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Utilizing Edge Cloud Computing and Deep Learning for Enhanced Risk Assessment in China's International Trade and Investment

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Abstract: Amidst a transformative economic milieu in China, domestic enterprises are venturing into the global market, exposing them to intensified perils in international trade and investment. This research elucidates the international trade and investment (ITI) context within China, establishing criteria for ITI risk evaluation through an analytical exploration of international trade interactions. A methodology has been developed to quantify ITI risk, employing deep neural networks (DNNs), with a particular focus on the potential impact of edge cloud computing on China's trading economy. Through the utilization of convolutional neural networks (CNN), risks in China's trade and investment are appraised across various dimensions, exhibiting a noteworthy accuracy rate of 90.38%. It is identified that while CNN exhibits exemplary performance in estimating severe and high-risk scenarios, its efficacy diminishes when discerning general investment perils. The analysis underscores that a substantial portion of investments, constituting 14.8%, emanates from The Association of Southeast Asian Nations (ASEAN) and China, with market dynamics and macroeconomic conditions markedly influencing the risk associated with Chinese investments. By extending the utilization of deep learning (DL) in financial investments and integrating edge cloud computing, this investigation augments the capabilities for assessing China's ITI risk, providing a valuable resource for comprehending the ITI landscape within China.

Keywords: Convolutional neural network; Advanced machine learning; International trade and investment; Risk analysis

1 Introduction

Amidst the burgeoning evolution of the global digital economy, activities anchored in digital technology, such as online R&D, design, production, and trading, have been catapulted into popularity. An enhancement in the dominance of digital trade on the global stage is witnessed, with the rise of global digital service trade by 3.8% in 2019 to attain a zenith of $3,192.6 billion, eclipsing the growth rates of both service and products trade and constituting 12.9% of all commerce and 52.0% of service trade [1, 2]. Subsequent to its accession to the WTO, regulatory enhancements governing digital trade have been fortified by China to more effectively cater to its national interests, evidenced by the ratification of over 20 trade agreements and active negotiation on an additional ten free trade accords [3, 4]. However, the pandemic-induced uncertainties loom, bearing the potential to amplify trade-restrictive measures [5, 6].

A fluctuation in China's foreign investment has been observed, with a decrement of actual foreign capital utilization by 1.3% YoY in the initial half of 2020, conversely elevating by 7.1% YoY in June [7]. The influence of enigmatic elements in a sophisticated global economic environment on foreign investment has been noted, rendering the attainment of stable foreign investment a persisting challenge [8, 9]. Emphasis by China on high-performance computing has been elucidated through policies spearheading the advancement of supercomputing facilities and initiatives such as "East-West Computing". A consequential amplification in advancements in digital technology and the economy is foreseen through cloud-edge collaboration, signaling a pivotal developmental trajectory forward [10].

Historical examinations of the risks entwined with global trade and investment have been extensive. Recognizing risks and proffering solutions pertinent to corporate finance, investment climates, governmental management, and decision-making, Buckley et al. [11] have charted these perils. Additional research has dissected the risks engulfing Chinese foreign investment, spanning political, economic, cultural, and M&A dimensions [12], while a spotlight has also been cast upon risks affiliated with China's "Belt and Road"(B&R) initiative [13]. Despite numerous academics delving into the quantitative assessment of trade and investment risks, a comprehensive evaluation, encapsulating manifold risk constituents, remains elusive [14–17]. Employment of DL in this research endeavors to evaluate China's ITI risk has been articulated, offering a synopsis of the contemporary ITI landscape within China, formulating risk evaluation criteria grounded in international trade relations, and architecting a risk assessment system underpinned by DNNs. Cognizance has been taken of the results yielded from ITI risk training, in conjunction with trade and investment volumes and ratios, as well as the risk pertaining to foreign investments, subject to varied influential variables. Furthermore, a DL-supported ITI risk assessment system has been developed, illuminating the applicability of DL in research concerning financial investments [18].

In summation, the exploration delineates challenges entwined with foreign investment, delineates the metamorphosis of digital trade, and elucidates China's standing within the global economy. An exposition of the capabilities of DL in the evaluation of ITI risk is spotlighted, alongside a detailed analysis of China's entanglement in global trade dynamics.

