JDI
JOURNAL OF DEVELOPMENT AND INTEGRATION

JOURNAL OF DEVELOPMENT AND INTEGRATION
No. 78 (2024) 99-106 | jdi.uef.edu.vn

Analysis and forecasting of the importance of smart contracts and blockchain technology in SCM in Vietnam by using DEA and Grey model

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KEYWORDS

DEA,
Blockchain,
Smart contracts,
Supply chain management,
Transparency.

ABSTRACT

In the context of a complex and demanding business environment, blockchain and smart contracts are becoming increasingly important in supply chain management in Vietnam. The application of these technologies can help to optimize processes, create a reliable platform for tracking, managing, and forecasting supply chains, and enhance transparency and integrity. In the study of supply chain management in Vietnam, the methods applied are DEA (Data Envelopment Analysis) and the Grey forecasting model. These two methods not only focus on optimizing current processes but also create opportunities for analyzing, evaluating, and forecasting the importance of blockchain technology and smart contracts.

This research topic not only raises questions about the potential for optimizing current processes, but also proposes innovative solutions to enhance transparency, integrity, and responsiveness to volatile markets. Additionally, the research aims to propose appropriate strategies for applying these new technologies to business practices in Vietnam, creating a flexible, secure, and adaptable supply chain system that is responsive to the changing business environment of the present.

1. Introduction

In the current context of rapidly evolving business environments, the integration of innovative technologies like blockchain and smart contracts has emerged as a crucial focal point for enhancing efficiency and transparency in supply chain management. This research delves into the Vietnamese context, aiming to critically analyze and forecast the pivotal role of these technologies in reshaping the country's supply chain dynamics.

The urgency of this study is underscored by Vietnam's burgeoning economic context, where the optimization of supply chain processes has become imperative for sustainable growth and competitive advantage. The need to explore the application and

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https://doi.org/10.61602/jdi.2024.78.13
Received: 22-Feb-24; Revised: 23-May-24; Accepted: 07-Jun-24; Online: 31-Aug-24
ISSN (print): 1859-428X, ISSN (online): 2815-6234

impact of blockchain technology and smart contracts within this context is paramount, given their potential to revolutionize traditional supply chain practices. A number of studies have explored the potential benefits of blockchain and smart contracts for SCM. For example, a study by the World Economic Forum found that blockchain could save businesses up to $10 billion per year by 2025 (Cann, 2016). A study by IBM found that smart contracts could save businesses up to 20% on transaction costs (IBM, 2016).

This research endeavors to address the fundamental query regarding the potential and relevance of blockchain and smart contracts within Vietnam's supply chain ecosystem. By employing the Data Envelopment Analysis (DEA) and Grey forecasting models, the study seeks to identify their efficacious integration strategies and forecast their transformative influence. The core objectives include assessing their potential in enhancing transparency, efficiency, and adaptability in supply chain operations, offering insights crucial for strategic decision-making and fostering innovation in the Vietnamese business context.

This study's significance lies in its contribution to the academic discourse on the practical applications of blockchain and smart contracts in a specific regional context. It aims to provide actionable insights for businesses and policymakers, facilitating informed decisions to optimize supply chain processes, bolster competitiveness, and navigate the evolving market context efficiently.

2. Literature Review and Methodology

2.1. Literature review

The literature on the application of blockchain and smart contracts in supply chain management is growing rapidly. A number of studies have explored the potential benefits of these technologies, including:

The article "Improving Hyperconnected Logistics With Blockchains and Smart Contracts"of Quentin Betti et al was explores how blockchain technology can be used to improve hyperconnected logistics systems, which are characterized by extensive interconnectedness and real-time data sharing. It highlights the potential benefits of blockchain in enhancing transparency, security, efficiency, and sustainability within these systems (Betti et al., 2019). The simulation models a simplified "megacity" with different zones and hubs. Shipments are transported between zones by couriers, riders, and shuttlers. A blockchain-enabled tracking system is implemented to store shipment tracking data. Each agent has an account on a private Ethereum blockchain network and can submit transactions containing tracking actions. Smart contracts are used to store the actions. The implementation allows the agents to share a common, trusted tracking system rather than isolated systems. It also enables adding new agents easily regardless of company affiliation.

Potential issues include blockchain size and redundant data, access control and confidentiality of data, and performance limitations of blockchain platforms. Solutions are proposed such as storing only hashes on-chain. The paper demonstrates the applicability of blockchain to hyperconnected logistics in the Physical Internet vision, though some challenges remain to be addressed. Overall it provides a valuable practical example and analysis (Betti et al., 2019).

