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Agroeconomic Indexes and Big Data: Digital Marketing Analytics Implications for Enhanced Decision Making with Artificial Intelligence-Based Modeling

Nikolaos T. Giannakopoulos [1,*], Marina C. Terzi [1], Damianos P. Sakas [1], Nikos Kanellos [1], Kanellos S. Toudas [1] and Stavros P. Migkos [2]

[1] Bictevac Laboratory—Business Information and Communication Technologies in Value Chains Laboratory, Department of Agribusiness and Supply Chain Management, School of Applied Economics and Social Sciences, Agricultural University of Athens, 118 55 Athens, Greece
[2] Department of Management Science and Technology, School of Economic Sciences, University of Western Macedonia, 501 00 Kozani, Greece
* Correspondence: n.giannakopoulos@aua.gr; Tel.: +30-694-00-13-673

Abstract: Agriculture firms face an array of struggles, most of which are financial; thus, the role of decision making is discerned as highly important. The agroeconomic indexes (AEIs) of Agriculture Employment Rate (AER), Chemical Product Price Index (CPPI), Farm Product Price Index (FPPI), and Machinery Equipment Price Index (MEPI) were selected as the basis of this study. This research aims to examine the connection between digital marketing analytics and the selected agroeconomic indexes while providing valuable insights into their decision-making process, with the utilization of AI (artificial intelligence) models. Thus, a dataset of website analytics was collected from five well-established agriculture firms, apart from the values of the referred indexes. By performing regression and correlation analyses, the index relationships with the agriculture firms' digital marketing analytics were extracted and used for the deployment of the fuzzy cognitive mapping (FCM) and hybrid modeling (HM) processes, assisted by using artificial neural network (ANN) models. Through the above process, there is a strong connection between the agroeconomic indexes of AER, CPPI, FPPR, and MEPI and the metrics of branded traffic, social and search traffic sources, and paid and organic costs of agriculture firms. It is highlighted that agriculture firms, to better understand their sector's employment rate and the volatility of farming, chemicals, and machine equipment prices for future investment strategies and better decision-making processes, should try to increase their investment in the preferred digital marketing analytics and AI applications.

Keywords: agroeconomic indexes; big data; AI; ANN; digital marketing; digital transformation; predictive analytics; agriculture; decision support systems (DSS)

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1. Introduction

In a contemporary landscape characterized by the confluence of burgeoning global populations, escalating environmental concerns, and the proliferation of data-driven solutions, agriculture emerges as a pivotal sphere in the endeavor to meet the pressing needs of food security and environmental sustainability [1]. Approximately one quarter of the world's labor force is engaged in agriculture, underscoring the central role of the agricultural sector in both sustaining the world's population [2] and addressing broader challenges such as climate change and resource conservation [3]. As the agriculture sector undergoes significant transformations driven by technological advancements, market dynamics, and environmental concerns, it becomes increasingly imperative to assess its decision making and sustainability comprehensively [4]. Agriculture indexes, a set of vital economic indicators, offer a lens through which one can examine the sector's health, stability, and impact on the broader economy [5]. To navigate these intricate challenges, a sophisticated framework of these agroeconomic indexes has evolved as an indispensable tool. Within this framework, several key indices assume a prominent position, including the Agriculture Employment Rate (AER), the Chemical Product Price Index (CPPI), the Farm Product Price Index (FPPI), and the Machinery Equipment Price Index (MEPI).

These agroeconomic indices transcend mere numerical representations; they serve as vantage points to discern the underlying dynamics of the agricultural sector. The Agriculture Employment Rate (AER) provides valuable insights into the labor force within the sector, enabling a nuanced understanding of employment trends and their implications for economic and social well-being [6]. Meanwhile, the Chemical Product Price Index (CPPI) encapsulates the volatility and trends in the pricing of agricultural inputs, reflecting both domestic and international dynamics [7]. The Farm Product Price Index (FPPI) sheds light on the pricing dynamics of agricultural outputs, reflecting changes in demand, supply, and global market conditions [8]. Lastly, the Machinery Equipment Price Index (MEPI) offers a lens through which to scrutinize the evolving costs associated with capital investment in agricultural equipment, indicative of technological innovation and mechanization [9]. These indexes, though not standardized across regions or widely recognized in the previous literature [10], offer unique insights into various facets of agriculture, from labor market dynamics to the pricing of essential inputs and outputs. By analyzing these indexes in tandem with big data, this study seeks to bridge the gap between macroeconomic indicators and micro-level firm sustainability, thereby providing a holistic perspective on the agriculture sector's future.

Notwithstanding the prevailing consensus regarding the significance of sustainable development, a fundamental challenge persists. According to Long and Ji [11], the complexities and uncertainties associated with measuring the quality of economic growth pose a substantial obstacle, preventing governments from formulating empirically grounded strategies. While several researchers have delved into the sustainability aspects of the agricultural sector using big data [12–14], certain pivotal questions continue to pique researchers' curiosity. We find ourselves pondering how this wealth of big data information deciphers the digital behaviors of customers and how, in turn, agroeconomic indexes exert their influence on the sustainability of businesses. Given the contemporary shift of companies toward customer-centric strategies as a means to remain competitive and enhance their performance outcomes [15], the incorporation of behavioral analytics metrics has become imperative [16]. The systematic scrutiny of expansive datasets, facilitated by the burgeoning domain of big data and behavioral metrics, bestows upon stakeholders in the realm of agriculture the capacity to engage in informed, data-driven decision making, optimize the allocation of resources, and elevate the overall sustainability quotient. The application of this approach has manifested notable success within the realm of supply chain transportation indexes, rendering consequential and valuable results [17].

Until now, the agricultural sector has not fully embraced marketing technology, and incorporating digital marketing practices has the potential to substantially improve the marketing capabilities of agricultural producers and startups [18]. Berbel and Martinez-Dalmau [19] present an agroeconomic model aimed at optimizing agricultural practices at the farm level. Similarly, Storm et al. [20] employ advanced computational techniques, specifically machine learning and AI models, to analyze and extract meaningful insights from complex agroeconomic data. While these studies provide a broader perspective on applying these techniques in agricultural economics, the current research takes a more focused approach, narrowing its scope to specific agroeconomic indexes pertinent to digital marketing analytics. This targeted exploration within the agricultural domain aims to deepen the understanding of how data-driven approaches can revolutionize decision making in the strategic realms of agricultural marketing.

The study intertwines insights from Klerkx et al.'s [21] research paper to elucidate the societal dimensions of integrating agroeconomic indexes into digital marketing analytics, emphasizing the influence on agricultural decision making. Additionally, Lioutas et al.'s study [22] serves as a framework, guiding the investigation into how agroeconomic indexes, big data, and AI-based modeling practically impact decision making, especially within digital marketing analytics for agriculture. This interdisciplinary approach marks a significant contribution to the intersection of agricultural economics and big data analytics, offering a novel and practical roadmap for fostering sustainable and resilient agricultural marketing activities.

The present paper is organized as follows for better comprehension and elaboration of the related fields and research items. In Section 2, the main concept of the study and the related current literature are analyzed. In Section 3, the research hypotheses, diagnostic model, and information regarding the collected sample can be discerned. Furthermore, in Section 4, the utilized methods for the extraction of the study's outcomes are provided, followed by Sections 5 and 6, where the theoretical and practical implications of the present research are highlighted.

2. Motivation and Background of the Research

2.1. Implications of AI Models for Decision Making in Agriculture

The infusion of artificial intelligence (AI) models into agricultural decision making represents a watershed moment in the sector's trajectory [23]. This paradigm shift elevates digital marketing from its conventional operational role to an integral component within the theoretical framework governing strategic decisions [24,25]. In the realm of precision agriculture, the influential role of AI models, particularly artificial neural networks (ANNs), is pronounced as they adeptly assimilate expansive datasets [26]. This assimilation optimizes digital marketing strategies, concurrently impacting economic indexes entwined with marketing costs and resource efficiency [27,28]. The strategic recalibration of resource allocation facilitated by using AI models—specifically ANNs—emphasizes dynamic resource optimization aligned with sustainability goals [29,30]. This process underscores the nuanced interplay between operational decisions and the effectiveness of marketing strategies.

AI models, particularly ANNs, contribute significantly to early disease detection, influencing strategic decisions related to digital marketing initiatives [31]. This not only safeguards crop yields but also influences economic indexes associated with digital marketing ROI and the cost-effectiveness of disease management strategies [32–34]. In the domain of market trends and price forecasting, AI models, including ANNs, enhance the competitiveness of agricultural enterprises [35,36]. This influence extends to strategic decisions tied to digital marketing campaigns and economic indexes linked to market trends and pricing dynamics [18].

The integration of AI models, notably ANNs, into decision support systems (DSS) tailored for agriculture, signifies a transformative paradigm [24,37]. This integration intricately weaves digital marketing strategies into decision support systems, impacting economic indexes tied to agricultural decision dynamics [24]. Beyond traditional decision-making realms, AI models, especially ANNs, augment digital marketing activities by revealing intricate relationships between agroeconomic indexes and key web metrics [38–40]. This nuanced insight empowers agriculture firms to strategically refine and optimize digital marketing endeavors, profoundly impacting sectoral decision making and its correlation with economic indexes. In conclusion, the implications of AI models, particularly ANNs, extend beyond technological advancements, shaping the fabric of decision making within agriculture [41]. This underscores the strategic integration of marketing decisions for informed and impactful outcomes.

2.2. Big Data and Digital Marketing in Agriculture

The pervasive influence of agroeconomic indicators on marketing strategies underscores their indispensability as tools for navigating the ever-evolving economic landscape [42]. Essential agroeconomic indices provide marketers with invaluable insights into consumer behavior, purchasing power, and the broader economic context [43]. These indicators shape pricing strategies, allowing adjustments based on inflation rates and economic stability, and influencing decisions related to advertising budgets and resource allocation during economic expansions or contractions [44–46].

