mathematics

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Supervised Learning by Evolutionary Computation Tuning: An Application to Blockchain-Based Pharmaceutical Supply Chain Cost Model

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Abstract: A pharmaceutical supply chain (PSC) is a system of processes, operations, and organisations for drug delivery. This paper provides a new PSC mathematical cost model, which includes Blockchain technology (BT), that can improve the safety, performance, and transparency of medical information sharing in a healthcare system. We aim to estimate the costs of the BT-based PSC model, select algorithms with minimum prediction errors, and determine the cost components of the model. After the data generation, we applied four Supervised Learning algorithms (k-nearest neighbour, decision tree, support vector machine, and naive Bayes) combined with two Evolutionary Computation algorithms (ant colony optimization and the firefly algorithm). We also used the Feature Weighting approach to assign appropriate weights to all cost model components, revealing their importance. Four performance metrics were used to evaluate the cost model, and the total ranking score (TRS) was used to determine the most reliable predictive algorithms. Our findings show that the ACO-NB and FA-NB algorithms perform better than the other six algorithms in estimating the costs of the model with lower errors, whereas ACO-DT and FA-DT show the worst performance. The findings also indicate that the shortage cost, holding cost, and expired medication cost more strongly influence the cost model than other cost components.

Keywords: Blockchain-based pharmaceutical supply chain; Supervised Learning algorithms; Evolutionary Computation algorithms; Blockchain technology

MSC: 90B06

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Citation: Havaeji, H.; Dao, T.-M.; Wong, T. Supervised Learning by Evolutionary Computation Tuning: An Application to Blockchain-Based Pharmaceutical Supply Chain Cost Model. *Mathematics* **2023**, *11*, 2021. https://doi.org/10.3390/math11092021

Academic Editor: Ripon Kumar Chakrabortty

Received: 13 March 2023
Revised: 16 April 2023
Accepted: 18 April 2023
Published: 24 April 2023

1. Introduction

The supply chain system (SCS) is an accepted approach to increase profit margins, protect the pharmaceutical industry against introduced pressures, and overcome obstacles for obtaining high efficiency while taking the limited available resources into account [1]. Conversely, the pharmaceutical supply chain (PSC) is a system of processes, operations, and organisations involved in drug discovery, development, and production. PSC processes are crucial for ensuring medication quality and favourable final patient outcomes [2]. As a system of processes, operations, and organisations, the PSC plays a significant role in delivering the right medication to the right customers (patients) at the right time and in the right conditions. In the current SCS, pharmacies and manufacturers cannot track their products and have no clear system visibility. Recalls are costly and complicated in the SCS, making follow-up with patients difficult for companies. Therefore, the current SCS in the pharmaceutical industry appears to be outdated and may not provide visibility and control for manufacturers and regulatory authority over drug distribution [3]. In particular, it cannot withstand 21st century cybersecurity threats [3]. The use of a Blockchain-based pharmaceutical supply chain (BT-based PSC) appears to be necessary for any pharmacy system. A BT-based PSC helps the system improve the safety, performance, and transparency of medical information sharing and the data transformation cost/time as well as the manufacturing process, the distribution of the materials/drugs, and the tracking of the materials/drugs sourced for manufacturing. BT in a PSC system can develop patient data cards for other medical practitioners' centres, especially in hospitals, leading to saved time and improved healthcare service. In this system, patients and healthcare centres can have different accessibility choices with the PSC data. In addition, any block in BT contains the medical information with a hash connecting it to another block.

In contrast to several previous studies that have reported on the advantages and disadvantages of using BT in a PSC, the present study seeks to address the cost problem of a BT-based PSC. Other studies do not provide a cost mathematical model or related cost components for a PSC system based on the BT approach. This paper differs from others by introducing a cost mathematical model for the BT-based PSC system and providing the cost components of the system. The cost factor is important to managers because the knowledge of costs helps them to control all the financial resources employed in the performance of the system, control the cash flow, identify the rate of return and profitability, and correctly decide whether the new system benefits their organisation. Moreover, the knowledge of costs helps to monitor the business financial health, optimize the institution's financial planning, reduce expenses, stay within the budget, and analyse the information to identify unnecessary costs and better business opportunities. Another important contribution of this study is to provide a PSC system with BT. BT can improve the safety, performance, and transparency of medical information sharing in a healthcare system, minimise the data transformation cost and time, and maintain the financial statements in hospitals.

The purpose of this study is to estimate the costs of the BT-based PSC model in a hospital, select algorithms with the minimum prediction errors, and determine the cost components of the BT-based PSC model in a hospital. To understand the importance of the BT-based PSC cost model, determining the cost components of the model is essential. Thus, this paper also aims to measure the importance of each cost component (feature) of the model, which is the degree of relevance of each feature to the model. To achieve these objectives, this research attempts to respond to the following research questions: (i) What are the cost components of the BT-based PSC cost model in a hospital, and what is the mathematical cost model? (ii) Which algorithms show better performance in minimising the prediction errors of the BT-based PSC cost model? (iii) What are the important cost components of the model? The research questions were answered using the following directions. First, we designed a mathematical BT-based PSC cost model after determining the cost components. Then, following the data generation, we applied four Supervised Learning (SL) algorithms (k-nearest neighbors (KNN), decision tree (DT), support vector machine (SVM), and naive Bayes (NB)) combined with two Evolutionary Computation (EC) algorithms (ant colony optimization (ACO) and the firefly algorithm (FA)) for a total of eight algorithms. These algorithms were selected because they are well-known algorithms that have been successfully applied to solve many engineering problems, which can facilitate the discussion of their behaviours in our new cost model. Finally, four performance metrics were used to evaluate the cost model, and the total ranking score (TRS), which is a score-based ranking system, was used to determine the most reliable predictive algorithms.