In other research "An Application of Ethereum smart contracts and IoT to logistics" of Leonor Augusto et al. This article proposes a blockchain application for use in logistics, utilizing IoT devices to track a product's journey. A smart contract system is implemented with an RBAC system, product tracking and a clearance/quality control system, providing trustworthy information on the products being supplied. Our blockchain application uses smart contracts and RBAC to ensure secure tracking updates. IoT devices with limited permissions are associated to their owners and can only generate readings for products whose bearer corresponds to their owner entity. Authors have developed a blockchain smart contract system to manage products in a logistics system, with features such as Role Based Access Control, product tracking and tracing and semi-automatic clearance procedures. However, there are limitations to applying these solutions to real-world use, such as scalability, storage and integration difficulties (Augusto et al., 2019). Besides that, the research of Omar Alkhoori et al with the name "Design and Implementation of CryptoCargo: A Blockchain-Powered Smart Shipping Container for Vaccine Distribution" was show that DApp is developed to monitor GPS violations using Web3.js, Google Maps APIs, and Bootstrap. Data from the blockchain is decoded and displayed to the user, while Canvas.js is used to display a pie chart visualizing the violations recorded on the blockchain. They used used Infura to access an Ethereum node, Metamask to generate an Ethereum wallet, and Remix to deploy a smart contract. Web3.min.js was downloaded and imported into our code, and Web3 provider was defined through an HTTP link to our Infura endpoint. ABI was used to create the Web3 contract instance. The research introduced a blockchain-powered solution, CryptoCargo, that tracks shipments and identifies threats to the health of the package. The solution uses cloud-based services to achieve real-time communication with the smart container and accurate reporting and analytics (Alkhoori et al., 2021).

Future research could focus on mitigating scalability issues, refining integration methods, and exploring practical implementations of these technologies to address real-world supply chain complexities. Additionally, investigating regulatory and standardization aspects could pave the way for widespread adoption.

2.2. Methodology

In order to achieve the goals of this study, the following mathematical model and process will guide the authors. This study will take 6 cases of 6 Logistics company in the world then use DEA model to know how infection of them and use Grey forecasting model to forecast the importance of this kind of advantage in Logistics field. The results must be consistent with the purpose of the paper.

2.1.1. Research Framework

Figure 1 describes how will the process of research be along with each defining procedures.

Phase 1. The historical data were gathered from web database of Morningstar.com, a global market research firm. These past data values will be used as the preliminary values (historical data) for the Grey prediction model.

