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Engineering Supply Chain Transportation Indexes through Big Data Analytics and Deep Learning

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Abstract: Deep learning has experienced an increased demand for its capabilities to categorize and optimize operations and provide higher-accuracy information. For this purpose, the implication of deep learning procedures has been described as a vital tool for the optimization of supply chain firms' transportation operations, among others. Concerning the indexes of transportation operations of supply chain firms, it has been found that the contribution of big data analytics could be crucial to their optimization. Due to big data analytics' variety and availability, supply chain firms should investigate their impact on their key transportation indexes in their effort to comprehend the variation of the referred indexes. The authors proceeded with the gathering of the required big data analytics from the most established supply chain firms' websites, based on their (ROPA), revenue growth, and inventory turn values, and performed correlation and linear regression analyses to extract valuable insights for the next stages of the research. Then, these insights, in the form of statistical coefficients, were inserted into the development of a Hybrid Model (Agent-Based and System Dynamics modeling), with the application of the feedforward neural network (FNN) method for the estimation of specific agents' behavioral analytical metrics, to produce accurate simulations of the selected key performance transportation indexes of supply chain firms. An increase in the number of website visitors to supply chain firms leads to a 60% enhancement of their key transportation performance indexes, mostly related to transportation expenditure. Moreover, it has been found that increased supply chain firms' website visibility tends to decrease all of the selected transportation performance indexes (TPIs) by an average amount of 87.7%. The implications of the research outcomes highlight the role of increased website visibility and search engine ranking as a cost-efficient means for reducing specific transportation costs (Freight Expenditure, Inferred Rates, and Truckload Line Haul), thus achieving enhanced operational efficiency and transportation capacity.

Keywords: supply chain modeling; supply chain analytics; operation optimization; deep learning; feedforward neural network (FNN); big data; digital marketing strategy; decision support systems (DSSs)

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Citation: Sakas, D.P.; Giannakopoulos, N.T.; Terzi, M.C.; Kanellos, N. Engineering Supply Chain Transportation Indexes through Big Data Analytics and Deep Learning. *Appl. Sci.* **2023**, *13*, 9983. https://doi.org/10.3390/app13179983

Academic Editors: Ahmed Shaban, Giulio Di Gravio, Francesco Costantino and Riccardo Patriarca

Received: 26 July 2023
Revised: 1 September 2023
Accepted: 2 September 2023
Published: 4 September 2023

1. Introduction

1.1. Supply Chain Transportation Indexes Importance

Supply chain transportation is an important indicator of economic development from both a macroeconomic and microeconomic perspective, as well as one of the backbones of international trade, able to predict future trends and identify new opportunities for production, distribution, and consumption [1]. According to Statista [2], the market size of the logistics sector is worth ten trillion U.S. dollars globally and is projected to exceed 14.08 trillion U.S. dollars by 2028. These thrilling statistics, coupled with the evolution of smart technologies, come with both opportunities and threats. On the one hand, the explosion of Industry 4.0, which is associated with various innovations, has expanded businesses' operations by opening up new markets and increasing the customer base [3]. On the other hand, the occurrence of environmental factors, such as natural disasters and the COVID-19 pandemic, has affected the smooth operations of the industry, resulting in disruptions and increased vulnerabilities [4].

Until recently, the focal point of supply chain management was mainly cost-centered [5]. However, improving the performance of the supply chain requires more than just cutting costs. The elevation of the supply chain to become a source of competitive advantage has forced supply chain firms to adopt an integrated profile in which customer satisfaction is equally important [6]. This holistic approach has forced supply chain transportation firms to establish an environment of consistent supply chain visibility to avoid potential supply chain breakdowns while simultaneously meeting or exceeding customers' expectations by offering exceptional services.

The turn of the decade with the onset of the pandemic has highlighted the role of reliability and resilience as key quality factors for the optimization of supply chain transportation [7]. Such optimization is based on specific transportation indexes that assess the health of the supply chain. According to the Bureau of Transportation Statistics, "The Bureau of Transportation Statistics (BTS) Transportation Services Index (TSI), the Dow Transportation Index, and the Cass Freight Index represent transportation economic indicators that reflect the responses of transportation providers to the economy's demands for moving freight and/or passengers" [8]. There are several transportation indexes, such as the Freight Transportation Service Index (TSI), the Baltic Dry Index (BDI), the China Containerized Freight Index (CCFI), and the Air Cargo Index (ACI), among others, that serve as important tools to analyze transportation trends and assess the overall supply chain's transportation efficiency.

Lu et al. [9], acknowledge the National Logistics Performance Index (LPI) as "an interactive benchmarking tool to identify possible challenges and opportunities about the performance of trade logistics". Kumar & Anbanandam [10], have developed a social sustainability index for freight transportation systems. Azevedo et al. [11], propose the LARG index as a risk management tool to respond rapidly and cost-effectively to unpredictable changes and unexpected disturbances within the automotive supply chain. To this end, the performance of the supply chain is affected by specific transportation indexes.

To sum up, supply chain transportation indexes are essential tools for performance measurement, economic indicators, industry benchmarking, and risk management that enable businesses to optimize their logistics operations, adapt to changing market conditions, and maintain a competitive advantage. Although several researchers have investigated the sustainability performance of the supply chain through key transportation performance indexes [12], there are still some burning questions in mind. Have global supply chains adjusted to the new digital normal? What is the impact on supply chain transportation indexes due to the advancement of cutting-edge technologies, such as big data? Are supply chain transportation firms equipped to optimize their operations by unlocking the dynamics of behavioral analytics? Despite the vast literature on supply chain transportation operations [13], descriptive, predictive, and prescriptive analytics considering the optimization of key transportation indexes through big data analytics and deep learning techniques such as SVM, KNN, CNN, LSTM models, etc., are still lacking.

Existing research regarding supply chain transportation issues only concerns how to maximize profits and improve performance [14,15], providing less information on customers' digital behavior. Since companies are now moving to customer-centricity approaches to remain competent and improve performance outcomes [16], adopting behavioral analytics metrics becomes of the essence. The accuracy of supply chain customers' demands through deep and machine learning contexts, such as SVM, naïve Bayers, KNN, CNN, and LSTM models, could enhance the efficiency and performance of supply chain firms [17]. Moreover, the reduction in inventory storage costs and the increase in supply chain firms' profits are among the other benefits of deep learning procedures' capitalization (such as LSTM and LGBM models) combined with big data analytics [18]. Lastly, deep learning methodologies, such as CNN and SBO models, in the supply chain context tend to remove uncertainties that are based on firms' expenses, competitiveness, operational efficiency, etc. [19].

The purpose of the current study is to provide fruitful insights into the impact of website visibility and search engine ranking on key transportation performance indexes for supply chain firms. The authors have identified the potential of utilizing deep learning methods and opted to apply a simple version of the FNN to estimate the behavioral metrics of 100,000 supply chain firms' website visitors. Hence, with the assistance of deep learning methods (the FNN procedure), the developed hybrid simulation model showed that the more visitors supply chain websites have, the lower their transportation performance indexes (TPIs) obtained based on the FNN visitors' behavioral metrics estimation. The TPIs that indicate enhanced operational efficiency when having lower values are Freight Expenditure, Inferred Rates, and Truckload Line Haul. Big data analytics from corporate websites have been found to be capable of reducing the operation costs of supply chain firms in a cost-efficient manner. The main managerial and practical implications of the present paper are summarized below in the following categories:

- Supply chain marketers could use the firm's website's big data analytics to optimize its search engine results and obtain a higher ranking in search engines.
- The operational staff of supply chain firms could estimate specific metrics of corporate transportation costs and their impact on the firm's operational performance based on website big data analytics.
- The potential of deep learning methods, such as the FNN, as an efficient decision-making tool for supply chain firms seeking to simulate multiple website visitors' behavioral metrics.

1.2. Structure of the Paper

Regarding the formulation of the paper, the required sections have been constructed to support the findings and the implications of its results. The Introduction part provides the definitions and main research topics of the paper; the Materials and Methods section analyzes the utilized methodological framework and research hypotheses' development; and the Results part concerns the statistical tools (correlation and linear regression analysis) and methods elaborated to extract the required statistical metrics for the latter simulation process (Hybrid Modeling). Lastly, in the Discussion and Conclusions section, the primary results and implications of the simulation process are elaborated, while important insight is presented for supply chain firms' key performance indicators.

1.3. Website Big Data Analytics and Deep Learning

The popularity of social media generates a tsunami of digital data, which is perceived as a challenging process to analyze and manage [20]. Even though big data offers an ocean of opportunities due to its transformational impact on various sectors, it further brings challenges on how to harness the available data, especially regarding data mining and information processing [21]. To mitigate the uncertainties generated by big data analytics, artificial intelligence techniques, such as evolutionary algorithms (EAs) and artificial neural networks (ANNs), have emerged in an attempt to provide accurate, factual, and scalable results [22].

