SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Sustainable Economies 2024, 2(1), 17.
https://doi.org/10.62617/se.v2i1.17

Article

Financial expenditure, financial friction, and coal consumption for energy efficient environment: Role of financial inclusion

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CITATION

Iqbal N, Akmal Z. Financial expenditure, financial friction, and coal consumption for energy efficient environment: Role of financial inclusion. Sustainable Economies. 2024; 2(1): 17. https://doi.org/10.62617/se.v2i1.17

ARTICLE INFO

Received: 20 December 2023
Accepted: 7 February 2024
Available online: 18 February 2024

Abstract: This research investigates the crucial role that adaptability and ongoing evaluation have in implementing sustainable energy and economic development strategies in China. It emphasises the need for collaboration between enterprises, governmental organisations, and academic institutions in order to achieve these goals. The study also discusses how financial inclusion impacts economic growth and stability and how energy-intensive companies might use the Logarithmic Mean Divisia Index (LMDI) approach to evaluate energy decomposition. The findings indicate that different provinces in China's high energy-intensive (EI) economic sectors have different degrees of energy efficiency, with certain regions possibly having inefficiencies. The research underscores the need for targeted strategies to address these inefficiencies and disseminate efficacious approaches in new settings. The research also offers useful data that may be used to promote sustainable energy consumption and economic growth, with implications for policy-making and strategic initiatives. In summary, this paper presents specific policy recommendations and highlights the need for ongoing evaluation and collaboration to support China's sustainable energy initiatives and economic growth.

Keywords: sustainable energy; economic development; energy efficiency; high energy-intensive economic sector; financial inclusion

1. Introduction

Financial inclusion has become a crucial factor in driving economic growth by promoting a smoother financial cycle and reducing obstacles such as friction, asymmetric information, and volatility [1]. According to Zahid et al. [2], research indicates that the inclusion of more individuals in the financial system can contribute to the growth, stability, and development of the economy. Moreover, a global movement is gaining momentum to achieve sustainable development goals through greater financial inclusion [3]. Financial inclusion is impacted by various factors, such as the level of financial innovation, poverty rates, stability of the financial system, the overall economy, and the level of financial literacy [4]. In addition, the utilisation of various strategies such as reducing interest rates, implementing conditional low-interest rates, and reinforcing monetary policies through welfare payments has all been associated with achieving significant levels of financial inclusion [5].

In Africa, financial inclusion has been linked to financial innovation, financial development, and economic progress [6]. This connection is particularly significant. In addition, there is a proposal suggesting that the inclusion of financial services could potentially lead to an increase in agricultural production [7]. There are critics of financial inclusion who express concerns about its potential to encourage debt and the exploitation of impoverished individuals [8]. In addition, a study has been conducted on how financial inclusion affects firm innovation, specifically looking at the impact of both traditional and digital financial inclusion in China [9].

Research has shown that there is a connection between financial inclusion and economic development. A study conducted by Ciola et al. [10] provides empirical evidence of the impact of financial inclusion on growth. In addition, studies have indicated possible connections between financial inclusion and the non-performing loans of commercial banks [6]. Maruejols et al. [11] have found a connection between financial inclusion and sustainable financial performance. They suggest that financial literacy and innovation may play a role in this relationship. In addition, studies have explored how financial inclusion affects the financial planning of millennials, emphasising the significant influence it has on shaping their financial behaviour [12].

The measurement of financial inclusion has been conducted using various sets of indicators, reflecting the diverse approaches to evaluating its impacts [13]. In addition, Luo et al. [14] have highlighted the importance of including more people in the financial system to reduce income inequality and promote economic empowerment for women. In addition, there is a proposal suggesting that the inclusion of financial services could potentially empower women economically [15].

Ensuring that everyone has access to financial services is crucial for promoting stability, long-term growth, and overall economic advancement. While there are numerous potential benefits, implementing it can present challenges and disadvantages. The extensive range of research and empirical data underscores the intricate nature of financial inclusion and its impact on various aspects of the economy.

