Exploring Agricultural Livestreaming and Agricultural Supply Chain Management Empowered by the Internet of Things and Artificial Intelligence

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ABSTRACT This study aims to investigate the integration of the Internet of Things (IoT) and artificial intelligence (AI) technologies in agricultural livestreaming and the management of agricultural product supply chains to address the multifaceted challenges prevalent in contemporary agriculture. AI is utilized to enhance the efficiency of agricultural livestreaming and agricultural product supply chain management. Specifically, the system dynamics (SD) method evaluates risks in the agricultural product supply chain. The random forest algorithm is chosen to establish a prediction model and analyze historical data to study the correlation between weather variables and product sales slowdown, to predict potential risk factors that may affect the efficiency of agricultural product circulation. By conducting a questionnaire survey, data from professionals, experts, and consumers engaged in the agricultural e-commerce domain are collected to quantitatively evaluate the impact of risk indicators. Utilizing pomegranate livestreaming sales in County X as a case study, an empirical analysis is conducted to mitigate the issue of unsold products arising from weather-related factors. Subsequently, the efficacy of risk mitigation measures is simulated and examined using the questionnaire data. The findings demonstrate that these measures positively influence the performance and risk management of the agricultural livestreaming supply chain. However, the study also identifies a certain delay in the effectiveness of risk mitigation, underscoring the significance of timely risk prevention measures. Overall, this study amalgamates SD with empirical investigation to delve into supply chain management challenges in agricultural livestreaming, proposing an enhanced digital supply chain model. Moreover, it furnishes valuable insights for practical implementation in the agricultural sector and offers theoretical and empirical support for the enhancement and optimization of agricultural product supply chains.

Keywords Internet of Things, agricultural livestreaming, agricultural product supply chain, system dynamics, random forest, data analysis

I. INTRODUCTION

In recent years, the increasing disposable income has reshaped consumer preferences in the agricultural products sector, leading to a shift from quantity to quality, with an emphasis on sustainability and uniqueness. Green, pollution-free, and organic agricultural products have witnessed a surge in popularity [1,2]. Nevertheless, the absence of information within the agricultural product supply chain poses challenges in meeting consumer demand for high-quality agricultural products, thereby hindering their ability to command premium prices [3-5]. Online livestreaming platforms have emerged as a supportive tool to address communication inefficiencies between producers and consumers [6].

With the proliferation of internet users in China, online shopping has become a ubiquitous activity and a pivotal avenue for consumer consumption [7, 8]. Concurrently, advancements in new infrastructure, such as 5th Generation Mobile Communication Technology (5G) networks and Artificial Intelligence (AI), have propelled goods livestreaming into a burgeoning consumption trend [9]. The fusion of e-commerce (EC) with livestreaming presents a novel trajectory for advancing rural economies, fostering innovation, diversifying channels, and alleviating poverty in rural EC [10]. Capitalizing on the momentum of the internet economy and EC, EC livestreaming, as an emergent sales paradigm, is poised to pave new developmental pathways for the agricultural economy [11].

In the era of personalized EC, traditional supply chain models are insufficient to meet the demands of the digital era, with supply chain competition emerging as a primary battleground for EC entities. As EC continues to burgeon, the management of the agricultural product market's supply chain has transitioned from conventional models to EC-centric frameworks [12-15].

In the context of livestreaming, manufacturers engage customers via hosts, while farmers directly connect with end consumers through similar intermediaries, bypassing traditional agricultural EC platforms or distributors. This trend imposes heightened demands on the agility of the agricultural product livestreaming supply chain [16,17]. The exchange of significant orders within compressed timeframes, coupled with the frequent occurrence of incidents in agricultural livestreaming, underscores the imperative for the supply chain to augment its management practices, service standards, and operational efficiency. Such enhancements are critical for meeting consumer expectations and ensuring the smooth development of the agricultural product supply chain [18,19].

As socio-economic development progresses rapidly and global climate change intensifies, agriculture production encounters increasingly formidable challenges. Traditional agricultural sales models exhibit inherent limitations in adapting to market dynamics and mitigating climate uncertainties. Hence, this study elucidates the potential of harnessing the Internet of Things (IoT) and artificial intelligence (AI) to bolster the efficiency of agricultural livestreaming and enhance agricultural supply chain management, thus addressing the multifaceted complexities of contemporary agriculture. Key study inquiries encompass the effective utilization of IoT technology and AI to augment the efficiency of agricultural livestreaming supply chain management. It also seeks to discern the prevailing market demand for specific fruits, such as pomegranates, and ascertain the impact of external factors like climate change on the production and distribution of these fruits. Moreover, it is imperative to scrutinize the challenges prevalent in the current fruit market, including information asymmetry within the supply chain and seasonal fluctuations. Furthermore, this study delves into the intricacies of agricultural product supply chain management under the pure EC platform model. In addition to theoretical inquiry, it endeavors to proffer innovative solutions for the practical operation of agricultural product supply chains. While an extant study has addressed agricultural livestreaming and supply chain management independently, there exists a notable research gap in integrating these domains, particularly in the absence of a risk assessment method grounded in system dynamics (SD). To bridge this gap, this study amalgamates empirical research with SD modeling to explore the intricacies of agricultural livestreaming supply chain management and propose an enhanced digital supply chain model. This holistic investigation yields novel insights for agricultural practice and offers both theoretical and practical support for optimizing and refining agricultural product supply chains. The IoT facilitates device interconnection over the Internet to enable seamless data transfer and intelligent operations, while AI encompasses computer systems simulating human cognitive functions. In addition, SD provides an analytical framework for studying interactions within systems. Under the background of agricultural livestreaming, IoT enables crop growth monitoring and real-time data aggregation, while AI aids in forecasting market demands and optimizing supply chain logistics. SD assists in risk identification, quantification, and supply chain efficiency enhancement. The integration of these technologies augments the development prospects of agricultural livestreaming platforms, boosting the agility and adaptability of the entire agricultural product supply chain. Moreover, SD's risk assessment methodology aims to identify risks in the management of agricultural product supply chains via livestreaming and propose effective risk mitigation strategies. Through empirical investigation into the livestreaming sales dynamics of pomegranates in X County, this study seeks to alleviate unsold inventory pressures stemming from inclement weather conditions and promote the implementation of a digital model for agricultural product supply chains. In essence, this study aspires to furnish comprehensive theoretical underpinnings and empirical insights for the agricultural sector, catalyzing the modernization and digitization transformation of agricultural product supply chains.

II. LITERATURE REVIEW

Numerous researchers globally have analyzed the development status of agricultural EC from various perspectives. Currently, agricultural EC has attained maturity and establishment in several developed nations. Zhong et al. (2021) underscored the diverse advertising methods and channels offered by the Internet for agricultural EC, facilitating the establishment of regional brand images for agricultural products [20]. The convergence of EC with the Internet in agriculture has emerged as a novel trend in agricultural advancement, despite encountering constraints hindering its development. Li et al. (2020) investigated the developmental stage of agricultural EC in developing countries and noted that the environment and information technology support policies remarkedly influenced its practical advancement level [21].

