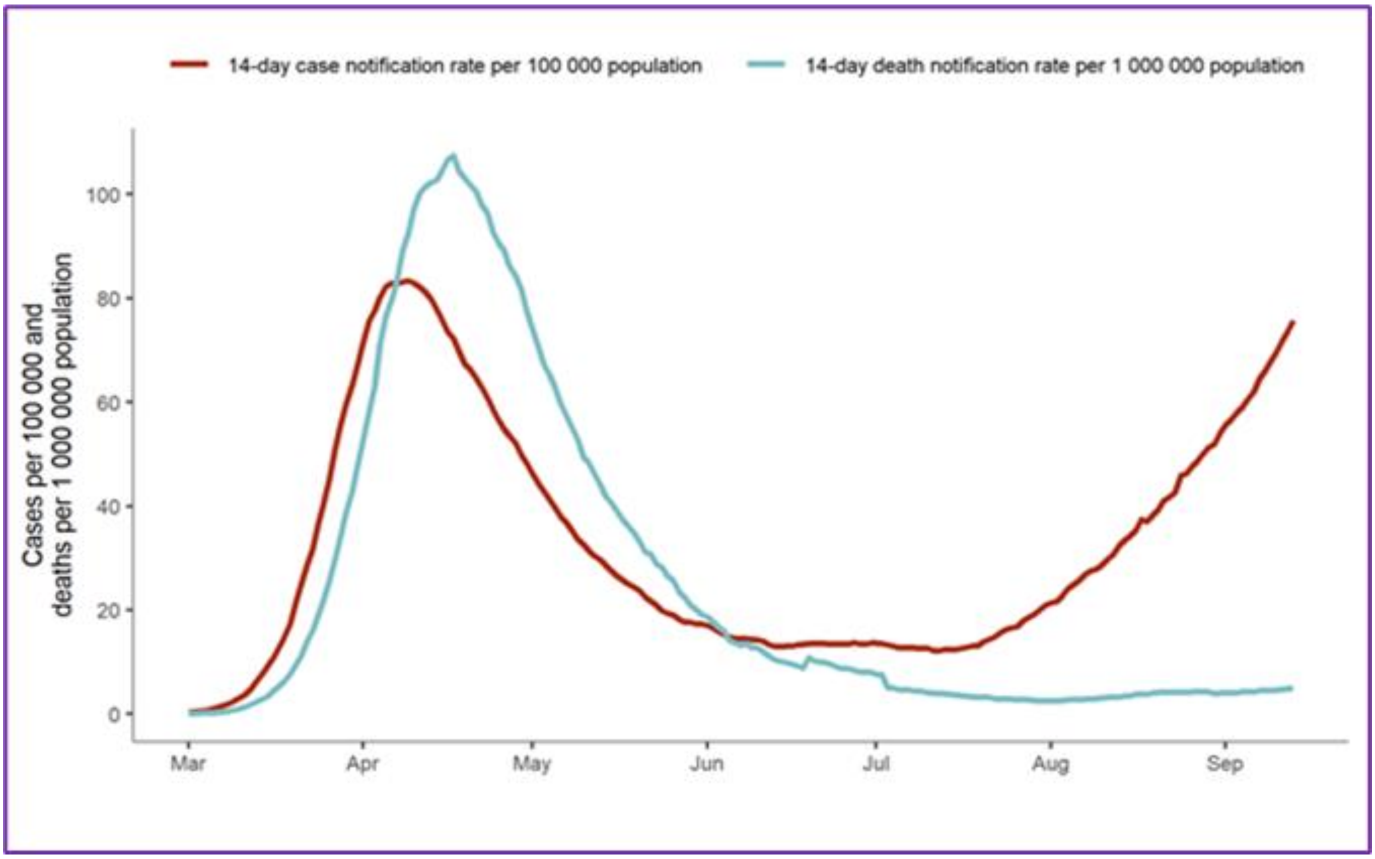


Figure 2. COVID-19 confirmed cases from March 2020. Obtained from European Centre for Disease Prevention and Control (www.ecdc.europa.eu; accessed on 5 January 2022).

The creation of FCM is easily adapted to the current data and situations and is also based to a large extent on human knowledge and know-how. The use of FCMs has been shown to help visualize decision-making systems in many different areas of science.