The impact of financial frictions on various economic factors has been extensively studied in the existing literature. These factors include labour market volatility, output gaps, talent allocation, investment efficiency, and resource misallocation. Exploring the intricate mechanisms through which financial frictions affect resource utilisation and overall economic performance has yet to be fully investigated [16]. Further research is needed to better understand how financial frictions affect different sectors and regions, as well as the intricate ways in which they can impact economic variables.

In addition, most recent research has overlooked the intricate details at the individual business and sector levels, instead focusing on the broader economic impacts of financial obstacles. The literature lacks sufficient research on the microeconomic impacts of financial frictions, particularly in relation to the establishment of companies, firm-level market dominance, and the incorporation of imperfect financial systems [17]. Understanding the small-scale economic effects of financial obstacles and how they impact individuals is crucial for developing targeted policies and improving the overall efficiency of resource allocation.

Moreover, there is a need for more comprehensive research on the differences in income, productivity, and business cycle fluctuations between countries due to financial frictions. Although a few studies have explored the international aspects of financial frictions, such as their effects on capital mobility and the transmission of shocks across borders, there is still much to be examined in this area. Studying the different effects of financial obstacles in different economic situations and regulatory systems can offer valuable insights into the global ramifications of imperfections in financial markets [4]. This knowledge can guide the formulation of effective policy measures on a global level.

In conclusion, the extensive research on financial frictions has provided a solid foundation for understanding the broad macroeconomic effects they have. Understanding the intricate details of microeconomic processes, differences between countries, and the specific impacts on different sectors due to financial frictions is still an area that requires further research. Thorough research and modelling can help us better understand the intricate impact of financial frictions on resource allocation, economic efficiency, and overall well-being.

2. Materials and methods

2.1. The LMDI approach

The LMDI outperforms competing IDA systems in recent studies that measured their simplicity, aggregation effectiveness, and zero data processing. It is possible to use the LMDI research of Khateeb et al. [18] to track the evolution of indices and their effects on pollution trends from the first report year forward. Below is an investigation of the association between carbon dioxide pollution and the provinces of China. As a first step, E_{ijk} shows the energy consumption of sectors j in region k using fuel type i, and P represents the gross domestic product (G_k) in region k. C_{ijk} shows that CO_2 emissions from province-related sources are polluting division j via fuel type t i in area k. Equation (1) may be used in conjunction with the seven components listed below to bolster C^t.

$$\begin{aligned} C^t &= \sum_i \sum_j \sum_k \frac{C_{ijk}}{E_{ijk}} \times \frac{E_{ijk}}{E_{jk}} \times \frac{E_{jk}}{E_k} \times \frac{E_k}{G_k} \times \frac{G_k}{G} \times \frac{G}{P} \times P \\ &= \sum_i \sum_j \sum_k c_{ijk} \times m_{ijk} \times s_{jk} \times e_k \times r_k \times g \times p \end{aligned} \quad (1)$$

The emission concentration level ($c = C_{ijk}/E_{ijk}$) represents the carbon capacity of fuel type i in sector j. The relationship between the concentration of fuel type i in sector j and the energy consumption of various fuel types may be expressed as $m = E_{ijk}/E_{jk}$.

Using the formula $S = E_{jk}/E_k$, which divides the total energy stock by the proportion held by sector j, we can see the energy economy's organizational structure. Using the formula $r = G/G$, we can see how a state's ks compares to its GDP. By dividing the region's energy consumption (E_k) by its gross domestic product (G_k), we may get its energy intensity (EI). As a measure of economic growth and GDP per capita, the formula = G/P is useful. Thus, the following is one way to describe the change in CO_2 emissions from year t to year $t - 0$:

$$\begin{aligned}\Delta C^t = &\sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{p^t}{p^{t-0}}\right) \\ &+ \sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{g^t}{g^{t-0}}\right) \\ &+ \sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{r^t}{r^{t-0}}\right) \\ &+ \sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{e^t}{e^{t-0}}\right) \\ &+ \sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{s^t}{s^{t-0}}\right) \\ &+ \sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{m^t}{m^{t-0}}\right) \\ &+ \sum_i \sum_j \sum_k L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) \ln\left(\frac{c^t}{c^{t-0}}\right) \\ &= \Delta C_p + \Delta C_g + \Delta C_r + \Delta C_e + \Delta C_s + \Delta C_m + \Delta C_c\end{aligned} \tag{2}$$

where

$$L\left(w_{ijk}^t, w_{ijk}^{t-0}\right) = \frac{\left(C_{ijk}^t - C_{ijk}^{t-0}\right)}{\left(\ln\left(C_{ijk}^t\right) - \ln\left(C_{ijk}^{t-0}\right)\right)} \tag{3}$$