The rest of the paper is organised as follows. First, we provide an overview of BT in a PSC, EC, and SL in Section 2. Next, we discuss the methodology and data generation used to optimize the estimation of the BT-based PSC cost model in Section 3. Then, the design of the mathematical cost model for the BT-based PSC is outlined in Section 4. All experiments and results are described in Section 5. Then, the results, limitations, and future research are discussed in Section 6, which is called Discussion. Finally, we briefly present the conclusions in Section 7.

2. Literature Review

This background explains the related literature regarding the PSC and its components for a hospital, how BT drives PSC, Evolutionary Computation, and Supervised Learning (ACO and FA; KNN, DT, NB, and SVM).

2.1. PSC and Its Components for a Hospital

The SCS is required for any industry that moves materials and goods in any way; on the other hand, the PSC is important for tracking the materials and goods sourced for manufacturing and for the distribution of the products [4]. PSC processes affect the quality of medication and patient outcomes [2]. As an accepted approach, the SCS protects the pharmaceutical industry against the introduced pressures, increases profit margins, and overcomes efficiency issues [1]. PSCs seek to ensure that the right people receive the right medication at the right time and in the right conditions [5]. These responsibilities of PSCs are complex and increase their vulnerability and the probability of distribution [5]. A PSC can be defined as "the integration of all activities associated with the flow and transformation of drugs from raw materials through to the end user, as well as the associated information flows, through improved SC relationships to achieve a sustainable competitive advantage" [6]. The pharmaceutical industry is a system of processes, operations, and organisations involved in drug detection, development, and production [7]. In [7], the PSC is described as an approach with a suitable quality that distributes drugs at the right time and place to reach the customers. The healthcare sector includes publicly traded companies supporting all facets of the healthcare sector [3]. The authors of [3] state that the healthcare sector consists of clinical, preventive, treatment, and therapeutic services and providers, including doctors, nurses, hospitals, drugs, medical equipment suppliers, and health insurance companies in addition to other private, government, and voluntary institutions such as residential, educational, dental, domestic health, medical, surgical, and ambulatory institutions, and medical and diagnostic laboratories. The PSC includes three significant players: producers, purchasers, and pharmaceutical providers [6]. The authors of [6] describe the producers as the pharmaceutical companies, medical–surgical product companies, device manufacturers, capital equipment manufacturers, and information systems manufacturers. According to Uthayakumar and Priyan [6], purchasers comprise the grouped purchasing organisations, the pharmaceutical wholesalers, the medical–surgical distributors, independently contracted distributors, and the product representatives. The authors of [6] also explain that providers include hospitals and their systems, integrated delivery networks, and alternative site facilities. The BT-enabled PSC cost model in this article contains eight elements: (a) regular purchases cost, (b) emergency purchases cost, (c) shipping cost, (d) expired medication cost, (f) holding cost, (g) shortage cost, (h) Blockchain transaction cost, (i) Blockchain installation cost.

2.2. BT Drives PSC

The current PCS of the pharmaceutical industry appears to be outdated, does not provide visibility and control for manufacturers and drug distributions, and cannot withstand current cybersecurity threats [3]. BT is a cutting-edge technology that has been used in different applications such as cryptocurrency, financial services, risk management, and public and social services [8]. BT can be public, private, hybrid, or part of a consortium. Each BT type has various advantages and disadvantages that influence its optimal applications. According to Haq and Esuka [3], the defects of the SCS are as follows: information is not shared between systems, manufacturers cannot track their products, the drug regulatory authority has no visibility of the system, recalls are complicated and costly, and the healthcare system cannot follow up with patients. Haq and Esuka [3] also mention that the products in a PSC are verifiable without any information about the manufacturer's private techniques.

Conversely, Haq and Esuka [3] believe that it is possible to share the patient's medical record with various participants on the network without disclosing the patient's private data. Several players move a product throughout the PSC: (i) primary manufacturers,