4.2. FCM Analysis with Factors from the Model

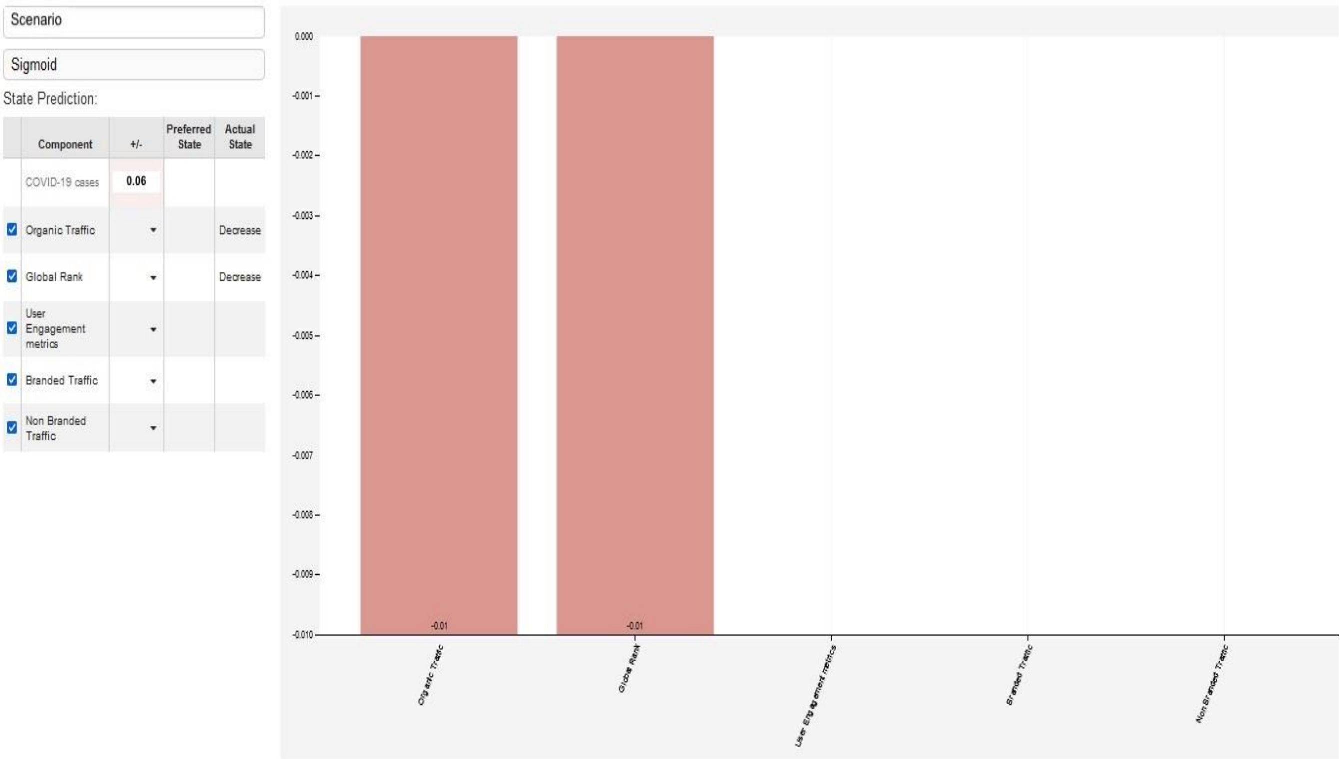
Through the analysis of the FCM concept map, it is understood that the number of daily new infections referred to as the "pandemic severity measurement" of COVID-19 risk is changing for the better as the crisis escalates and affects consumers' behavior. It also increases the impact of the COVID-19 crisis phenomenon on the search engine rankings of the main sites of the payment system. Organizations will be helped to design effective marketing processes during times of crisis, based on the key interactions that crisis variables bring to e-branding rankings.

During the COVID-19 crisis, indicators that measure user loyalty show increased loyalty since users search the Internet for more information on the problems caused by the crisis in electronic payments.

The analysis of the FCM concept map shows that the loyalty of users and KPI indicators of organic traffic to central payment system sites is increasing, leading, respectively, to positively cost-effective e-branding strategies.

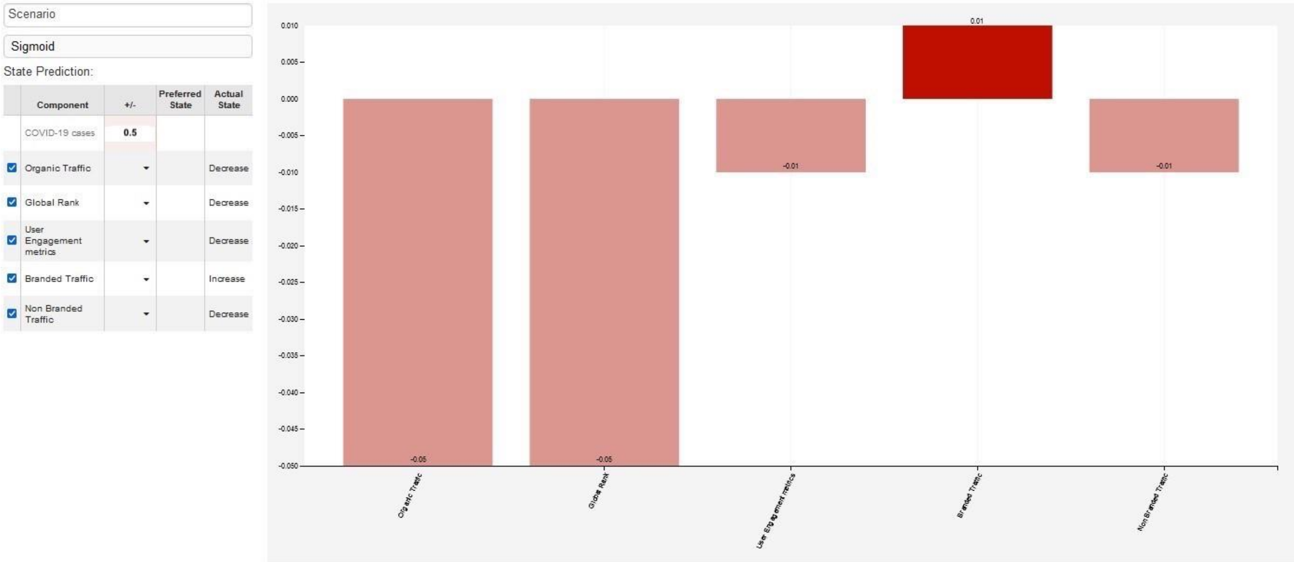
A branded company is more likely to attract visitors to its website than an unnamed company. However, crisis situations lead users to adopt new consumer habits. The analysis of the FCM concept map shows that the brand influences the organic traffic of the central payment network websites.