Phase 2. The application of the GM (1,1) is to

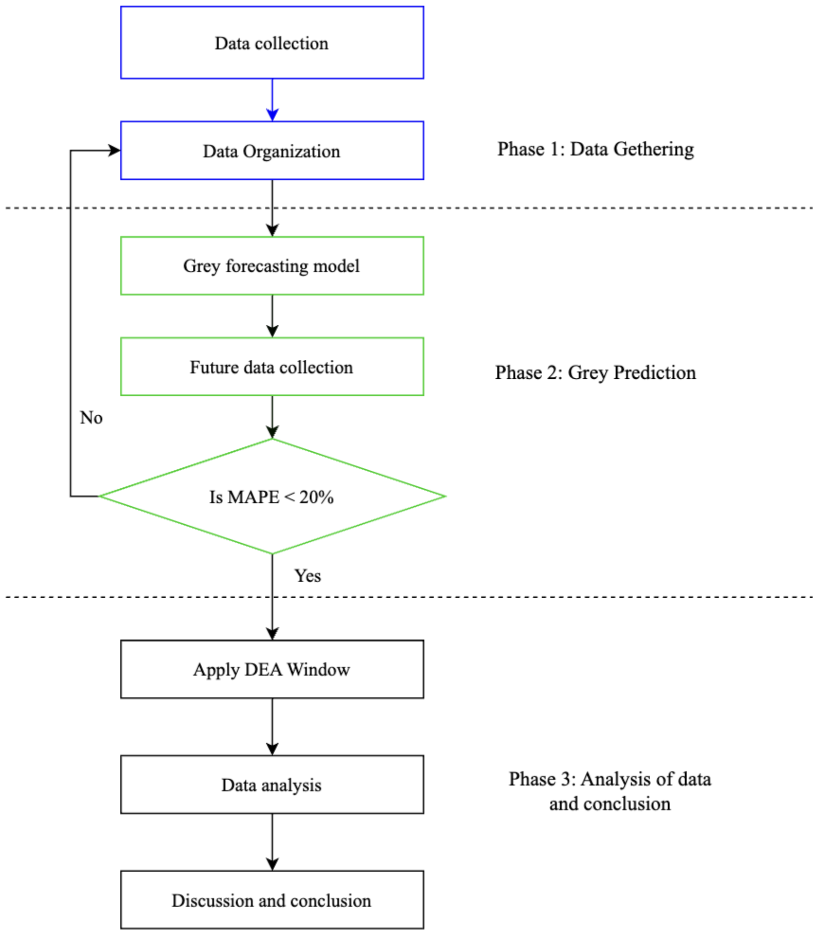

Figure 1. The research process flowchart

assist for uncomplicated forecasting by using only a minimum of four years historical data. The forecast will then be used in the process of DEA for evaluation of performance.

Phase 3. All of the data, historical and future, will be processed using DEA Window model to calculate the efficiency during the certain periods. The authors will use the 2-window setup to have a comprehensive comparison between the past and the future.

2.1.2. Grey Model and MAPE

Based on a time series domain with differential equations in forecasting data, the GM has gained its popularity to many users. It became more popular due to its capabilities to produce acceptable and reliable forecast that requires only at least four period of historical data, Ju-long (1982) and Tseng (2001) (Khan, 2023). The process of GM is described below:

- Series x0 will be encoded as historical data
- Then x0 generates the values for $x^1(k)$
- A partial data will be generated from $x^1(k)$ which is $z^1(k)$
- The calculation of coefficient a and grey input b
- Construction of GM (1,1) forecasting equation
- Calculation of average residual y

Using x^0 as a primitive variable series, the process of the prediction method is described in Equation (1).

$$X(0) = [x^{(0)}(1), x^{(0)}(2), \ldots, x(n)],\ n \geq 4 \quad (1)$$

Wherein x0 is a positive sequence together with the total number of historic data n.

Where n is the total count of historic data along with a positive sequence x0. A minimum of four historic data is required to facilitate prediction process using grey model. This property is very necessary which makes the model an advantageous method in forecasting.

Equation (2) describes the partial data series:

$$z^{(0)} = [z^{(1)}(1), z^{(1)}(2), \ldots, z^{(1)}(n)] \quad (2)$$

Where the mean value z1(k) is also defined in Equation (3) as:

$$Z^{(1)}(k) = 1/2 \times [X^{(1)}(k) + X^{(1)}(k-1)]$$
$$k = 2,3,\ldots, n \quad (3)$$

The first order differential equation x(1) (k) of grey model can be acquired through Equation (4) as described by Julong (1989):

$$\frac{dx^{(1)}(k)}{dk} + ax^1(k) = b \quad (4)$$

The least square method, Equation (5), will be used to solve the above equation.

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a} \quad (5)$$

In which $\hat{x}^{(1)}(k+1)$ represents the predicted value of x at k +1 point in time. The values of [a,b] T will be generated using the ordinary least square (OLS) method as defined by Equations (6) to (8).

$$[a,b]^T = (BTB)^{-1}B^TY \quad (6)$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots\cdots\cdots \\ \cdots\cdots\cdots \\ x^{(0)}(n) \end{bmatrix} B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots\cdots\cdots & \cdots \\ \cdots\cdots\cdots & \cdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \quad (7)$$

In which $[a,b]^T$ is the parameter series, Y and B are referred to as the data series and data matrix, consecutively.

The $\hat{x}^{(1)}(k)$ values is calculated by having $\hat{x}^{(0)}$ as the predicted series.

$$\hat{x}^{(0)}\ x^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n) \quad (8)$$

in which $\hat{x}^{(0)}(1)$ is equal to x(0)(1)

The final equation (11) can be obtained by applying the inverse accumulated generation operation (AGO).

$$X^{(0)}(k+1) = (X^{(0)}(1) - b/a)e^{-ak}(1-e^{a}) \quad (9)$$

Mean absolute percentage error (MAPE) measure the accuracy of the predicted values and is defined by Equation (11).

$$MAPE = \frac{1}{n}\sum\left(\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}\right) \times 100\% \quad (10)$$

The MAPE of the predicted data represents its acceptability rate. Wherein lower value depicts highly accurate predictions while higher value means otherwise. Accuracy table was categorized into four by as displayed in Table 1.