(ii) secondary manufacturers, (iii) distribution centers/wholesalers, and (iv) retailers (i.e., pharmacies/hospitals) [9]. BT improves safety, displays information, achieves transparency, and is used for health record keeping, clinical trials, and patient monitoring [10]. According to Zahiri et al. [9], BT maintains financial statements in the hospitals and minimises the time and cost of data transformation. Haleem et al. [10] highlight that BT preserves and exchanges patient data via hospitals, diagnostic laboratories, pharmacy firms, and physicians in a healthcare system. BT in the PSC can detect fake medicines by facilitating the proper control over the supply and demand of the drugs and can enable pharmaceutical companies to control fake and unregistered medicines [11]. Kumar Badhotiya et al. [11] assert that fake and unregistered medicines with no medical recovery pose a significant threat to human life, causing many side effects leading to severe damage to health or even death. Therefore, BT's advantages improve the performance, security, and transparency of medical data sharing in the healthcare system [10]. Haleem et al. [10] also state that BT gains insight and enhances the analysis of medical records in medical institutions. BT applied within a PSC enables data integration, secure transactions, serialisation, and traceability [8]. Importantly, Haq and Esuka [3] note that visibility and privacy are largely contradictory, and to obtain one, the other is often lost. They [3] clarify that BT can guarantee the verification of the origin of data that are made available publicly while keeping the private data of an entity secret without compromising privacy. According to these authors [3], the decentralized nature of BT allows patients, doctors, and healthcare providers to share data quickly and securely. Hosseini Bamakan et al. [8] also show that traceability plays a significant role in securing drugs and is the basis for the reliance by the consumer on the PSC and its products. They [8] continue that the traceability of BT enables the PSC to verify the background of a product and tracks the path of all the locations and the participants that handle it. They also state that [8] BT can also provide transparency to the PSC and considers the needs of the suppliers, producers, logistics, distributors, and customers in the PSC. They [8] assert that all pharmaceutical institutions adhere to patient protection maintenance, and intelligent contracts can facilitate this process if a system applies BT. Among all the factors of a BT-enabled PSC, the cost factor is significant for an organisation. Supervised Learning (SL) algorithms can predict the costs of the system and Evolutionary Computation is applied to optimize the hyperparameters of SL to build a model, allowing the exploration of the possible combinations of parameters.

2.3. Evolutionary Computation and Supervised Learning

The Evolutionary Computation (EC) algorithm is the main object of interest in evolutionary computation [12]. The scientific community has demonstrated that metaheuristics are a viable and often superior alternative to the more traditional (exact) methods of mixed-integer optimization such as branch and bound algorithms and dynamic programming [13]. Metaheuristics often offer a better trade-off between solution quality and computing time, particularly for complicated problems or large problem instances [13]. Using metaheuristic techniques, reasonably good solutions are obtained without exploring the whole solution space [14]. Rather than searching for the global optimum solution, these techniques aim to find sufficiently "good" solutions to efficiently exploit the characteristics of the problem and provide an attractive alternative for large-scale applications [15]. SL tries to predict the output feature's value based on the input features' values [16]. The authors of [16] point out that SL learns the relationship between the target feature and the input features from the training data for which the target feature value is already known.

2.3.1. ACO and FA

Metaheuristics are powerful techniques for solving complex real-world problems in many application domains [17]. The behaviour and performance of EC algorithms depend strongly on their ability to efficiently explore and exploit the search space [17]. The authors of [17] state that ACO is a well-known EC that was inspired by the collective performance of real-life ant colonies and has been used to solve many engineering problems. The

ACO algorithm employs a colony of simple cooperating agents and solves combinatorial optimization problems [18]. The FA is mainly inspired by the light connection between fireflies [7]. Goodarzian et al. [7] explain that in swarm intelligence the cooperation (and possibly the competition) of more straightforward and less intelligent members creates a higher degree of intelligence that certainly cannot be achievable by any of the components alone. Thus, according to Goodarzian et al. [7], the FA is inspired by the natural species behaviour to optimize nonlinear functions that simultaneously use low-cost algorithms. Each member of the fireflies' group in the FA moves to a point where their most efficient outcome has occurred [19].

2.3.2. KNN, DT, NB, and SVM

SL is defined as the use of labeled datasets to train algorithms that classify datasets or predict outcomes accurately [12]. Zhang et al. [12] mention that SL adjusts the weights until the model is fitted appropriately after inputting the data into the model. According to Zhang et al. [12], the cross-validation process ensures that the model can avoid overfitting and under-fitting. They [12] present SL using several methods, including neural networks, naïve Bayes (NB), linear regression, logistic regression, random forest, and support vector machine (SVM).

K-nearest neighbors (KNN) is an SL algorithm used in classification and regression problems [20]. The authors of [20] highlight that KNN is applied in a variety of applications such as text categorisation, agriculture, medicine, finance, facial recognition, economic forecasting, and heart disease diagnosis. They [20] express that KNN calculates the distance between each unlabelled data point and all other points in the dataset to classify the unlabelled data. Then, KNN, according to these authors [20], assigns each unlabelled data point to the class of the most identically labelled data by finding patterns in the dataset.

A DT is an SL algorithm primarily used to analyse data and perform regression and classification problems [21]. The authors of [21] explain that DT contains decision nodes (to test the value of an attribute), edges (to determine the outcome of a test and connect with the next node), and a leaf node (to predict the result), all of which are combined and comprise a complete structure of the DT. In the DT, according to these authors [21], each dataset attribute is treated as a node, and a special and unique node is a root node. The process starts with a unique node and proceeds down the tree to satisfy the parameters and decision [21]. The authors of [21] believe this procedure is carried out until a terminal node is encountered.

An NB classifier is a simple probabilistic classifier that has been widely used due to its high efficiency, solid theoretical foundation, and good generalisation ability [22]. According to Ren, et al. [22], NB assumes that the attribute variables are conditionally independent when class variables are given. To classify the given item, they [22] state that NB determines the probability of each category appearing under the condition of the occurrence of this item and classifies the item that belongs to the category with the highest probability [22].