Ning & Yu [23], acknowledge the potential of leveraging deep learning techniques, such as variational autoencoders (VAEs), for hedging against uncertainty in data-driven optimization. Deep learning plays a key role in providing big data predictive analytics solutions, as shown with Restricted Boltzmann Machines (RBMs) exploitation [24]. Deep learning is used to analyze both structured and unstructured data by identifying new patterns and developing knowledge [25]. Especially for the supply chain industry, as data continues to grow exponentially, it will continue to be exploited to unearth new patterns, understand potential causes, and interpret the available data.

Organizations within the supply chain industry have to invest in innovative approaches that will prevent operational inefficiencies, poor customer satisfaction, and revenue loss. Technology is one of the key trends that impacts the sustainability of the supply chain. As such, artificial intelligence and big data have the potential to become a powerful analytics pairing [26], a tool for companies that aspire to obtain the most out of their data analytics.

In summary, big data analytics provide the necessary infrastructure and scalability, while deep learning leverages the power of big data to train models and perform advanced analytics tasks. Therefore, overcoming supply chain disruptions and ensuring the sustainability of the sector lie in the proper management of data growth into organized intelligence [27,28]. Until now, even if big data offers great potential for revolutionizing all aspects of supply chain firms and immense value to different industries, there is still uncertainty over its use [29]. To maximize resilience, secure agility, and achieve the optimization of the supply chain transportation industry, companies need to invest in emerging technologies to develop innovative, data-driven applications based on both big data and deep learning techniques.

1.4. Supply Chain Operations' Engineering through Deep Learning

Supply chain operations engineering involves the design, analysis, and optimization of the supply chain elements and processes to ensure the efficient flow of goods and services from suppliers to end customers [30]. With the revolution of smart technologies, supply chain engineering should be seen as an innovation able to achieve radical business transformation [31]. In other words, this is a common ground for applied sciences, information technology, and supply chain management to increase the effectiveness of supply chain demand while simultaneously adding flexibility and decreasing costs [32].

During the past years, numerous companies have been rocked by unforeseen supply-chain vulnerabilities and disruptions, leading to revenue loss and poor customer satisfaction [33]. In an attempt to change the current landscape and balance competing goals such as risk, vulnerability, and financial risk against reliability and operational efficiency [34], deep learning methods such as variational autoencoders (VAEs) can be utilized. By using applied sciences, firms could leverage the dynamics of immersive technology to analyze and optimize elements and processes of the supply chain to meet specific business requirements. When applied to the supply chain, deep learning algorithms, such as deep learning-augmented decision-making (DLADM), enhance the efficiency of companies and improve the decision-making process [35].

Recently, the deep learning algorithm of the multilayer feedforward artificial neural network (MLFANN) has been used in a study to estimate customers' demand [5]. The authors highlight the importance of using deep learning in developing an improved demand forecasting model based on customers' behavior through historical sales data. Identifying when customers obtain it is the key factor for business performance in the digital age [36]. For example, businesses can use algorithms powered by deep learning to examine past sales data, purchasing behaviors, and other key information to forecast supply chain demand. This data can be utilized to discover new behavioral patterns, ensuring the overall advancement and sustainability of the supply.

Despite their great importance, deep learning methods, such as deep neural networks (DNNs), are challenged by the need to use large quantities of data to validate the outcome [37]. Tolk [38] has introduced the concept of combining big data, deep learning methods (SVM, KNN, CNN, and LSTM models), and simulation as a holistic approach to supporting observation, analysis, and application for unbiased data evaluation by repeatable mechanisms. To this end, the current paper has developed an agent-based model based on an ever-increasing number of agents to validate the outcomes, reduce potential errors, and optimize the simulation results. The agents represent the visitors of a supply chain firm's website, and the hybrid simulation model applies FNN deep learning processes by adjusting the number of website visits and the number of website visitors to optimize the paper's transportation indexes.

2. Materials and Methods

The methodological framework of the paper was based on the significance of the connection between supply chain firms' website big data analytics and the optimization of key transportation performance indexes. Through the collection of big data analytics from the selected supply chain firms, the authors opted to utilize innovative methods to simulate and elaborate on big data analytics' impact on supply chain firms' operations optimization. Therefore, the framework of the present methodology consists of the following stages:

The first stage of the framework concerns the collection of the required big data analytics from the websites of the supply chain firms and their declared transportation index results for 2022. In this stage, the utilization of Decision Support Systems (DSS) enables the gathering of historical and daily data on specific web analytic metrics (KPIs) from these websites. The second stage of the context concerns the deployment of the proper statistical analysis tools to extract insights regarding the selected big data analytics relationships. Correlation and linear regression coefficients of the supply chain big data analytics' impact on their transportation indexes will be extracted to support the development of the hybrid simulation model while also verifying or rejecting the paper's research hypotheses.

In the last stage, the authors chose to develop a Hybrid Model (HM) that consists of both Agent-Based (ABM) and System Dynamics (SD) models [39], based on data elaboration from an FNN [40] and deep learning (DL) procedure [41]. This stage aims to deploy a simulation model that would predict the selected supply chain firms' transportation index results based on the coefficients of the statistical analysis of stage 2. At the same time, the FNN process would produce coherent outputs for selected big data analytic metrics [42] to accurately simulate the trajectory of the five supply chain transportation performance indexes.

2.1. Research Hypotheses

The purpose of the present research is to examine the implications of FNN deep learning procedures for supply chain firms' transportation performance based on big data analytics. As analyzed above, the improvement of supply chain firms' transportation indexes is crucial and, as a result, should be the utmost goal for the managerial staff of supply chain firms. The selected indexes represent key transportation performance indicators for supply chain firms while providing important insights for their expense management and finance departments. It has been indicated that supply chain firms should observe any variations in their transportation performance indexes originating from various sources. The utilization of big data analytics from their corporate websites has been discerned as an important factor for their sustainability and financial performance [43,44]. In this context, the benefits of using big data analytics from corporate websites could be extended to supply chain firms' transportation performance, given the fact that a notable and significant relationship arises among them. Therefore, the authors seek to investigate the impact of specific big data analytics from the websites of supply chain firms on key transportation performance indicators (indexes). Since the selected indexes contain elements of corporate expenses, some of the selected big data analytics focused on the organic and paid campaign costs of supply chain firms.

More specifically, the following research hypotheses have been settled based on the literature review and the focus of this study, as see in Figure 1.

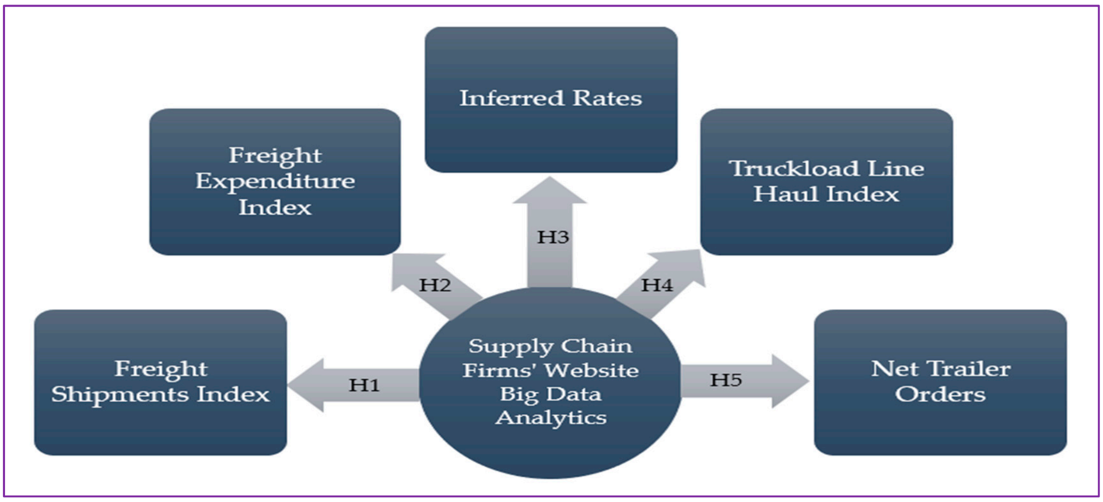


Figure 1. Conceptual Framework.

The Freight Shipments Index (FSI) [45] shows the volume of cargo and shipment transportation for supply chain firms. This metric, foremost, indicates the demand of supply chain firms' clients for goods transportation, making its prediction highly valuable. For supply chain firms to discover a new context of prediction factors for their transportation volumes, multiple benefits could emerge, first and foremost for their financial performance as well as for their expenses' repercussions. The potential prediction of their customers' demand constitutes another important benefit for supply chain firms to start analyzing key big data analytics from their websites.

Hypothesis 1 (H1): The Freight Shipments Index of supply chain firms can be reduced by the adjustment of their website's big data analytics.