In this study, another nonparametric model of DEA will be used and is referred to as the Window model. In this mathematical model, n is considered to be the summation of all the units being observed and will be called the DMUn while the input variable is m and output variable is s. Integrating an element of time series t, it will become DMU_n^t. Then, the input and output generated into a vector called X_n^t and Y_n^t,

Table 1. MAPE equivalent forecast categories

MAPE	Categorical Value
10% and below	Highly Accurate
10 to 20%	Moderately Accurate
20 to 50%	Acceptable
51% and higher	Unacceptable

as describe by the Equations (11) and (12).

$$X_n^t = [x_n^{1t} \vdots x_n^{mt}] \quad (11)$$

$$Y_n^t = [y_n^{1t} \vdots y_n^{st}] \quad (12)$$

The point k (1≤k≤T) is the starting point in time T and has a width magnitude w (1≤w≤T-k) , wherein each window kw will be represented by the input matrix Xkw and output matrix Ykw as shown in the equations below.

$$X_{kw} = [x_1^k\ x_2^k\ \dots\ x_n^k\ x_1^{k+1}\ x_2^{k+1}\ \dots\ x_n^{k+1}\ \vdots \vdots \ddots \vdots\ x_1^{k+w}\ x_2^{k+w}\ \dots\ x_n^{k+w}] \quad (13)$$

$$Y_{kw} = [y_1^k\ y_2^k\ \dots\ y_n^k\ y_1^{k+1}\ y_2^{k+1}\ \dots\ y_n^{k+1}\ \vdots \vdots \ddots \vdots\ y_1^{k+w}\ y_2^{k+w}\ \dots\ y_n^{k+w}] \quad (14)$$

The DEA Window analysis will commence right after the input and output were substituted to the DMU_n^t equation (Öztürk et al., 2022).

3. Results and Discussion

3.1. Selection of DMUs

Another crucial task in the research process is the proper selection of the decision-making units (DMUs). These are the subjects in which the data will be gathered upon and will represent the whole Logistics industry in the world. So, the authors have selected those company which have been a contributor not only to the industry but also to the country. Table 2 shows the list of the Logistics enterprise which applied the blockchain in their own product.

Table 2. List of Logistics company in the world which applied Blockchain in supply chain management

DMU	Logistics Company
DMU1	IBM
DMU2	Walmart
DMU3	Procter & Gamble
DMU4	Deloitte
DMU5	Maersk
DMU6	UPS

With the rapid development of the Logistics company, more and more company are emerging and participating in this potential market with many different way of management.

3.2. Identifying Input and Output Factors

After the significant DMUs have been selected, the next step is to identify the input and output factors that will be considered for the analysis. These factors must have important impact to the performance of the logistics company. The thesis consider those factors that are commonly used by the previous studies. Table 3 lists down the input and output factors and their definitions.

Table 3. Input and output factors and definitions

Input	Description
Retirement-related plans–cost (RRC)	Retirement plan costs encompass fees for fund management, administrative expenses, and investment-related charges. The choice of plan often depends on individual preferences, employer offerings, and long-term financial goals.
Total operating costs (TO)	Total Operating Costs (TO) encompass all expenses associated with a business's regular operations. The formula to calculate TO typically involves summing up the costs related to production, administration, and day-to-day activities.
Recorded investment (RI)	Pre-tax refers to financial figures or amounts that are calculated or reported before taxes are deducted. It denotes income, profits, expenses, or deductions that haven't yet had taxes subtracted from them.
Amortized cost (A)	Amortized cost refers to the gradual allocation of a certain expenditure or expense over a specific period. It involves spreading out the cost of an asset or expense incrementally across its useful life, reflecting a more accurate representation of its impact on financial statements.
Output	**Description**
Revenue (R)	Revenue represents the total income generated by a company from its primary operations, typically from sales of goods or services
Net income (NI)	It represents the company's profitability, calculated by subtracting operating expenses, taxes, interest, and other costs from the total revenue

Table 4. Average values (in Millions USD) of the factors for the year 2019 – 2022.

AVE.	RRC	TO	RI	A	R	NI
2019	21.231	82.823	7.232	47.254	141.296	11.544
2020	20.0375	74.511	4.455	36.668	140.074	13.318
2021	24.186	47.048	3.502	39.140	134.382	12.737
2022	2.5385	4.6085	2.463	28.366	158.961	15.572

Table 5. Average values (in Millions) of the factors for the year 2023 – 2026.