Furthermore, although the behavior of the "Average Daily COVID-19 Cases" fluctuates at constant levels, it is obvious that the variables global rank, organic traffic, non-branded traffic, and bounce rate show positive fluctuations in contrast to branded traffic, average time on site, and average pages/visit located on the negative axis. Figure 3 shows the results of the concept map (FCM), which presents the correlations between the variables in three different phases of the COVID-19 cases.

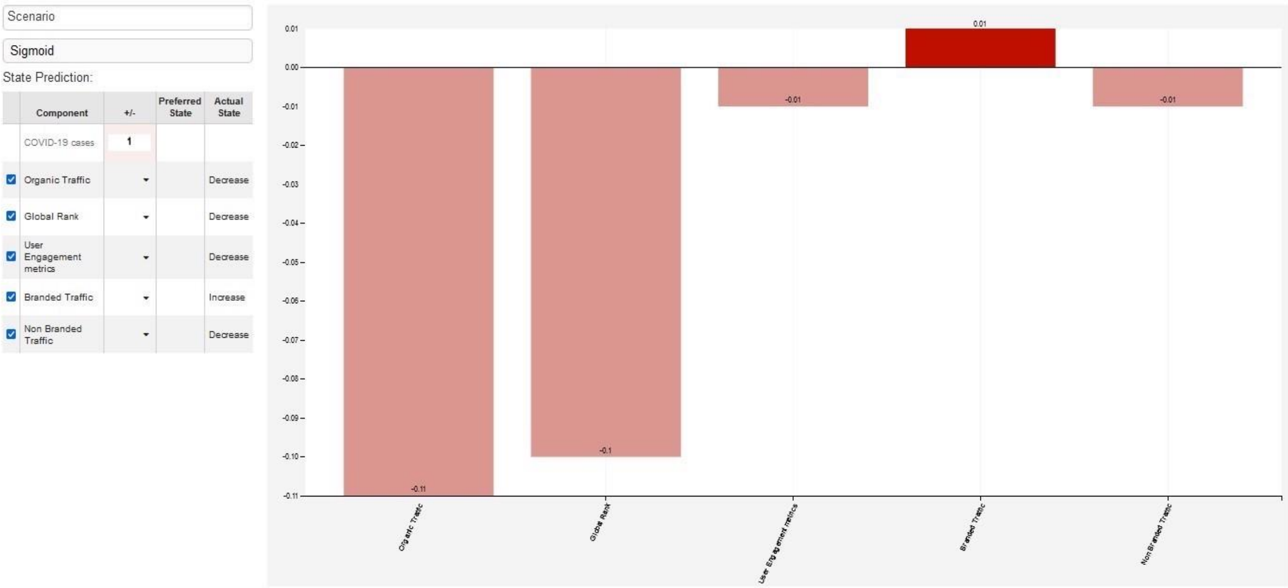


(**a**)

Figure 3. *Cont.*



(**b**)



(**c**)

Figure 3. The results of the concept map (FCM), presents the correlations between the variables. Figure 3 presents three phases of the model depending on COVID-19 cases. (**a**) presents lower cases, (**b**) presents medium cases, and (**c**) presents higher cases of the COVID-19 pandemic.

5. Results

5.1. Statistical Analysis

In this section, we see in Table 2 the descriptive statistics' outcomes regarding the 5 selected centralized payment network websites. Mean, max, min, and std deviation statistics have been chosen. Table 3 shows the Pearson correlations.

Table 2. Descriptive statistics of centralized payment network websites.

	Mean	Min	Max	Std. Deviation
Average Daily COVID-19 Cases	249,368.25	0	630,774	230,319.450
Global Rank	161,912.93	133,568	190,861	20,999.987
Organic Traffic	53,517,713.60	48,526,821	62,016,293	4,785,161.121
Bounce Rate	0.44	0.35	1.18	0.2044
Averages Pages/Visit	822.79	724	887	45.835
Average Time on Site	52,463.53	45,167	58,196	3521.240
Branded Traffic	15,999,920.00	13,624,700	17,720,600	1,143,240.497
Non-Branded Traffic	811,486.67	591,400	1,926,500	376,880.225

N = 180 observation days for 5 centralized payment network websites.

Table 3. Variables correlations.

Variables	Average Daily COVID-19 Cases	Organic Traffic	Global Rank	Average Pages/Visit	Bounce Rate	Average Time on Site	Branded Traffic	Non-Branded Traffic
Average Daily COVID-19 Cases	1	0.933 **	−0.848 **	0.724 **	−0.309	0.494	0.792 **	−0.489
Organic Traffic	0.933 **	1	−0.873 **	0.578 *	−0.339	0.339	0.841 **	−0.454
Global Rank	−0.848 **	−0.873 **	1	−0.643 **	0.427	−0.492	−0.783 **	0.540 *
Average Pages/Visit	0.724 **	0.578 *	−0.643 **	1	−0.010	0.892 **	0.648 **	−0.646 **
Bounce Rate	−0.309	−0.339	0.427	−0.010	1	−0.047	−0.222	−0.009
Average Time on Site	0.494	0.339	−0.492	0.892 **	−0.047	1	0.498	−0.579 *
Branded Traffic	0.792 **	0.841 **	−0.783 **	0.648 **	−0.222	0.498	1	−0.817 **
Non-Branded Traffic	−0.489	−0.454	0.540 *	−0.646 **	−0.009	−0.579 *	−0.817 **	1

* and ** indicate statistical significance at the 95% and 99% levels, respectively.