2 Methodology

2.1 Chinese Trade's Exemplary Adaptations

Initiation of modified import tax rate applications was witnessed in China, with reductions enacted for upwards of 700 items starting January 2019, an additional 850 items from January 1, 2020, and a further 298 information technology products as of July 1. The mitigation of these tariffs is perceived to enhance the procurement of high-calibre global commodities, thereby ameliorating the domestic supply chain, and accommodating production requisites [19]. Consequently, diversification in the import market's structure was identified. Trade transactions between China and nations affiliated with the (B&R) initiative was reported to aggregate 4.2 trillion yuan during the first half of 2020, constituting 29.5% of total trade and manifesting a 0.7% increment relative to the preceding year.

This expansion in imports, which ostensibly underscores China's fidelity to international responsibilities, concomitantly fosters global economic growth. By refining the business environment, a simplification in trade processes has been introduced in China. Reforms have culminated in a reduction of obligatory documentation for customs declarations and clearances from 86 to 44, thus streamlining transactional activities [20]. Between the years 2017 and 2019, implementation of automated online verifications was correlated with a 42% and 65.3% decline in export and import compliance costs respectively.

The establishment of free trade zones and cross-border e-commerce pilot zones has been associated with enhancements in trade quality. In H1 2020, the emergence of new pilot zones, inclusive of those dedicated to cross-border e-commerce, was linked with a 28.7% surge in exports and a 33.4% amplification in market procurement, thereby rejuvenating the transmutation and development of international trade [21]. Despite a contraction in global Information Technology and Investment (ITI), an escalation in China's ITI has been discerned, bolstering an open global economy. During the first half of 2020, a 0.5% ascent in foreign capital utilisation was observed, whilst international trade witnessed a year-over-year (YOY) augmentation of 6.5%, with exports and imports expanding by 10.4% and 1.6% respectively, highlighting China's proliferating influence within the international market [22].

2.2 Implications of Chinese Exports Through Edge Cloud Computing

In the conceptual expansion of cloud computing, edge cloud computing has emerged, where computational capacity is strategically positioned at the network's edge, thereby facilitating reduced processing times for proximal requirements. Typically utilised for local decision-making, real-time data processing, and the deployment of time-sensitive services, this approach has been adopted with an aim to enhance collaborative efforts amidst the completion of cloud computing. Categorically, edge computing mirrors cloud computing, bifurcating into Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) tiers, encompassing technologies such as edge gateways, integrated computers, and computational platforms.

Such technologies, wherein GPUs and various computational tools are employed, are designed to expediently access edge devices, facilitate data acquisition, and integrate protocols, tailoring their functionalities to specific circumstances. Analogous to cloud-native technology, edge cloud systems incorporate lightweight virtualization, a strategy that has been implemented by manufacturers, including but not limited to Huawei, Kingsoft, and Baidu [23]. These platforms are often instituted across varied locations to accommodate the prerequisites of edge intelligence and Artificial Intelligence (AI) deployment. In parallel with the evolution of China's cloud service market, which witnessed a 57.10% YoY proliferation in 2019 [24], edge cloud computing has demonstrated congruent growth. Notably, in the realm of edge applications, the burgeoning popularity of cloud-native solutions, underscored by scalable and uniform design, addresses challenges pertinent to application distribution delivery and maintenance by proffering integrated application distribution support.

2.3 The Determination of Risk Indicators

Global trade, facilitated by the division of labour and encompassing the exchange of goods and services between nations, is posited as an indispensable avenue for international integration. Such interactions underline the economic interdependence amongst countries, giving due regard to their cumulative bilateral transactions. The delineation of factors influencing the inherent risks of China's ITI can be observed in Figure 1.