An SVM is a binary classification model that has been widely used due to its global optimization capability and good robustness in fields such as environment, medicine, and finance [23]. The authors of [23] explain that the basic principle of SVM requires that, when solving a classification problem, the distance from the nearest sample point to the decision surface is the largest; that is, the minimum distance maximises the two classes of the sample points to separate the edges. A straight line in a two-dimensional space makes it the most suitable segmentation line in the middle of the two data classes, and SVM finds an optimal decision plane as the classification benchmark in the high-dimensional dataset [23]. The next section explains the methodology of the study and the procedure to generate data.

3. Methodology and Data Generation

In this section, we introduce the procedure of data generation as well as the methodology for the optimization of the estimation of the BT-based PSC cost model in a hospital. We first used Python software to generate raw data for the nonlinear BT-based PSC cost model, including the cost components of a hospital. The widely known tool for the generation of random data in Python is its random module, and we applied randint() as an inbuilt function of the random module. This module returns a random integer value from the inclusive range between the two lower and higher limits (including both limits) provided as two parameters. In the data generation step, the following features, which are the components of the model, were generated using a Python program: $C_{p,Regular\_Purchases}$; $C_{p,Emergency\_Purchases}$; $C_{p,Shipping}$; $C_{p,Expired\_Medication}$; $C_{p,Holding}$; $C_{p,Shortage}$; $C_{p,BT\_Transaction}$; $C_{p,BT\_Installation}$. A total of 5000 series of the generated raw data for all 8 components of the BT-based PSC cost model and the total cost were uploaded to https://data.mendeley.com/datasets/jxv5jrydnc (accessed on 1 November 2022) [24]. The research method selected in this paper is to combine two approaches (EC and SL) for the evaluation of the BT-based PSC cost model: for EC, the ACO and FA are used, and for SL, the KNN, DT, SVM, and NB algorithms are used. These algorithms are well-known and can be successfully applied to solve many engineering problems, which can facilitate the discussion of their behaviours in our new cost model. Here, ACO and the FA are used to improve the parameters of the KNN, DT, SVM, and NB algorithms, as well as to minimise the model prediction errors. The parameters of SL algorithms are usually set empirically, and it takes much time to test and find the best predictive performance of the model. Therefore, the EC algorithms explore the possible combinations of parameters, optimize the hyperparameters of the SL algorithms, and reduce the prediction errors of the SL algorithms. Therefore, the EC algorithms play a significant role in enhancing the performance of the selected SL algorithms. Thus, EC, combined with four algorithms (KNN, DT, SVM, and NB) is used to reduce prediction errors. The generated dataset has eight features (including $C_{p,Regular\_Purchases}$; $C_{p,Emergency\_Purchases}$; $C_{p,Shipping}$; $C_{p,Expired\_Medication}$; $C_{p,Holding}$; $C_{p,Shortage}$; $C_{p,BT\_Transaction}$; and $C_{p,BT\_Installation}$), and has the total cost (C_{Total}) as the label in the regression process (see https://data.mendeley.com/datasets/jxv5jrydnc (accessed on 1 November 2022) [24]). Although the dataset was generated using Python, the implementation of the algorithm, as illustrated in the flowchart presented in Figure 1, was carried out in MATLAB. Figure 1 illustrates the flowchart of the methodology for the four SL algorithms and two EC algorithms. The flowchart starts with creating the population and initialising the parameters. In the next step, the Feature Weighting (FW) approach, which is one of the most efficient approaches, is applied to evaluate the importance of features, assign an appropriate weight to each feature, and estimate the degree of relevance of each feature to the model. The FW process is executed by multiplying the value of every instance of all the features and orders them by their values [25]. FW is considered to be more efficacious than the Feature Selection process in several problems and cases because the features are very sensitive, so removing these kinds of features may negatively affect the classification performance [25]. Traditionally, all of the selected features are equally important when estimating the output, but if some features have a higher weight than others, the results can be strongly influenced by them, affecting the performance and the accuracy of the overall algorithm. The dataset was then participated with 70% of the dataset used for training, while the remaining 30% was used for testing. Four different SL algorithms were used to find the optimal method to estimate the cost of the BT-based PSC cost model, including KNN, DT, SVM, and NB. In the next step, we applied two EC algorithms, ACO and the FA, to improve the performance of the SL algorithms and optimize their hyperparameters, reducing the prediction errors. Four metrics were used to evaluate the cost model, including the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (R^2). Therefore, this approach produced results for the following metrics: eight FWs (one weight for each feature), MSE, RMES, MAE, and R^2. Eventually, a score-based ranking system called total ranking score (TRS) was used to determine the most reliable predictive algorithms. In TRS, each method received a score based on the calculated MSE, RMES, MAE, and R^2 values. Finally, the ranking position of each model was assigned based on the sum of all obtained score states. The following section models the casts of the BT-based PSC system based on the literature review and the methodology.