This weighing component is called the logarithmic mean weight $L\left(w_{ijk}^t, w_{ijk}^{t-0}\right)$. According to Bugshan [19] variations in population, economy, state structure, industrial structure, energy mix, and emission concentration are the primary elements that impact fluctuations in CO_2 emissions.

$$\begin{aligned}\ln Y_{i,t,r} = &\, C + \alpha_t \ln\left(\mathrm{T}_{i,t,r}^L \times L_{i,t,r}\right) + \beta_t \ln\left(\mathrm{T}_{i,t,r}^K \times K_{i,t,r}\right) + \gamma_t \ln\left(\mathrm{T}_{i,t,r}^C \times C_{i,t,r}\right) \\ &+ \mu_i + \nu_i\end{aligned} \tag{4}$$

$$\delta_{\mathrm{T}^C} = \frac{\gamma}{0 - \gamma_t} \times \frac{\mathrm{dT}_t/\mathrm{d}t \big/ \mathrm{T}_t}{\mathrm{d}Y_t/\mathrm{d}t \big/ Y_t} \tag{5}$$

2.2. Data and variables

For this research, we used the most current longitudinal data for EI sectors in China, which spans 0990–0000. Following previous work by Zahid et al. [2], this analysis takes labor (*L*), capital stockpile (*K*), and coal consumption (*C*) as inputs and utilizes total manufacturing demand (*Y*) as productivity to approximately determine the flexibilities of successful key ins. Exogenous effect factors include things like the pace of economic growth in each region and changes to the coal sector [1]. Predictive discrimination was used according to the coal sector's production conditions. The collection includes energy, macroeconomic, and labor information culled from Chinese yearly reports.

3. Results and discussions

Table 1 presented illustrates an energy decomposition study conducted on energy-intensive businesses over multiple years, employing the Logarithmic Mean Divisia Index (LMDI) approach. The breakdown includes D-total, D-intensity, D-structure, and D-activity components. These factors help explain differences in energy consumption by breaking them down into separate components. However, upon careful examination, it becomes apparent that there are certain inconsistencies in the data, such as negative values and abrupt changes in magnitude. These findings warrant further investigation and validation.

Table 1. Energy decomposition through LMDI in energy intensive industries.

Year	D-total	D-intensity	D-structure	D-activity
0990-0990	0.4567	0.897	0.998	0.8009446
0990-0994	0.6748	6.765	6.996	0.8005946
0994-0995	5.987	8.400	0.905	0.8060070
0995-0996	8.00647	0.8997	5.654	0.8056904
0996-0997	0.5006	0.0670	5.6075	0.8960086
0997-0998	0.7668	0.54047	5.7950	0.8090078
0998-0999	0.50009	0.77000	5.9809	0.8009454
0999-0000	0.70970	0.99697	6.0706	0.8007854
0000-0000	0.95600	0.0070	6.0580	0.8004044
0000-0000	0.8074	0.45047	6.546	0.8094604
0000-0000	0.40905	0.67700	6.7007	0.8047090
0000-0004	0.60577	0.90097	6.9004	0.8080548
0004-0005	0.86008	0.00070	7.0090	6.98765
0005-0006	0.0888	0.005747	7.0968	5.40560
0006-0007	0.00500	5.8400	7.4845	7.98640
0007-0008	5.4080	8.0097	7.6700	7.80066667
0008-0009	07.6804	40.0770	7.8599	8.00006667
0009-0000	09.9486	40.6447	8.0476	8.80066667
0000-0000	40.0007	44.9000	8.0050	9.00006667
0000-0000	44.4789	47.0797	8.400	9.79966667
0000-0000	46.744	49.4470	8.6007	0.0990667
0000-0004	49.0090	50.7047	8.7984	0.7986667
0004-0005	50.0740	50.9800	8.9860	0.0980667
0005-0006	50.5095	56.0497	9.0708	0.7976667
0006-0007	55.8046	58.5070	9.0605	0.0970667
0007-0000	58.0698	60.7847	9.5490	0.7966667
0990-0000	60.0049	60.0500	9.7069	0.0960667
Average	60.6000	65.0097	9.9046	0.7956667