Regarding the Freight Expenditure Index (FEI), supply chain firms can calculate every year the expenses related to their cargo and freight transportation. For these firms, being able to simulate freight costs could prove beneficial. If a connection is being developed between freight expenditures and the big data analytics of supply chain firms, then they could proceed to a proper adjustment of the big data analytical metrics. Thus, given that supply chain firms could discern that their freight expenditures decreased with the adjustment of specific big data analytics, they would be able to predict and reduce their costs.

Hypothesis 2 (H2): The Freight Expenditure Index of supply chain firms can be reduced through the adjustment of their website's big data analytics.

Inferred Rates (IR) as an index of supply chain firms' performance show the analogy of expenses by the number of deliveries to help depict the transportation performance per activity. Knowledge of the specific big data analytics that are strongly connected with supply chain firms' Inferred Rates provides a solid framework for these firms to further try to reduce this index. Again, the proper adjustment of big data analytics could indicate changes to the Inferred Rates index, given that it is closely connected with specific metrics.

Hypothesis 3 (H3): There is a strong connection between supply chain firms' website big data analytics and their Inferred Rates.

For the next hypothesis of the paper, the authors discern the role of the Truckload Line Haul Index as another key transportation performance index. The purpose is to examine big data analytics' impact on truckload linehaul prices. The finding that specific supply chain website analytical metrics can predict the reduction of their truckload linehaul prices is crucial. Through the proper adjustment of website big data analytics, supply chain firms can simulate truckload linehaul prices' course and, hence, enhance their decision-making procedures.

Hypothesis 4 (H4): Supply chain firms' website' big data analytics are capable of decreasing their Truckload Line Haul Index.

Lastly, concerning the supply chain firms' Net Trailer Orders (NTO), the authors seek to investigate the effect of various big data analytics on the number of orders placed by supply chain firms for trailers. Therefore, if any variable of the big data analytics from the supply chain firms is connected positively with their tendency to place orders for trailers, then these firms could more efficiently observe important factors connected to their performance and expenses. The more orders for trailers supply chain firms place, the more transportation needs they have and, thus, more expenses.

Hypothesis 5 (H5): Net Trailer Orders and supply chain firms' websites' big data analytics are connected positively.

2.2. Sample and Retrieval of Data

For the sample and the retrieval of the big data analytic metrics from corporate websites, the authors selected the five most successful supply chain firms in 2022. The firms' selection was based on their performance over returns on physical assets (ROPA), revenue growth, and inventory turnover [46]. These supply chain firms refer to Cisco Systems [47], Schneider Electric [48], Colgate-Palmolive [49], Johnson & Johnson [50], and PepsiCo [51]. Moreover, the authors collected information regarding the referred companies' performance in key supply chain transportation indexes, as seen in Table 1. For big data analytics retrieval, the website-based decision support platform (DSS) of Semrush [52] was utilized, where website data can be collected through proper payment. To discern the data collection period, the authors started the daily retrieval of big data analytics, which can be seen in Table 1, from 1 July 2022, up to 31 January 2023.

Table 1. Supply Chain and Website Analytic metrics.

Metrics	Description of the Analytic Metrics
Freight Index Shipments	The index's information includes cargo quantities by rail, vehicle, air, and all other types of national shipment transport. Agriculture, vehicle, chemical-based sales, massive machinery, manufactured products, and numerous other industries and freight are represented [52].
Freight Index Expenditures	This indicator consists of the real cargo expenditures of the firms whose transport operations Cass analyzes every year [45].
Inferred Rates	Cass Inferred Freight Rates are derived from the Cass Freight Score details by dividing expenses by deliveries and creating a set of information describing the overall cost change in expense per cargo [52].
Truckload Line Haul Index	The Cass Truckload Linehaul Indicator measures economic changes in per-mile truckload linehaul prices, excluding additional expense elements such as energy and accessorial charges [53].
Net Trailer Orders	The number of orders placed specifically for trailers by supply chain firms.
Authority Score	The Authority Score is a multi-metric that assesses the general integrity of a website or webpage [54].
Branded Traffic	The amount of traffic that ends up on a website is based on the visitors' familiarity with the firm's brand name.
Organic Traffic	Organic traffic is defined as any web traffic that arrives on a website from search engine results nevertheless is not paid for. Every organic search result will be generated through internal marketing and SEO activities [55].

Table 1. *Cont.*

Metrics	Description of the Analytic Metrics
Organic Costs	The expenses associated with the activities for attracting organic traffic to a website.
Paid Traffic	Paid search traffic is any website visitors generated by an advertising effort that firms run on a search engine such as Google or Bing [55].
Paid Costs	The expenses associated with the activities for attracting paid traffic to a website.
Bounce Rate	The proportion of website visits that are single-page meetings, with somebody departing before reading another page, is known as the bounce rate [56].
Pages per Visitor	The proportion of website visits that are single-page meetings, with somebody departing before reading another page, is known as the bounce rate [57].
Time on Site	The overall amount of time spent traveling on a web page is referred to as "time on site", additionally referred to as "session length" [58].
Website Visitors	The number of unique visitors that enter a webpage, is measured in terms of IP address singularity.
Website Visits	Each time a visitor lands on a webpage, the website visit metric is increased. No distinction is made regarding their IP address singularity.

3. Results

3.1. Statistical Analysis

This section of the study focuses on the extraction of important statistical metrics and coefficients for the imminent deployment of simulation models based on FNN deep learning procedures. The authors opted to perform descriptive statistics, correlation, and linear regression analyses to gather the required coefficients. For the descriptive statistics analysis, the metrics of mean, minimum, maximum, and std. deviation were used to provide important information regarding the variables' distributions (both dependent and independent ones), which can be seen in Table 2. To aid in the selection of independent variables for the linear regressions and the simulation models, the authors performed a correlation analysis based on Pearson's coefficient (Table 3). The most significant correlations are presented with * and ** to indicate statistical significance at the 95% and 99% levels, respectively.

Table 2. Descriptive Statistics of the five Supply Chain Firms during the past six months.

	Mean	Min	Max	Std. Deviation
Freight Index Shipments	1.20	1.12	1.28	0.04
Freight Index Expenditures	4.44	4.10	4.67	0.17
Inferred Rates	3.70	3.47	3.88	0.11
Truckload Line Haul Index	158.93	149.23	168.60	6.64
Net Trailer Orders	28,630.75	16,400.00	56,949.00	12,846.14
Authority Score	72.40	72.20	72.80	0.20
Branded Traffic	55.78	50.20	61.40	3.87
Organic Traffic	14,647,035.33	11,882,021.00	17,824,613.00	1,888,192.67
Organic Costs	24,437,840.08	17,760,939.00	30,389,621.00	4,516,413.74
Paid Traffic	394,464.33	163,806.00	574,521.00	122,727.12
Paid Costs	1,363,788.41	717,103.00	2,676,244.00	500,493.54
Bounce Rate	0.61	0.57	1.00	0.03
Pages per Visit	2.50	2.00	3.00	0.20
Time on Site	696.74	555.00	1006.00	168.60
Website Visitors	15,888,074.43	13,230,273.00	18,363,549.00	1,812,070.90
Website Visits	39,887,735.57	34,754,017.00	44,989,600.00	4,231,610.37

N = 180 observation days for the five selected Supply Chain Firms.

Table 3. Correlation analysis matrix.