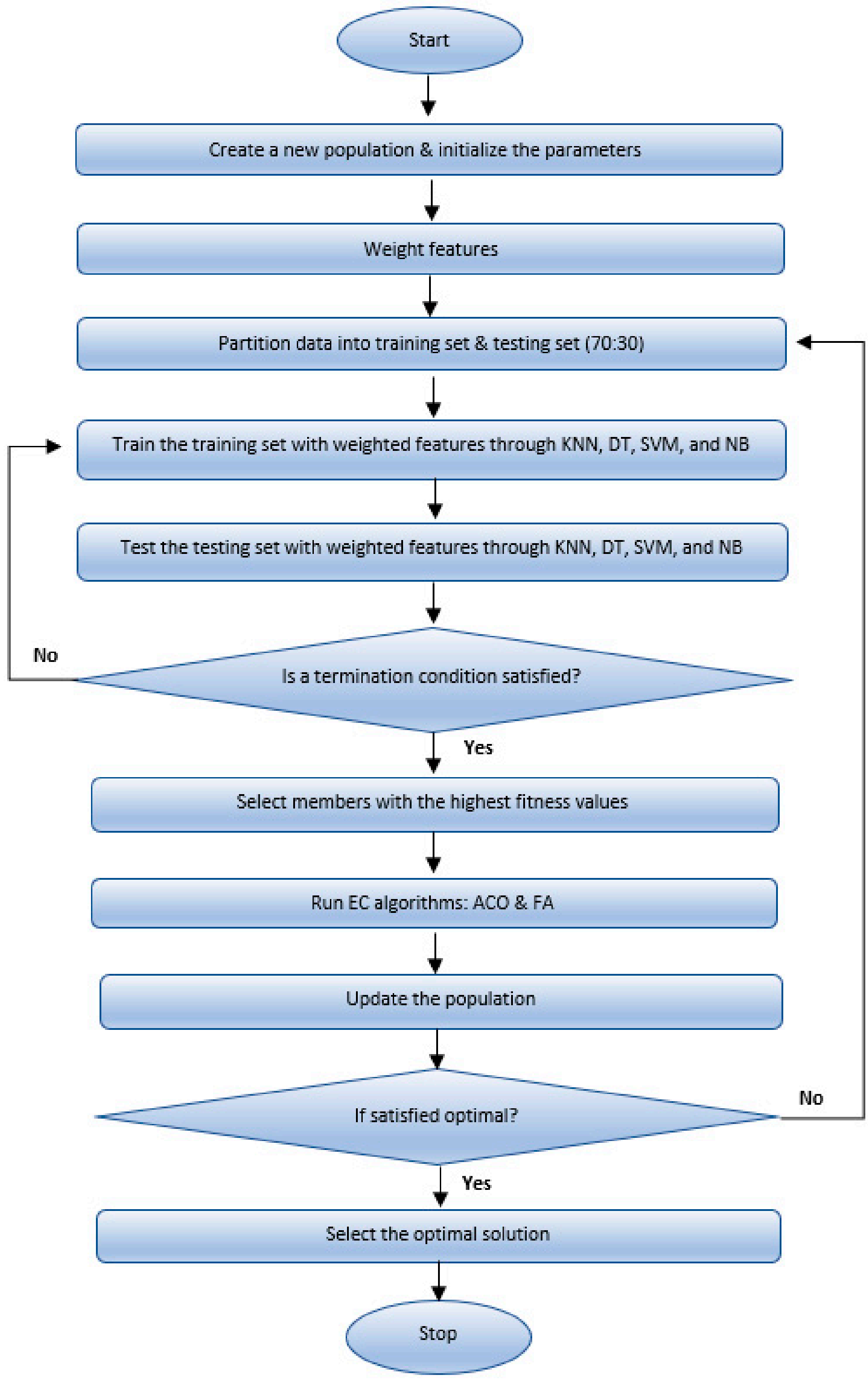

Figure 1. Flowchart of the methodology.

4. Mathematical Cost Model for BT-Based PSC

This section proposes the nonlinear BT-based PSC cost model for a hospital. The model focuses on the costs of a pharmaceutical supply chain that used a public Blockchain as a modern, trustworthy, and traceable database. Inspired by recent articles by Weraikat, Kazemi Zanjani, and Lehoux [26], Franco and Alfonso-Lizarazo [27], and Havaeji, Dao, and Wong [28], we determine that the cost components of the BT-based PSC model are regular purchases cost, emergency purchases cost, shipping cost, expired medication cost, holding cost, Shortage cost, Blockchain transaction cost, and Blockchain installation cost. Based on these references and our knowledge, this research proposes a mathematical model and assumptions to estimate the costs of a PSC based on Blockchain technology in a hospital. Equations (1) and (2) show the cost components of the mathematical model. The assumptions of the mathematical model in the approach are as follows:

A 1. The planning horizon is one year.

A 2. The drug expiration date is constant, and the producer ships drugs with a long life cycle to the hospital to reduce the likelihood of expiration.

A 3. The hospital orders medicines in bulk packs (and not units).

A 4. At the beginning of the planning horizon, the age and the number of medications available in the hospital (including the initial stock) are zero.

A 5. Demand should be satisfied at all levels in a hospital. Emergency purchases are made if the hospital's pharmacy has a drug shortage. The price of emergency medicine is equal to or higher than its regular purchase price.

A 6. Medicines in the form of both regular and emergency purchases are available.

A 7. The producer ships only fresh medications to the hospital to minimise the likelihood of expiration.

A 8. The cost of medicines is determined at the cycle time when a decision to purchase is made. This is because drug prices can change every period.