Scholars have proposed numerous solutions to foster the rapid expansion of agricultural EC. Juan and Yadong (2021) advocated leveraging stored data to develop agricultural product query and tracking functionalities, thereby enhancing logistics development in agricultural EC [22]. Matkovski et al. (2021) posited that labeling agricultural products and enhancing specialization levels could foster the growth of agricultural EC, leading to augmented market share and sales of agricultural products [23].

The agricultural supply chain concept has been extensively researched by foreign scholars over an extended period. Concerning channel selection in the agricultural supply chain, Dosso et al. (2022) observed that agricultural cooperatives broaden the distribution channels of agricultural products, enabling individual farmers to evade intense competition and pursue their respective interests [24]. Han and Lin (2021) argued that the modern agricultural supply chain transcended traditional offline entity sales channels, evolving into a blend of online and offline channels [25].

Tošović-Stevanović et al. (2020) examined the relationship between sales channel selection for organic farms entering the market and product competition. Their findings revealed that the concurrent selection of ordinary and organic retailer types resulted in oversupply, prompting organic farms to typically opt for individual retailers [26]. Regarding optimizing and coordinating the agricultural supply chain, Jifroudi et al. (2020) asserted that the economic consumption level of consumers was intricately correlated with the coordination efficiency of the agricultural product distribution supply chain. They proposed a novel coordination mechanism for the agricultural supply chain [27]. Liu et al. (2023) scrutinized the mutual coordination issues among the production, circulation, and sales links within the supply chain. Their results elucidated that disparate manufacturers sought to maximize profits while minimizing costs to attain Pareto optimality for supply chain members [28].

In the application of the IoT and AI, Chen et al. (2024) focused on optimizing social goals, especially optimizing opinions at equilibrium points, by controlling some individuals to achieve [29]. LIN et al. (2024) proposed a novel data representation method for compactly representing time-varying scientific data for uncertainty visualization and analysis. This method decoupled data in the time domain into two types of distributions and stored them. One distribution summarized the data values in the time domain, while the other distribution described the probability of data values occurring in the time domain. Thus, it can offer scientific data analysis of the evolution of detailed time characteristics with uncertainty quantification and fewer storage requirements [30]. TSAI et al. (2024) introduced a novel dynamic productivity prediction method and a new production feature selection method, using a genetic ant colony algorithm to predict dynamic productivity based on real-time production information, to reduce errors between production time planning and actual operations. By analyzing historical production information, the optimal correlation coefficient was selected for new production feature selection to reduce the difference between production productivity predictions and actual results [31].

Theoretical exploration into the application of IoT and AI in agricultural livestreaming and supply chain management reveals the following insights. Over the years, IoT technology has emerged as a pivotal factor in enhancing the transparency and traceability of agricultural supply chains. Kumar et al. (2023) delved into the achievement of real-time monitoring of crop growth conditions by deploying various sensors on farms [32]. Data gathered from these sensors aids in forecasting crop yields and adjusting supply chain strategies promptly. Additionally, Wu et al. (2024) underscored the significance of employing RFID tag systems to track every stage of agricultural products from the field to the consumer's table, ensuring food safety and furnishing source information to consumers [33]. AI, when combined with IoT technology, assumed an indispensable role in managing the voluminous data generated in the supply chain. Chelliah et al. (2024) deliberated on the analysis of agricultural sales data utilizing machine learning (ML) algorithms, facilitating more precise predictions of market demand and optimization of inventory levels [34]. Simultaneously, Sangers et al. (2014) elucidated the utilization of AI for personalized recommendations to cater to consumer preferences for specific agricultural products, thereby boosting sales during livestreaming events [35]. Beyond conventional monitoring and tracking functions, IoT had the potential to enrich the interactive experience of agricultural livestreaming. Kumar et al. (2024) explored how farmers streaming their farms and products using mobile devices and IoT gadgets displaying real-time crop status could captivate customers and bolster consumer trust [36]. Molęda et al. (2023) denoted that the incorporation of predictive maintenance models leveraging AI and IoT minimized the risk of equipment failure during livestreaming, ensuring uninterrupted streaming activities [37]. In summary, the application of IoT and AI technologies in agricultural livestreaming and supply chain management was diverse and promising. Integrating these advanced technologies into the agricultural sector notably enhanced supply chain efficiency, transparency, and consumer engagement.

Previous studies on supply chains predominantly focused on expanding distribution channels while neglecting issues about information flow, logistics, and other pertinent aspects of the agricultural supply chain. Concerning the coordination mechanism of agricultural supply chains, prior studies remained relatively macroscopic, lacking in-depth examinations at the operational level. The impetus and driving force of this study were to rectify these deficiencies by amalgamating the application of IoT and AI in agricultural livestreaming and supply chain management. Moreover, this study employed an SD approach and empirical research to delve into the advancement of these technologies in agricultural modernization, proposing more practical and viable digital supply chain models.

III. RESEARCH METHODOLOGY

A. EC LIVESTREAMING EMPOWERED BY IOT AND AI

As modern technology advances and 5G networks become more widespread, online streaming continues to evolve, permeating various sectors such as gaming, shopping, sports, and education, thereby facilitating profound interactions across diverse domains. EC has actively integrated the “Live+” domain and leveraged the advantages and characteristics of livestreaming to propel its advancement, continuously expanding the scope of the “Live+” domain. However, due to the relatively nascent nature of online EC, academia and industry alike have yet to establish a definitive definition, and research on this subject remains relatively limited [38, 39].

This study delves into agricultural livestreaming, wherein internet-enabled livestreaming platforms allow hosts to showcase products up close, fostering real-time interaction with consumers and augmenting their inclination to make purchases [40]. Specifically, this study centers on the analysis of pure EC livestreaming platforms and investigates the supply chain management of agricultural products within this platform. Illustrative examples encompass platforms like Taobao Live and JD Live, which utilize EC platforms for live selling, product recommendation and demonstration, and incentivizing consumer purchases [41, 42].

B. THE CHARACTERISTICS AND ISSUES OF THE AGRICULTURAL PRODUCT SUPPLY CHAIN DURING THE AGRICULTURAL LIVESTREAMING PROCESS

Table I provides an overview of the principal attributes of the agricultural livestreaming supply chain, encompassing intricate interconnections, a notable surge in demand, dispersed farmers and crops, elevated logistics requisites, substantial demands for information processing capacity, and novel media content production. These characteristics underscore the intricacy and multiplicity inherent in supply chain management in the agricultural livestreaming field.

TABLE I

THE MAIN CHARACTERISTICS OF THE AGRICULTURAL LIVESTREAMING SUPPLY CHAIN

Characteristics	Description
Complex Links	Suppliers involve multiple subjects, requiring complex coordination and connections.
Sharp Increase in Demand in a Short Time	Online sales of agricultural products experience a rapid surge in demand within a short time, posing a challenge to the supply chain's rapid responsiveness.
Dispersed Farmers and Crops	Farmers and cooperatives are scattered, with relatively small quantities of products, necessitating effective mobilization and organization to meet sales demands.
High Logistics Requirements	Agricultural products require high freshness and timeliness, demanding the selection of suitable storage and transportation methods and the improvement of the cold chain distribution system to minimize damage.
High Information Processing Capacity Demand	Agricultural livestreaming involves market demand research, supplier selection, and product feature inspection, requiring high levels of information processing and advanced data analysis.
New Media Content Production	The EC selection team needs to tap into new media content production capabilities to ensure the quality of selling agricultural products, placing high demands on the application of internet technology.