	Freight Index Shipments	Freight Index Expenditures	Inferred Rates	Truckload Line Haul Index	Net Trailer Orders	Authority Score	Branded Traffic	Organic Traffic	Organic Costs	Paid Traffic	Paid Costs	Bounce Rate	Pages per Visit	Time on Site	Website Visitors	Website Visits
Freight Index Shipments	1	0.618 *	−0.313	0.352	−0.330	0.136	−0.461	0.138	0.634 *	−0.650 *	−0.604 *	−0.335	0.699	0.088	−0.164	−0.110
Freight Index Expenditures	0.618 *	1	0.552	0.472	−0.446	0.107	−0.555	0.382	0.430	−0.453	−0.298	−0.267	0.654	0.428	−0.330	−0.213
Inferred Rates	−0.313	0.552	1	0.208	−0.198	−0.002	−0.179	0.329	−0.158	0.143	0.287	0.102	0.006	0.819 *	−0.425	−0.269
Truckload Line Haul Index	0.352	0.472	0.208	1	−0.654 *	0.457	0.062	0.729 **	0.268	−0.287	0.180	−0.766	0.692	0.658	−0.662	−0.538
Net Trailer Orders	−0.330	−0.446	−0.198	−0.654 *	1	−0.307	0.191	−0.408	−0.308	0.507	0.111	0.559	−0.785 *	−0.623	0.397	0.198
Authority Score	0.136	0.107	−0.002	0.457	−0.307	1	−0.306	0.858 **	−0.375	−0.277	0.093	−0.200	0.484	−0.087	0.205	0.208
Branded Traffic	−0.461	−0.555	−0.179	0.062	0.191	−0.306	1	−0.269	−0.139	0.574	0.483	0.498	−0.756 *	−0.318	0.349	0.298
Organic Traffic	0.138	0.382	0.329	0.729 **	−0.408	0.858 **	−0.269	1	−0.258	−0.289	0.130	−0.712	0.574	0.436	−0.375	−0.301
Organic Costs	0.634 *	0.430	−0.158	0.268	−0.308	−0.375	−0.139	−0.258	1	−0.327	−0.349	−0.493	0.693	0.399	−0.554	−0.529
Paid Traffic	−0.650 *	−0.453	0.143	−0.287	0.507	−0.277	0.574	−0.289	−0.327	1	0.740 **	0.493	−0.975 **	−0.258	0.457	0.341
Paid Costs	−0.604 *	−0.298	0.287	0.180	0.111	0.093	0.483	0.130	−0.349	0.740 **	1	0.193	−0.751	−0.152	0.016	−0.116
Bounce Rate	−0.335	−0.267	0.102	−0.766	0.559	−0.200	0.498	−0.712	−0.493	0.493	0.193	1	−0.657	−0.321	0.825 *	0.741
Pages per Visit	0.699	0.654	0.006	0.692	−0.785 *	0.484	−0.756 *	0.574	0.693	−0.975 **	−0.751	−0.657	1	0.193	−0.533	−0.440
Time on Site	0.088	0.428	0.819 *	0.658	−0.623	−0.087	−0.318	0.436	0.399	−0.258	−0.152	−0.321	0.193	1	−0.494	−0.327
Website Visitors	−0.164	−0.330	−0.425	−0.662	0.397	0.205	0.349	−0.375	−0.554	0.457	0.016	0.825 *	−0.533	−0.494	1	0.972 **
Website Visits	−0.110	−0.213	−0.269	−0.538	0.198	0.208	0.298	−0.301	−0.529	0.341	−0.116	0.741	−0.440	−0.327	0.972 **	1

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

In Tables 4 and 5, the Freight Shipments Index and Freight Expenditure Index were used as dependent variables, with the rest of the big data analytic metrics used as independent ones. The model with the best score in terms of R^2, *p*-value, and Akaike criterion was selected. The Freight Shipments Index's linear regression is verified overall with $R^2 = 1.00$ and a *p*-value = 0.000 < a = 0.01 level of significance. All of the independent variables had *p*-values below the a = 0.01 level of significance. For every 1% increase in the authority score, paid costs, bounce rate, time on site, and website visits, the Freight Shipments Index increases by 1.7%, decreases by 105.1%, increases by 32.2%, decreases by 7.5%, and increases by 64% accordingly. Therefore, the first research hypothesis (H1) is verified, and the Freight Shipments Index of supply chain firms can be affected by the big data analytics of their websites.

Table 4. Impact of Supply Chain Firms' Big Data Analytic Metrics on their Freight Shipments Index.

Variables	Standardized Coefficient	R^2	F	*p*-Value
Constant	-			0.000 **
Authority Score	0.017			0.000 **
Paid Costs	−1.051	1.000	-	0.000 **
Bounce Rate	0.322			0.000 **
Time on Site	−0.075			0.000 **
Website Visits	−0.640			0.000 **

** indicate statistical significance at the 99% level.

Table 5. Impact of Supply Chain Firms' Big Data Analytic Metrics on their Freight Expenditure Index.

Variables	Standardized Coefficient	R^2	F	*p*-Value
Constant	-			0.000 **
Authority Score	−0.225			0.000 **
Paid Costs	−1.207	1.000	-	0.000 **
Bounce Rate	0.555			0.000 **
Time on Site	0.248			0.000 **
Website Visits	−0.747			0.000 **

** indicate statistical significance at the 99% level.

The linear regression of supply chain firms' Freight Expenditure Index is also overall verified with $R^2 = 1.00$ and a *p*-value = 0.000 < a = 0.01 level of significance. The independent variables of website big data analytics with the most significant impact on the dependent variable were the same as the Freight Expenditure Index's regression model. When authority score, paid costs, bounce rate, time on site, and website visits increase by 1%, the Freight Expenditure Index varies by −22.5%, −120.7%, 55.5%, 24.8%, and −74.7%, respectively. Hence, the paper's second research hypothesis (H2) is also verified, meaning that the Freight Expenditure Index of supply chain firms can be reduced by the adjustment of their website big data analytics.

Next, for the analysis of the impact of supply chain firms' website big data analytics on Inferred Rates, Truckload Line Haul Index, and Net Trailer Orders, the authors deployed three linear regression models. The first regression model with Inferred Rates as the dependent variable was verified overall with $R^2 = 1.00$ and a *p*-value = 0.000 < a = 0.01 level of significance, as seen in Table 6. The independent variables of the authority score, paid costs, bounce rate, time on site, and website visits were found to be statistically significant with *p*-values = 0.000 < a = 0.001 significance level. For every 1% increase in authority score, paid costs, bounce rate, time on site, and website visits, supply chain firms' Inferred Rates variate up to −69.9%, −68.8%, 70.1%, 87.1%, and −43.9% accordingly. The third research hypothesis (H3) is verified, and it means that there is a strong connection between supply chain firms' website big data analytics and their Inferred Rates.

Table 6. Impact of Supply Chain Firms' Big Data Analytic metrics on their Inferred Rates.

Variables	Standardized Coefficient	R^2	F	*p*-Value
Constant	-	1.000	-	0.000 **
Authority Score	−0.699			0.000 **
Paid Costs	−0.688			0.000 **
Bounce Rate	0.701			0.000 **
Time on Site	0.871			0.000 **
Website Visits	−0.439			0.000 **

** indicate statistical significance at the 99% level.

In Table 7, the linear regression model of the Truckload Line Haul Index is produced, which is verified overall with R^2 = 1.00 and a *p*-value = 0.000 < a = 0.01 level of significance. Supply chain website authority score, paid costs, bounce rate, time on site, and website visits had a significant impact on the Truckload Line Haul Index, with *p*-values < a = 0.01 significance level. The Truckload Line Haul Index decreases by 27.6%, 76%, and 22.3%, increases by 37.2%, and decreases by 44.7% when the authority score, paid costs, bounce rate, time on site, and website visits increase by 1%. Thus, the fourth research hypothesis (H4) is verified, with supply chain firms' website big data analytics being capable of decreasing their Truckload Line Haul Index.

Table 7. Impact of Supply Chain Firms' Big Data Analytic Metrics on their Truckload Line Haul Index.

Variables	Standardized Coefficient	R^2	F	*p*-Value
Constant	-	1.000	-	0.000 **
Authority Score	−0.276			0.000 **
Paid Costs	−0.760			0.000 **
Bounce Rate	−0.223			0.000 **
Time on Site	0.372			0.000 **
Website Visits	−0.447			0.000 **

** indicate statistical significance at the 99% level.

Regarding the last linear regression model of supply chain Net Trailer Orders, it was verified overall with R^2 = 1.00 and a *p*-value = 0.000 < a = 0.01 level of significance, as observed in Table 8. All of the independent variables included in Table 8 had a statistically significant effect on supply chain firms' Net Trailer Orders dependent variable. With every 1% rise in the authority score, paid costs, bounce rate, time on site, and website visits, supply chain firms' Net Trailer Orders variate up to −23.5%, 20.1%, 85.7%, −44.1%, and −70.9%, respectively. Hence, the fifth and final research hypothesis (H5) of the present research is verified, which means that Net Trailer Orders and supply chain firms' website big data analytics are connected positively.

Table 8. Impact of Supply Chain Firms' Big Data Analytic Metrics on their Net Trailer Orders.

Variables	Standardized Coefficient	R^2	F	*p*-Value
Constant	-	1.000	-	0.000 **
Authority Score	−0.235			0.000 **
Paid Costs	0.201			0.000 **
Bounce Rate	0.857			0.000 **
Time on Site	−0.441			0.000 **
Website Visits	−0.709			0.000 **

** indicate statistical significance at the 99% level.

3.2. Hybrid Model and Deep Learning Engineering

In the Hybrid Model (HM) simulation process, a proper model has been developed for the prediction of key supply chain transportation indexes' trajectory over time, based on the impact of big data analytics [42] and the application of a simplified FNN. The deployment of the Hybrid Model was based on both Agent-Based (ABM) and Systems Dynamic (SDM) modeling processes [39]. The authors inserted the extracted coefficients and descriptive statistics from the Results section into the Hybrid Model, as a necessary step for its operational procedures [39]. The FNN method has as inputs the behavioral data of supply chain firms' website visitors and, through a hidden layer procedure, produces an estimation of key big data analytics of supply chain websites (time on site, pages per visit, bounce rate, organic traffic, and paid traffic) [59]. The FNN model's estimation is affected by the number of the simulation model's agents. For the learning process of the model, various numbers of agents were used, aiming to enhance its outcomes. The simulation model aims to simulate and predict the variation of supply chain transportation indexes (Freight Shipments Index, Freight Expenditure Index, Inferred Rates, Truckload Line Haul Index, and Net Trailer Orders) in 360 days from the examination of the impact of their website big data analytics (bounce rate, pages per visit, time on site, website visitors, website visits, etc.) through FNN deep learning procedures.