The connection between agroeconomic indicators and digital marketing strategies reflects a potential means of observing and predicting the former, through the adjustment of the latter. The insights gleaned from agroeconomic indicators empower marketers to navigate the nuanced landscape of consumer behavior, ensuring that messages resonate effectively with specific economic demographics [47]. Additionally, the adaptability afforded by pricing strategy adjustments in response to economic indicators enhances the agility of marketing campaigns, aligning them with the prevailing economic conditions [48]. Digital marketing strategies are an effective tool for shaping businesses' financial performance and decision-making processes, including agriculture firms; one could presume that they could potentially help analyze specific agroeconomic index variations. Marketers, armed with insights from economic indices, are better equipped to craft strategies that not only weather economic fluctuations but also leverage them strategically to optimize outcomes.

The reverberations of agroeconomic conditions extend seamlessly into the realm of digital marketing, exerting a profound influence on consumer behavior and shaping strategic initiatives in the online domain [49]. Particularly during economic downturns, marketers adopt a strategic approach to website optimization, prioritizing elements such as pricing transparency, tangible discounts, and value propositions crafted to resonate with the prevailing cost-conscious sentiments of consumers [50]. This nuanced optimization aims not only to enhance the user experience but also to align the online presence of brands with the economic realities faced by consumers.

Within the realm of website design and functionality, the meticulous tailoring of the user experience (UX) reflects a deliberate effort to synchronize with evolving expectations influenced by the undulating nature of economic fluctuations [51]. Marketers, recognizing the importance of seamless user interaction, invest efforts in optimizing navigation, reducing loading times, and ensuring mobile responsiveness to adeptly meet the dynamic needs of consumers [52]. This conscientious optimization not only enhances the overall user experience but is also a strategic response to the changing economic conditions that influence online consumer behavior.

Agroeconomic factors exert their influence on various facets of digital marketing, extending beyond the technical aspects of website design. Content marketing and search engine optimization (SEO) strategies, critical components of the digital marketing landscape, are also significantly impacted [53]. The need for adaptation arises as economic conditions fluctuate, requiring marketers to address economic concerns, deliver insightful content, and realign SEO strategies to resonate with emerging user search behaviors influenced by the prevailing economic climate [54]. This interdependence underscores the paramount importance for marketers to maintain a nuanced understanding of agroeconomic indicators [55], ensuring a continual refinement of strategies that remain agile and responsive to the dynamic demands of users navigating the fluid and ever-changing economic landscape, particularly within the intricate realm of digital marketing.

Within the domain of firm sustainability, the fusion of big data analytics assumes a heightened significance within the landscape of agricultural digital marketing activities and the discernment of user online behavior [12]. The integration of big data analytics equips stakeholders with sophisticated insights into various dimensions, including consumer behavior, prevailing market trends, and the environmental impact associated with agricultural practices [56]. This data-driven approach plays a pivotal role in shaping marketing strategies and facilitating informed decision making across the agricultural supply chain.

In summary, the symbiosis of agroeconomic indicators, big data analytics, and digital marketing strategies emerge as a linchpin in propelling sustainability initiatives within the agricultural sector. This synergistic approach not only enhances the precision of marketing strategies but also aligns them with broader sustainability objectives. The integration of these key components serves as a foundational cornerstone, fostering a holistic and data-informed approach to sustainable practices in agriculture.

2.3. Agroeconomic Index Connections with AI-Modeled Digital Marketing Analytics

To the best of our knowledge, the majority of research papers on big data in agriculture have predominantly analyzed its contributions from a technical standpoint. For instance, Kamilaris et al. [57] conducted a comprehensive review, scrutinizing thirty-four research papers to assess the problems addressed, proposed solutions, tools and techniques employed, and the types of data utilized in the agricultural domain. Similarly, Tseng et al. [58] focus on the application of big data analytics in an Intelligent Agriculture IoT system, aiming to evaluate environmental factors and enhance decision making for crop selection in response to challenges posed by climate change. In another recent study, Misra et al. [13] explore the disruptive role of IoT, big data, and AI in agri-food systems, examining their applications in agriculture, supply chain management, social media, food quality assessment, and safety. This study, noteworthy for considering social media as a crucial source of user-generated big data, specifically highlights its impact on consumer behavior.

Addressing this aspect, Caiazza and Bigliardi [59] underscore the importance for researchers and practitioners to account for diverse consumer behaviors within the agri-food sector, emphasizing the need for more extensive research due to existing gaps in in-depth analysis and comprehensive statistics. Bhat et al. [60] further assert that big data are widely employed across sectors to analyze and customize product prices based on a precise understanding of customer behavior, thereby enhancing operational efficiency and reducing costs. They also note the utilization of big data analytics by social networking platforms like Facebook and X (formerly Twitter) to study users' social behaviors, interests, and connections, facilitating targeted product endorsements. Driven by the observed deficiency in comprehensive analysis regarding consumers' online behaviors in the agricultural sector, this study attempts to explore potential links between specific agroeconomic indexes and the digital marketing analytics of agricultural firms.

The infusion of artificial intelligence (AI) models into agricultural decision making signifies a transformative leap, revolutionizing key aspects of the sector. A pivotal dimension impacted by this transformation is predictive analysis, where the amalgamation of historical agroeconomic data and real-time marketing insights, monitored through web analytics, empowers farmers with proactive decision-making capabilities [60]. Utilizing data on branded traffic, organic traffic, and paid traffic, AI models may optimize planting schedules and estimate crop yields [61], as well as strategically plan marketing initiatives [62]. Through web analytics metrics like bounce rate, page per visit, and time on site, digital marketing strategies can be refined [63], thereby enhancing overall efficiency, resource allocation, and the effectiveness of marketing initiatives in agriculture.

Moreover, the amalgamation of agroeconomic indexes with AI models, tracked through web analytics tools, can enhance precise market forecasting [64] This allows real-time adjustments to commodity prices, demand–supply dynamics, and economic indicators. By analyzing data on organic costs, paid costs, and the performance of different traffic sources, farmers could make informed decisions leading to improved revenue streams, profitability, and overall resilience in the agricultural marketplace. Simultaneously, marketers of agriculture firms, armed with data on social sources, search sources, and referral sources, could tailor strategies to respond to forecasted market conditions [65]. This dynamic interaction between agroeconomic indexes and AI-modeled digital marketing analytics, grounded in web analytics metrics, holds promise for cultivating a more adaptive and efficient agricultural landscape.

AI models, utilizing agroeconomic insights tracked via web analytics, possess the potential to enhance targeted marketing strategies in agriculture similar to their impact in other domains [38]. Verma et al. [66] state that among disruptive technologies, artificial intelligence (AI) stands as the most recent disruptor, offering significant potential for sectors such as manufacturing, pharmaceuticals, healthcare, agriculture, logistics, and digital marketing. By utilizing data on branded traffic, organic traffic, paid traffic, and direct sources, personalized marketing approaches are crafted [67]. AI models could craft personalized campaigns using agroeconomic factors and regional variations, with web analytics providing insights into user behavior and enhancing communication with farmers. These approaches align marketing efforts with regional economic conditions and consumer preferences, potentially resulting in the optimization of resource utilization and enhanced profitability for farmers. Additionally, web analytics metrics such as bounce rate and pages per visit offer insights into user engagement, aiding in the adaptability of pricing strategy adjustments in response to economic indicators [68]. This may contribute to the agility of marketing campaigns, aligning them with prevailing economic conditions.

Furthermore, the integration of agroeconomic data into AI models, monitored through web analytics, has the potential to enhance supply chain efficiency [69]. Insights into production, transportation, and market demands, along with web analytics metrics on site traffic patterns, could streamline the agricultural supply chain. This involves optimizing inventory management and aligning production levels with market needs. The data-driven decision-making approach, facilitated by the amalgamation of agroeconomic indexes and AI-driven digital marketing analytics grounded in web analytics metrics, provides historical context, economic trends, and real-time insights into consumer behavior and market dynamics [70].

In summary, the incorporation of AI models, observed through web analytics, has the potential to revolutionize decision-making processes in agriculture. Through the analysis of diverse datasets, the utilization of predictive analytics, and the implementation of targeted marketing strategies based on web analytics metrics, AI appears to empower agricultural stakeholders to make well-informed and strategic decisions. This capability to anticipate future trends, optimize resource allocation, and streamline supply chain processes could position agricultural firms for increased efficiency, adaptability, and sustainability. The seamless integration of agroeconomic data into AI models monitored through web analytics could facilitate a nuanced understanding of the dynamic agricultural landscape, enabling proactive responses to market fluctuations and ensuring optimal outcomes for farmers and stakeholders. In essence, AI models, guided by web analytics, act as catalysts for transformative decision making, fostering a resilient and forward-looking agricultural sector.

RQ: Is there any potential connection between the digital marketing analytics (website user behavioral data) and the agroeconomic indexes of AER, CPPI, FPPR, and MEPI, and can there emerge any implications for agriculture firms' decision making from the referred connections and the utilization of AI modeling processes?

2.4. Hypotheses Development

After presenting the relative literature and the required definitions of the terms and economic indexes included in our analysis, the development of the research hypotheses was completed. In Table 1, the various agroeconomic indexes are analyzed and key information is provided regarding their description, measurement, period of observation, etc.

The first hypothesis postulates a potential connection between digital marketing analytics and the AER index of the agribusiness sector. More specifically, it aims to examine which specific analytics, whether they refer to website visitors' behaviors, general webpage metrics, digital marketing KPIs, etc., appear to have a strong connection with the variation in AER. Such a finding could also indicate that the fluctuation in some digital marketing analytics of agricultural firms is capable of predicting or estimating the Agricultural Employment Rate index, thus assisting in their decision making. In summary, this hypothesis sets the stage for empirical research to delve into the potential interplay between technological innovation, online presence, and employment dynamics within the agricultural sector, with implications for the sector's future sustainability and efficiency.