AVE.	RRC	TO	RI	A	R	NI
2023	1.587	3.336	1.053	7.3004	40.465	4.019
2024	0.957	2.380	0.986	5.211	30.986	3.122
2025	0.584	1.878	0.954	3.733	23.789	2.434
2026	0.361	1.624	0.948	2.684	18.315	1.905

This chapter discusses the data gathered through the application of GM and the Window model of Data Envelopment Analysis. Using the historical data collected from online sources, these were used to generate predicted data for all the input and output factors. The complete historical and future data were then used for the Window model to generate efficiency index which will be the basis of the company performance.

3.3. Actual Historical Data

To produce future predictions using the grey forecasting model, a required minimum of past or historical data must be collected. These data must conform with the recommended factors that have an impact on the performance of the banking industry. The authors have chosen the factors as discussed in the third chapter and summarized the historical data represented by averages in Table 4.

As discussed in the third chapter, GM minimum requirement of up to four periods of historical data are enough to make accurate forecast. However, the accuracy will depend on the values of historical data if increasing or not. More historical data used will result to more accurate predictions. But also, it must be considered that this study has limitations in the source of data. Since the only available data are from 2019 to 2022, these are enough to be used in Grey forecasting Model.

3.4. Results of Grey Prediction

The grey prediction model was used to project the values of the input and output factors that will be later used for DEA analysis.

The values of the variables acquired after processing the Grey prediction is noticed to be increasing from 2023 to 2026 as seen in Table 5 above. The closer the predicted value from the actual values means an accurate prediction. However, the accuracy of the prediction is not measured just in terms of how close the values are to each other. The Mean Absolute Prediction Error formula can calculate how accurate the predictions are. This method was introduced in the third chapter and will now be applied to the acquired date to see if the prediction values are acceptable.

3.5. MAPE Results

Table 6 below shows the average MAPE scores for every DMUs together with respective input and output factors. This is to know whether the predicted values will be accepted before proceeding with the DEA.

It can be seen above shows the MAPE scores of all the DMUs with respect to each of the variables. It can be seen that most of the scores are in the “Highly Accurate” level which means that the resulting data are acceptable. There are instances of above 20% results for all factor, but these numbers are still in the “Moderately Accurate” level.

3.6. Efficiency Index

Once all data are confirmed to be acceptable, the xDEA analysis will proceed. With the use of the DEA Window analysis, the efficiency index of the past in Table 7 and future in Table 8 are calculated.

Table 7 and 8 shows that the future periods have more perfect efficiency results as compared to the past

Table 6. MAPE results for the year 2020 – 2023

	RRC	TO	RI	A	R	NI
DMU1	14.53%	15.26%	1.40%	12.01%	12.71%	19.74%
DMU2	18.72%	14.60%	32.36%	17.59%	18.32%	15.18%
DMU3	34.01%	27.34%	20.10%	16.53%	18.48%	13.86%
DMU4	42.42%	14.84%	26.41%	9.97%	23.28%	25.42%
DMU5	32.92%	18.01%	29.32%	14.02%	18.20%	16.26%
DMU6	17.81%	31.26%	13.50%	12.01%	13.88%	20.06%

Table 7. Efficiency indices from 2019 – 2022

	2019	2020	2021	2022	Ave.
DMU1	0.552710226	1	1	1	0.888
DMU2	1	0.975651217	1	1	0.993
DMU3	0.527439024	0.380472901	0.325736689	0.684162102	0.479
DMU4	0.450335734	0.307285592	0.280987386	1	0.509
DMU5	0.584041416	0.573162948	0.754358631	1	0.727
DMU6	0.637778622	0.935543315	1	1	0.893

Table 8. Efficiency indices from 2023 – 2026

	2023	2024	2025	2026	Ave.
DMU1	1	1	1	1	1
DMU2	1	1	1	1	1
DMU3	0.389013212	0.447463016	0.516347386	0.616890731	0.389013212
DMU4	0.905162838	0.93973501	0.969978157	1	0.905162838
DMU5	1	1	0.980595908	1	1
DMU6	1	0.959003	0.913092	0.863281	0.933844

periods. It can be noted that the DMU1 has reached high efficiency performance for five consecutive years of 2023 to 2026. However, it was not able to maintain this result as the efficiency of the past data only has a perfect efficiency on the year 2020-2023. DMU1 and DMU2 both have consecutive 1.000 scores for the years 2023 and 2026, but only DMU3 has again received not perfect efficiency for the future period. Most of the DMUs do not get a score of 1.000 and some have very high efficiencies. Even though DMU3 and DMU4 did not get any perfect efficiency for most of the past and future period, they are able to score 1.000 for the year 2026 for DMU4 which is resulted from their increasing efficiency.