A 9. The medicines are used to satisfy the demand and/or are kept in the inventory after arrival.

Hospitals are highly recommended to have a high level of technology and infrastructure that would facilitate the future implementation of a technological system supporting BT. As the main customers of medications, hospitals adopt conservative inventory control policies by keeping large quantities of drugs in stock [26]. The demand of the hospital should be fulfilled by the producer over the planning horizon because of the importance of the medications [26]. In addition, the producer communicates with the hospital to decide on a minimum amount of each medication that must be available in the hospital stock at all times in the safety stock level [26]. Medications move from the producer, via a transportation provider, to the hospital site to satisfy its demand in each period of the planning horizon [26]. Leaving expired medications at customer zones and disposing them improperly can both generate a significant negative environmental footprint [26]. Once the medicine arrives, it can be used to satisfy the demand and/or be kept in inventory by using the age-based inventory constraints and the age of medicines to model the perishability [27]. After a number of cycles, some medicines expire during the time that passes; therefore, if there is not enough medicine on inventory to satisfy the demand, which is also a random element, an emergency purchase can be made to satisfy the demand, but the purchase will be made at a higher price [27]. Any medication that reaches the end of its shelf life is quarantined and then shipped to government safe disposal sites, while unexpired medications remain at the hospital to be used in a next period [27]. The parameters, variables, and constraints used in the model are listed in Table 1.

Table 1. Parameters, variables, and constraints of the BT-based PSC cost model.

Parameters	Explanation	Constraints
M	Number of medication types in the PSC variables ($p = 1, 2, 3, \ldots, \mathrm{M}$)	45
U	The number of Blockchain users	4
$\mathrm{C_s}$	Cost of storage per year (USD/TB) for public outbound bandwidth service [29]	USD $20 \times 12 = 2400$ USD/yr
$\mathrm{G_u}$	The amount of ether gasUsed per day	USD $1.31 \leq \mathrm{G_u} \times g \leq$ USD 3.94
g	Number of gWei to be paid for gasUsed per day	
i_p	Inventory level of medication type p	$25 \leq i_p \leq 140$ (integer)
q_p	Order quantity for the pth medicine product per year	$10 \leq q_p \leq 100$ (integer)
s	The storage size to store the data	2 TB/yr $\leq s \leq$ 5 TB/yr
eq_p	Number of lots of medicine types p purchased in case of emergency	$1 \leq eq_p \leq 40$ (integer)

Table 1. *Cont.*

Parameters	Explanation	Constraints
exq_p	Quantity of expired medication type p sent to the government disposal site	$1 \leq exq_p \leq 25$ (integer)
s_p	Shortage quantity of medication type p that is needed to be outsourced	$1 \leq s_p \leq 40$ (integer)
r_p	Regular cost of medicine type p (USD)	$15 \leq r_p \leq 250$ $r_p \leq e_p$
e_p	Emergency cost of medicine type p (USD)	$20 \leq e_p \leq 300$
$^{t}_{p}$	Shipping cost of medication type p shipped to the hospital (USD)	$5 \leq {}^{t}_{p} \leq 35$
ex_p	Costs obligated by governments for each unit of medication type p disposed at their sites (USD)	$5 \leq ex_p \leq 10$
tex_p	Shipping cost of expired medication type p sent to the government disposal site (USD)	$1 \leq tex_p \leq 15$
h_p	Holding cost of medication type p at the hospital site (USD)	$20 \leq h_p \leq 30$
π_p	Penalty that the producer pays to the hospital for each unit of shortage in the supply of medication type p (USD)	$10 \leq \pi_p \leq 20$
o_p	Cost of outsourced medication type p that the producer could not satisfy (USD)	$12 \leq o_p \leq 18$
c_{fixed}	The initial fixed cost per year	$580 \leq c_{fixed} \leq 680$
$c_{onboarding}$	The onboarding cost	USD $20 \leq c_{onboarding} \leq$ USD 28
c_{mc}	The unit maintenance cost; $c_{mc} + c_{mo}$ is 15–25% of the project value	USD $15 \leq c_{mc} + c_{mo} \leq$ USD 25
c_{mo}	The unit monitoring cost; $c_{mc} + c_{mo}$ is 15–25% of the project value	

Equations (1) and (2) describe the components of the model mathematically.

$$\text{Min TC} = \text{Min}\Big(\sum_{p=1}^{M}\big[C_{p,Regular\_Purchases} + C_{p,Emergency\_Purchases} + C_{p,Shipping} + C_{p,Expired\_Medication} + C_{p,Holding} + C_{p,Shortage} + C_{p,BT\_Transaction} + C_{p,BT\_Installation}\big]\Big) \quad (1)$$

$$\text{Min TC} = \text{Min}\sum_{p=1}^{M}\big[r_p \times q_p + e_p \times eq_p + (eq_p + q_p + s_p) \times t_p + (ex_p + tex_p) \times exq_p + h_p \times i_p + (\pi_p + o_p) \times s_p\big] + \mathrm{G_u} \times g \times 365 + s \times \mathrm{C_s} + C_{fixed} + (C_{onboarding} \times \mathrm{U} + C_{mc} + C_{mo}) \times (eq_p + q_p + S_p) \quad (2)$$

Equation (2) specifies the objective function that seeks to minimise the producer costs that involve the following elements:

$C_{p,Regular\_Purchases}$: The regular purchases cost is the cost of buying different types of medicines ($r_p \times q_p$).