Tables 4 and 5 show the outcomes of Levene's statistic for independent *t*-tests performed for centralized payment network websites' organic traffic and global rank variables. According to Levene's statistic [79], levels of significance below 0.01 indicate inequality of variances between two chosen variables' variations. This means that for organic traffic, the variables do not have equal variances (*p*-level = 0.009) between and after the selected time period of data segregation, while the global rank variable marginally does not have equal variances at the selected periods (since significance levels of equal variances have lower *p*-level than equal variances assumption (*p*-level = 0.000)).

Table 4. Organic traffic independent sample *t*-test before and after COVID-19 crisis.

	F	*t*-Test	*p*-Value	Hypotheses	*p*-Values
Organic Traffic	9.459	−2.076	0.009 **	Equal variances assumed	0.058
		−4.226		Equal variances not assumed	0.001 **

** indicate statistical significance at the 99% levels.

Table 5. Global rank independent sample *t*-test before and after COVID-19 crisis.

	F	*t*-Test	*p*-Value	Hypotheses	*p*-Values
Global Rank	4.348	2.665	0.057	Equal variances assumed	0.019 *
		5.479		Equal variances not assumed	0.000 **

* and ** indicate statistical significance at the 95% and 99% levels, respectively.

Through Tables 6 and 7, we get the impact that specific user engagement metrics, such as bounce rate, average time on site, and average pages per user, cause centralized payment websites' organic traffic and global rank. Almost all engagement variables are statistically significant, with *p*-value levels below 0.05, except for average time on site for global rank dependent variable and bounce rate for the organic traffic one. Both regressions were verified overall with levels of significance below 0.05. More specifically, they had $p = 0.009$ and $p = 0.011$, as well as $R^2 = 0.637$ and $R^2 = 0.622$ accordingly. Centralized payment websites' global rank variates up to −1.066 from average pages per visit, 0.439 from bounce rate, with organic traffic variating up to 1.409 from average pages per visit and −0.936 from average time on site. This means that for every 1% increase in average pages per visit and bounce rate, global rank decreases by 106.6% and increases by 43.9%, respectively, while organic traffic increases by 140.9% and decreases by 93.6% accordingly.

Table 6. User engagement metrics impact on centralized payment network websites' global rank.

Variables	Standardized Coefficient	*t*-Test	R^2	F	*p*-Value
Constant	-	5.648	0.637	6.422	0.009 **
Average Pages/Visit	−1.066	−2.641			0.023 *
Bounce Rate	0.439	2.405			0.035 *
Average Time on Site	0.480	1.187			0.260

* and ** indicate statistical significance at the 95% and 99% levels, respectively.

Table 7. User engagement metrics impact on centralized payment network websites' organic traffic.

Variables	Standardized Coefficient	*t*-Test	R^2	F	*p*-Value
Constant	-	0.182	0.622	6.029	0.011 *
Average Pages/Visit	1.409	3.421			0.006 **
Bounce Rate	−0.368	−1.977			0.074
Average Time on Site	−0.936	−2.269			0.044 *

* and ** indicate statistical significance at the 95% and 99% levels, respectively.

In Table 8, the influence of branded and non-branded traffic on centralized payment websites' organic traffic is estimated. By applying the linear regression method, we see that the generated regression model is overall verified with *p*-level of significance below 0.01, more specifically $p = 0.000$ and $R^2 = 0.872$. Centralized payment websites' organic traffic variates up to 1.415 from branded traffic and 0.702 from non-branded traffic. Thus, for every 1% increase in branded traffic and non-branded traffic, organic traffic increases by 141.5% and 70.2%, respectively.

Table 8. Brand awareness impact on centralized payment network websites' organic traffic.

Variables	Standardized Coefficient	*t*-Test	R^2	F	*p*-Value
Constant	-	−3.571	0.872	40.750	0.000 **
Branded Traffic	1.415	7.888			0.000 **
Non-Branded Traffic	0.702	3.913			0.002 **

** indicate statistical significance at the 99% levels.

5.2. Development of Predictive and Simulation Model

In this section, the deployment of agent-based model (ABM) analysis takes place. For ABM deployment, the dynamic correlation and dependent and independent variables' coefficients are used. This leads to potential prediction model efficiency by enhancing its consistency [80]. The main goal of the model's deployment is the examination of centralized payment network websites' global rank and organic traffic trajectory, both brand name variables, during the crisis of rising confirmed COVID-19 cases. In the ABM procedure, a group of agents (visitors) intercommunicates with each other and gives valuable intel for organizations' decision-making processes [81]. Agents are instructed to comply with specified commands, set by parameters such as COVID-19 daily cases, average pages per visit, average time on site, etc., and various operators, such as 'if', et al.

There exist multiple advantages for centralized payment network organizations from adopting ABM analysis. Possible variables of the analysis are website global rank, organic traffic, engagement metrics, etc. In order to do so, these web analytic metrics should be aligned with organizations' preferred key performance indicators. This will enable precise daily counting and observation of metrics' chronological trajectory. Our model utilizes correlations and regression coefficients of crowdsourced data, in a 360-days' time period, using one-time snapshot measurement, as can be seen in Figure 3.