To utilize deep learning processes, the model consists of various layers of information processing, where structured and unstructured data are processed and transformed into valuable knowledge in specific fields [42]. In this research, structured data refers to known website visitor metrics (such as visits, pages per visit, etc.), and unstructured webpage data (such as date of visits, form filling, opened videos, etc.) [60], both created from website visits to the model's supply chain firms' web pages, were transformed into important insights regarding the potential benefits of their performance. The structured data of this study were stored in Excel sheets for further direct processing, whereas the unstructured data were gathered in media files that were utilized with specific tools, such as PowerBI, and various Excel add-ins. These website visits were represented by both the website visits and website visitors' metrics, which were associated with the number of agents used in the model. The number of agents (website visitors) that were used for the model deployment varied between 1 and 100,000, based on the requirements set by the FNN simulation. The simulation process runtime was set to 360 days, and the agents' movement was based on primary commands such as or, and, if, etc., and the connection of the various factors and variables. The authors utilized the Anylogic [61] software as a basis for the development of the model while applying a simplified FNN algorithm.

On the one hand, the data type that was used referred to quantitative data that were extracted from statistically significant linear regression models and correlations. These data were inserted into the model and represent the relationships that developed among the variables. On the other hand, the iteration of data measurement was supported by the one-time snapshot process to depict the model's outcomes at all of the agents' levels, aiming to collect the necessary data in the predefined time window. In Figure 2 below, the FNN model and the simulation procedure for the prediction of Transportation Performance Indexes (TPI) are presented. For the deployment of the preferred process, a Java algorithm has been created, which can be discerned in Table A1 in the Appendix A section.

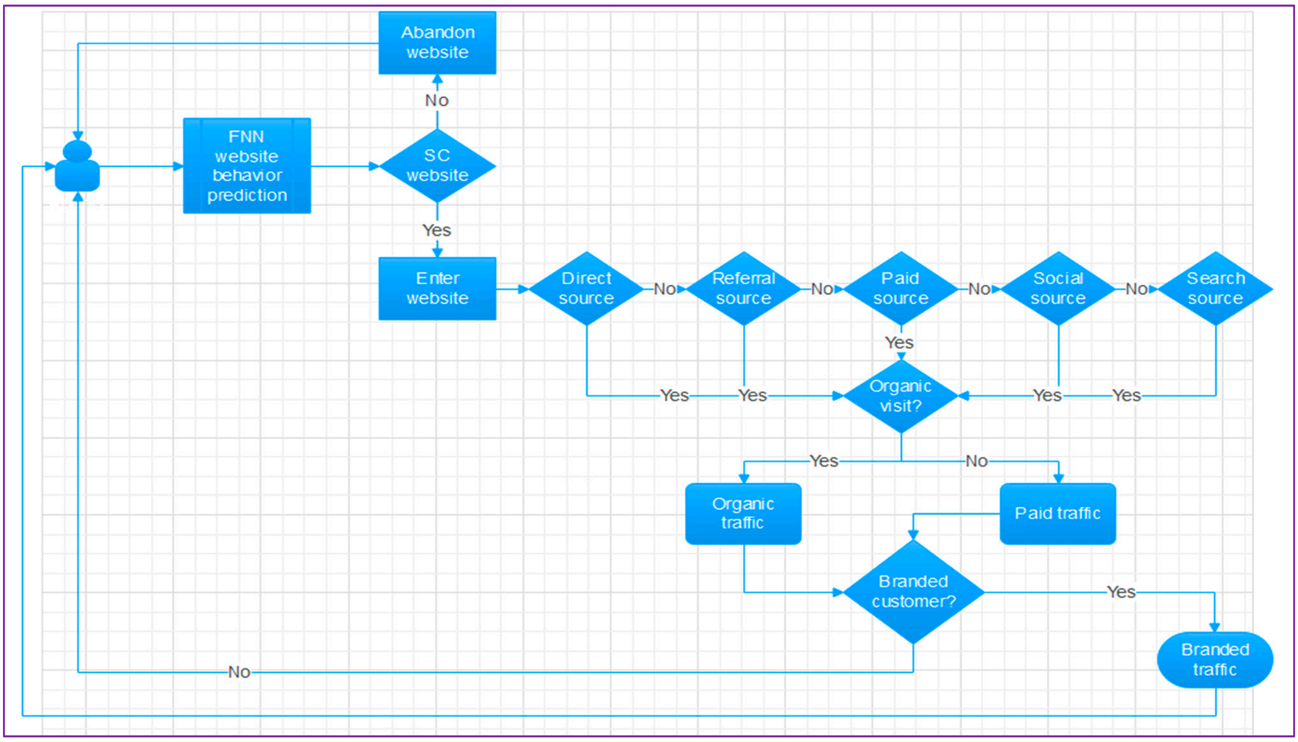


Figure 2. The system architecture of the simulation model.

The Hybrid Model's framework is presented in Figure 3, where the simulation process starts with the statechart of potential supply chain customers. Each supply chain customer could reach a firm's website through either the statecharts of direct, referral, paid, social, or search sources, based on their utility frequency. In the meantime, when the agents (website visitors) enter the bounce rate statechart, where based on the generated website abandoning rate, the agents return to the primary statechart (potential supply chain customers) or continue to explore the supply chain webpage, the dynamic variables of bounce rate, pages per visit, and time on site generate their values. Website visitors-visits that stay on the supply chain website, pass the intermediate (dummy) statechart of bounce rate to traffic and end up with either the organic or paid traffic statechart, based on the search method the website visitors (agents) prefer to use each time to visit supply chain firms' websites. Finally, the statechart of branded traffic is being reached by both the statecharts of organic and paid traffic since they provide information about the preferences of specific, well-known firms. At the same time, the dynamic variables of supply chain firms' authority score, freight shipments index, freight expenditure index, inferred rates, truckload line haul index, and net trailer orders were impacted, following the characteristics of the agents that ultimately reached those statecharts.

For the simulation process, various numbers of agents were deployed, ranging from 100 to 100,000 agents, and each time their key website behavioral metrics were calculated from the FNN to create deep learning procedures and predict the outcome of optimization on five key transportation performance indexes of supply chain firms. The model aims to predict and correct the errors [62] that might arise from the simulation of the supply chain website visitors' behavior in the context of their impact on key transportation performance indexes by increasing the number of website visitors and visits. Therefore, for this FNN procedure, and after having deployed the hybrid model that simulates the behavior and decisions made by supply chain firms' customers when they visit their website, four different levels of potential supply chain customers were summoned. In the first 2 levels, 100 and 1000 agents were selected as points of measurement for the examination of potential customer's behavior, which could lead them to supply chain firms' websites, generating website visits.