(1) $C_{p,Emergency\_Purchases}$: The emergency purchases cost, at a higher price than the regular cost, can be made to satisfy the demand if there is not a sufficient amount of drugs in the inventory or if some medicines are expired ($e_p \times eq_p$).
(2) $C_{p,Shipping}$: The shipping cost of medications from the producer site to the hospital site is $((eq_p + q_p + s_p) \times t_p)$. During shipping, it is necessary to keep some medications in certain conditions (such as temperature, light, or humidity). Therefore, the transportation cost varies with each medication type, although the distance between the producer and the hospital is constant.
(3) $C_{p,Expired\_Medication}$: The expired medication cost involves the safe disposal fees for different types of expired medication at government sites and the cost of shipping from the hospital to the safe government disposal sites $((ex_p + tex_p) \times exq_p)$. Expired medications incur governmental penalties and environmental forfeits due to their negative impact on the environment.
(4) $C_{p,Holding}$: The holding cost is the inventory cost of the different types of medications at the hospital site ($h_p \times i_p$).
(5) $C_{p,Shortage}$: The Shortage cost is the cost that producers pay to the hospital due to the shortage in the supply of different types of medications (unsatisfied demand) and due to the outsourced medication cost satisfied by another pharmaceutical producer $((\pi_p + o_p) \times s_p)$.

(6) $C_{p,BT\_transaction}$: The BT transaction cost consists of gasCost (gasUsed × gasPrice) and Storage cost ($G_u \times g \times 365 + s \times C_s$) [24,30–32]. $G_u \times g$ is the BT transaction cost per day, and $s \times C_s$ is the storage cost per year. A secured cloud-based warehouse stores the actual data off-chain. An IBM Cloud website was used to calculate the storage cost [29].

(7) $C_{p,BT\_Installation}$: The BT installation cost includes the Fixed cost (c_{fixed}), Onboarding cost ($c_{onboarding}$), Maintenance cost (c_{mc}), and Monitoring cost (c_{mo}) (c_{fixed} + ($c_{onboarding}$ × U + c_{mc} + c_{mo}) × (eq_p + q_p + s_p)) [24,33].

The most widely used consensus protocol in the public Blockchain is Proof-of-Work (PoW) (used in, e.g., Bitcoin and Ethereum) [34]. The cost of the Blockchain transaction consists of gasLimit and gasPrice. The gasLimit is the maximum amount of gas used to execute the transaction and is purchased from the sender's account balance. At the end of the transaction, any unused gas is refunded to the sender's account [24,32]. According to Wood [32], gasPrice (a scalar value) is the number of Wei to be paid for each unit of gas and consists of all computation costs incurred as a result of the execution of this transaction. The ETH Gas Station is a suitable place to calculate $G_u \times g$ and incentivise computation within the network [31,35]. The gWei includes the cost of a transaction on the Ethereum Blockchain as well as the cost of the transaction validators and the network. To convert gWei to USD, we can use the ETH Gas Station website based on the current price of Ethereum [35]. In Table 1, to calculate the $G_u \times g$ cost and convert the gWei cost to USD via the ETH Gas Station website, the gasUsed (as the total gas used in transactions) is 21,000 (a scalar value), and the range of the gasPrice is between 20 and 60 gWei. The range of $G_u \times g$ is between USD 1.31 and USD 3.94. This transaction cost was calculated using the ETH Gas Station website [35].

The cost of Blockchain installation consists of the Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost [24,33]. The Onboarding cost is the cost of training clients and suppliers to become active users of a service or product (training cost) and is the cost related to integrating new employees into a company to learn and train in BT. The c_{mc} and c_{mo} costs are 15–25% of the project value per year [33,36]. After designing the mathematical model, it is necessary to evaluate it statistically, which is discussed in the next section.

5. Results

This section comprehensively presents all experiments and the obtained results and shows the performance metrics of eight algorithms on the generated dataset in addition to the weights of the cost features of the BT-based PSC cost model. The numerical examples examined in this research validate the proposed methodology and the cost model and demonstrate the performance of the proposed approach. We designed and executed the proposed method using MATLAB software to validate the BT-based PSC cost model. We used the FA and ACO (EC algorithms) to improve the results of the KNN, DT, SVM, and NB SL algorithms. To reduce prediction errors and improve the SL results, this combination provides eight algorithms, namely, FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB. The MSE, RMSE, MAE, and R^2 performance metrics were used to evaluate the efficiency of the proposed algorithms. We also used the FW approach to estimate the influencing features for the generated dataset in the cost model. FW has an important role in analysis without changing the initial data content. The authors ran each algorithm (FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB) for 10 runs (80 runs in total) with 1000 iterations. These algorithms helped us validate our results. This experiment assessed the "average" of the performance metrics and the "average" of the weight of the cost features to improve the reliability of all methods in eighty (4 × 10 + 4 × 10) runs. These averages are used because the runs can have various outcomes, and they can help us achieve stability and reliability in behavioural data. Each run was performed for, at most, 1000 iterations. Therefore, instead of comparing the predictions of the BT-based PSC cost model in each run, we compared the average of every

10 runs. This research finally used TRS to determine the most reliable predictive algorithms for the BT-based PSC cost model. Tables 2–9 present the related results.