Hypothesis 1 (H1). *The Agriculture Employment Rate (AER) of agriculture firms is connected to the digital marketing analytics of their websites.*

Table 1. Agroeconomic Indexes Characteristics.

Agroeconomic Indexes	Description and Measurement	Code	Countries of Reference	Observation Period
Agriculture Employment Rate (AER)	Agriculture and Related Industries, Thousands of Persons, Monthly, Seasonally Adjusted	LNS12034560	USA	1 July 2022–31 January 2023
Chemical Product Price Index (CPPI)	Producer Price Index by Industry: Pesticide and Other Agricultural Chemical Manufacturing: Agricultural and Commercial Pesticides and Chemicals, Monthly, Not Seasonally Adjusted	PCU3253203253201	USA	1 July 2022–31 January 2023
Farm Product Price Index (FPPI)	Producer Price Index by Commodity: Farm Products, Monthly, Not Seasonally Adjusted	WPU01	USA	1 July 2022–31 January 2023
Machinery Equipment Price Index (MEPI)	Producer Price Index by Commodity: Machinery and Equipment: Agricultural Machinery and Equipment, Monthly, Not Seasonally Adjusted	WPU111	USA	1 July 2022–31 January 2023

Source: FRED, Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/ (accessed on 8 November 2023).

Hypothesis 2 posits that the CPPI of agricultural firms is positively influenced by the utilization of their website digital marketing analytics. In essence, it suggests that as agricultural firms increasingly employ digital marketing strategies, specific analytical metrics (website visitors' behaviors, general webpage metrics, digital marketing KPIs, etc.) may have a favorable impact on their CPPI, reflecting the pricing dynamics of chemical products within the agricultural domain. Moreover, such digital analytical metrics could indicate a potential prediction of the course of chemical products' prices, and enhance the decision-making processes of agribusiness firms. In essence, H2 lays the groundwork for further investigation into the influence of data-driven practices on the economic aspects of agricultural firms, offering insights into the role of technology in shaping pricing dynamics within the sector.

Hypothesis 2 (H2). *The Chemical Product Price Index (CPPI) of agriculture firms is positively impacted by the digital marketing analytics of their websites.*

Hypothesis 3 suggests the emergence of a robust relationship between the digital marketing analytics implemented on the websites of agriculture firms and the FPPI index. In other words, it posits that the extent to which agricultural firms engage in advanced digital marketing analytics on their websites could be strongly linked to the FPPI, which reflects the pricing dynamics of farm products. H3, in essence, paves the way for further investigation into the intricate interplay between digital marketing strategies and pricing mechanisms within the agricultural sector, shedding light on the role of digital marketing analytics in shaping pricing dynamics or evaluating the trajectory of farming products' prices that could further affect agribusiness decision making.

Hypothesis 3 (H3). *Between agriculture firms' website digital marketing analytics and their Farm Product Price Index (FPPI), a strong relationship emerges.*

Hypothesis 4 suggests a positive impact on the MEPI index of the agriculture sector and the utilization of digital marketing analytics on agribusiness firms' websites. In essence, it implies that agricultural firms increasingly harvest digital marketing analytics on their websites to define or more probably to estimate and comprehend the pricing dynamics of machinery and equipment used in agriculture. H4 thus lays the groundwork for further exploration into the role of the adjustment of specific digital marketing analytics in affecting or estimating mechanical equipment price variations for agricultural firms, while also offering insights for enhanced decision making.

Hypothesis 4 (H4). *Agriculture firms' Machinery Equipment Price Indexes (MEPIs) are affected strongly by their websites' digital marketing analytics.*

3. Materials and Methods

3.1. Methodological Framework

Having reviewed the literature review regarding the agriculture economic indexes and the decision-making processes of agriculture firms, the authors developed an innovative methodological process by utilizing ANN models. These methods included the collection of website big data, their grouping, and organizing processes, followed by their statistical and modeling analyses, including the AI model. Hence, to aid the procedure of testing the paper's research hypotheses, as well as the clarification of the impact of agriculture firms' big data on their agroeconomic indexes, the following systematic analytical process was applied.

- Collection and organization of big data from corporate websites combined with the gathering of the required indexes: For this phase, the website platform DSS, which enables website analytical data from corporate websites, is utilized to extract the historical values of the selected big data metrics. For the agroeconomic indexes of this study, the database of the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/ (accessed on 8 November 2023) was accessed. The authors extracted historical data referring to the period of 1 July 2022 up to 31 January 2023.
- Development of statistical analysis followed by a conceptual framework using the Fuzzy Cognitive Mapping (FCM) process takes place by utilizing the MentalModeler [71] website platform DSS. In this step, the authors performed the required statistical analyses (descriptive statistics, correlation, and linear regression models) for extracting valuable coefficients for the variables' relationships. Then, the correlation and linear regression coefficients (OLS), as well as the variables' descriptive statistics were inserted into the FCM model. In this way, the FCM output provided this study with a concept for representing the interrelationships of the total of the analyzed factors [72]. The latter model served as a conceptual framework for understanding the overall environment and the included variables in the analysis.
- Deployment of a hybrid modeling process to assist the depiction of agroeconomic index variations through time based on the trajectory of digital marketing analytics by capitalizing on the AnyLogic [73] simulation modeling DSS: This hybrid model (HM) consists of agent-based models (ABMs) and system dynamics (SD) to represent the effect of the dynamic variables, as well as the agent-related ones on the agroeconomic indexes during the simulation period. Regarding the agriculture website users' behavioral metrics, an ANN model [56] was used to simulate the selected digital marketing analytic metrics of agriculture website visitors' online behaviors. This prediction was based on the concept that these digital behavioral metrics should represent the visitors' responses and simulate the normal distribution course. The repletion of the following procedure produced the results of the simulation: agents (ABM), representing agriculture website visitors, enter the website statecharts of the model based on their digital behavior metrics calculated by the ANN model (set to simulate the normal distribution). From the agents' movements, the dynamic variables of the model constantly vary the values of their factors. To perform the task of the overall HM simulation, the coefficients and descriptive statistics of the previous step are required as input.

3.2. Research Sample

For the deployment of the research methodology referred to above, the acquisition of the required big data from the agriculture firms was necessary. To complete this task, the authors selected the following 5 agriculture firms that operate worldwide based on their market capitalization [74] in 2023 [75]: AGCO [76], Corteva [77], Escorts Kubota [78], Hektas [79], and Olam Group [80]. The big data for this study were gathered from the websites of the selected agriculture firms, and the values of the referred indexes were extracted from the platform Statista for the period of 1 July 2022 up to 31 January 2023. For the collection of the big data from the selected agriculture firms, the DSS platform of Semrush [81] was utilized for the same period (1 July 2022 up to 31 January 2023). Regarding the selected firms, more information is presented in Table 2.

Table 2. Description of the study's agriculture firms.

Firms	Market Cap Q3 2023 USD	Number of Employees	Total Revenue 2023 TTM USD	Fields of Operation	HQ Location(s)
AGCO	9.22B	25,600+	14.176M	Machinery equipment, hay and forage, seeding and tillage, smart farming, grounds care, grain storage, etc.	USA, South Africa, China, Australia, Brazil, Switzerland
Corteva	33.13B	21,000+	17.344M	Seeds, crop protection—fungicides, herbicides, insecticides, seed treatments, etc.	USA
Escorts Kubota	3.70B	10,000+	1.08B	Agri-machinery, construction and material handling equipment, railway equipment and auto components, etc.	India
Hektas	48.18B	31,000+	5.26B	Crop protection, plant nutrition, seeds, animal health, environmental health, etc.	Turkey
Olam Group	3.75B	82,000+	24.685B	Farming food products, technology solutions, start-up growth initiatives, packaged food, palm oil, etc.	Burkina Faso

4. Results

4.1. Statistical Analysis

To extract the required statistical measures for the following diagnostic and hybrid modeling processes, the authors deployed a descriptive statistics analysis (Table 3) for all the variables of the analysis, and also a correlation analysis, based on Pearson's coefficient (Table 4). At first, the descriptive statistics provided a clear image of the variables' descriptive metrics and their relationships. Then, concerning the dependent and independent variables' relationships, the authors proceeded to the development of simple linear regressions (SLRs).

Table 3. Descriptive Statistics of the five Agriculture Firms during the past six months.

	Mean	Min	Max	Std. Deviation
Agriculture Employment Rate	2,250,428.57	2,173,000.00	2,412,000.00	85,168.18
Chemical Product Price Index	179.29	168.00	192.00	9.24
Farm Product Price Index	252.40	247.00	261.00	6.43
Machinery Equipment Price Index	309.25	303.00	315.00	5.52
Branded Traffic	56.23	44.00	73.00	9.54
Organic Traffic	364,217.41	345,548.00	423,170.00	20,663.04
Organic Costs	246,029.00	146,762.00	426,498.00	89,276.45
Paid Traffic	92.83	0.00	648.00	206.21
Paid Costs	96.66	0.00	762.00	227.75
Direct Sources	323,284. 57	263,604.00	411,527.00	53,683.07
Referral Sources	373,087.43	265,622.00	552,072.00	88,429.30
Social Sources	5985.14	2431.00	10,992.00	2996.30
Search Sources	147,035.29	96,976.00	193,138.00	32,360.16
Bounce Rate	0.53	0.49	0.57	0.034
Pages per Visit	2.75	2.62	2.85	0.095
Time on Site	500.14	370.00	691.00	114.01

N = 180 observation days for the five selected agriculture firms.

Table 4. Correlation analysis matrix.