Figure 2 above shows that many DMUs are performing at a high efficiency level which is above 0.2 They may not be consistent in every year periods, but it can't be noted that they are still high enough. However, two DMUs are performing below this level. DMU2 performs higher than the others around 1 which is kind of the highest performance indices. Also, it can be observed that DMU3 and 4 started in a low efficiency in 2019 but were able to increase by the next periods until they reach 1, respectively.

Figure 3 shows that DMU 1, 2, 4 all started in a high efficiency level but was able to reach the highest efficiency of 1.000 in the years 2024, 2025, 2026 and that shows us that these company are strongly developing throughout the years after they apply Blockchain in Logistics management.

4. Conclusion

In the application of blockchain and smart contracts within supply chain management, companies like IBM, Walmart, and P&G… have showcased notable strides toward transparency, traceability, and operational efficiency. These advancements hint at a promising future for Vietnam's supply chain context.

Looking ahead, integrating blockchain and smart contracts into Vietnam's supply chains is anticipated to foster greater trust, security, and transparency. Enhanced traceability in logistics and streamlined processes

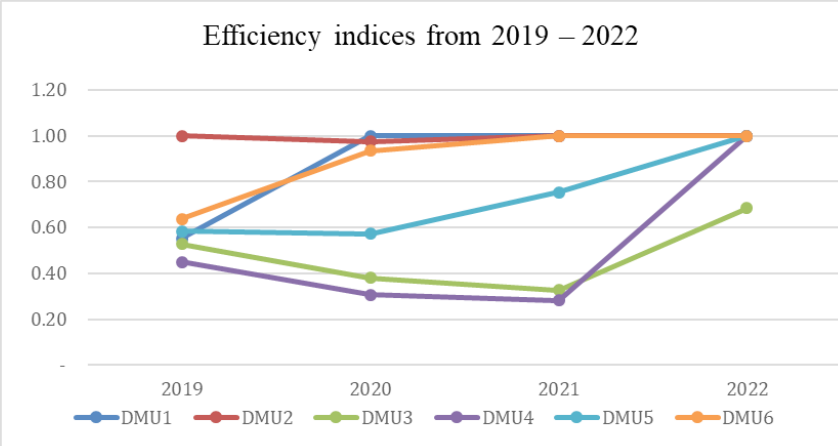

Figure 2. Graphical presentation of the efficiency indices from 2019 to 2022

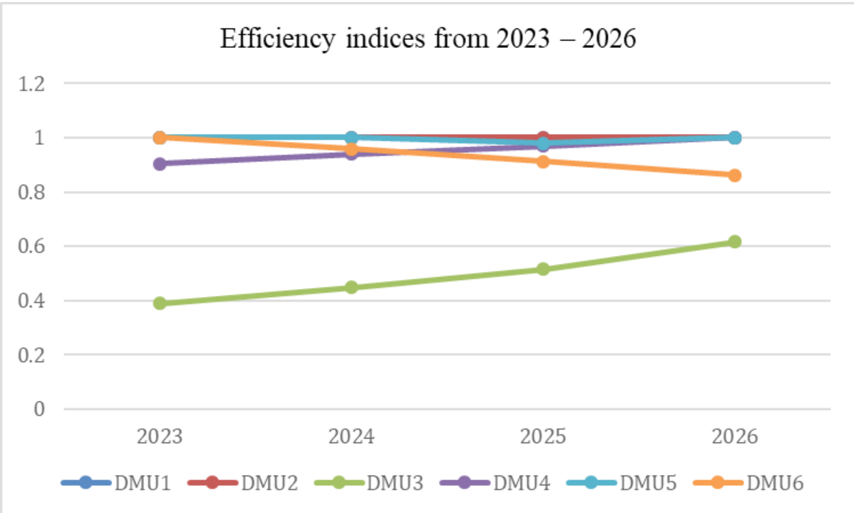

Figure 3. Graphical presentation of the efficiency indices from 2023 to 2026

are anticipated, enabling reduced inefficiencies and minimizing risks associated with counterfeit products.

Vietnam's supply chains are set to benefit immensely from these technologies, potentially transforming the country into a regional hub of innovation and reliability. As technology adoption matures, collaborations among industries and regulatory support will be key factors in harnessing the full potential of blockchain and smart contracts, empowering Vietnamese businesses to thrive within global supply networks.

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