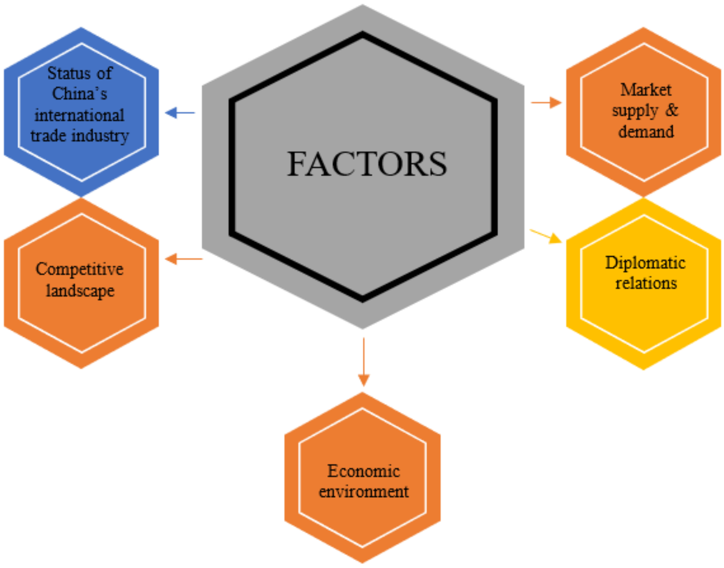

Figure 1. Influential determinants of China's ITI risks

As depicted in Figure 1, the determinants of risks in China's ITI have been compartmentalized into five predominant clusters. The interplay amongst these clusters mirrors the tension between global market dynamics and China's commercial and investment paradigms. In economies driven by commodities, the symbiotic relationship between product supply and market demand is manifested, thereby highlighting the consonance between production processes and market consumption patterns. Policy milieu, in this context, pertains to the gamut of regulatory interventions that bolster China's transnational trade and investment trajectories. Furthermore, the technological milieu encompasses salient sociological and technological facets directly pertinent to the ITI landscape in China. Embedded within this are the national technical blueprint, technological governance, degrees of technological advancement, and patterns of technological evolution.

Figure 2 then elucidates commonly employed techniques for risk assessment.

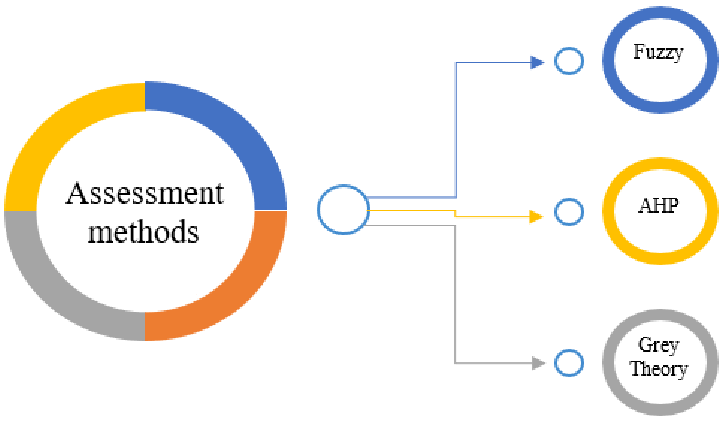

Figure 2. Prevalent methodologies for risk evaluation

Within the precincts of China's ITI, nations are categorized grounded on the congruence of their investment risk profiles [25]. Additionally, methods for gauging attributes and for hierarchically ranking alternatives have been profusely applied within the theoretical frameworks of fuzzy set and its amalgamated paradigms [26, 27]. It is noteworthy that such methodologies find versatile applicability, spanning sectors from economics to healthcare.

2.4 DNN Model Optimisation Process

DL is recognised for synthesising lower-level features to create intricate, high-level features, thereby revealing sparse feature representations within data, elucidating attribute categories, or features. The merits of identifying risks pertinent to China's trade and investment through the adoption of DL methodologies are illustrated in Figure 3.

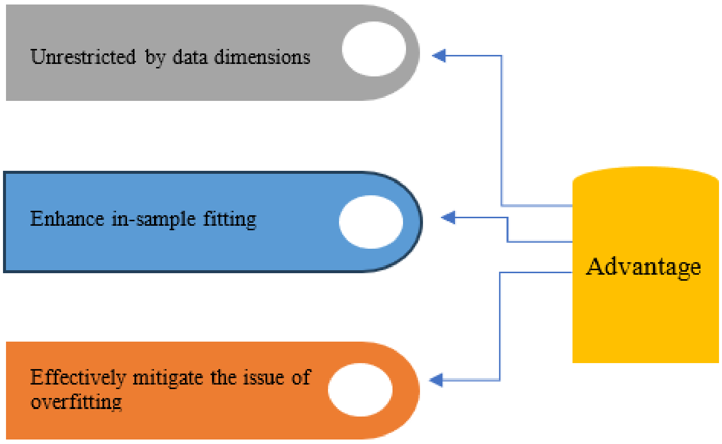

Figure 3. Merits of constructing China's trade and investment risks through DL methodologies