	Agriculture Employment Rate	**Chemical Product Price Index**	**Farm Product Price Index**	**Machinery Equipment Price Index**	**Branded Traffic**	**Organic Traffic**	**Organic Costs**	**Paid Traffic**	**Paid Costs**	**Direct Sources**	**Referral Sources**	**Social Sources**	**Search Sources**	**Bounce Rate**	**Pages per Visit**	**Time on Site**
Agriculture Employment Rate	1	0.236	0.466	−0.064	0.939 **	−0.059	−0.425	−0.402	−0.400	−0.568	−0.433	−0.345	0.078	−0.455	−0.003	−0.367
Chemical Product Price Index	0.236	1	−0.315	−0.768 *	0.259	−0.025	−0.270	0.587	0.590	−0.129	0.645	−0.392	0.770 *	−0.036	0.297	0.217
Farm Product Price Index	0.466	−0.315	1	0.504	0.269	−0.381	−0.400	−0.369	−0.370	−0.745	−0.656	−0.006	−0.176	−0.187	−0.651	0.075
Machinery Equipment Price Index	−0.064	−0.768 *	0.504	1	0.003	0.403	0.516	−0.450	−0.451	−0.424	−0.696	0.283	−0.561	−0.133	−0.785 *	0.136
Branded Traffic	0.939 **	0.259	0.269	0.003	1	0.196	0.212	−0.081	−0.153	−0.540	−0.332	−0.442	−0.005	−0.387	−0.040	−0.302
Organic Traffic	−0.059	−0.025	−0.381	0.403	0.196	1	0.474	−0.117	−0.087	−0.132	−0.057	0.052	−0.072	−0.221	−0.268	0.142
Organic Costs	−0.425	−0.270	−0.400	0.516	0.212	0.474	1	−0.268	−0.221	0.096	−0.056	0.371	−0.133	−0.154	−0.313	0.322
Paid Traffic	−0.402	0.587	−0.369	−0.450	−0.081	−0.117	−0.268	1	0.987 **	0.148	0.890 **	−0.383	0.281	0.576	−0.012	0.742
Paid Costs	−0.400	0.590	−0.370	−0.451	−0.153	−0.087	−0.221	0.987 **	1	0.147	0.891 **	−0.382	0.285	0.573	−0.011	0.741
Direct Sources	−0.568	−0.129	−0.745	−0.424	−0.540	−0.132	0.096	0.148	0.147	1	0.430	0.223	−0.126	0.292	0.753	−0.225
Referral Sources	−0.433	0.645	−0.656	−0.696	−0.332	−0.057	−0.056	0.890 **	0.891 **	0.430	1	−0.433	0.290	0.615	0.379	0.376
Social Sources	−0.345	−0.392	−0.006	0.283	−0.442	0.052	0.371	−0.383	−0.382	0.223	−0.433	1	0.255	−0.618	−0.017	0.027
Search Sources	0.078	0.770 *	−0.176	−0.561	−0.005	−0.072	−0.133	0.281	0.285	−0.126	0.290	0.255	1	−0.487	0.208	0.213
Bounce Rate	−0.455	−0.036	−0.187	−0.133	−0.387	−0.221	−0.154	0.576	0.573	0.292	0.615	−0.618	−0.487	1	0.003	0.223
Pages per Visit	−0.003	0.297	−0.651	−0.785 *	−0.040	−0.268	−0.313	−0.012	−0.011	0.753	0.379	−0.017	0.208	0.003	1	−0.565
Time on Site	−0.367	0.217	0.075	0.136	−0.302	0.142	0.322	0.742	0.741	−0.225	0.376	0.027	0.213	0.223	−0.565	1

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

In Tables 5 and 6, the first two simple linear regressions were produced by using the referred AER and CPPI indexes as dependent variables. The rest of the agriculture firms' website big data were used as independent variables, seeking to analyze their effect on the mentioned indexes. From the linear regressions of AER (OLS), only those of branded traffic were verified overall with a p-value < a = 0.01 level of significance and an $R^2 = 0.881$. For the dependent variables of AER, CPPI, FPPI, and MEPI, the variables of branded traffic, organic costs, social sources, search sources, time on site, pages per visit, and old visitors were selected as the independents to analyze the indexes' variations. For CPPI, only the linear regression (OLS) of search sources was verified overall with a p-value < a = 0.05 level of significance and an $R^2 = 0.593$. When branded traffic increases by 1%, AER variates by 93.90%, and when search sources increase by 1%, CPPI variates by 77.00%. Thus, from the verification of AER's and CPPI's linear regressions, we can summarize that the first (H1) and second (H2) research hypotheses were verified, meaning that the Agriculture Employment Rate (AER) of agriculture firms is connected to the digital marketing analytics of their websites (H1), which also impact positively the Chemical Product Price Index (CPPI) of agriculture firms (H2).

Table 5. Impact of Big Data Analytics on Agriculture Firm AER (OLS).

Variables	Standardized Coefficient	R^2	F	p-Value
Branded Traffic	0.939	0.881	37.042	0.002 **
Organic Costs	−0.425	0.181	1.102	0.342
Social Sources	−0.345	0.119	0.677	0.448
Search Sources	0.078	0.006	0.030	0.869
Time on Site	−0.367	0.135	0.779	0.418
Old Visitors	−0.517	0.267	1.823	0.235

** Indicates statistical significance at the 99% level.

Table 6. Impact of Big Data Analytics on Agriculture Firm CPPI (OLS).

Variables	Standardized Coefficient	R^2	F	p-Value
Branded Traffic	0.259	0.067	0.359	0.575
Organic Costs	−0.270	0.073	0.393	0.558
Social Sources	−0.392	0.153	0.906	0.385
Search Sources	0.770	0.593	7.278	0.043 *
Time on Site	0.217	0.047	0.247	0.641

* Indicates statistical significance at the 95% level.

Regarding Tables 7 and 8, where the simple linear regressions (OLS) with FPPI and MEPI were used as dependent variables, the analysis showed that only the regression model of MEPI with pages per visit was verified overall, with p-values < a = 0.05 level of significance and an $R^2 = 0.617$. Every 1% of the increase in pages per visit causes a variation of −78.50% in MEPI. Hence, by verifying MEPI's linear regression, it can be discerned that the fourth (H4) research hypothesis of the paper was verified, but the third hypothesis (H3) was not verified, meaning that between agriculture firms' website digital marketing analytics and their Farm Product Price Index (FPPI), no strong relationship emerges; therefore, agriculture firms' Machinery Equipment Price Indexes (MEPIs) are strongly affected by their websites' digital marketing analytics.

Table 7. Impact of Big Data Analytics on Agriculture Firm FPPI (OLS).

Variables	Standardized Coefficient	R^2	F	*p*-Value
Branded Traffic	0.269	0.072	0.389	0.560
Organic Costs	−0.400	0.160	0.954	0.374
Social Sources	−0.006	0.001	0.001	0.989
Search Sources	−0.176	0.031	0.161	0.705
Time on Site	0.075	0.006	0.028	0.873

Table 8. Impact of Big Data Analytics on Agriculture Firm MEPI (OLS).

Variables	Standardized Coefficient	R^2	F	*p*-Value
Branded Traffic	0.003	0.001	0.001	0.995
Organic Costs	0.516	0.266	1.812	0.236
Social Sources	0.283	0.080	0.434	0.539
Search Sources	−0.561	0.314	2.294	0.190
Time on Site	0.136	0.019	0.094	0.771
Pages per Visit	−0.785	0.617	8.042	0.036 *

* Indicates statistical significance at the 95% level.

4.2. FCM Model for Conceptual Framework

After the extraction of the correlation coefficients, this study focused on the development of a diagnostic model that shows the total of the deployed relationships of the included variables. Fuzzy Cognitive Mapping (FCM) is a modeling technique used in various fields, including decision support, expert systems, and system dynamics. It is a method for representing and analyzing complex systems and relationships between various factors or concepts [82]. FCM begins with the identification of key concepts or factors that influence a particular problem or system. These concepts are typically represented as nodes in a network diagram. For each pair of concepts, the direction and strength of the causal relationship between them is defined. These relationships can be positive (promoting or reinforcing) or negative (inhibiting or detracting). The strength of these relationships is often represented using fuzzy logic, which allows for degrees of influence. Also, blue arrows represent the positive relationship of the variables, while red arrows represent the negative ones.

The relationships between concepts are then represented as weighted connections or edges between the nodes in the FCM framework, as shown in Figure 1. The weights indicate the strength of influence, and they can take on fuzzy values to account for uncertainty and imprecision. FCM is used for decision support and scenario planning [83]. FCM can assist agriculture firm owners in making informed decisions by providing insights into the potential outcomes of different actions and policies. FCM is a versatile tool for modeling complex, dynamic systems and understanding the interdependencies among various factors. It allows for the representation of uncertainty and imprecision, making it suitable for situations where precise data are unavailable or where human judgment plays a significant role in understanding and managing complex systems [72]. In our study, FCM is used as a mind map that depicts the total of the deployed relationships among the study's variables [82].