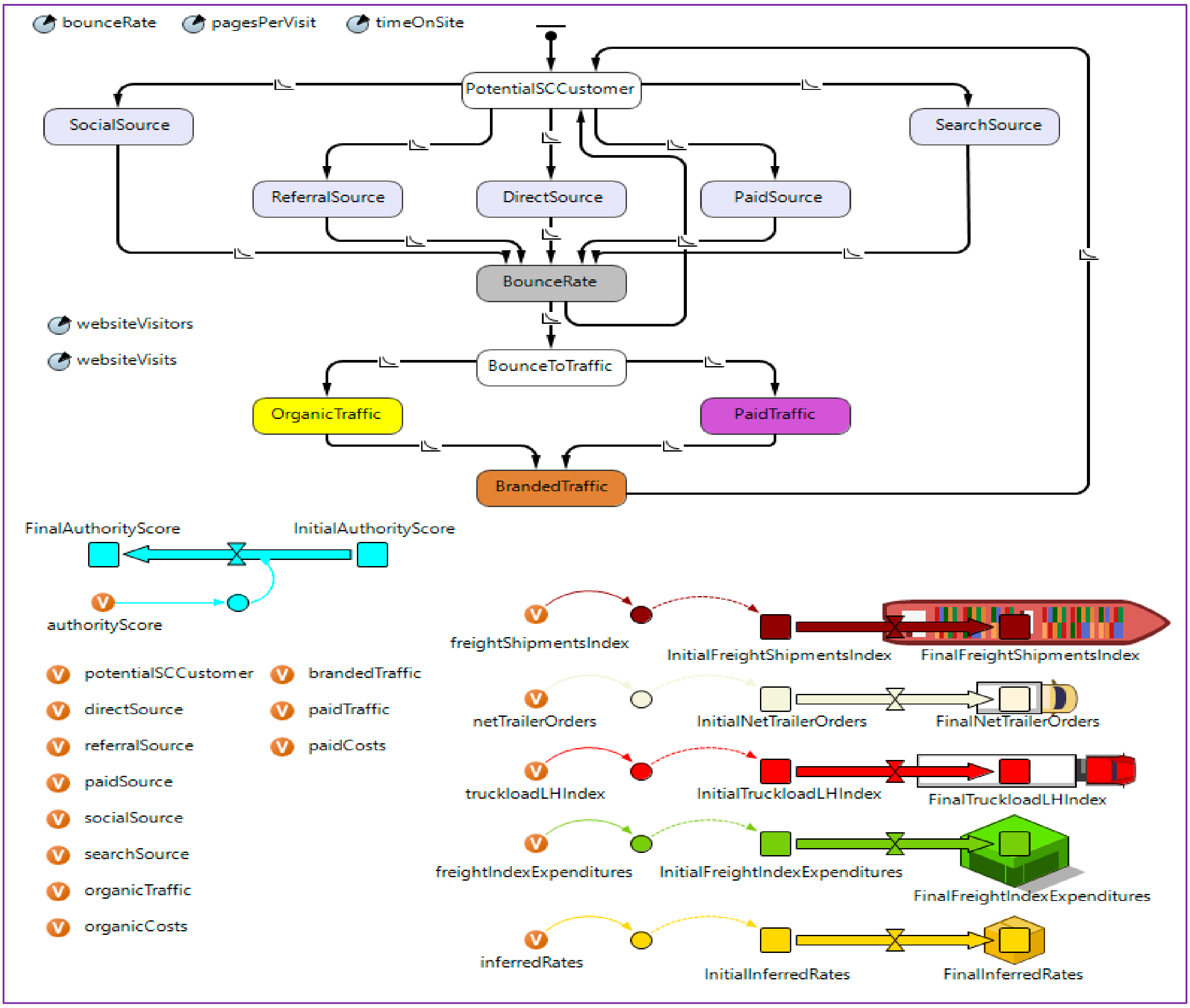
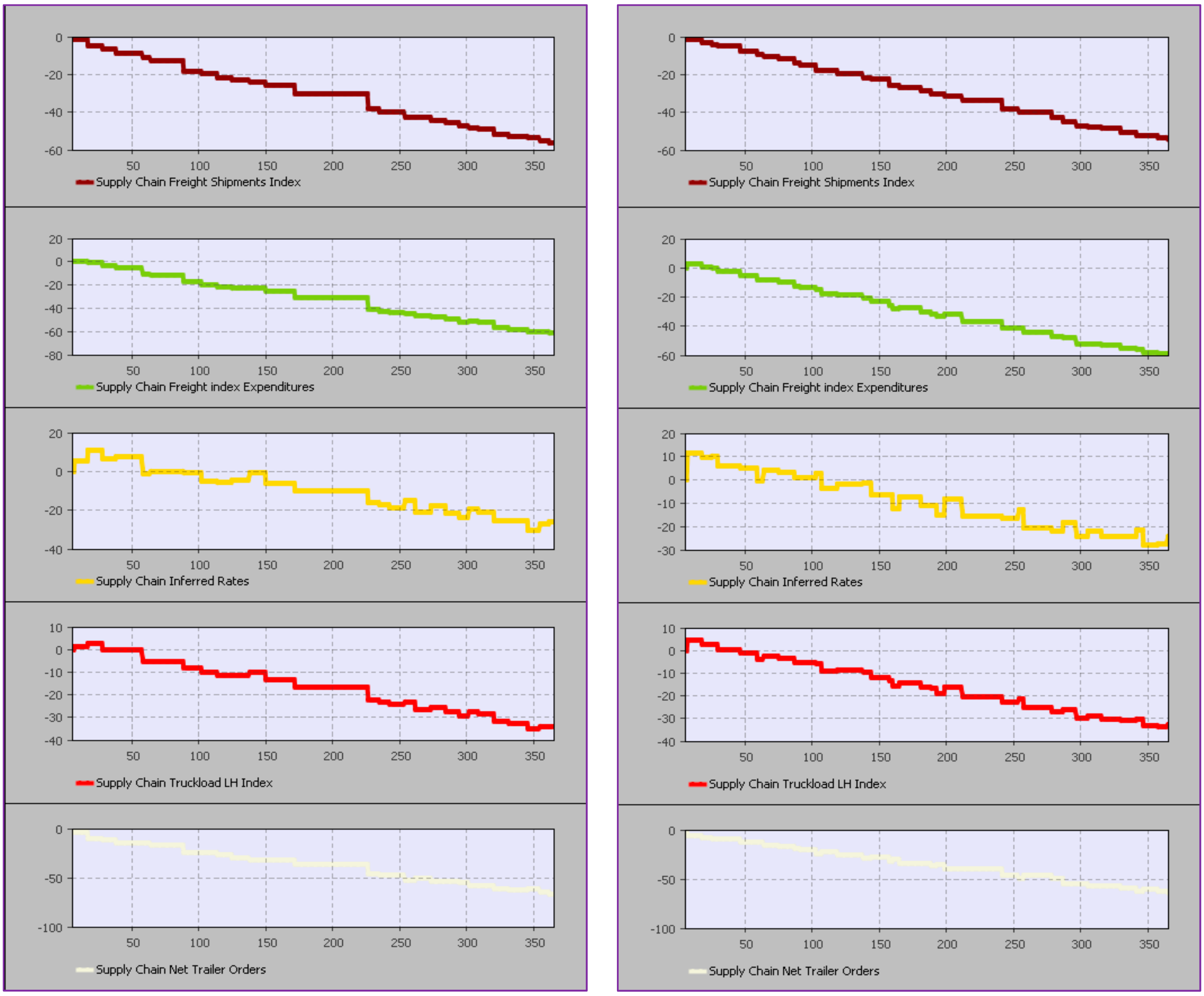


Figure 3. Deployment of a supply chain analytics Hybrid Model.

In this way, the simulation model developed through this FNN deep learning process [40] could obtain valuable insights regarding the connection between the number of website visitors and visits for supply chain firms, as well as their behavioral patterns. In Figure 4a, the variation of the Freight Shipments Index, Freight Expenditure Index, Inferred Rates, Truckload Line Haul Index, and Net Trailer Orders is presented when the level of potential supply chain customers is 100. On the contrary, in Figure 4b, the number of potential supply chain customers is increased to 1000, provoking a differentiation in the referred transportation indexes' variation. As we can discern, compared to the simulation of 100 agents, the simulation of 1000 agents produces more stable and predictable variations in the selected supply chain transportation performance indexes. Moreover, throughout the 360 days, the total of the transportation indexes reached lower values than at the beginning of the simulation, as well as with the use of 1000 agents compared to 100, except, in this case, for the indexes of Freight Expenditure and Inferred Rates. At this point, we should mention that based on the nature of the specific indexes, an improvement in the performance of supply chain firms' operations is observed when the indexes of Freight Expenditure, Inferred Rates, and Truckload Line Haul take lower values since they depict increased costs for a firm, while the indexes of Freight Shipments and Net Trailer Orders declare an improvement in supply chain operations' performance when receiving higher values [45,52,53].



(**a**) (**b**)

Figure 4. Supply chain transportation indexes simulation procedure with 100 (**a**) and 1000 (**b**) agents in 360 days.

Next, the model increased the number of potential supply chain customers in the model to reduce potential errors and optimize the simulation results. The checkpoints for the key transportation performance indexes' variation were set to 10,000 and 100,000 agents. Again, due to the website visitors' correlation with the rest of the supply chain transportation indexes, we have a first prediction of their course over the simulation period. More specifically, in Figure 5a,b, the more potential supply chain customers there are, the more website visitors and visits are generated, meaning that the chosen transportation performance indexes tend to obtain lower values. Firstly, regarding the use of 10,000 agents, although the variation of the supply chain transportation indexes appears smoother and more stable throughout the 360 simulation days, their values do not show a great deviation from the simulation of 1000 agents. Since their values at the end of the simulation time are alike, we can highlight the fact that at this stage of the FNN, the process is optimally adjusted and no further optimization can be conducted to change the transportation indexes' outcomes. Then, in the checkpoint of 100,000 agents, the deep learning procedure reached the full capacity of available agents to generate website visits and visitors and, thus, to obtain the supply chain transportation indexes to their lowest recorded values. The computing power demands increased rapidly at this stage, and all of the key transportation performance indexes were optimized; compared to the 10,000 agents' checkpoints, their values decreased, up to a point.