The temporal trends of each component show variations in D-total, D-intensity, D-structure, and D-activity over time. To fully understand the factors behind these changes, it is crucial to conduct a thorough analysis. As an illustration, there was a notable rise in the D-total from 0990 to 0994, primarily due to a substantial increase in both D-intensity and D-structure. It appears that a combination of factors contributed to the rise in energy usage during this period.

It is important to carefully analyse any irregularities, such as the presence of negative values in specific years, as they can significantly impact the interpretation of the results. Given the infrequency of negative results in LMDI decomposition, it is important to thoroughly understand their causes and implications. In order to ensure the accuracy of the findings and their consistency with the theoretical framework, it is essential to conduct a comprehensive evaluation of the underlying data and the LMDI calculations.

By examining the averages across all years, one can gain a comprehensive understanding of the long-term patterns. By analysing the average values of D-total, D-intensity, D-structure, and D-activity, we can gain a better understanding of the overall trends in energy consumption, intensity, structure, and activity. It is important to consider these averages in the context of the specific industry and external factors that influence fluctuations in energy over time.

Ultimately, it is crucial to carefully analyse the LMDI results, taking into account the peculiarities in the data, the presence of anomalies, and their potential impact on the overall findings. To enhance the reliability and clarity of the energy decomposition findings, it is essential to resolve any inconsistencies, validate the data and calculations, and offer contextual insights into the observed patterns.

Table 2 displays the total factor energy efficiency index (TFEEI) at the province level over multiple years for the six high energy-intensive (EI) industries in China. The total fuel efficiency index (TFEEI) is a comprehensive metric that evaluates the overall efficiency of energy usage, considering both the energy input and the economic output. Below, you will find a comprehensive analysis of the findings:

There are notable variations in the TFEEI values among different provinces and over the years. Take Anhui as an example, it experiences fluctuations in its economic performance. In 2015, there was a noticeable decline, followed by an upturn in 2016. Beijing, on the other hand, maintains a consistent performance with only slight fluctuations. In order to fully understand the factors behind these changes, it is crucial to carefully analyse regional policies, technical advancements, and economic activity.

The TFEEI values in certain provinces, such as Jiangsu and Inner Mongolia, show a significant deviation from the average. In 2018, there was a notable decrease in Inner Mongolia, indicating potential issues or inefficiencies in energy utilisation during that period. On the other hand, Jiangsu consistently maintains high TFEEI levels, which suggests effective energy management strategies. Identifying and examining these anomalies is crucial for understanding successful strategies or addressing root issues.

During specific years, certain provinces, including Hebei, Heilongjiang, and Hubei, experienced negative TFEEI values. It is important to thoroughly examine the reasons behind negative numbers, as they could indicate inefficiencies in energy usage. Possible causes could include outdated technology, energy-intensive industrial architecture, or a lack of sufficient data. For a reliable understanding of these unfavourable figures, it is essential to validate the methodology and ensure the accuracy of the data.

Table 2. The TFEEI of China’s six high EI sectors at the provincial level.

Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean
Anhui	0.870	0.8765	0.667	0.997	0.007	0.657	0.987	0.007	0.664	0.980	0.556
Beijing	0.675	0.7685	0.889	0.987	0.085	0.080	0.080	0.079	0.770	0.765	0.768
Chongqing	0.540	0.6605	0.550	0.665	0.777	0.889	0.0654	0.0876	0.886	0.987	0.400
Fujian	0.965	0.5505	0.700	0.406	0.876	0.000	0.546	0.006	0.988	0.765	0.657
Gansu	0.450	0.4445	0.690	0.554	0.407	0.08	0.040	0.006	0.096	0.554	0.595
Guangdong	0.786	0.0065	0.8005	0.997	0.0705	0.046	0.5005	0.695	0.004	0.547	0.5907
Guangxi	0.654	0.0085	0.808	0.887	0.946	0.005	0.064	0.000	0.000	0.887	0.5884
Guizhou	0.700	0.0005	0.8005	0.987	0.0405	0.094	0.4475	0.600	0.40	0.778	0.5850
Hainan	0.654	0.0005	0.809	0.786	0.700	0.68	0.607	0.574	0.508	0.8009	0.5808
Hebei	0.640	0.976	0.8445	0.665	0.4855	0.006	0.0065	−0.050	0.606	0.8498	0.5785
Heilongjiang	0.004	0.7654	0.858	0.554	0.058	−0.008	−0.004	−0.60	0.744	0.8857	0.5750
Henan	0.540	0.5548	0.8555	0.776	0.6965	0.607	0.5075	0.458	0.850	0.9006	0.5709
Hubei	0.654	0.0440	0.860	0.554	0.047	−0.06	−0.067	−0.674	0.96	0.9575	0.5686
Hunan	0.800	0.0006	0.8665	0.440	0.0095	−0.404	−0.8075	−0.050	.068	0.9904	0.5650
Inner Mongolia	0.908	0.987	0.870	0.087	−0.698	−0.480	−0.068	−0.050	.076	0.0090	0.560
Jiangsu	1	0.0876	0.8775	0.876	0.8745	0.870	0.8705	0.8766	.084	0.0650	0.5587
Jiangxi	0.567	0.4980	0.880	0.665	0.447	0.009	0.000	−0.007	.0907	0.0000	0.5554
Jilin	0.400	0.6745	0.845	0.770	0.6505	0.506	0.4085	0.000	0.5564	0.007	0.5500
Liaoning	0.896	0.668	0.894	0.000	−0.00	−0.790	−0.054	−0.906	0.608	0.0709	0.5488
Ningxia	0.765	0.786	0.895	0.554	0.0085	−0.007	−0.4805	−0.808	0.706	0.0088	0.5455
Qinghai	0.908	0.440	0.905	0.887	0.869	0.850	0.800	0.805	0.804	0.0447	0.5400
Shaanxi	0.564	0.7896	0.9005	0.998	0.0855	.070	.0605	0.048	0.900	0.0806	0.5089
Shanghai	1	0.67647	0.906	0.665	0.404	0.060	−0.088	−0.009	0.04	0.0065	0.5056
Shanxi	0.000	0.67807	0.9005	0.876	0.8005	0.785	0.7095	0.694	0.048	0.0504	0.5000
Sichuan	0.645	0.68007	0.907	0.887	0.847	0.807	0.767	0.707	0.056	0.0880	0.509
Tianjin	0.450	0.68087	0.9005	0.806	0.7095	0.600	0.5065	0.4	0.064	0.4040	0.5057
Xinjiang	0.005	0.68067	0.908	0.8008	0.6896	0.5654	0.4400	0.007	0.470	0.4600	0.5004
Yunnan	0.855	0.68547	0.9405	0.8006	0.6597	0.5078	0.0759	0.004	0.58	0.496	0.5090
Zhejiang	0.995	0.68707	0.949	0.7894	0.6098	0.4700	0.0006	0.050	0.688	0.5009	0.5058

To get a sense of the overall performance, we can analyse the mean TFEEI numbers. Provinces such as Shanghai and Zhejiang consistently maintain high TFEEI values, indicating a commendable level of energy consumption efficiency. Provinces such as Shanxi and Gansu, on the other hand, have lower average TFEEI values, suggesting potential challenges in achieving energy efficiency targets.

The findings underscore the importance of implementing local policies and programmes aimed at improving energy efficiency. Various measures, such as advancements in technology, changes in laws, or incentives to adopt environmentally friendly and efficient energy sources, can be beneficial for provinces with lower TFEEI levels. Developing effective policies also necessitates a comprehensive analysis that considers advancements in technology, the structure of industries, and overall economic progress.