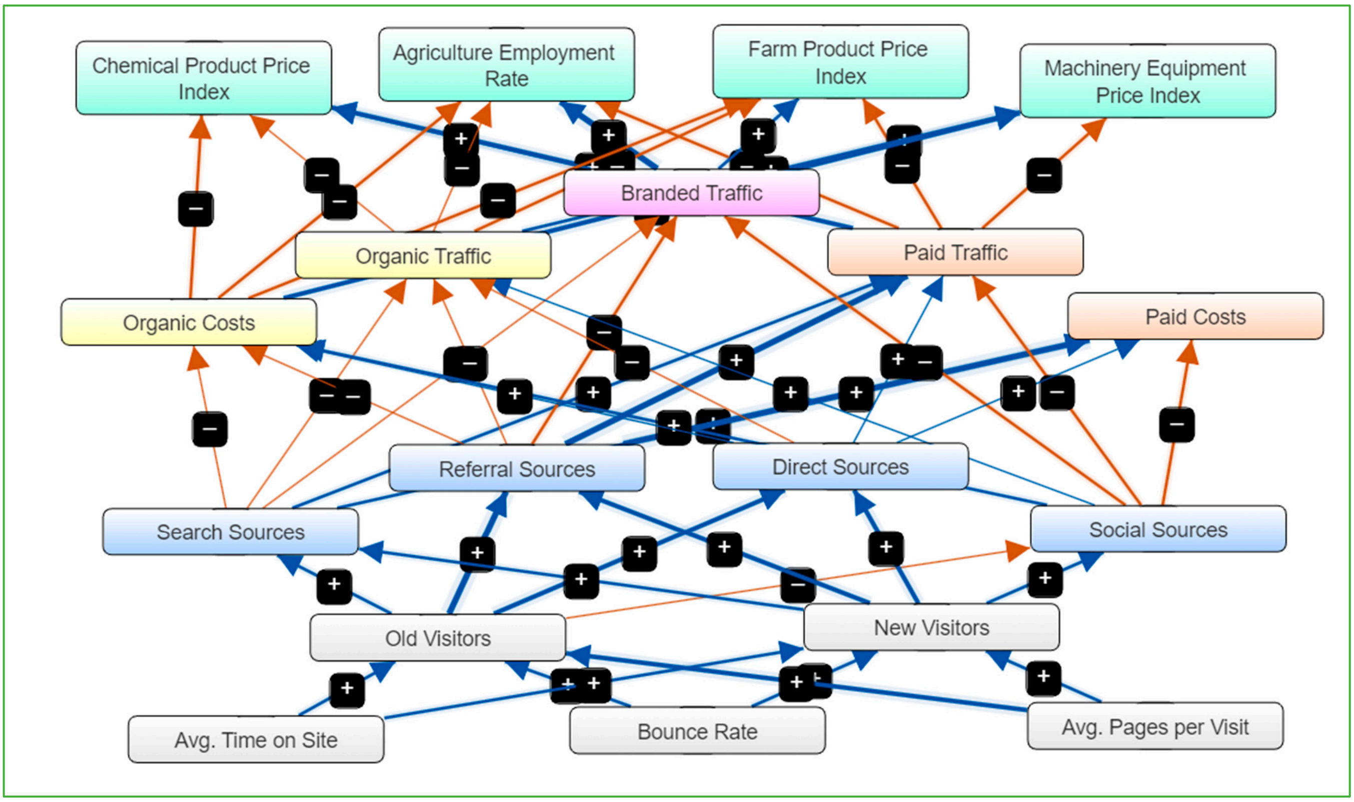

Figure 1. Fuzzy Cognitive Mapping Framework for Agriculture Indexes.

4.3. Hybrid Model and AI Procedures

To assess the impact of agriculture firms' website big data on key agriculture economic indexes, the authors opted to develop a hybrid modeling (HM) process. The deployed modeling process consists of both system dynamics (SD) and agent-based models (ABMs) [84]. ABM and SD methods are widely used throughout the literature in areas like supply chain sustainability, economics, environment, and other fields [85,86]. Their application aids the decision-making processes of businesses since these methods provide valuable information regarding the various factors of firms' internal and external environments. For the development of the hybrid modeling process, the DSS software AnyLogic 8.8.5 PLE [72] was utilized. The inputs for the hybrid model were the coefficients of the correlation and regression analyses, as well as the descriptive statistics of the included variables. In the ABM process, the agents represented agriculture website visitors, and their movement was determined by common operators (if, and, or, etc.). For the simulation, 10,000 agents were used, and the simulation period was set to 360 days.

An ANN [56] model was utilized to provide an estimation/prediction for the behavioral metrics of agriculture website visitors (visit duration, pages per visit, bounce rate, and old or returning visitors) based on the normal distribution function (Figure 2). Each time the agents, representing the agribusiness website visitors, enter the specified statecharts, the ANN model calculates the estimated outputs of the visit duration, pages per visit, and bounce rate variables, based on the normal distribution values from the collected sample. These variable outputs vary with each agent's movement and are used for the calculation of other dynamic variables of the model. This method aims to assist the hybrid model by supplying it with key digital marketing analytics to perform accurate simulations based on the coefficients of the regression and correlation analyses.

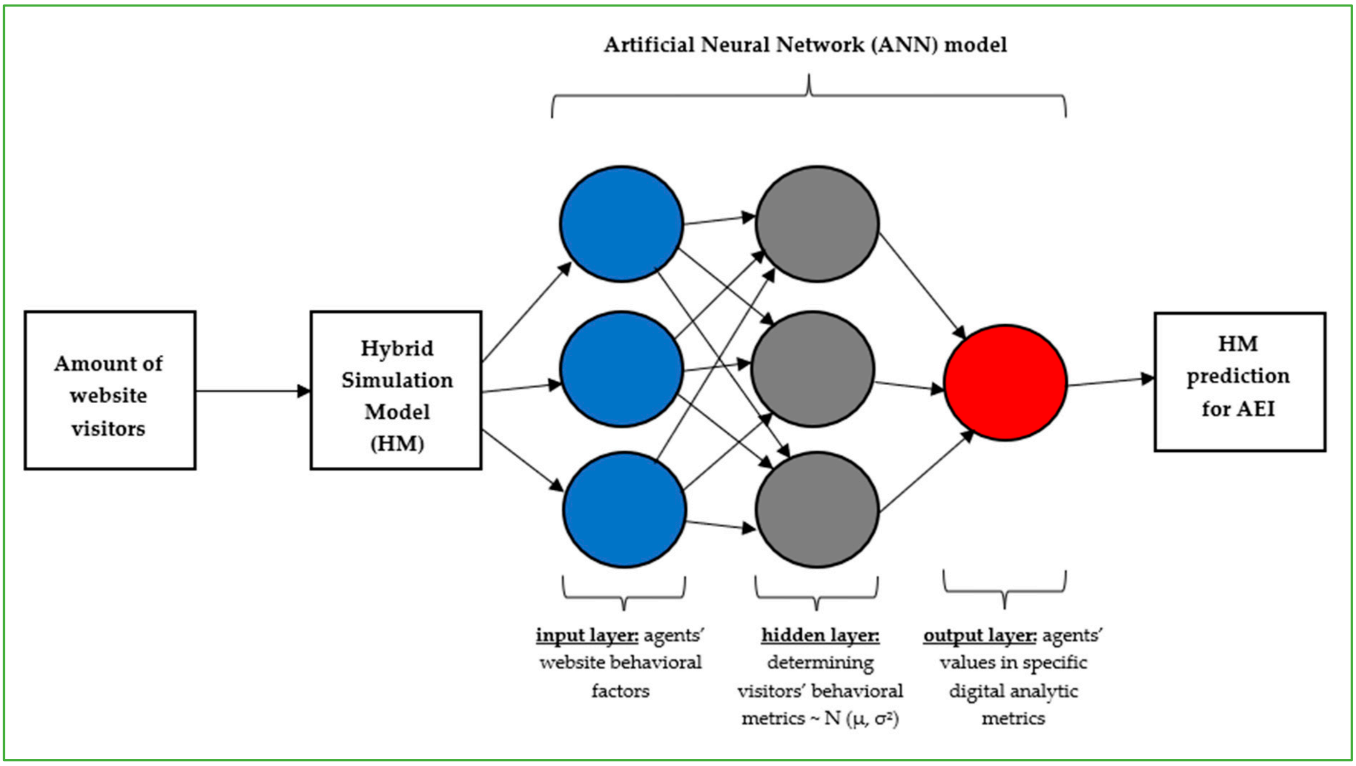

Figure 2. Artificial Neural Network (ANN) model structure.

In Figure 3, the simulation process of the hybrid model for the impact analysis of agriculture firms' website big data on their economic indexes is shown. The simulation process begins with the website visitor statechart; from there, the agents proceed based on either entering agriculture firms' websites for the first time (new visitors statechart) or returning to websites (old visitors statechart). Then, through the statechart of bounce rate, the visitors that abandon the agriculture websites are led back to the website visitor statechart, while those that continue surfing the websites stay. Based on their selected source of entrance to the agriculture firms' websites, the agents are split into the statecharts of referral, social, direct, search, and paid sources. After that, whether these agents have typed organic or paid keywords, they enter the statecharts of organic and paid traffic accordingly, thus leading to the statechart of branded traffic and contributing to the enhancement of agriculture firms' brand names. From this point, the dynamic variables of AER, CPPI, FPPI, and MEPI are impacted based on the coefficients of the linear regressions. Hence, in Table A1 (Appendix A), the Java algorithm of the referred simulation process can be seen.

From the above-developed hybrid model, the outcomes of Figure 4 arose. These refer to the simulation, through 360 days, of the agroeconomic indexes of the selected agricultural firms, as previously mentioned. It can be discerned that AER is relatively positively connected with the variations in agricultural firms' branded traffic. Moreover, increasing numbers of organic and paid costs and search and social traffic sources lead to lower FPPI and MEPI, and higher CPPI. This means that agriculture firms can observe and estimate the results of the prices of agriculture and chemical products and machine equipment through the course of their branded traffic, organic and paid costs, search, and social traffic sources.