DL algorithms, capable of leveraging exceedingly complex and abstract data features for prediction or classification tasks, afford the autonomous extraction of features from unsupervised data. The fundamental construct within DL is a DNN, utilised in the formation of DL models. An understanding of the perceptron model emerges as paramount prior to delving into the intricacies of the DNN. Figure 4 illustrates the perceptron model, which, in its configuration, harbours numerous inputs and outputs, representing input values as x_1, x_2, and x_3, whilst the activation function is denoted by f. The model identifies a linear relationship between inputs and outputs, consequently generating intermediate output results [28]. Given Eq. (1), the outcome is 1 or -1. This model is constrained to binary classification applications and lacks the capacity to learn more complex nonlinear models. The perceptron model's activation function, $\mathrm{sign}(z)$, albeit simple, suffers from restricted processing capacity. Alternative activation functions, commonly employed in neural networks (NNs), such as the Sigmoid function utilised in logistic regression, are denoted in Eq. (1):

$$f(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

The evolution of the perceptron concept precipitated the inception of NNs. A variant of NN, incorporating several hidden layers, is categorized as a DNN. Both multi-layer NN and DNN typically allude to an analogous concept. At times, DNN is alternatively termed a Multi-Layer Perceptron (MLP). Figure 4 elucidates the foundational structure of the DNN.

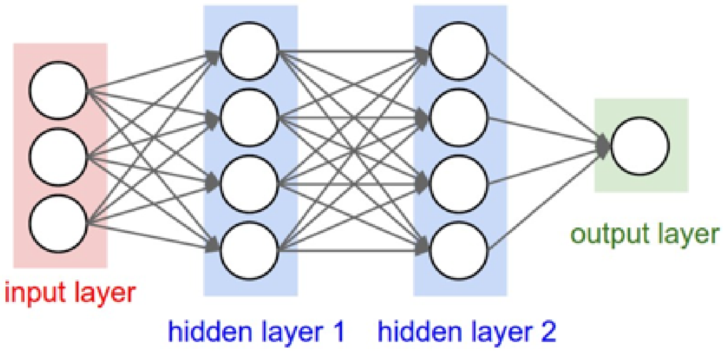

Figure 4. Fundamental structure of DNN

DNN segmentation, based on the locations of its constituent layers, is displayed in Figure 5. DNN incorporates three variants of layers: input, hidden, and output layers. Every neuron in the i-th layer necessitates connectivity to neurons in the $i+1-th$ layer, ensuring comprehensive connectivity across these layers. Despite DNN's apparent complexity, smaller, localized models exhibit perceptible similarities to the perceptron, indicating a linear relationship [29]. Assuming the chosen activation function is $\sigma(z)$ and the output value of both the hidden layer and the output layer is denoted as a, Eq. (2) elucidates the model expression:

$$a_j^l = \sigma\left(z_j^l\right) = \sigma\left(\sum_{k=1}^{m} w_{jk}^l a_k^{l-1} + b_j^l\right) \tag{2}$$

In Eq. (2), a_j^l signifies the output value of the j-th neuron in the l-th layer, while z_j^l conveys the net input of the j-th neuron in the 1-th layer, contrary to the initial statement which incorrectly designated it as the output value of the neuron in the $l-1$ th layer. Furthermore, b_j^l is accurately denoted as the bias, not the connection threshold, and w_{jk}^l symbolizes the weight connecting the k-th neuron in the $l-1$ th layer to the j-th neuron in the l-th layer. The term a_k^{l-1} refers to the output value from the k-th neuron in the $l-1$ th layer.

NNs can incorporate numerous hidden layers, facilitating the evolution of novel abstractions in higher hidden layers based upon preceding ones. However, an escalation in the number of hidden layers often engenders two prominent challenges: overfitting and the vanishing gradient problem. The vanishing gradient issue pertains to the gradual attenuation of the gradient, as information permeates through layers, thereby exerting a diminished influence on the network's weights. Overfitting transpires when a model becomes excessively intricate, manifesting exceptionally elevated recognition performance on training data yet potentially performing poorly on unseen data. To navigate these challenges, DNN methodologies traditionally employ the stochastic gradient descent approach for optimization.