Firstly, the connections within the supply chain exhibit complexity. An essential aspect of online agricultural product sales is the rapid surge in demand over a short timeframe [43-45].

Secondly, heightened logistics requirements are apparent. Agricultural products, particularly perishables containing numerous agricultural by-products, necessitate stringent freshness and timeliness standards. Enhancements in cold chain distribution systems can substantially mitigate agricultural product damage, thus increasing logistics demands [46, 47].

Finally, there exists a substantial demand for information processing capacity. In EC, the selection team must identify and capitalize on pivotal product sales points while ensuring continuous inventory availability and the quality of agricultural product sales through proficient new media content production. Consequently, a robust application of Internet technology is imperative, accompanied by high demands for information data collection, analysis, and processing [48-50].

Agricultural livestreaming enterprises face several challenges due to inherent traits of agricultural products, including pronounced seasonality, brief sales cycles, and incomplete supply chain information:

1. Limited information exchange hampers the resolution of mutual supply and demand constraints. Extensive information exchange and post-promotion services are thus essential [51].

2. The organizational structure becomes intricate as livestreaming platforms engage with multiple suppliers concurrently, resulting in elevated communication costs. The evolution in the domestic agricultural chain often involves temporary service personnel lacking adequate professional training, thereby diminishing consumer satisfaction [52].

3. Challenges arise in product quality control. The decentralized nature and environmental variability of farmers and agricultural products complicate the standardization of agricultural products [53].

C. THE OPERATIONAL MECHANISM AND RISK ASSESSMENT OF THE DIGITALIZED MODE IN THE AGRICULTURAL PRODUCT SUPPLY CHAIN

The digitalization of the supply chain is driven by a mechanism that integrates digital technology across various stages, serving as the core of the entire supply chain. Additionally, information and data are transmitted to other stages to enhance supply chain efficiency [54]. Figure 1 delineates the supplier-led digitalization movement within the agricultural product supply chain:

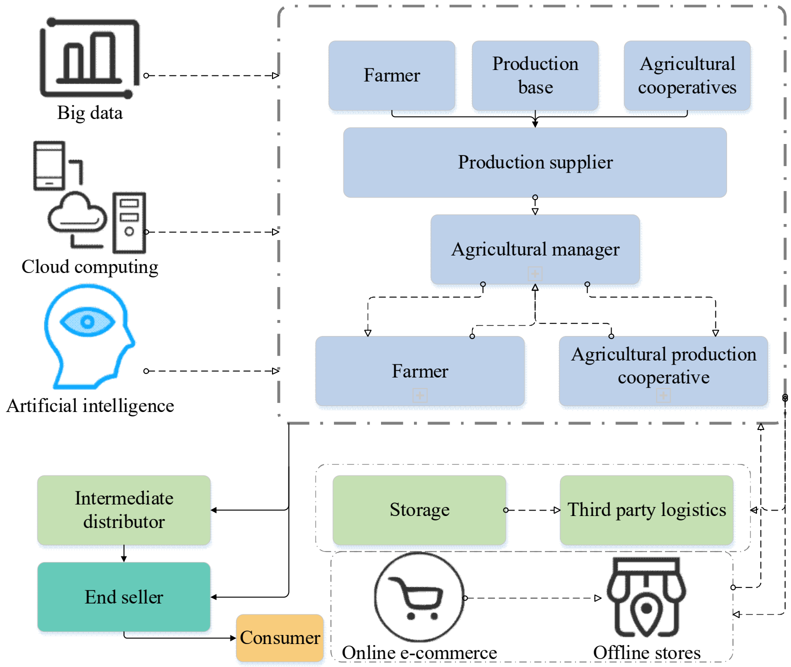

FIGURE 1. The supplier-led model of digitalization movement in the agricultural product supply chain.

Figure 1 showcases the integration of digital technology into the production and processing stages of the agricultural product supply chain. By leveraging digital technologies such as big data, cloud computing, and AI, production-based enterprises facilitate information sharing related to digital technology. This sharing encompasses details concerning agricultural products and their origins. Information is stored at the supply chain's terminus, effectively mitigating production risks and enhancing the cost-effectiveness and efficiency of agricultural product production.

This study employs SD to conduct a risk assessment of the agricultural product supply chain. SD enables the examination and analysis of the internal systems within the agricultural product supply chain, allowing for the exploration of relationships and mechanisms among diverse subsystems and risk indicators. Furthermore, it scrutinizes the role of each risk indicator in the risk control process for every risk link, rendering risk control more methodical and transparent. To construct a real-time agricultural product supply chain, an SD model is established. This model visualizes the dynamic behavioral relationships and feedback mechanisms among systems. By analyzing the online agricultural supply chain's comprehensive risk structure, a cause-and-effect diagram of the online agricultural supply chain risk system is derived, as illustrated in Figure 2.

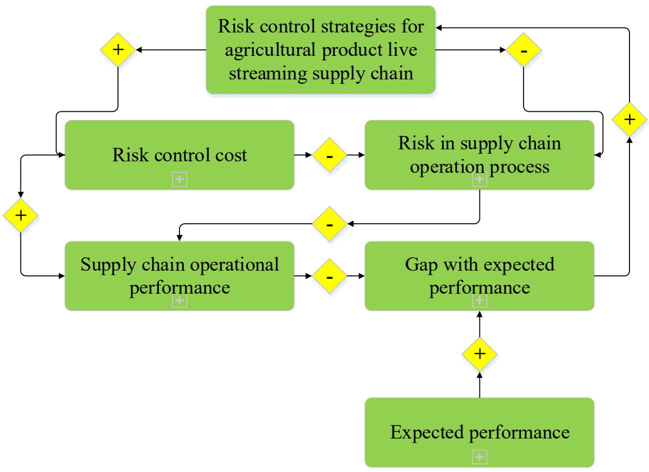

FIGURE 2. Overall cause-and-effect diagram of online agricultural supply chain risk system.

Figure 2 illustrates the key system components relevant to supply chain risk management in agricultural livestreaming. These components encompass business process risks, operational performance, risk control methods, and risk control costs. Leveraging insights from SD, the interrelationships among these four subsystems are expounded as follows: Supply chain risks directly impact supply chain performance. The effort to mitigate these risks aims to enhance supply chain performance while implementing essential cost-risk control measures. Consequently, as risk control measures are progressively enacted, supply chain performance improves, thereby alleviating the inherent direct risks in the agricultural livestreaming supply chain.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