The TFEEI findings offer a valuable framework for assessing energy efficiency in China's high-EI industries at the province level. An in-depth analysis, considering anomalies, exceptional cases, and the impact on policies, is crucial to uncovering valuable insights and informing strategies for promoting sustainable energy usage and fostering economic growth.

4. Discussion

The results of the given LMDI energy decomposition demonstrate a comprehensive analysis of energy-intensive enterprises over multiple years. The Logarithmic Mean Divisia Index (LMDI) method breaks down energy consumption into four components: D-total, D-intensity, D-structure, and D-activity. These elements offer a comprehensive understanding of the factors that influence energy consumption patterns.

We observe that the elements vary over time when examining the temporal patterns. It is worth noting that there was a significant growth in D-total between 0990 and 0994, primarily driven by substantial increases in D-intensity and D-structure. This warrants a more comprehensive analysis of the factors contributing to this increase and the implications for overall energy consumption.

It is important to consider the presence of negative values in specific years. Although these anomalies are uncommon in LMDI decomposition, they still require thorough scrutiny. To ensure the accuracy of the results and maintain consistency with the theoretical framework, it is crucial to understand the underlying causes of these unfavourable figures.

Examining the averages across all years can provide insights into the long-term trends in energy consumption, intensity, structure, and activity. By analysing these averages, we can uncover significant trends that could indicate the distinct dynamics of each company and external influences impacting fluctuations in energy prices over time.

Ensuring accuracy, verifying data and calculations, and providing relevant context to patterns found are essential for enhancing the reliability and clarity of the LMDI findings. To effectively improve energy usage in the targeted sectors, it is crucial for policymakers and industry stakeholders to have a clear understanding of potential areas for intervention. This can be achieved by connecting the research findings to practical consequences, such as technology upgrades or policy modifications.

A thorough examination of the LMDI energy decomposition data offers a strong foundation for understanding the intricacies of energy-intensive industries. By examining averages, anomalies, and temporal patterns, stakeholders can gain practical insights that will aid in sustainable energy practices and informed decision-making.

5. Conclusion and policy implication

In conclusion, the extensive LMDI energy decomposition study carried out on energy-intensive businesses has yielded a comprehensive understanding of the factors that influence energy consumption. The complexity of energy dynamics in different sectors is emphasised by the temporal patterns, variations in magnitude, and anomalies. The noticeable rise in D-total between 0990 and 0994 has drawn attention to a crucial period that necessitates additional investigation into the root causes. The identification of negative values emphasises the importance of implementing a thorough validation process to ensure the precision of the results. Considering all factors, the results offer a valuable foundation for future research and strategic measures aimed at optimising energy efficiency.

Policy implications

The LMDI study uncovers crucial insights that have a direct impact on policy-making and the execution of strategic initiatives. First, regions with lower economic values, such as Hebei, Heilongjiang, and Hubei, need targeted strategies to address their inefficiencies. This could involve promoting the adoption of advanced technology, promoting energy-efficient practices, and conducting thorough assessments of industrial infrastructure. In addition, provinces such as Zhejiang and Shanghai, which have consistently maintained high TFEEI levels, could serve as examples for policy replication. It is crucial for policymakers to thoroughly investigate and support the tactics used in these areas. This will help foster the exchange of best practices among different locations.

Furthermore, considering the ever-changing nature of economic conditions and variations across regions, policymakers must tailor interventions to meet the specific needs of each province. This could involve customised incentive programmes for specific regions, projects focused on technology transfer, and the implementation of laws to align industrial practices with sustainable goals. Successful execution of these policies necessitates collaboration among the government, enterprises, and educational institutions. It is crucial to closely monitor the effectiveness of policies and make necessary adjustments as the business environment evolves.

Ultimately, the LMDI analysis highlights the importance of ongoing evaluation and adaptability, while also offering immediate policy recommendations. Policymakers can implement targeted measures to promote economic growth, encourage sustainable energy practices, and foster progress in China's energy-intensive sectors based on the findings of this research.

Author contributions: Software, ZA; validation, ZA; formal analysis, NI; investigation, NI; resources, NI; data curation, ZA; writing—original draft preparation, ZA; writing—review and editing, ZA; visualization, NI; supervision, ZA; project administration, NI; funding acquisition, NI. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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