2.5 Assessment of China's ITI Risk Utilising DNN-Based System

The utilisation of NN Technology within the realm of DL has facilitated the attainment of intelligent decision-making in China's ITI. Figure 5 elucidates the ITI Risk Assessment System, developed via DNN methodologies.

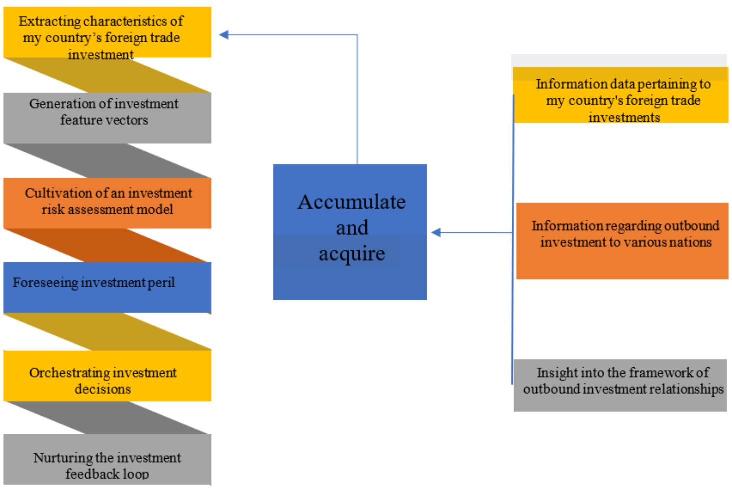

Figure 5. A DNN-based risk assessment system for China's ITI

Primary data, extracted from digital platforms, undergoes a process of vectorised feature extraction, as depicted in Figure 5. Subsequent analysis of the acquired data is executed in MATLAB for DNN training purposes. The z-score function, applied for the data normalisation, is employed in the context of studies [30–32], and is expressed as follows:

$$z = \frac{(x-\mu)}{\sigma} \tag{3}$$

In Eq. (3), the function z adheres to a normal distribution, wherein μ symbolises the mean, σ represents the standard deviation, and x indicates the input data pertaining to foreign trade investment. Upon extraction of feature vectors from the data related to China's foreign trade investments, a DNN model is constructed computationally. A model for investment risk assessment is consequently formulated, utilising pivotal feature vectors related to China's foreign trade investments. Ultimately, the developed model enables the forecasting of investment risks, thereby facilitating the formulation of informed investment decisions [33].

3 Results and Discussion

Data for most of the report were derived from diverse databases, the Ministry of Commerce, and national statistical data, with a focal point on utilizing DNN to evaluate the financial risk of listed firms. This was achieved by leveraging the broad spectrum of variables embedded within China's foreign trade and investment data, necessitating the implementation of parameter transfer learning. The dataset tailored for the risk assessment of listed firms is denoted as "Finance," whilst the dataset employed for gauging the financial risk of foreign trade investments by China is termed "Invest". The juxtaposition of training results between parameter transfer learning and DNN-based risk assessment pertaining to China's ITI is elucidated in Figure 6.

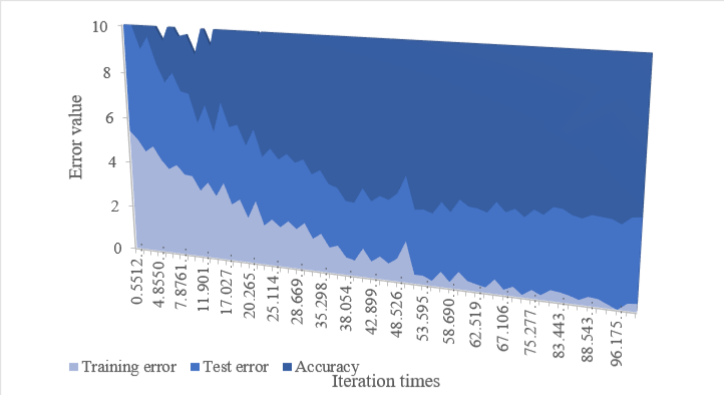

Figure 6. The comparative analysis of training outcomes between DNN risk training for China's foreign trade investment and parameter transfer learning

Figure 6 illustrates a decrement in training errors as the iteration number augments, enhancing judgement accuracy. The precision of the pre-trained Invest model is heightened during the Finance fine-tuning evaluation by the parameter-driven CNN, amplifying the model's convergence effect. This discovery underscores the robust generalization capability of CNN while formulating the risk associated with China's foreign trade investments. Figure 7, derived from CNN, delineates the proficient prediction of China's ITI risk [34, 35].