This study adopts the live sales of pomegranates in X County as a case study. To alleviate the burden of unsold inventory due to weather conditions, the EC platform expands consumer channels through live broadcasts to stimulate consumption. By actively collaborating with influential entities such as government bodies, academia, or internet celebrities, the EC platform bridges the gap between supply and demand for agricultural products, thereby reshaping the market into a novel consumption landscape. To examine the influence of various risk factors on agricultural product supply chain management performance, extensive historical data from pomegranate livestreaming sales in X County are utilized. Subsequently, a multivariate linear regression model is constructed to extract key performance indicators. Both fixed-effects and random-effects models are employed to capture the cross-sectional and longitudinal characteristics of the data. The most suitable model type is determined through the Hausman test, and the results of the Hausman test are outlined in Table II. Analysis of the multiple linear regression model reveals the following findings: weather risk significantly influences logistics punctuality (coefficient of -0.32), indicating a substantial impact of weather factors on logistics operations. Market demand fluctuations positively impact supply chain management performance (coefficient of 0.45), suggesting that market demand fluctuations can enhance the efficiency of supply chain management. Logistics punctuality demonstrates a more adverse effect on performance (coefficient of -0.65), highlighting the necessity to fortify management and improvement measures in the logistics domain. These findings offer pivotal insights for a deeper comprehension of the influence of diverse factors on agricultural supply chain management, facilitating the formulation of more effective strategies and measures to optimize supply chain operations. The results underscore the suitability of the fixed-effects model for analyzing this dataset, as evidenced by a significant Hausman test statistic (p-value < 0.05). This significance implies a correlation between unobservable individual-specific factors and explanatory variables, leading to the employment of the fixed-effects model to account for the unique impacts associated with each market or production region.

TABLE II

Hausman test results

Variable	Fixed Effects Estimate	Random Effects Estimate	Hausman Test Statistic	p-value
Weather Risk	-0.32	-0.28	5.48	0.019*
Market Demand Fluctuations	0.45	0.43	3.21	0.073
Logistics Timeliness	-0.65	-0.62	6.14	0.013*

Note: * indicates rejection of the random-effect model at a 5% significance level.

Expanding upon this, the study employs the Granger causality test to further investigate the interactions among risk factors, thereby revealing their inherent connections in supply chain management. This analysis aims to explore the impact of weather changes on logistics efficiency and how this, in turn, influences inventory management strategies within the supply chain. The results of the Granger causality test are presented in Table III. These findings indicate that variations in temperature and precipitation can forecast subsequent changes in logistics timeliness, emphasizing the significant predictive role of weather changes in logistics efficiency. Similarly, enhancements in logistics efficiency can effectively predict adjustments in inventory levels, thus illustrating a feedback effect.

TABLE III

Granger Causality Test Results

Causal Relationship	F-Statistic	p-value
Weather Risk → Logistics Timeliness	4.56	0.032*
Logistics Timeliness → Inventory Management	3.88	0.049*

Note: * indicates the presence of Granger causality at a 5% significance level.

Upon the completion of all model estimations, a robustness analysis is undertaken utilizing heteroscedasticity-robust standard errors and the White test to ensure that heteroscedasticity issues do not distort the model results. The outcomes of the heteroscedasticity test are listed in Table IV. Both heteroscedasticity-robust standard errors and the White test indicate an absence of heteroscedasticity in the regression model's error terms, thereby confirming the robustness of the estimation results. This bolsters confidence in the model's predictive and explanatory capabilities. The application of this comprehensive suite of rigorous econometric methods ensures that the study findings can offer dependable guidance to decision-makers in agricultural livestreaming and supply chain management.

TABLE IV

Heteroscedasticity Test Results

White Test Statistic	p-value
1.84	0.175

In Table IV, the value of 1.84 denotes the numerical value of the White test statistic, conventionally employed to assess heteroscedasticity in the errors of a regression model. A value of 1.84 alongside a p-value of 0.175 indicates that the model estimation results remain unaffected by heteroscedasticity issues. Consequently, the fixed-effects model is deemed more appropriate for analyzing this dataset than the random-effects model. Moreover, the Granger causality test elucidates the interactive relationships among risk factors. The model estimation results' robustness is affirmed by the heteroscedasticity test. These analyses collectively ascertain that weather risk and logistics timeliness significantly impact supply chain management performance, with a discernible bidirectional causal relationship. These empirical findings furnish valuable insights for agricultural livestreaming platforms and supply chain managers, facilitating a deeper comprehension and optimization of supply chain operations.

A. DATASETS COLLECTION

To assess the impact of risk indicators, researchers employ a questionnaire survey method to acquire data from professionals, experts, and consumers within the agricultural EC domain, quantifying the influence of these indicators. Stringent measures are undertaken during the questionnaire preparation phase to ensure the scientific validity and reliability of the study. Initially, questionnaires are crafted for distinct groups, including professionals, experts, and consumers, aligning with the study's objectives. Through targeted promotion within the agricultural EC sector and surveys conducted among relevant academic institutions and consumers, 200 questionnaires were successfully amassed, with 162 deemed valid post-validity checks. When determining the sample size, the study's complexity and the diversity of the target audience are comprehensively considered. Despite the seemingly restricted sample size of 160, meticulous sample selection and analysis can furnish representative insights into professionals, experts, and consumers within the agricultural EC realm. Furthermore, rigorous statistical methods and data analysis techniques are employed to ensure the accuracy and reliability of the study findings. Thus, the collection of 160 questionnaire responses adequately reflects market demand in EC to a certain degree, yielding significant conclusions and insights for the study. The compilation of questionnaire data encompasses multiple dimensions, covering professionals' opinions, experts' recommendations, and consumer demands, facilitating a comprehensive assessment of risk indicators' impact on agricultural supply chain management. When identifying relevant stakeholders, their roles and responsibilities in the agricultural EC sector are meticulously considered to better comprehend their perspectives and evaluations of risk factors. Utilizing a five-point Likert scale enables the quantitative assessment of their perceptions regarding the importance of various risk dimensions, furnishing a more compelling and actionable data foundation for the study. This approach not only assists in identifying pivotal viewpoints and demands but also enhances the comprehension of attitudes and preferences among different user groups, offering more comprehensive and in-depth data support for formulating research conclusions. Figure 3 showcases the demographic profile of survey participants.

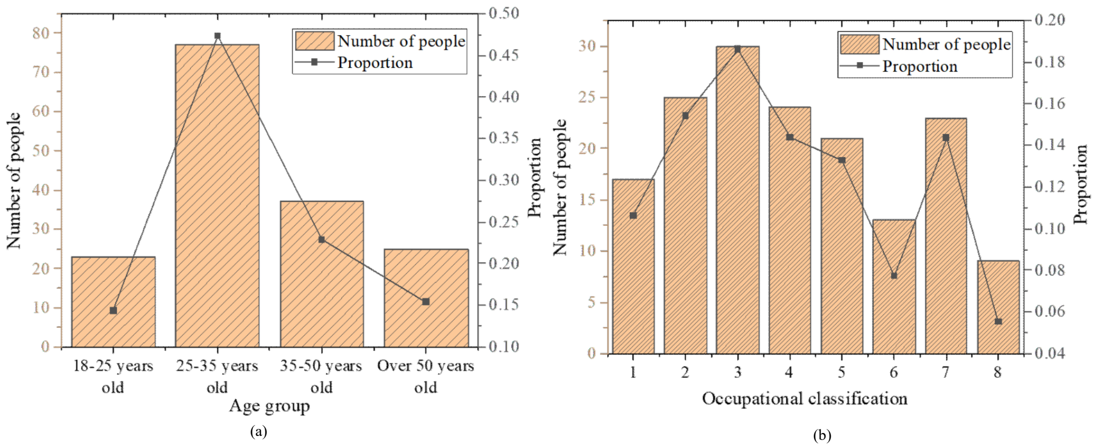

FIGURE 3. The statistical data of the survey participants ((a) age information; (b) occupational details. In which, "1~8" correspond respectively to the following livestreaming-related professions: students, teachers, production department, transportation department, storage department, technical research and development department, management personnel, and individuals.)