Next comes Figure 4, where the agent-based model begins the simulation process from the statechart of centralized payment network websites' potential visitors. During the model's runtime, the variation of the confirmed cases of COVID-19 is calculated based on the normal distribution function in order to compare it with global ranks' and organic traffic's distributions. The next statechart is centralized payment network websites keywords since potential visitors end to websites through typing specific keywords, with the discrimination of returning or unique visitors statecharts following (meaning that the referred visitors either have entered before or entered for the first time the websites). Then, according to whether potential visitors are classified as branded or non-branded sourced traffic they go through branded or non-branded traffic statecharts. Remaining visitors that do not abandon the website, through bounce rate statechart, contribute to centralized payment network website engagement statechart and then after to the organic traffic one. By reaching the organic traffic statechart, visitors cause a variation to centralized payment network website global rank. The whole process is visualized in Figure 3.

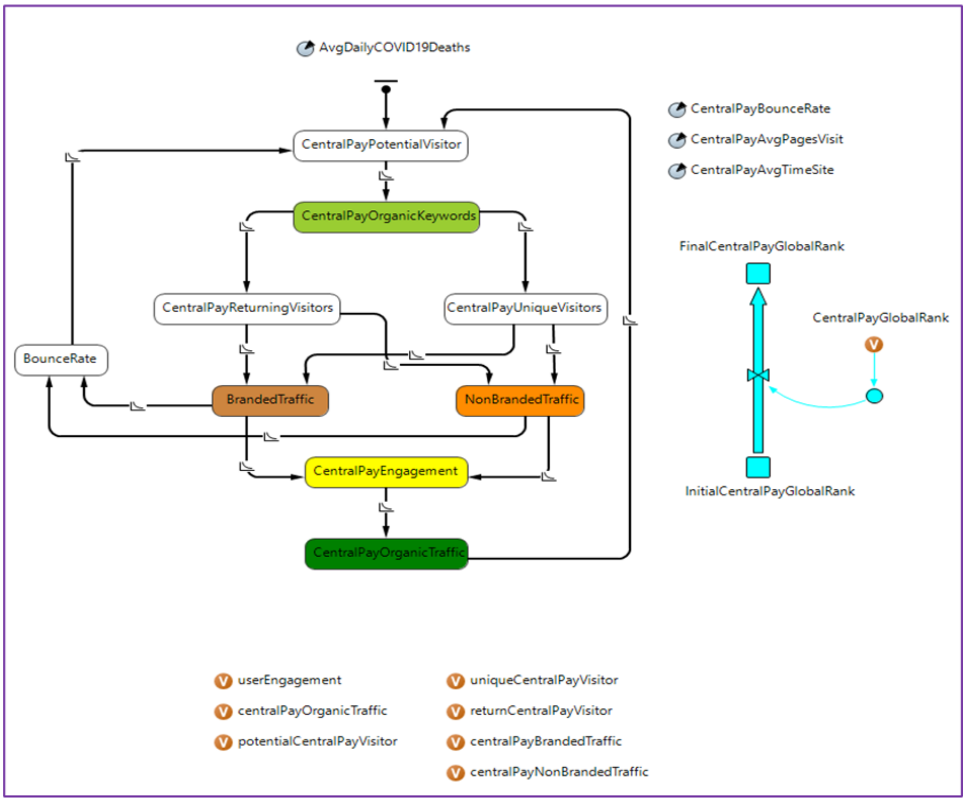
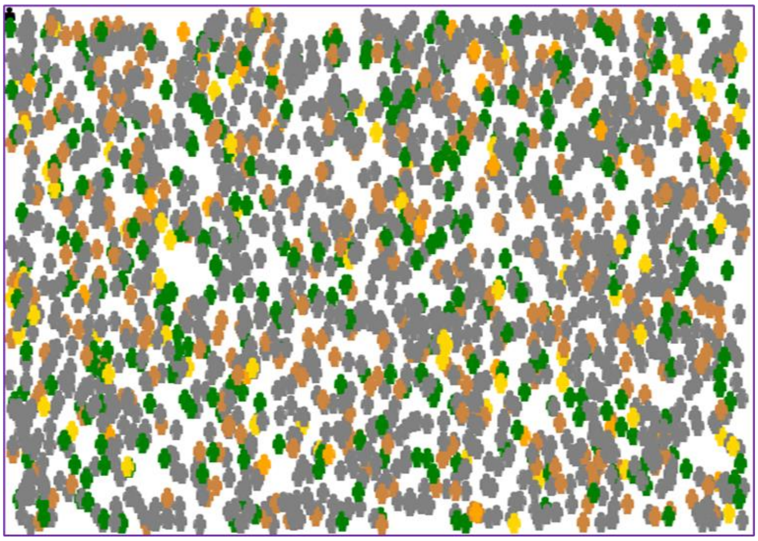
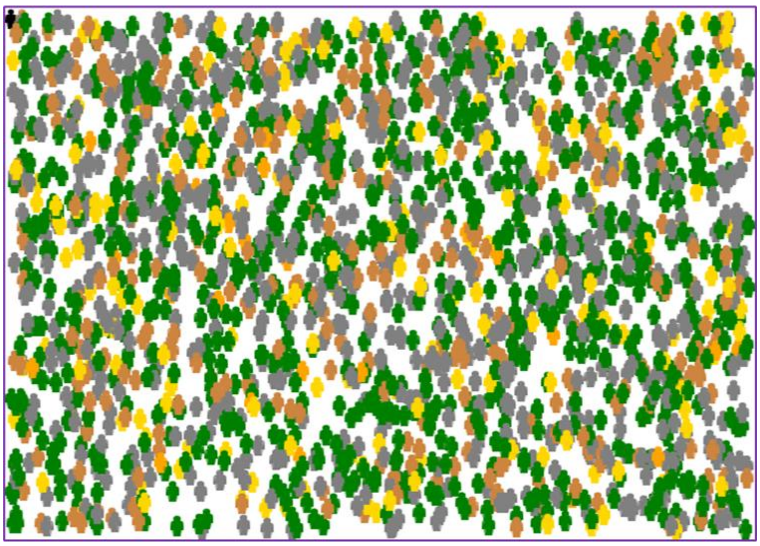


Figure 4. Agent-based model development for simulation of centralized payment websites metrics during COVID-19 crisis.