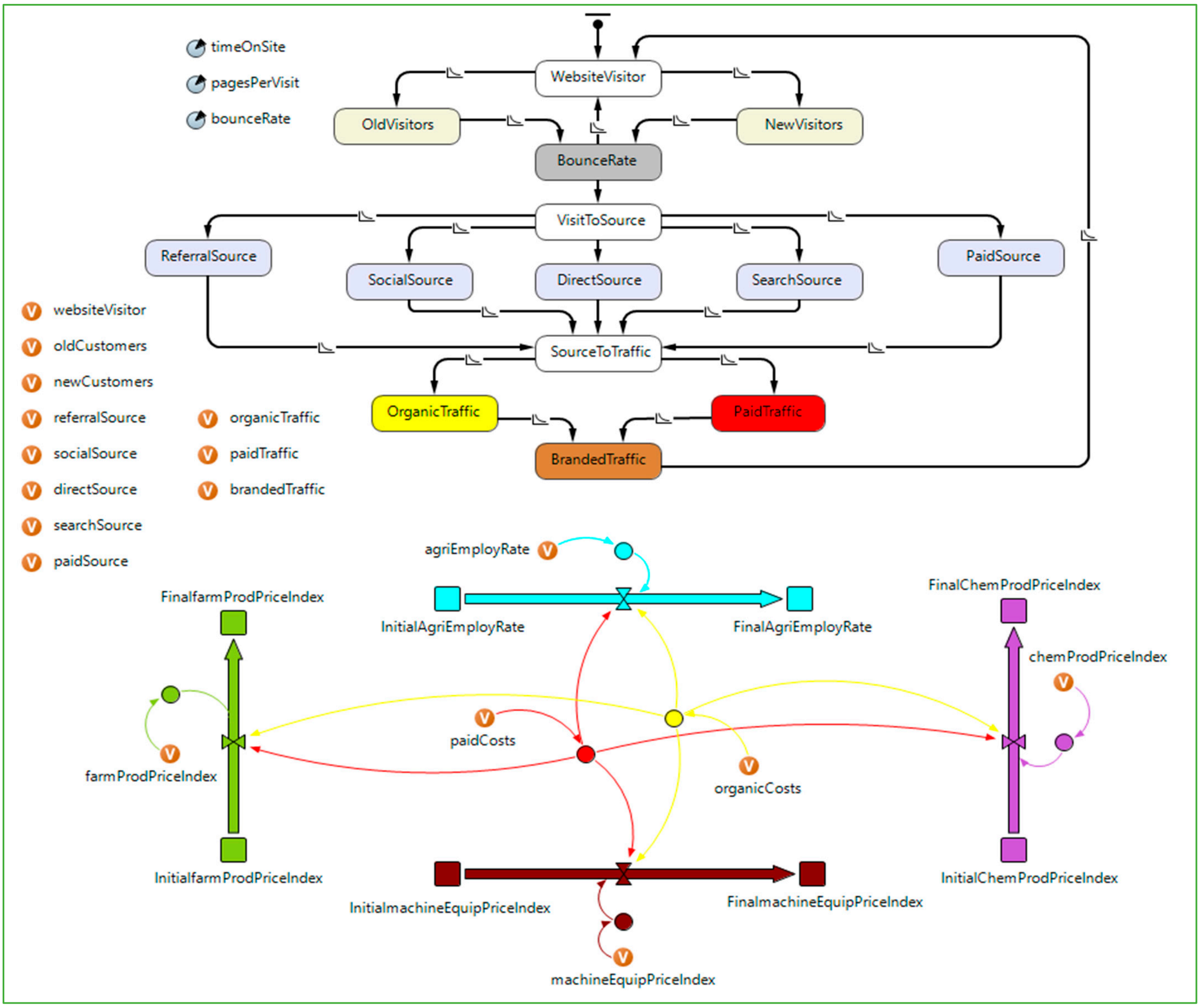

Figure 3. Hybrid Model Deployment of Agriculture Index Simulation Process.

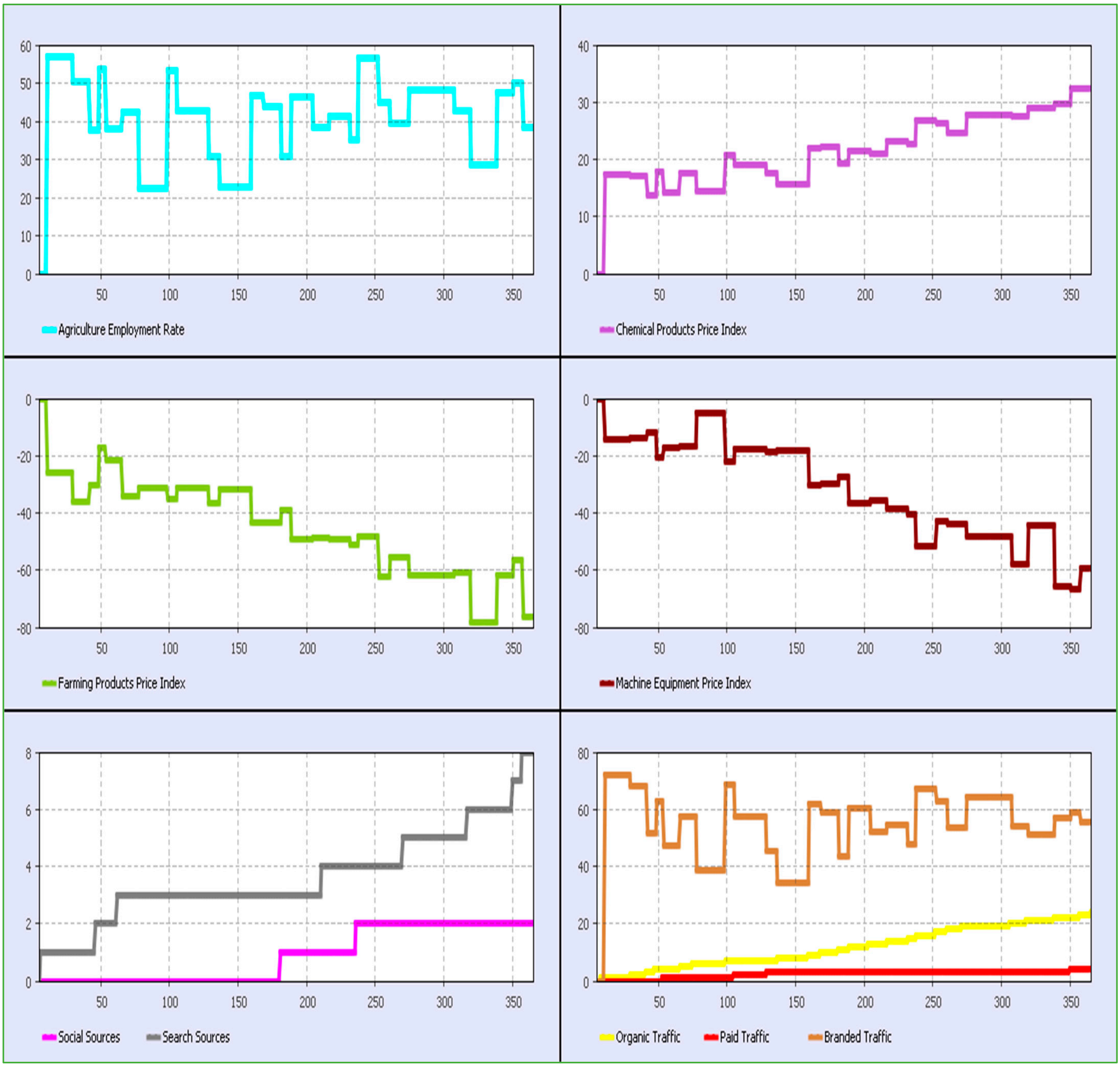

Figure 4. Simulation Process Outcome for Agriculture Indexes during a period of 360 days.

5. Discussion

The purpose of this study is to discern potential connections between specific agroeconomic indexes and agricultural firms' digital marketing analytics based on AI models, using a systematic analysis [87], to provide insights for enhanced decision making. To perform this task, the authors gathered big data from the websites of five agriculture firms that operate worldwide based on their market capitalization [59]. After this process, the impacts of each digital marketing metric from the firms' websites on the agroeconomic indexes of the study were analyzed. For the behavioral analytic metrics of the agriculture firms' website visitors, a simplified model of ANN was used to provide an estimation of their values [58], leading to the utilization of these metrics in the following stages of the HM simulation.

The findings indicate a potential decision-making performance enhancement in the utilization of agriculture firms' digital marketing activity. Therefore, as dependent variables, the agroeconomic indexes of AER, CPPI, FPPI, and MEPI were used, and as independent variables, those of branded traffic, organic costs, social sources, search sources, time on site, and old visitors were discerned as the most important [88].

From the produced linear regression models, it was discerned that all of them were verified overall (p-values < a = 0.01), meaning that the digital marketing metrics of agriculture firms' websites significantly affect the agroeconomic indexes. Hence, the research hypotheses H1, H2, and H4 were verified based on the outcomes of the linear regression models, while the hypothesis H3 was not verified. More specifically, the indexes of AER and CPPI tended to increase with every increase in the referred digital marketing analytics, while MEPI tended to decrease. CPPI did not seem to be affected by individual digital marketing analytic metric fluctuations. Based on the statistical analysis, enhanced decision-making performance for agriculture firms occurred with the increase in specific digital marketing and website visitors' behavioral metrics (branded traffic, organic costs, social sources, search sources, time on site, and old visitors).

Regarding the hybrid model deployment, through the 360-day simulation period, the agroeconomic indexes' values (AER, CPPI, FPPI, and MEPI) were variated based on their relationships with the constantly adjusting model variables. The main objective of the hybrid model, through the ABM process, is to project the course of visitors entering agriculture firms' websites and simulate the impact of their behavioral metrics. Moreover, through the SD process, the paid and organic campaign costs of the agriculture firms, accompanied by the dynamic variables of the AER, CPPI, FPPI, and MEPI indexes, were simulated. It was determined that for the estimation of the study's indexes, the variables of branded traffic, social and search traffic sources, as well as the paid and organic costs should be taken into consideration. More specifically, a strong positive connection was identified between AER and CPPI, with the digital analytic metrics of branded traffic, social and search traffic sources, and paid and organic costs, and a strong negative relationship was identified between FPPI and MEPI with the referred metrics. The values of AER and CPPI tended to increase when agriculture firms invested in enhancing the analytic metrics of branded traffic, social and search traffic sources, and paid and organic costs, while the values of FPPI and MEPI tended to decrease.