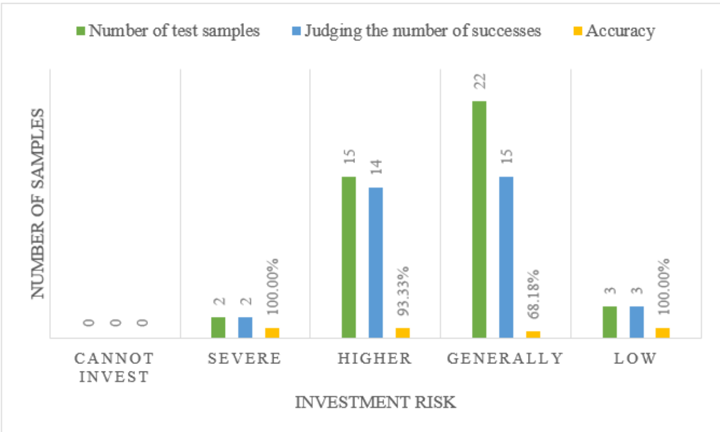

Figure 7. Predictive accuracy of China's ITI risk as analysed by CNN

As depicted in Figure 7, the prediction of risk levels is compartmentalised into five discrete strata. A multitude of samples from China's foreign trade investment are examined across these risk levels utilising CNN for risk evaluation. The results intimate that CNN manifests a remarkable average accuracy of 90.38% in predicting China's foreign trade investment risk, exemplifying its formidable predictive capacity. Remarkably, CNN achieves an unblemished accuracy of 100% when evaluating severe, higher, and lower risks linked to China's foreign trade investment. Its acumen in ascertaining overall investment risk, nonetheless, languishes at a considerably reduced 68.18%. Predictive errors generally tend towards higher investment risks in scenarios involving general investment risk, albeit they remain manageable and customarily do not transgress one risk category. In summary, CNN's risk assessment concerning China's ITI proffers a comparatively comprehensive and nuanced appraisal of risk tiers.

4 Conclusion

In this investigation, CNN were utilised to examine the outcomes of risk training pertinent to China's ITI, alongside a scrutiny into the magnitude and dispersion of investments enacted by China and its ITI collaborators. The inclusion of risk pertaining to China's foreign investments under various risk determinants was also encompassed in the analysis. Results have demonstrated that during Finance fine-tuning examinations, the accuracy of the Invest pre-trained model was enhanced by the parameter-based CNN, culminating in superior model convergence effects. A thorough risk analysis of China's ITI by CNN has been discerned.

Distinctively, 14.8% of the total investment was channelled into trade and investment relations with the ASEAN. Subsequent investments into the European Union, the United States, and Japan witnessed augmentations of 14.0%, 12.4%, and 6.6% respectively, whilst the countries aligned with the B&R initiative experienced a 24.8% enhancement. Market supply and demand, coupled with the overarching economic climate, were identified as exerting a substantial influence on the risk of Chinese investments abroad. It was discerned that the classification of investment risk levels was substantially impacted by risk-affecting elements.

This exploration underscores the economic pertinence embedded within DL, whilst concurrently extending deeper into the domain of DL, furnishing a rigorous examination and research on China's ITI risk assessment and thereby constituting a valuable reference. The array of variables impacting China's trade and investment risk has been identified as comprehensive, yet imperfectly honed, introducing a degree of subjectivity into the analytical outcomes. For a more pinpointed analysis, subsequent research endeavours are recommended to enhance the variables determining China's ITI risk. The synthesis of DL theory with finance and an embrace of the evolution of DL theory for ITI risk assessment may pave the way towards the establishment of a robust trade and investment risk assessment model.

Authors Contributions

MN: conceptualization, methodology, data analysis, and writing–original draft, MZ: resources, and writing–review and editing.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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