Simulation performance leads to results depicted in Figures 5 and 6. In Figure 5a,b, we see the dispersion of 2000 agents in the 360-days simulation period. Agents represent potential visitors of centralized payment network websites that follow the path described in Figure 4. So, centralized payment network websites' visitors that abandon the webpage are represented with a gray color. A brown color and black color are used to represent the visitors who end up to the websites through searching a company's brand name and those who do not search for that specific name, respectively. The yellow-colored agents present those agents who got engaged with the website and its contents and with the green color are depicted the agents that form websites' organic traffic. In the first part of Figure 5a, we see the allocation of agents when the confirmed COVID-19 cases were at a low level, at the beginning of the crisis, and at Figure 5b, the allocation of agents with an increasing number of confirmed COVID-19 cases, at the outburst period.



(**a**)



(**b**)

Figure 5. (**a**) Allocation of 2000 agents at the beginning of the COVID-19 crisis. Gray color: bounce rate metric; brown color: branded traffic; black color: non-branded traffic; yellow color: engaged visitors; green color: organic traffic. (**b**) Allocation of 2000 agents during the outburst of COVID-19 cases. Gray color: bounce rate metric; brown color: branded traffic; black color: non-branded traffic; yellow color: engaged visitors; green color: organic traffic.

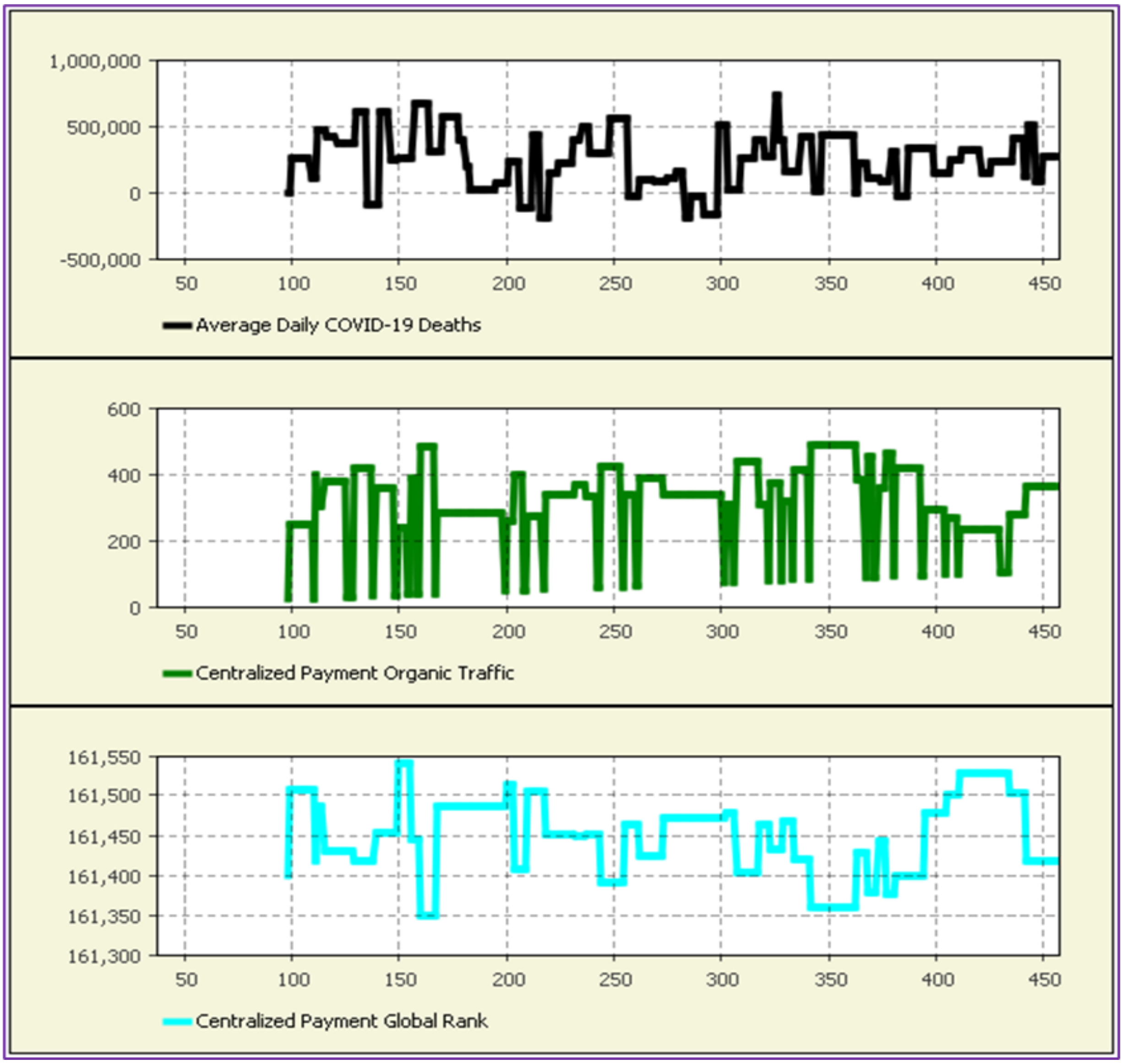


Figure 6. Illustration of centralized payment websites user engagement and its impact on their global rank and organic traffic during COVID-19 crisis.