Capitalization of such digital marketing analytics for the analysis of various economic indexes has been used in similar studies in the field. Wang and Wu [89] indicated that business analytics could assist in sales forecasting processes and derive operational efficiencies for firms in the supply chain sector, as well as in the digital transformation of businesses [90,91]. Big data analysis in the context of marketing performance grows business knowledge [92], while marketing analytics, through the usage of fuzzy sets, indicates the innovation levels of countries and companies [93]. This study focuses on the implications of digital marketing analytics for agriculture firms' agroeconomic indexes and performance, as has been analyzed for various other business firms, like the banking sector [88,94].

6. Conclusions

6.1. Theoretical and Practical Implications

The context of this research aims to indicate specific theoretical and practical implications for enhancing the decision-making processes of firms in the agriculture sector through the utilization of digital marketing analytics. In this research, the authors aimed to explore the implications of big data, specifically digital marketing analytics, for agroeconomic indexes, to extract valuable insights for agriculture businesses' decision-making processes. For this purpose, the agroeconomic indexes of the Agriculture Employment Rate (AER), the Chemical Product Price Index (CPPI), the Farm Product Price Index (FPPI), and the Machinery Equipment Price Index (MEPI) were selected since their value variations provide information about potential areas for enhancing decision-making outcomes. Knowledge of the areas of agriculture employment or various products used and produced by agriculture firms could indicate specific activities of these businesses that need to be optimized.

To this point, the implications of AI methods and models for enhancing business decision-making and management processes should be discerned. First and foremost, it is discerned that AI methods can enhance the knowledge of digital customers' behaviors in the agriculture market since they can efficiently represent digital behavioral metrics. Hence, agriculture firms can allocate their financial and nonfinancial resources toward the development of predictive models based on AI methods to deploy efficient simulations of their digital customers' behaviors. Then, a significant reduction in the corporate costs connected to previous activities (extensive marketing budget, salaries for marketing staff, etc.) could be achieved, without risking a loss of predictive efficiency.

The outcomes of this study also highlight the implications of AI models and procedures for businesses' decision-making and management processes. Related research in this field showed that firms' decision making can be enhanced in environmental and informational dimensions through content analysis and AI model utilization [95]. Little research has been conducted on AI and strategic decision making in firms' marketing processes [63], while utilization of DSS and predictive and modeling systems are discerned as necessary for further research [96]. Despite the research gap in AI and its implications for marketing and management procedures, light has been shed on specific areas like justice [97] and healthcare [98].

The integration of agroeconomic indexes and AI-modeled digital marketing analytics brings about significant and concrete contributions to the agricultural domain, as summarized in Figure 5.

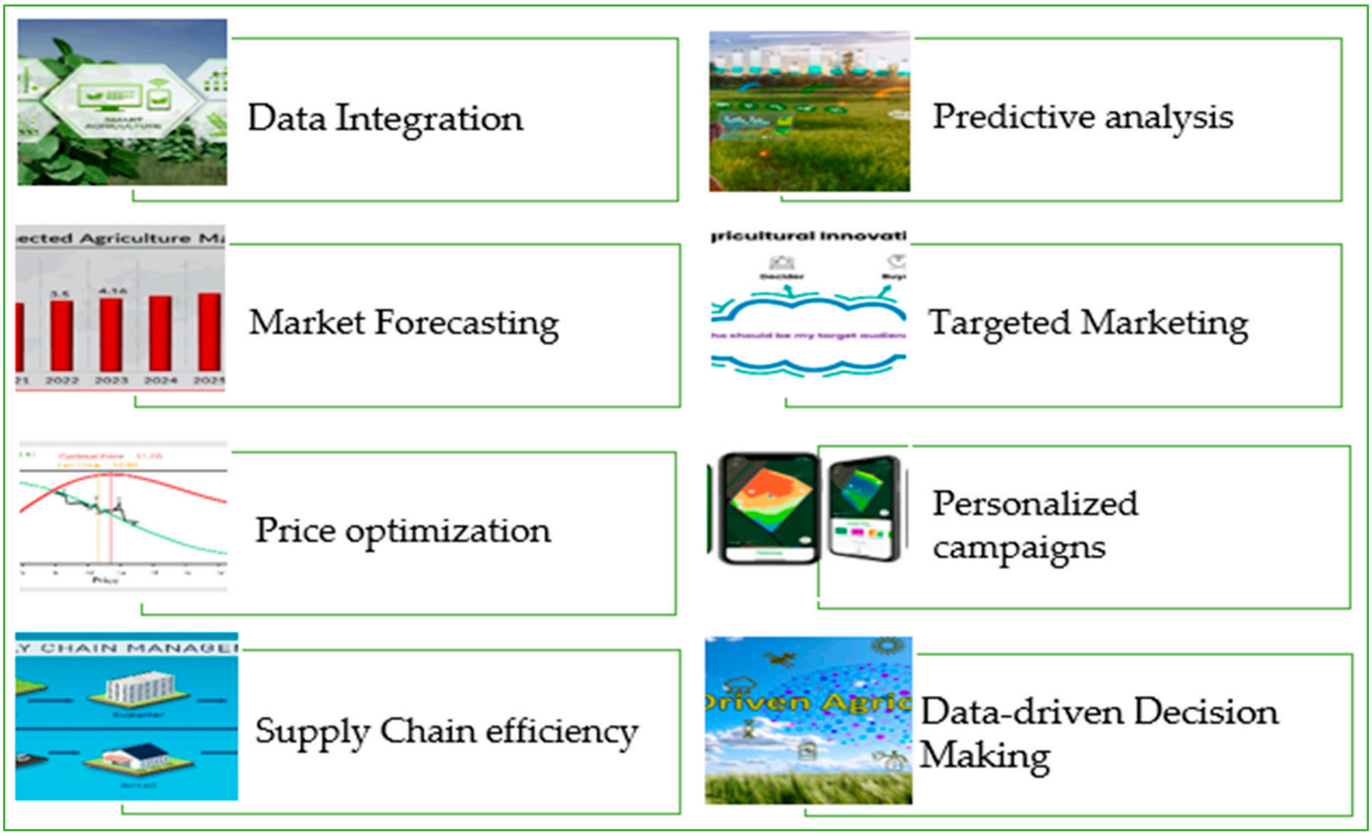

Figure 5. Summarization of AI-modeled digital marketing analytics integration in agribusiness.

- Data Integration

AI-modeled digital marketing analytics can integrate these agroeconomic indexes with marketing data, such as consumer behavior, market trends, and competitor activities, to create a comprehensive dataset.

- Predictive analysis

By leveraging historical agroeconomic data and marketing insights, AI models contribute significantly to anticipating future trends and market conditions. This innovation empowers farmers with actionable foresight, enabling them to anticipate optimal planting times based on historical weather patterns, estimate crop yields by analyzing past performance, and strategically plan marketing initiatives in anticipation of expected market fluctuations. Through predictive analytics, agriculture gains a forward-looking dimension, allowing stakeholders to make informed decisions that enhance crop productivity, resource allocation, and marketing strategies. Integrating AI-based predictions into the agricultural landscape exemplifies a concrete contribution by offering tangible benefits for farmers, fostering more resilient and adaptive agricultural practices, and ultimately optimizing yields and profitability.

- Market Forecasting

By integrating agroeconomic indexes with AI models, accurate market forecasts become possible, enabling stakeholders to anticipate supply and demand dynamics with precision. This contributes significantly to informed decision making in agricultural production and marketing strategies. For instance, farmers can proactively adjust their planting schedules and crop selections based on anticipated market demand, optimizing resource allocation. Simultaneously, marketers can tailor their strategies in response to forecasted market conditions, ensuring efficient distribution and promotion of agricultural products. The synergy between agroeconomic indexes and AI-driven market forecasting thus offers tangible benefits specific to agriculture, fostering a more adaptive and responsive approach to market dynamics, and ultimately improving overall efficiency and sustainability in the agricultural sector.

- Targeted Marketing

AI models, leveraging insights from agroeconomic data, contribute to the development of personalized marketing strategies that align with both economic trends and consumer preferences. This translates into concrete contributions to the agricultural sector, where farmers can tailor their marketing efforts based on regional economic conditions and consumer behaviors. For instance, personalized campaigns can be designed to promote crops or products that are in alignment with both economic indicators and consumer demands. This targeted marketing approach allows for more efficient resource utilization, reduced waste, and improved profitability for farmers. The fusion of agroeconomic data with AI-driven targeted marketing strategies thus emerges as a valuable tool in enhancing the precision and effectiveness of promotional efforts in the agricultural domain.

- Price optimization

By integrating agroeconomic data into AI models, farmers gain the ability to dynamically optimize prices based on changing market conditions. This contributes concretely to the agricultural sector by enabling farmers to make real-time adjustments in response to fluctuations in commodity prices, demand–supply dynamics, and economic indicators. For example, during periods of increased demand or scarcity, AI-driven price optimization allows farmers to adjust their pricing strategies, ensuring fair returns and efficient market participation. This flexibility contributes to improved revenue streams, profitability, and overall resilience in the face of market volatility, providing tangible benefits for farmers navigating the complexities of the agricultural marketplace.

- Personalized campaigns

By utilizing agroeconomic factors and regional variations, AI models can craft personalized campaigns that cater specifically to the unique needs and conditions of different agricultural regions. This contributes concretely to agriculture by enabling targeted and relevant communication with farmers. For instance, personalized campaigns can provide region-specific information on optimal planting times, recommended crop varieties, or even insights into market trends relevant to that specific area. This not only enhances the effectiveness of communication but also empowers farmers with tailored insights that align with their local agroeconomic context. The result is a more informed and engaged agricultural community, fostering sustainable practices, improved crop management, and ultimately contributing to the overall efficiency and resilience of the agricultural sector.