Figure 3 illustrates that the age group of 25-35 years represents the largest proportion among survey participants, comprising 47.34% of the total, with a relatively equitable distribution across diverse age segments. Concerning occupational categorization, the production department demonstrates the highest representation, constituting 18.62% of respondents, followed by faculty members and managerial staff. Figure 4 depicts the outcomes of the questionnaire's reliability and validity analysis. The alpha (α) coefficient for the overall index is calculated at 0.908, signifying a notable level of consistency and reliability for the comprehensive measurement tool. Moreover, the overall Kaiser-Meyer-Olkin (KMO) value is reported at 0.907, indicating the adequacy of the measurement model on the whole.

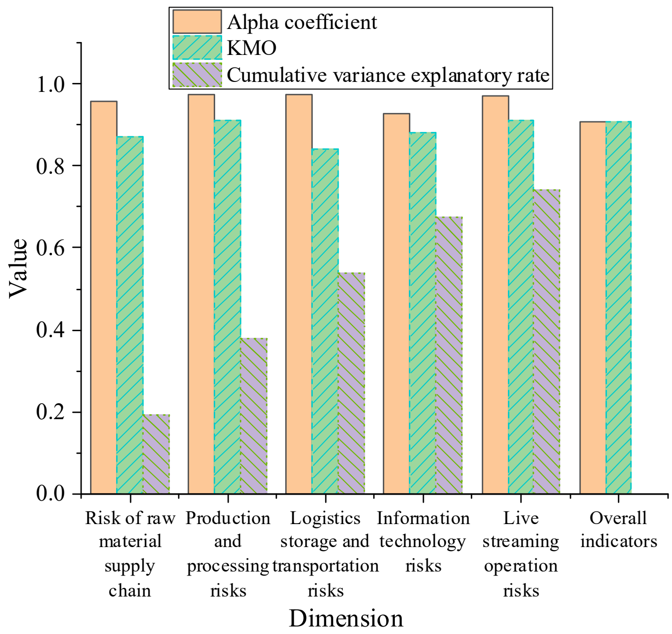

FIGURE 4. Results of questionnaire reliability and validity analysis.

B. EXPERIMENTAL ENVIRONMENT AND PARAMETERS SETTING

During the experiment, the risk control rate of the current model is adjusted from 0 to simulate a scenario without risk control measures. Concurrently, the risk control rate is maintained at 0.1 to reflect the actual implementation of risk control measures. This experimental design aims to assess the genuine impact of risk control on the agricultural livestreaming supply chain and elucidate any lag effects in risk control effectiveness.

C. PERFORMANCE EVALUATION

Within the experimental framework, diverse model techniques including SD, multiple linear regression models, and Granger causality tests are employed. The selection of these model techniques is predicated on the study's complexity and objectives, to provide a comprehensive assessment of risk factors in agricultural supply chain management. Dynamic modeling enables the assessment and prediction of risks over time, while multiple linear regression models facilitate the extraction of key performance indicators and the analysis of their influencing factors. Granger causality tests are utilized to explore the interrelationships among risk factors, revealing their roles in supply chain management. The comprehensive application of these model techniques enhances understanding and optimization of agricultural supply chain management.

In evaluating the relationship between agricultural livestreaming sales and supply chain management performance, this study conducts a thorough analysis of how livestreaming sales activities impact various facets of the supply chain through a panel data model. l. It examines whether livestreaming activities increase order quantities, thereby affecting logistics timeliness, and how information technology (IT) supports the maintenance of supply chain flexibility and responsiveness amidst rapid fluctuations in market demand. Table V presents the outcomes of the panel data model analysis:

TABLE V

Results of panel data model analysis

Variable	Coefficient	Standard Error	t-value	p-value
Livestreaming Sales	0.25	0.05	5.00	<0.001
Logistics Timeliness	-0.15	0.03	-5.00	<0.001
IT Support	0.20	0.04	5.00	<0.001

Note: All coefficients are significant at the 1% level of significance.

The fixed-effects model controls for factors that may vary over time but remain constant across different entities, such as the impact of specific seasons. Additionally, a Structural Equation Model (SEM) is employed to discern and validate the relationships among the three principal latent variables: livestreaming sales, logistics efficiency, and IT support. Constructing the SEM model relies on factor analysis and path analysis of relevant data to determine how these variables are interconnected and ultimately influence supply chain management performance. This comprehensive approach enables the measurement of direct effects while capturing indirect effects and intricate dynamic interactions between variables. The anticipated outcomes furnish actionable strategies for supply chain managers to optimize livestreaming sales activities and integrate supply chain resources, thereby bolstering the overall efficiency and competitiveness of the supply chain. The statistical outcomes of the path analysis in the SEM are denoted in Table VI:

TABLE VI

Statistical results of SEM path analysis

Path	Standardized Coefficient	Standard Error	z-value	p-value
Livestreaming Sales → Logistics Efficiency	0.45	0.07	6.43	<0.001
Logistics Efficiency → Supply Chain Performance	0.40	0.06	6.67	<0.001
IT Support → Supply Chain Performance	0.50	0.07	7.14	<0.001

Note: Standardized coefficients allow for the comparison of the relative importance of variables across different paths.

Utilizing the advantages derived from integrating panel data models and SEM, this study provides a comprehensive perspective to accurately comprehend the impact of livestreaming sales on supply chain management performance. This study emphasizes the critical importance of ensuring logistics efficiency and IT support to enhance overall supply chain performance. These analytical revelations furnish valuable insights for supply chain managers, facilitating more efficient resource allocation and process optimization tailored specifically to livestreaming sales activities. Consequently, this leads to an enhancement in overall supply chain efficiency and competitiveness.

Figure 5 illustrates the overall risk profile of the agricultural supply chain within the framework of "Agricultural Livestreaming." It suggests a widening risk disparity among different stages over time. Notably, the risk in the raw material supply stage exceeds that in the production and processing stage from the sixth day onward, emerging as the most significant risk stage in the supply chain. Subsequently, the risks in the production and processing stage, on-site operation stage, warehouse logistics and transportation stage, and IT stage follow in descending order.