Finally, in Figure 6 the variation throughout the 360-simulation days is presented. At the vertical axis, we see the amount of COVID-19 confirmed cases, the organic traffic of centralized payment network websites, and their global rank, while at the horizontal one model's time period can be discerned.

At this point, it is important to highlight that organic traffic and global rank data were divided regarding the occurrence of the COVID-19 crisis, which was set on the 1 May 2020. Hence, the variations of organic traffic and global rank that were tested pertained to 2 months before and 4 months after the crisis' burst. Through validation of independent sample *t*-test inequality of variances' significance, as shown in Tables 4 and 5, we can verify our first and second research Hypotheses, assuming that centralized payment network websites' organic traffic and global rank metrics were significantly impacted by the COVID-19 crisis.

The impact of average time on site to centralized payment websites' global rank and bounce rate to their organic traffic get significance levels above 0.05 (Tables 6 and 7), meaning they cause no important effect on these metrics. This leads us to the verification of the third and fourth research Hypotheses, meaning that centralized payment network websites' global rank and organic traffic are significantly impacted by the user engagement metrics. From Table 8's data, we conclude that our fifth and last Hypothesis is verified, meaning that both branded and non-branded traffic can cause significant effects on centralized payment network websites' organic traffic since their p-values are stated to be significant (below 0.05).

We suggest that, from the regression analysis that preceded, the rising number of COVID-19 cases provokes significant variation to centralized payment network websites' global rank and organic traffic. This effect on global rank and organic traffic variations show that before and after the outburst of confirmed COVID-19 cases, which was set by WHO at the beginning of March 2020, the distribution of global rank and organic traffic has been significantly altered. Then, by examining the impact of user engagement metrics and branded and non-branded traffic to global rank and organic traffic variables we saw that: centralized payment network websites' global rank decreases (enhances) when average pages per visit increase and rises when bounce rate increases, while organic traffic increases when average pages per visit, branded and non-branded traffic increase and decreases when average time on site increases. We also get the result that average time on site and bounce rate does not appear to cause significant impact to global rank and organic traffic, respectively, with p-values above 0.05, unlike the rest of engagement metrics.

What can be discerned from Figure 5a,b allocations is that, during the COVID-19 crisis, expressed via rising cases of the COVID-19 pandemic, the engagement levels of centralized payment network websites lead to higher numbers of centralized payment network website organic traffic. From the simulation results shown in Figure 6, we can see that when the COVID-19 confirmed cases spiked, during the course of the pandemic, centralized payment network websites' organic traffic increased and global rank decreased, meaning that both metrics performances were improved.

From the above results, a plethora of implementations arises regarding CPN companies. It can be discerned that CPN companies could face potential benefits during future crises, such as the COVID-19 crisis, mostly including website visitors' engagement. Increased visitor engagement means that the websites' content becomes more attractive to them, thus enhancing the visibility of pages' layout and features. In return, enhanced webpage layout and features visibility mean higher advertisement efficacy and better product/service placement with increased customers' demand - all of which potentially lead to increased CPN companies' profitability and sustainability. More specifically, the referred process of CPN companies' sustainability improvement could be also achieved from the increased organic traffic and enhanced (reduced) website global rank. Higher levels of website visitor engagement mean increased organic traffic and enhanced global rank for CPN companies, proving that more internet users land on the website through organic search and this happens also due to the highly identifiable CPN website.

This can potentially give valuable information to centralized payment network websites about the advantages of harvesting web analytics for website performance during crisis periods. Hence, it gets clearer that an optimized digital marketing strategy for centralized payment networks, based on enhancing their global rank and organic traffic, should aim in increasing the average pages visitors see, the branded and non-branded traffic they attract and reducing visitors bounce rate and the average time they spend on site.

6. Discussion

The purpose of this paper is to provide a deep understanding of the variables that mainly affect the brand name of FinTech platforms during a crisis. Having big data as the starting point, marketing managers will have an ample opportunity to redesign the company's marketing activities so as to heal the wounds that COVID-19 has left behind and move forward to the challenging post-COVID era [4,6,11].

A comprehensive agent-based model has been developed to offer useful pioneering-context insights pertaining to digital marketing refinement activities and based on behavioral KIPs so as to enhance organic traffic and global rank. Organic traffic, global rank, and specific users' engagement metrics were examined and proved to be crucial variables that every manager should invest in so as to employ successful digital marketing activities [11,12].

The main source of data gathering has been the five top FinTech websites, where the authors sought to acknowledge the impact of the crisis on brand awareness. The outcomes emerged from the research clearly stating that the rise of confirmed cases had a significant effect on organic traffic and global rank of centralized payment networks' websites. This outcome is significantly important in two ways: first, during novel crises, CPN with high organic traffic tends to convert new visitors on to actual customers if the right solution is being provided. Second, e-branding ranking leads to high conversion rates since it recalls customers' perception and experience [44].

The study further reveals the importance of behavioral KPIs when developing an effective crisis marketing campaign so as to eliminate risk [43]. For instance, global rank is positively affected by the average page/visit. It goes without saying that the more pages are visited, the more the audience is engaged with a company's website. This is an excellent way to measure interest and to provide the website with tailor-made content that will drive users into the conversion funnel. However, it is important to consider KPIs together to receive accurate judgments.