- Supply Chain efficiency

By providing insights into production, transportation, and market demands, agroeconomic data facilitates a more streamlined and efficient supply chain. For example, farmers can use these insights to align production levels with market demands, minimizing wastage and optimizing inventory management. Additionally, agroeconomic data aid in forecasting market needs, allowing for better planning of transportation logistics. This not only reduces inefficiencies in the supply chain but also enhances overall sustainability by minimizing resource wastage. The optimization of the agricultural supply chain through agroeconomic insights contributes tangibly to increased profitability for farmers and ensures the delivery of high-quality products to the market.

- Data-driven Decision Making

The amalgamation of agroeconomic indexes and AI-modeled digital marketing analytics for data-driven decision-making forms a cornerstone for informed choices in the agricultural domain. Concrete contributions emerge as both data sources enable a comprehensive understanding of the agricultural and marketing landscape. For instance, agroeconomic indexes provide historical context and economic trends, while AI analytics offer real-time insights into consumer behavior and market dynamics. This synergy empowers farmers and marketers alike to make decisions rooted in a holistic view of the entire value chain. From adjusting planting schedules based on historical crop performance to refining marketing strategies in response to current market trends, this data-driven approach enhances the efficiency and adaptability of decision-making processes in agriculture, fostering a more resilient and responsive industry.

Apart from the AI implications for business decision making and management, the connection between agriculture firms' website big data and the fluctuations in the selected agroeconomic indexes provides further insight. Agriculture firms are capable of simulating the effect of key digital marketing analytic metrics (branded traffic, organic costs, social sources, search sources, time on site, and old visitors) to estimate or calculate the course of their agroeconomic indexes (AGIs). Knowledge of the digital marketing analytic metrics that affect the value of agriculture, chemical, and machinery equipment product prices could lead to accurate adjustments and modifications to specific analytic metrics of agriculture firm websites. Moreover, some of the digital analytic metrics impact the employment rate of agriculture firms, providing more potential paths for exploitation. At this point, agriculture businesses could make decisions related to the relationship of each AGI with their websites' branded traffic, organic costs, social sources, search sources, time on site, and old visitors. Therefore, to enhance the decision-making and management procedures of agriculture firms, the digital analytic metrics of branded traffic, organic costs, social sources, search sources, time on site, and old visitors should be examined and modified based on adjusted marketing campaigns that aim to impact these metrics positively or negatively. The incorporation of digital marketing analytics and AI-based simulation could substantially improve the management and decision making of agriculture firms while also improving their marketing capabilities.

6.2. Limitations

The present study has some known limitations based on the data collection and the selection of the KPIs used as the study's dependent and independent variables for the analysis. For the needs of this research, the authors collected the values of four agroeconomic indexes and twelve digital marketing analytics. In favor of a more in-depth analysis of the various marketing analytic factors that impact the decision-making processes of agriculture firms, the following limitations were identified. The direction and casualty of the performed regressions could indicate a subjective approach to the research, while the connection between digital marketing analytics and agroeconomic indexes could lead to other outcomes if studied contrariwise.

Further limitations concern the amount of agroeconomic indexes and digital marketing analytics used for extracting results for agribusiness decision making. Moreover, limitations regarding the ANN model used might arise, which refer to limited historical data, computational resources, and time for model training; ANN models often assume that historical patterns will repeat in the future. This assumption may not always hold in agribusiness, where unexpected events like climate change, new diseases, or market disruptions can significantly impact outcomes. Combining ANN predictions with domain expertise and other data sources can help address some of these challenges and enhance the overall effectiveness of decision support systems in agribusiness.

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Appendix A

Table A1. Java code for agriculture index modeling process.

Java Code of AnyLogic Hybrid Model and AI Algorithm

@Override
@AnyLogicInternalCodegenAPI
public void enterState (short _state, boolean _destination) {
switch (_state) {
case WebsiteVisitor://(Simple state (not composite))
statechart.setActiveState_xjal (WebsiteVisitor);
{
websiteVisitor++;

Table A1. *Cont.*

Java Code of AnyLogic Hybrid Model and AI Algorithm

```
public static void main(String[] args) {
//bounceRate
double[] input = {dataSet};
double[] output = {0.034, 0.53};
DataSet dataSet = new DataSet(input.length, output.length);
dataSet.addRow(new DataSetRow(input, output));
NeuralNetwork neuralNetwork = new MultiLayerPerceptron(input.length, 2, output.length);
BackPropagation learningRule = new BackPropagation();
neuralNetwork.setLearningRule(learningRule);
int maxIterations = 1000;
for (int i = 0; i < maxIterations; i++) {
neuralNetwork.learn(dataSet);
double[] inputToTest = {0.034, 0.53};
neuralNetwork.setInput(inputToTest);
neuralNetwork.calculate();
double[] predictedOutput = neuralNetwork.getOutput();
System.out.println("Predicted Output: " + predictedOutput [0]);

//timeOnSite
double[] input = {dataSet};
double[] output = {500.14/60, 114.015/60};
DataSet dataSet = new DataSet(input.length, output.length);
dataSet.addRow(new DataSetRow(input, output));
NeuralNetwork neuralNetwork = new MultiLayerPerceptron(input.length, 2, output.length);
BackPropagation learningRule = new BackPropagation();
neuralNetwork.setLearningRule(learningRule);
int maxIterations = 1000;
for (int i = 0; i < maxIterations; i++) {
neuralNetwork.learn(dataSet);
double[] inputToTest = {500.14/60, 114.015/60};
neuralNetwork.setInput(inputToTest);
neuralNetwork.calculate();
double[] predictedOutput = neuralNetwork.getOutput();
System.out.println("Predicted Output: " + predictedOutput [0]);

//pagesPerVisit
double[] input = {dataSet};
double[] output = {2.75, 0.095};
DataSet dataSet = new DataSet(input.length, output.length);
dataSet.addRow(new DataSetRow(input, output));
NeuralNetwork neuralNetwork = new MultiLayerPerceptron(input.length, 2, output.length);
BackPropagation learningRule = new BackPropagation();
neuralNetwork.setLearningRule(learningRule);
int maxIterations = 1000;
for (int i = 0; i < maxIterations; i++) {
neuralNetwork.learn(dataSet);
double[] inputToTest = {2.75, 0.095};
neuralNetwork.setInput(inputToTest);
neuralNetwork.calculate();
double[] predictedOutput = neuralNetwork.getOutput();
System.out.println("Predicted Output: " + predictedOutput [0]);;}
```

Table A1. *Cont.*

Java Code of AnyLogic Hybrid Model and AI Algorithm

transition1.start();
transition2.start();
return;
case OldVisitors://(Simple state (not composite))
statechart.setActiveState_xjal (OldVisitors);
{
oldVisitors++
;}
transition7.start();
return;
case BounceRate://(Simple state (not composite))
statechart.setActiveState_xjal (BounceRate);
transition8.start();
transition9.start();
return;
case VisitToSource://(Simple state (not composite))
statechart.setActiveState_xjal (VisitToSource);
transition11.start();
transition12.start();
transition13.start();
transition14.start();
transition15.start();
return;
case DirectSource://(Simple state (not composite))
statechart.setActiveState_xjal (DirectSource);
{
directSource++
;}
transition16.start();
return;
case SourceToTraffic://(Simple state (not composite))
statechart.setActiveState_xjal (SourceToTraffic);
transition5.start();
transition6.start();
return;
case OrganicTraffic://(Simple state (not composite))
statechart.setActiveState_xjal (OrganicTraffic);
{
organicTraffic++;
organicCosts = normal(8.927645357, 24.6029)
;}
transition3.start();
return;
case BrandedTraffic://(Simple state (not composite))
statechart.setActiveState_xjal (BrandedTraffic);
{
brandedTraffic = normal(9.54142, 56.2333);
agriEmployRate = brandedTraffic*(0.944) + organicCosts*(−0.366) + socialSource*(0.195) +
searchSource*(0.007) + timeOnSite*(0.047) + oldVisitors*(−0.082);
farmProdPriceIndex = brandedTraffic*(−0.145) + organicCosts*(−0.576) + socialSource*(0.005) +
searchSource*(0.050) + timeOnSite*(0.419) + oldVisitors*(−0.986);
chemProdPriceIndex = brandedTraffic*(0.209) + organicCosts*(0.029) + socialSource*(−0.474) +
searchSource*(0.768) + timeOnSite*(0.057) + oldVisitors*(0.290);
machineEquipPriceIndex = brandedTraffic*(−0.375) + organicCosts*(0.424) +
socialSource*(−0.118) + searchSource*(−0.130) + timeOnSite*(0.118) + oldVisitors*(−0.931);
;}

Table A1. *Cont.*

Java Code of AnyLogic Hybrid Model and AI Algorithm

transition.start();
return;
case PaidTraffic://(Simple state (not composite))
statechart.setActiveState_xjal (PaidTraffic);
{
paidTraffic++;
paidCosts = normal(0.966667, 2.2775838)
;}
transition4.start();
return;
case ReferralSource://(Simple state (not composite))
statechart.setActiveState_xjal (ReferralSource);
{
referralSource++
;}
transition18.start();
return;
case SocialSource://(Simple state (not composite))
statechart.setActiveState_xjal (SocialSource);
{
socialSource++
;}
transition17.start();
return;
case PaidSource://(Simple state (not composite))
statechart.setActiveState_xjal (PaidSource);
{
paidSource++
;}
transition19.start();
return;
case SearchSource://(Simple state (not composite))
statechart.setActiveState_xjal (SearchSource);
{
searchSource++
;}
transition20.start();
return;
case NewVisitors://(Simple state (not composite))
statechart.setActiveState_xjal (NewVisitors);
{
newVisitors++
;}
transition10.start();
return;
default:
super.enterState (_state, _destination);
return;
} }

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