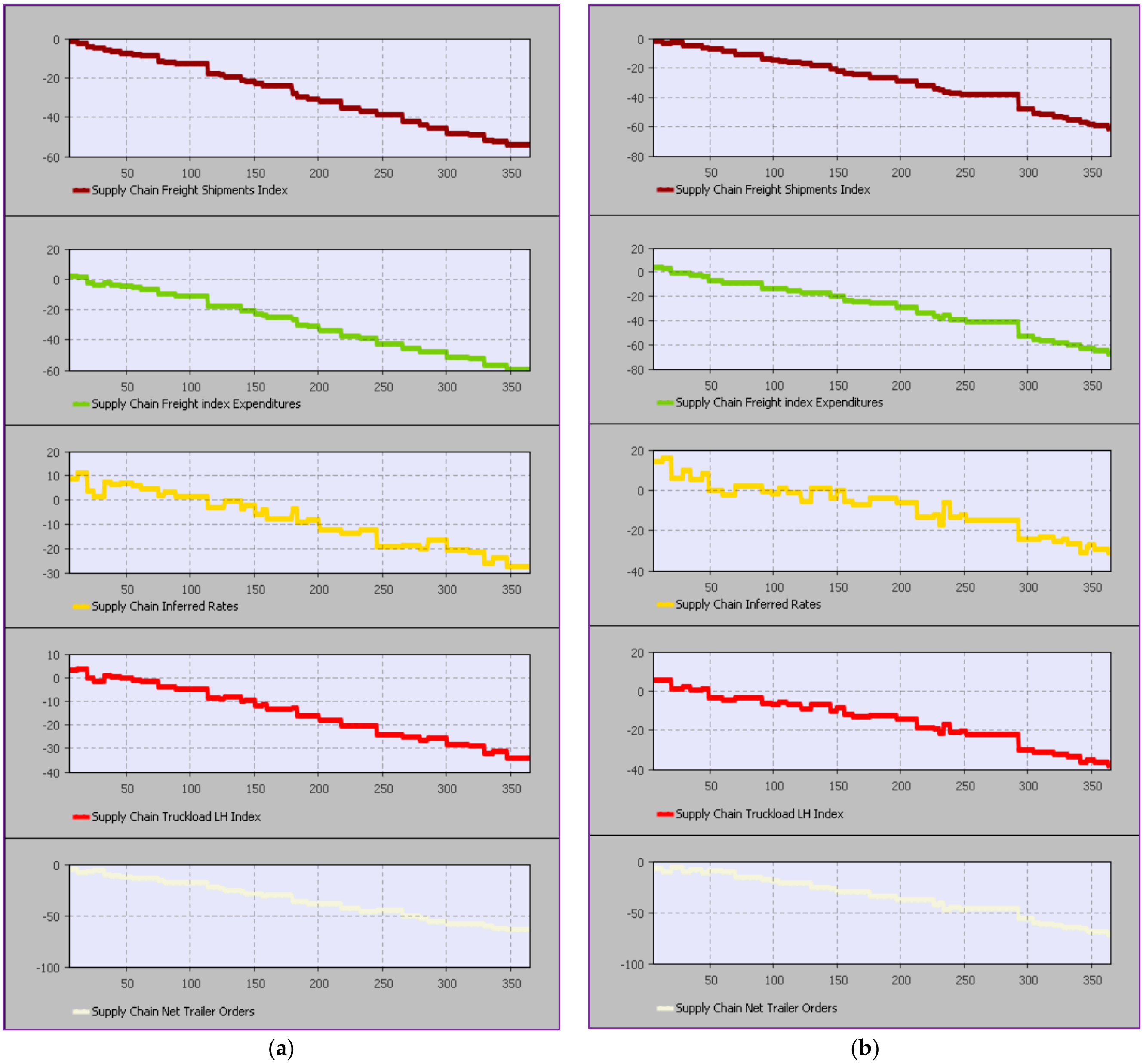


Figure 5. Supply chain transportation index simulation procedure with 10,000 (**a**) and 100,000 (**b**) agents in 360 days.

4. Discussion

Following the engineering stage of the hybrid model and the FNN deep learning procedure of supply chain website visitors' behavior and the predicted variation of key transportation performance indexes to perform this, the authors examined the big data analytics from the selected supply chain firms' websites and proceeded to capitalize on deep learning methods to optimize the results of the transportation indexes. More specifically, the adopted FNN processes aimed to estimate the behavioral metrics (time on site, pages per visit, bounce rate, organic traffic, and paid traffic) of the agents/website visitors of the simulation model, thus aiding the prediction process of the hybrid model on supply chain firms' key transportation performance indexes.

The produced linear regression models concerned as dependent variables the following supply chain transportation indexes: Freight Shipments Index, Freight Expenditure Index, Inferred Rates, Truckload Line Haul Index, and Net Trailer Orders. These indexes represent the performance of supply chain firms in terms of transportation efficacy. Generally, when the indexes of Freight Expenditure, Inferred Rates, and Truckload Line Haul decrease, they indicate enhanced transportation performance for the supply chain firm since they depict key expenses' reduction, while when the indexes of Freight Shipments and Net Trailer Orders increase, the transportation performance of the firm increases; such indexes represent measurement metrics for supply chain firms' activity.

Regarding the research hypotheses set at a previous stage of this study, it can be stated that the total of the included regression models was found to be verified overall. More specifically, the research hypotheses H1, H2, H3, H4, and H5 were verified, which means that big data analytics of supply chain firms' websites were found to impact key transportation performance indexes of these firms. The transportation indexes selected for this study represent the main areas of interest for supply chain firms' transportation performance enhancement since they depict the efficiency of these firms in terms of freight shipping volumes, transportation expenses, and net orders for vehicles (trailers).

Reaching the Hybrid Model (HM) simulation and FNN procedure, the authors capitalized on the extracted coefficients from the regression and correlation analysis to simulate the transportation indexes' estimation process through the agents' number adjustment and the system's produced information. The model's agents represented the potential supply chain website visitors. Furthermore, the simulation model specifically utilized the relationships between the variables of website visitors and visits and the rest of the transportation indexes and variables. Moreover, through the FNN procedure, the simulation model obtained precise analytical metrics regarding specific behavioral patterns of the agents/visitors, which were utilized for predicting the selected supply chain transportation performance indexes (TPIs). Therefore, various insights arose from the simulation analysis, indicating that increased website visits and visitors tend to decrease the values of the Freight Shipments Index, Freight Expenditure Index, Inferred Rates, Truckload Line Haul Index, and Net Trailer Orders indexes.

Relevant studies in the field of deep learning and supply chain firms' performance have highlighted various fields of deep and machine learning implications. The utilization of machine learning applications can effectively benefit potential transformation plans for supply chain firms [63], with big data analytics playing a significant role in these procedures. Furthermore, the application of deep and machine learning applications in supply chain firms through the capitalization of big data has led to enhanced decision-making in the sectors of selecting and segmenting suppliers, estimating demand and sales, production, inventory management, transportation and distribution, and sustainable development [64]. Our paper focuses on the effects of big data analytics originating from corporate websites on supply chain firms' transportation performance, based on FNN deep learning procedures. Hence, the implication of big data analytics on corporate websites is highlighted as of increased importance since they can help supply chain firms enhance their transportation performance and capacity.

5. Conclusions

5.1. Theoretical and Practical Implications

A plethora of theoretical and practical implications arise from the harvesting of the referred methodological and research context, which concerns supply chain big data analytics and deep learning simulation procedures. The main aim of the research was to discern the impact of the big data analytics of supply chain websites on their transportation performance indexes. The selected referred indexes consist of the Freight Shipments Index, Freight Expenditure Index, Inferred Rates, Truckload Line Haul Index, and Net Trailer

Orders Index, which reflect the transportation performance of supply chain firms, with variables such as expenses, shipment volumes, and trailer orders included. For the execution of this study, vast amounts of data were extracted from the 5 selected supply chain firms' websites by using the Semrush online platform [54], which refers to approximately 3,000,000 observations. These data sets are big data analytics [65], and their elaboration was performed through traditional analysis, which includes statistical, simulation, and deep learning procedures.

From the results of the statistical analysis, the Hybrid Model (HM), and the Deep Learning (DL) process of FNN, more significant insights have been discerned. The linear regression models verified the research hypotheses regarding the impact of big data analytics on supply chain firms' websites on their transportation performance indexes. The hybrid model simulation, combined with the examination of various levels of supply chain website visits and visitors, led to results assuming that the more their website visibility and traffic increases, the more their Freight Shipments Index, Freight Expenditure Index, Inferred Rates, Truckload Line Haul Index, and Net Trailer Orders indexes decrease. More specifically, a decrease in the indexes of Freight Expenditure, Inferred Rates, and Truckload Line Haul indicates an enhancement of supply chain firms' transportation performance, while a decrease in the indexes of Freight Shipments and Net Trailer Orders indicates a deterioration in firms' transportation performance. It was discerned that by increasing the number of website visitors to supply chain firms, their key transportation performance indexes (TPIs), which are related to transportation expenditure, improved by up to 60%. More specifically, increased supply chain firms' website visibility provokes a decrease in the study's transportation performance indexes (TPIs) by an average of 87.7%. These results highlight the importance for supply chain firms to improve their website visibility and ranking through search engines as a cost-efficient means for enhancing their operational efficiency originating from transportation performance and capacity.