A significant amount of research has been conducted in numerous aspects of the banking sector, including competitiveness and profitability, under the scope of big data [82]. Chauhan et al. analyze 88 scientific papers, between 2001 and 2021, examining different aspects of digital banking [83]. They conclude that functional, mechanic, and humanistic clues determine customer satisfaction. However, even if an analysis of website attributes, design, and perceived usability has been the point of several studies [83], none of them have further investigated users' online behavior based on big data.

In the digitalized era, crowdsourcing services prove to be useful due to the large amount of available data. Online consumers leave their fingerprint each time they visit a website. Without any exaggeration, marketing activities should largely depend on big data. User engagement metrics tend to receive much interest lately, confirming the outcomes of our research [3,84,85].

Additional insight for the organic traffic and global rank is provided by other users' engagement metrics as well. For example, CPNs' organic traffic increases as branded and non-branded traffic increases and decreases when bounce rate is high. As a consequence, if optimizing SEO strategy and improving digital branding is the pivotal aim, companies should invest in users' behavior metrics and allocate enough resources to develop efficient marketing strategies so as to create awareness and online mobility.

7. Conclusions

COVID-19 has changed the field of e-business by leading users to acquire new consuming habits and to adapt e-commerce solutions. The banking sector, especially centralized payment system network companies, are battered but not beaten by COVID-19 disruption [52]. These companies are required to see the pandemic as an opportunity to redesign their online presence and take advantage of the current environment [86,87]. Wang et al. acknowledge the importance of crowdsourced data and big data analytics in healthcare organizations [88]. Several studies have been conducted on the importance of crowdsourcing as a source of competitive advantage [89], to improve business processes [90] and to facilitate acquiring knowledge, creativity, and new content [91]. However, the importance of analyzing big data and transferring the knowledge to crowdsourcing has been the point of least research within the banking sector (especially when digital marketing comes to matter).

The outcomes of the current research clearly demonstrate the importance of employing a SEO strategy based on big data. Important users' engagement metrics, such as average pages per visit, bounce rate, average time on site, and web traffic are considered to be crucial variables, able to predict customers' behavior [92]. The pain point of every CPN company is to find those specific variables, or a combination of them, that predominantly shape the perceptions of online users towards a brand. This will enable marketing managers to better allocate the resources on marketing activities that will generate new traffic and not just gain traction from users already interacting with the company's brand.

The current research has focused on the impact of users' online behavior to influence the brand name of CPN companies. A great opportunity for brand awareness is for companies to use crowdsourcing as a marketing tool [93], especially during novel crises periods. Being able to engage with a company's audience through crowdsourcing is considered as one of the best strategies in order to generate value for business without ignoring employees' satisfaction [90,94]. For instance, one company can deliver a website with a professional content (content creation) that favors users' perceptions as being reliable and trustworthy. By providing customers with tools, this not only creates positive brand experience but also converts consumers to brand evangelists.

CPN companies are not known for providing personalized customer experiences [95]. To this end, big data and web analytics could contribute to tailor-made, non-obtrusive experiences in a simple and cost-effective way. This is the first step to high engagement success by determining accurate behavioral KPIs and acknowledging market trends. This will save them time and will lead them in making accurate and timely decisions on optimizing the content of the website. It is a cost-efficient and added-value way to better allocate resources on paid advertisements, exclusive offers and deals, and to invest on a successful SEO strategy and brand empowerment based on specific keywords. CPN's marketing department could daily observe the website's performance, in terms of visitors' traction, and monitor how content strategy aligns with users' interest.

Loads of information is born constantly due to big data, leading to the conclusion that e-business is no longer static. Big data solution tools permit not only to make future predictions but also to target the right audience in a more efficient and low-budget way. The updated and precise picture of the market demand that big data constantly provides and empowers data-driven business to succeed enormously.

8. Research Limitations and Future Research

The main focus of this paper is to identify the importance of using big data and web analytics to predict consumers' behavior and to better acknowledge behavioral KPIs related to digital brand names. However, the findings of this study have to be seen in the light of some limitations. Five top payment networks' websites were examined in a period of time from one-hundred and eighty days to two years. Although the sample is representative for the purpose of the current study, more CPN websites should be examined to verify our hypothesis and provide a deeper understanding on users' online behavior.

In addition, specific user engagement metrics were examined and proved to have significant cause on CPN organic traffic and global rank. It would be interesting to examine other user engagement metrics within the banking sector, such as retention rate and session length, so as to gain a deeper understating on users' online attitude and purchasing intention. The outcomes would help CPN companies to properly allocate resources on the development of effective websites (e.g., to display related content) based on visitors' preferences.

Eventually, our proposed methodology and framework could offer deep insights to other markets as well and reflect users' behavior before, during, and after crises when organic traffic and global rank come to matter. Therefore, it should be expanded to and examined in other sectors, such as the healthcare sector, transportation sector, etc. The collection of suitable users' engagement metrics could provide accurate and handful insights to marketing managers and contribute to a company's viability and brand empowerment, during crisis periods.

As previously stated, in crisis situations, users show increased loyalty to branded websites. The outcomes of the current research could be used to measure CPN brand name performance and to optimize digital marketing strategy based on users' engagement metrics. However, much is still unknown on which users' engagement metrics contribute to social media strategies. Since big data is able to offer personalized experiences, based on their choices and likes. Future studies should focus on the effectiveness of a social media strategy, having behavioral KPI's as a solid base for future marketing campaigns.

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