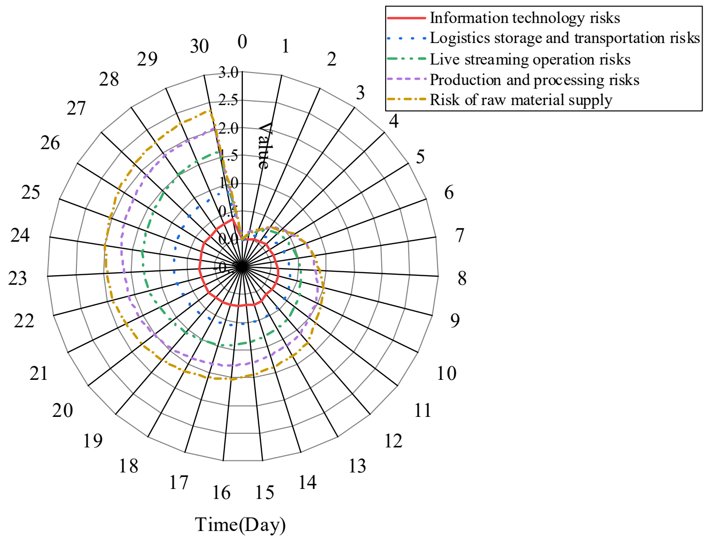

FIGURE 5. Comprehensive risks in the agricultural product supply chain under the background of agricultural livestreaming

To assess the effectiveness of risk control measures within the system model concerning risk management in the agricultural livestreaming supply chain, adjustments are made to the risk control rates of the five subsystems in the current model (Current 1). These adjustments set the rates to 0, reflecting the absence of risk control measures. Conversely, the current model maintains its original coefficient of 0.1, signifying the implementation of risk control and illustrating its efficacy. Figure 6 depicts the simulation outcomes regarding the effectiveness of risk control measures on risk management within the agricultural livestreaming supply chain. In Figure 6, "Current 1" denotes the scenario where the risk control rate of the five subsystems in the current model is adjusted to 0, thus reflecting the impact of the absence of risk control measures. Meanwhile, "Current" represents the scenario where the risk control rate in the current model is sustained at 0.1, showcasing the actual impact of risk control measures. By comparing the simulation results of these two scenarios, an assessment of the practical effectiveness of risk control measures in risk management within the agricultural livestreaming supply chain can be conducted.

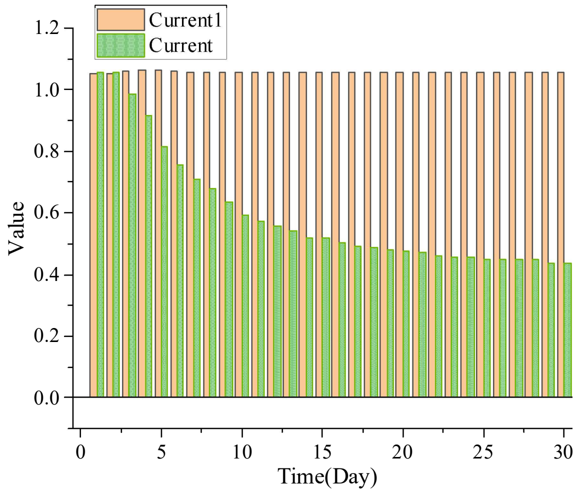

FIGURE 6. Simulation results of the effectiveness of risk control measures on risk management in the agricultural livestreaming supply chain.

Figure 6 demonstrates that the ineffectiveness of risk control measures across items 1 to 5 results in a substantial enhancement of risk control levels throughout the value chain, particularly in the storage and transportation, production and processing of raw materials, logistics, IT, and operational aspects of the supply chain. Consequently, risk control measures efficiently oversee supply chain performance and process management, contract and relationship management, and play a pivotal role in risk mitigation. Furthermore, a gradual decline in risk levels is observed after the second day of supply chain operations, illustrating a lag in the effects of risk control measures. It underscores the importance of promptly addressing risks in the agricultural product supply chain and continually preparing for risk reduction to minimize potential losses.

Figure 7 depicts the risk adjustment of the agricultural product supply chain under IT support. It illustrates a noticeable trend of improvement in IT risks as information asymmetry risks decrease. This observation implies that reducing information asymmetry risks contributes, to some extent, to an overall enhancement of IT support. Additionally, the reduction of risks associated with information traceability and network security vulnerabilities positively influences IT risks, albeit with a relatively moderate improvement effect.

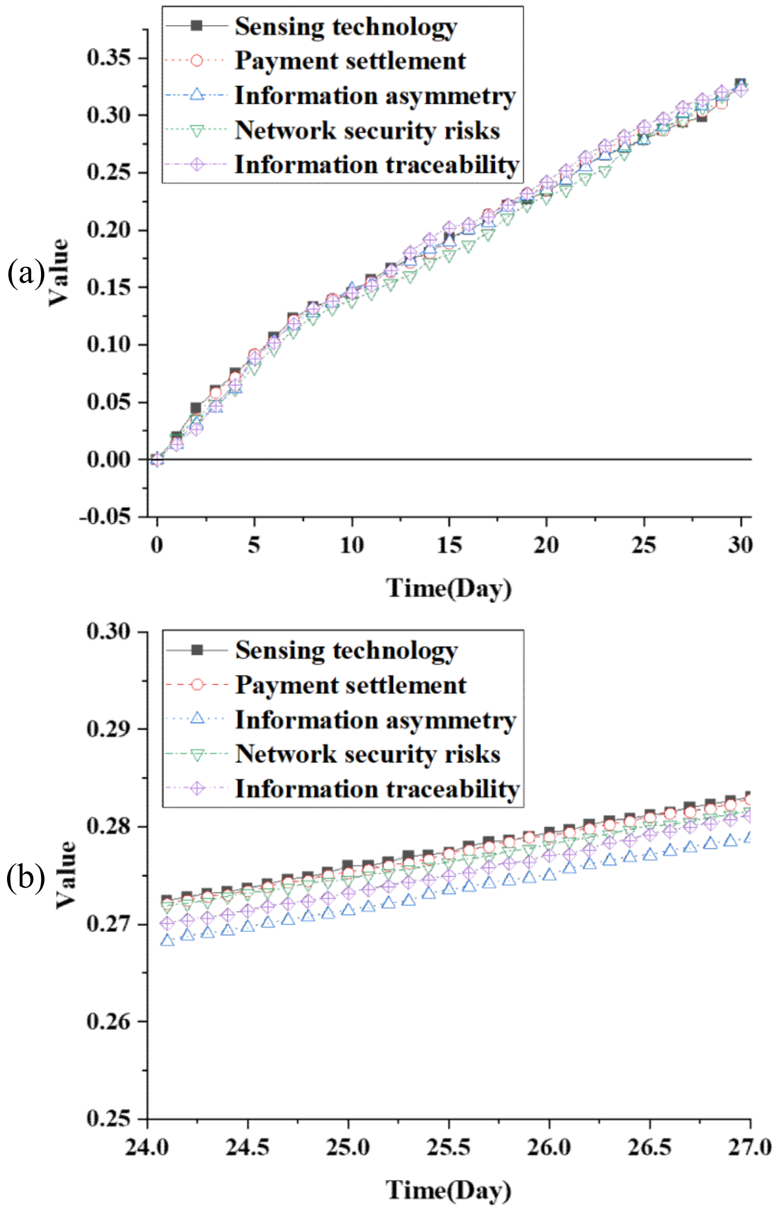

FIGURE 7. Risk adjustment in the agricultural product supply chain under information technology support ((a) Before technical adjustment, (b) After technical adjustment).