This paper's results are aligned with multiple other studies in the field of machine and deep learning processes for supply chain firms based on big data utilization. First of all, according to Sanders [66] and based on the study's outcomes, supply chain firms can transform their supply chain operations by using big data analytics. Islam & Amin [67], harvest deep and machine learning techniques, similar to our research direction, to predict and model the backorder products of supply chain firms. The importance of big data analytics in developing efficient supply chain models has been pointed out by many studies [68]. Machine and deep learning techniques could also indicate specific areas for supply chain firms' decision-making processes to further improve the efficiency of their firms' collaboration with other organizations [34]. Our work has highlighted the fact that deep learning techniques can decrease transportation expenses for supply chain firms when they are based on the adjustment of specific website big data analytics closely related to the firms' expenses.

Concerning the implication of deep learning methods in this study, the utilization of the FNN technique was selected for the estimation of specific website analytical metrics referring to the simulation model's agents. Based on the number of agents used in the model (100, 1000, 10,000, and 100,000), the FNN process rapidly estimated their behavioral analytical metrics, and its outputs were used further in the simulation model for the prediction of the TPI values. Overall, the selected deep learning method's exploitation led to the accurate and fast estimation of the agents/website visitors' metrics, which were key inputs for the calculation of the supply chain transportation indexes.

The research's technical contributions are mainly based on the collaboration of deep learning methods with big data analytics for the development of a predictive simulation model. Many recent studies have analyzed the role of deep learning methods in the accuracy and processing efficiency of big data analysis techniques [20,69]. On the contrary, the present study focused on the collaboration of big data analytics and deep learning methods (FNN), despite their core differences and challenges in their common application [70]. Although the authors utilized a simplified FNN with a single hidden layer for the estimation of the selected web analytic metrics of the website visitors, the combination of the deep learning method with the extracted big data analytics resulted in accurate simulation outcomes in a timely processing period.

Furthermore, the practical implications of this paper are focused on the roles of the marketing and operational departments of supply chain firms. By studying specific big data analytics of their firms' websites, marketing, and operational departments' staff, they can predict and forecast specific transportation performance indexes [71]. Moreover, based on the findings of Schoenherr & Speier-Pero [72], our research model of engineering supply chain firms' transportation indexed with deep learning shows a potential pattern for firms in the sector to observe and study big data analytics originating from various sources, such as a website, to apply an innovative process for optimizing their supply chain performance indexes. Hence, it has been highlighted that the role of deep learning procedures for supply chain firms through big data utilization is beneficial and can lead to enhanced transportation performance in terms of cost reduction. Such a finding could improve the sustainability of supply chain firms through the utilization of big data analytics [73,74] and deep learning processes [65].

5.2. Limitations

Regarding the potential limitations that applied to the execution of the present study, it should be mentioned that these refer to the utilization of specific big data analytic metrics and FNN procedures. The authors opted to extract 10 specific analytic metrics from the websites of well-established supply chain firms, while the variety of available big data analytics is vast. Furthermore, the FNN procedures used, as well as the simulation model, have some other obvious but not restricting limitations. The simulation time of the model was set to 360 days to represent a whole year of supply chain firms' operations, providing useful insights. This simulation period could be further increased to grant even more accurate and foreseeable outcomes. The FNN procedure was based on simulating the behavior of supply chain website visitors (agents in the model) through the input of information, behavioral characteristics, etc. [62]. Such a method led to a specific range of simulation results and information through the use of other deep learning methods, such as CNN, LSTM models, etc., and machine learning methods, such as KNN, SVM, etc., or a precise combination of them.

5.3. Future Work

Based on the outcomes of the present analysis, the authors could seek the exploitation of multiple methods combined for analyzing big data analytics' effect on firms and market sectors. More specifically, the authors focused on the analysis of supply chain big data analytics' impact on their key transportation performance indexes. For this reason, the utilized indexes refer to supply chain firms' freight expenses, volumes, inferred rates, trailer orders, etc. In the future, more light should be shed on the examination of other supply chain performance indicators. Moreover, upcoming research in this field could be aimed at the capitalization of more complex deep learning methods, such as Generated Adversarial Networks (GAN), Convolutional Neural Networks (CNNs), or Recurrent Neural Networks (RNNs), that could include spatial and temporal agents' interactions, as well as other performance indexes apart from transportation ones, such as the supply chain Pressure, Stability, and Volatility Indexes [75].

Author Contributions: Conceptualization, D.P.S. and N.T.G.; methodology, D.P.S. and N.T.G.; software, N.T.G.; validation, M.C.T. and N.K.; formal analysis, M.C.T. and N.K.; investigation, N.T.G., M.C.T. and N.K.; resources, N.T.G. and M.C.T.; data curation, M.C.T.; writing—original draft preparation, N.T.G. and M.C.T.; writing—review and editing, D.P.S. and N.T.G.; visualization, D.P.S. and N.T.G.; supervision, D.P.S. and N.K.; project administration, D.P.S. and N.T.G.; funding acquisition, N.K. and M.C.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors acknowledge the support of this work by the project "SMART AGRI-CULTURE AND CIRCULAR BIO-ECONOMY—SmartBIC". (MIS MIS5047106), which is implemented under the Action "Reinforcement of the Research and Innovation Infra-structure", funded by the Operational Programme "Competitiveness, Entrepreneurship, and Innovation" (NSRF 2014–2020), co-financed by Greece and the European Union (European Regional Development Fund).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Pseudocode for supply chain analytics deep learning simulation.

Pseudocode of Anylogic Java Output

```
procedure enterState(_state, _destination):
switch_state:
case PotentialSCCustomer:
setActiveState(PotentialSCCustomer)
potentialSCCustomer += 1
transition11.start()
transition12.start()
transition13.start()
transition14.start()
transition15.start()

case DirectSource:
setActiveState(DirectSource)
directSource += 1
transition6.start()

case BounceRate:
setActiveState(BounceRate)
websiteVisits += 1
websiteVisitors = websiteVisits * 0.972
transition4.start()
transition16.start()

case BounceToTraffic:
setActiveState(BounceToTraffic)
transition3.start()
transition5.start()

case OrganicTraffic:
setActiveState(OrganicTraffic)
transition.start()

case BrandedTraffic:
setActiveState(BrandedTraffic)
brandedTraffic = normal(3.86919, 55.7833)
freightShipmentsIndex = authorityScore * 0.017 + paidCosts * −1.051 + bounc-eRate * 0.322 +
timeOnSite * −0.075 + websiteVisits * −0.640
netTrailerOrders = authorityScore * −0.235 + paidCosts * 0.201 + bounceRate * 0.857 + timeOnSite
* −0.441 + websiteVisits * −0.709
truckloadLHIndex = authorityScore * −0.276 + paidCosts * −0.760 + bounceRate * −0.223 +
timeOnSite * 0.372 + websiteVisits * −0.447
```

Table A1. *Cont.*

Pseudocode of Anylogic Java Output
freightIndexExpenditures = authorityScore * −0.225 + paidCosts * −1.207 + bounceRate * 0.555 + timeOnSite * 0.248 + websiteVisits * −0.747 inferredRates = authorityScore * −0.699 + paidCosts * −0.688 + bounceRate * 0.701 + timeOnSite * 0.871 + websiteVisits * −0.439 transition2.start() case PaidTraffic: setActiveState(PaidTraffic) transition1.start() case SocialSource: setActiveState(SocialSource) socialSource += 1 transition9.start() case SearchSource: setActiveState(SearchSource) searchSource += 1 transition10.start() case ReferralSource: setActiveState(ReferralSource) referralSource += 1 transition7.start() case PaidSource: setActiveState(PaidSource) paidSource += 1 transition8.start() default: super.enterState(_state, _destination) end switch end procedure function feedforward_neural_network(input_features): input_size = length(input_features) hidden_size = 1 output_size = 1 hidden_weights = random_matrix(hidden_size, input_size) hidden_biases = random_vector(hidden_size) output_weights = random_matrix(output_size, hidden_size) output_biases = random_vector(output_size) hidden_activations = relu(dot(hidden_weights, input_features) + hidden_biases) output = dot(output_weights, hidden_activations) + output_biases return output function relu(x): return max(0, x)

Table A1. *Cont.*

Pseudocode of Anylogic Java Output
function normal_distribution(x): normal_value = scipy.stats.norm.cdf(x) return normal_value input_feature = [timeOnSite, pagesPerVisit] predicted_output = feedforward_neural_network(input_feature) normal_value = normal_distribution(predicted_output) print("Predicted Output (Normal Distribution Value):", normal_value) input_feature = [bounceRate] predicted_output = feedforward_neural_network(input_feature) normal_value = normal_distribution(predicted_output) print("Predicted Output (Normal Distribution Value):", normal_value) input_feature = [organicTraffic] predicted_output = feedforward_neural_network(input_feature) normal_value = normal_distribution(predicted_output) print("Predicted Output (Normal Distribution Value):", normal_value) input_feature = [paidTraffic] predicted_output = feedforward_neural_network(input_feature) normal_value = normal_distribution(predicted_output) print("Predicted Output (Normal Distribution Value):", normal_value)

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