Figure 8 illustrates the technology-enabled risk adjustment within the agricultural product supply chain during agricultural livestreaming. An evident reduction in the risks associated with live operations is observed concurrently with the decrease in organizational management risks. This suggests that mitigating organizational risks has positively influenced live operations, albeit to a certain extent, by alleviating uncertainties. The improvement in risks at other stages has a comparatively minor impact on live operations, albeit contributing to an overall increase in risk levels to some degree. However, the effectiveness of this enhancement is relatively modest. Hence, to bolster the overall operational efficiency of agricultural livestreaming and agricultural product supply chains, prioritizing the reduction of organizational management risks is imperative.

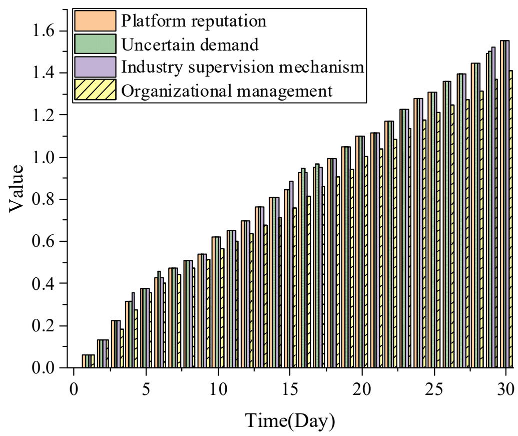

FIGURE 8. Technology-empowered risk adjustment in the agricultural product supply chain during agricultural livestreaming.

This study introduces ML algorithms to enhance the accuracy of predicting and detecting the likelihood or risk values associated with slow-moving products in agricultural product supply chains. By investigating the correlation between weather variables and the deceleration of product sales in historical data, a predictive model is developed to proactively identify and address risk factors that could impede the efficiency of agricultural product circulation. Considering the complex nature of data features and prediction objectives, the Random Forest (RF) algorithm is selected to establish the predictive model. RF, functioning as an ensemble learning technique, demonstrates effectiveness in handling extensive datasets and shows robustness against outliers and noise. In this risk value prediction, independent variables such as air temperature, rainfall, humidity, wind speed, and illumination are utilized. Among them, air temperature refers to the temperature of the air and is a common weather variable. Changes in air temperature directly impact the growth, ripening, and sale of agricultural products. High temperatures may hinder crop growth or cause premature ripening, while low temperatures may affect the quality and yield of agricultural products, thereby impacting sales speed and circulation efficiency. Rainfall denotes the amount of precipitation per unit of time and is another crucial weather variable. Variations in rainfall directly influence the growth and quality of agricultural products. Excessive or insufficient rainfall may affect the yield and quality of agricultural products, thereby impacting sales speed and circulation efficiency. Humidity represents the amount of water vapor in the air, usually expressed as relative humidity. Changes in humidity affect the storage conditions of agricultural products. High humidity may cause agricultural products to rot or mold, while low humidity may cause agricultural products to dry out and deteriorate, thereby affecting sales speed and quality. Wind speed indicates the speed of airflow per unit time. Changes in wind speed affect the growth environment and growth status of agricultural products. For instance, excessive wind speed may cause crops to lodge or wither, thereby affecting yield and sales speed. Illumination refers to the intensity of sunlight or other light sources shining on the ground. Changes in illumination directly affect the photosynthesis and growth rate of plants, thereby influencing the yield and quality of agricultural products, and consequently, the efficiency of sales and product circulation. The parameter settings for this experiment are exhibited in Table VII.

TABLE VII

Setting Parameters of RF Experiment

Parameter	Settings
Number of trees	100
Maximum depth of tree	10
Minimum number of split samples	2
Minimum number of samples for leaf nodes	1
Maximum number of features	2.236
Random seed	42

The Mean Absolute Error (MAE), Symmetric Mean Absolute Percentage Error (SMAPE), and Root Mean Square Error (RMSE) are used as performance evaluation metrics for prediction. The results of risk value prediction are depicted in Figure 9.

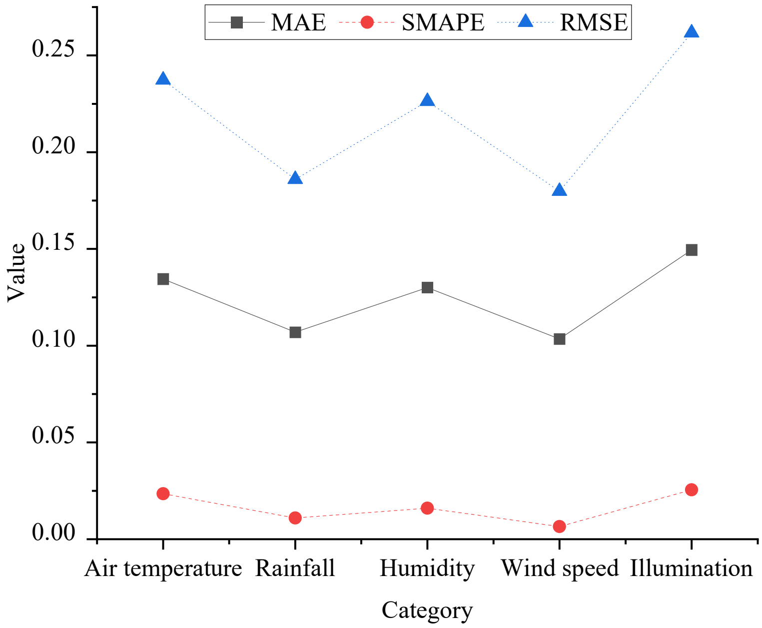

FIGURE 9. The results of risk value prediction.

Following training and validation, the RF model has exhibited a robust predictive capacity concerning weather-related risks and their implications for slowing product sales. Leveraging temperature, rainfall, and other relevant weather indicators, the model adeptly forecasts potential sales risks, providing timely decision-making support for supply chain managers. Through empirical findings, ML models effectively uncover the underlying correlations between weather variables and the sale of agricultural products. Furthermore, the model aids decision-makers in the early risk detection and mitigation associated with sluggish product turnover, thus mitigating product backlog and losses stemming from weather-related factors.

The impact of various factors on risk value is as follows. Weather elements such as temperature, rainfall, and humidity directly influence the growth, maturation, and quality of agricultural products, thereby exerting significant effects on the speed of product sales and circulation efficiency. High temperatures, heavy rainfall, or high humidity may lead to reduced yields or quality deterioration, consequently increasing the risk value associated with product backlog and losses. Variations in wind speed affect the growth environment and status of agricultural products, potentially causing crops to topple or wither, thereby affecting yields and sales speed, consequently increasing the risk value. Illumination plays a critical role in plant growth rate and photosynthesis, directly influencing the agricultural products' yield and quality. Optimal illumination conditions promote plant growth, thereby enhancing both yield and quality and reducing the risk value associated with product backlog and losses.

D. DISCUSSION

When addressing the management strategies for agricultural supply chains in the context of IoT and AI-enabled agricultural livestreaming, this study concentrates on comprehensive risk assessment within the agricultural supply chain management process and evaluates the effectiveness of risk management interventions on operational risks within the supply chain. Lele et al. (2023) highlighted the potential of digital technology to facilitate information sharing among production-based enterprises, thereby enhancing production efficiency, a notion that aligns with the proposed supplier-driven digital agricultural supply chain model [55]. The integration of digital technology into production processes can effectively boost efficiency, mitigate production risks, and enable the digitization of agricultural product supply chain operations. Consistent with this perspective, Yazdani et al. (2021) stressed the significance of risk assessment in agricultural product supply chains, utilizing SD for comprehensive risk evaluation, consistent with the study approach employed here [56]. Ali and Govindan (2023) underscored the systematic nature of risk assessment, advocating for a thorough understanding of the interrelationships and operational mechanisms among different subsystems [57]. Through simulation analysis, this study validates the efficacy of risk control measures in agricultural product livestreaming supply chains, offering empirical validation for risk management practices in agricultural product supply chains. In the agricultural supply chain management domain, Zhao et al. (2022) emphasized the significance of targeted consumer selection and precise characterization based on consumer behavior and psychology to better comprehend consumer needs and execute refined marketing strategies. Concurrently, supply chain development should foster enhanced collaboration between upstream and downstream enterprises, facilitating the evolution of the supply chain system into a more sophisticated model, aligning with the proposed actions here [58]. Focusing on the application of EC livestreaming in agriculture, Zheng et al. (2023) demonstrated that within the agricultural livestreaming framework, EC platforms can effectively bridge the gap between supply and demand for agricultural products through collaboration with governmental bodies, academia, and influencers, nurturing the market's transition into a novel consumption paradigm [59]. This resonates with the empirical findings from the study on pomegranate livestreaming sales in X County, highlighting the practical impacts of agricultural livestreaming in alleviating sales pressures stemming from adverse weather conditions.

V. CONCLUSION

This study provides both novel theoretical frameworks and empirical evidence to explore the integration of IoT and AI within agricultural livestreaming and agricultural product supply chain management. By merging SD methodology with empirical investigation, it delves into contemporary challenges within the agricultural sector. Utilizing pomegranate livestreaming sales in County X as a case study, this study empirically validates the tangible efficacy of agricultural livestreaming in mitigating sales pressures arising from adverse weather conditions. Employing questionnaire surveys and simulation analyses, it systematically evaluates the impact of risk control mechanisms on agricultural livestreaming supply chains, imparting valuable insights for streamlining agricultural product supply chains. The findings suggest that risk control measures positively influence the performance and risk management of agricultural livestreaming supply chains, albeit with a certain delay in their efficacy, underscoring the significance of proactive risk mitigation. By integrating SD with empirical inquiry, an enhanced digital supply chain model is proposed, which enhances the efficiency and adaptability of agricultural product supply chains. The utilization of the fixed-effects model proves suitable for dataset analysis, while Granger causality tests unveil the interdependent relationships among risk factors. In summary, weather-related risks and logistics punctuality substantially influence supply chain management performance, signifying a reciprocal causal relationship. These study findings provide empirical support for agricultural livestreaming platforms and supply chain managers, facilitating a deeper understanding and optimization of supply chain operations. Through these analyses, reliable guidance is extended to decision-makers, fostering the ongoing advancement of agricultural livestreaming and supply chain management. The contributions of this study are outlined as follows:

1. Theoretical and Empirical Foundation: By examining the utilization of IoT and AI in agricultural livestreaming and agricultural product supply chain management, this study furnishes novel theoretical and empirical backing. It addresses research lacunae in pertinent domains and augments the theoretical underpinnings for contemporary agricultural challenges.

2. Integration of SD Methodology: By amalgamating SD methodology with empirical inquiry, this study probes into the intricacies of agricultural livestreaming and supply chain management. This methodological approach facilitates a systematic assessment of the impact of risk control on agricultural livestreaming supply chains, thereby offering a comprehensive viewpoint for enhancing agricultural product supply chains.

3. Empirical Validation through Case Study: By scrutinizing pomegranate live sales in County X, this study empirically substantiates the tangible effectiveness of agricultural livestreaming in alleviating sales pressures stemming from weather conditions. The empirical validation provided by this case study enhances the credibility of the study's conclusions.

4. Assessment of Risk Control Efficacy: The findings underscore that risk control measures positively impact the performance and risk management of agricultural livestreaming supply chains, emphasizing the importance of proactive risk mitigation. These findings offer actionable insights for managers of agricultural product supply chains to ensure smooth operations and timely risk mitigation.

Practically, the outcomes of this study can offer concrete operational directives for agricultural producers, managers of agricultural product supply chains, and allied professionals. These stakeholders can implement more efficacious strategies to optimize the management of agricultural product supply chains based on the efficacy analysis of proposed risk control measures. Furthermore, this study imparts practical insights into the utilization of IoT, AI, and SD methodologies in agricultural contexts. It aids the agricultural industry in adapting to the exigencies of rapid development and market fluctuations, thereby promoting agricultural modernization and digital transformation.

This study not only investigates the application of the IoT and AI in agricultural livestreaming and agricultural product supply chain management but also provides a novel perspective on intelligent science and sustainable development. The fusion of SD methodology with empirical research fills research gaps in related fields and offers a deeper theoretical foundation for contemporary agricultural challenges. From the perspective of intelligent science, this study employs AI algorithms to construct a risk prediction model, effectively analyzing the correlation between meteorological variables and sluggish product sales, and offering timely decision support for decision-makers. The application of ML models reveals the potential relationship between weather variables and agricultural product sales, equipping agricultural producers and supply chain managers with more accurate forecasting tools to reduce product backlog and losses caused by weather factors, thereby enhancing the intelligent management level of the supply chain. In terms of sustainable development, the digital supply chain model and risk control measures proposed in this study pave the way for a more sustainable development trajectory in agricultural production. Timely risk warnings and effective supply chain management can curtail unnecessary resource waste and environmental pollution, promoting the sustainable development of agricultural production. Additionally, the empirical case validation of agricultural livestreaming in alleviating sales pressure and optimizing supply chains also provides a more sustainable sales approach for agricultural producers. Therefore, this study not only furnishes new theoretical and empirical support for intelligent science and sustainable development but also offers practical operational guidance for agricultural producers and supply chain managers, advancing the development of intelligent agriculture and sustainable agriculture. This achievement not only propels agricultural modernization and digital transformation but also facilitates the intelligent management and sustainable development of agricultural supply chains.

While this study has made strides in investigating the utilization of IoT and AI in agriculture, several limitations persist. The comprehensive applicability of agricultural livestreaming across diverse regions and agricultural products remains underexplored and calls for further investigation in subsequent research endeavors. Additionally, there is a need for deeper exploration into parameter selection and sensitivity analysis within SD models to bolster their interpretability and applicability. Future investigations could expand the scope of inquiry into IoT and AI applications in agriculture and explore novel digital supply chain models. Future investigations could expand the scope of inquiry into IoT and AI applications in agriculture and delve into innovative digital supply chain models. Enriching case studies spanning various regions and agricultural products would contribute to the development of a more holistic theoretical framework. Methodologically, the exploration of more sophisticated data analysis techniques and model optimization methods holds promise for enhancing the scholarly and practical significance of research findings. In summary, this study provides valuable insights and lays the groundwork for future research endeavors in the agricultural modernization and supply chain management domains.

Ethics Statement

This study was approved by the Ethics Committee of Business School, Ningbo City College of Vocational Technology, with ethics approval reference 2022/9203.384.

Verbal informed consent was obtained from the patients for their anonymized information to be published in this study.

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