5.1. FA Combined with Four SL

In this step, the FA was combined with four SL algorithms (FA-KNN, FA-DT, FA-SVM, and FA-NB) and was run 40 times) each algorithm was executed 10 times) in 1000 iterations. Four performance metrics and the weights of eight cost features were evaluated for the BT-based PSC cost model in the 40 runs. Table 2 presents the 8 weights of the cost features and the 4 performance metrics for the 4 algorithms in 40 runs. The average values for each performance metric and each cost feature are presented in Table 2. Tables 3 and 4 are derived from Table 2.

Table 2. Feature weighting and performance evaluation for FA combined with four SL algorithms in 10 runs for each.

		Feature Weighting								**Performance Metrics**			
	Run	**W_ (Regular_ Purchases)**	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
FA_ KNN	1	0.42761	0.70372	0.4019	0.77805	0.66441	0.54303	0.3898	0.75549	6,410,531.181	2531.9027	1911.4867	0.93669
	2	0.38097	0.40696	0.67108	0.07136	0.57776	0.96633	0.25649	0.71504	6,543,559.636	2558.0382	1844.5367	0.95009
	3	0.39918	0.22744	0.88195	1	0.45745	0.60981	0.28345	0.49667	7,109,497.639	2666.3641	1895.78	0.94165
	4	0.48472	0.70427	0.11742	0.56176	0.60325	0.55416	0.72756	0.70165	4,820,413.661	2195.544	1861.4267	0.94784
	5	0.44293	0.36279	1	1	0.27841	1	0.53327	0.66643	8,836,400.862	2972.6084	2380.51	0.95397
	6	0.57136	0.43084	0.086856	0.80261	0.38824	0.61953	0.7207	0.56945	3,341,730.069	1828.04	1563.43	0.96499
	7	0.29971	0.25515	0.25957	0.56899	0.69676	0.89902	0.37948	0.58159	7,298,087.42	2701.4973	2191.1033	0.93169
	8	0.51998	0.39227	0.11292	0.50207	0.30936	0.73901	0.25718	0.71075	4,636,038.367	2153.1462	1730.3067	0.95829
	9	0.38097	0.40696	0.67108	0.07136	0.57776	0.96633	0.25649	0.71504	6,543,559.636	2558.0382	1844.5367	0.95009
	10	0.39918	0.22744	0.88195	1	0.45745	0.60981	0.28345	0.49667	7,109,497.639	2666.3641	1895.78	0.94165
Average		**0.430661**	**0.411784**	**0.5084726**	**0.63562**	**0.501085**	**0.750703**	**0.408787**	**0.640878**	**6,264,931.611**	**2483.15432**	**1911.88968**	**0.947695**
		Feature Weighting								**Performance Metrics**			
	Run	**W_ (Regular_ Purchases)**	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
FA_ DT	1	0.47321	1	0	0.55029	0.077932	0.98129	0	0.76499	20,931,129.39	4575.0551	3459.9621	0.78428
	2	0.68103	0	0.22354	0	0.86119	0.38003	0.88603	0.64452	35,006,777.18	5916.6525	4540.5366	0.71695
	3	0.15466	0.5686	0.54932	0.7612	0.58896	0.79381	0	0.2224	15,666,495.59	3958.0924	3054.3802	0.69542
	4	0.69663	0.44451	0.60297	0.45421	0.66456	0.24065	0.2454	0	19,723,753.67	4441.1433	3129.7053	0.82664
	5	0.019254	0.20955	0.56631	0.74343	0.6613	0	0.05882	0.92978	30,911,374.48	5559.7999	4279.7594	0.70113
	6	0.88511	0.14417	0.80373	0	0.8651	0.45487	0.46228	0.6855	16,236,754.9	4029.4857	3445.5285	0.8264
	7	0.47321	1	0	0.55029	0.077932	0.98129	0	0.76499	20,931,129.39	4575.0551	3459.9621	0.78428
	8	0.68103	0	0.22354	0	0.86119	0.38003	0.88603	0.64452	35,006,777.18	5916.6525	4540.5366	0.71695
	9	0.15466	0.5686	0.54932	0.7612	0.58896	0.79381	0	0.22248	15,666,495.59	3958.0924	3054.3802	0.69542
	10	0.69663	0.44451	0.60297	0.45421	0.66456	0.24065	0.2454	0	19,723,753.67	4441.1433	3129.7053	0.82664
Average		**0.4915424**	**0.437994**	**0.41217**	**0.427483**	**0.5911684**	**0.524643**	**0.278396**	**0.487918**	**22,980,444.11**	**4737.11722**	**3609.44563**	**0.757411**
		Feature Weighting								**Performance Metrics**			
	Run	**W_ (Regular_ Purchases)**	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
FA_ SVM	1	0.23175	0.2259	0.53019	0.00011658	0.98963	0.99971	0.37348	0.32717	173,343.7829	416.3457	333.2585	0.99958
	2	0.49827	0.1213	0.044341	0.37469	0.078956	0.076338	0.84056	0.025916	123,519.554	351.4535	295.5338	0.99944
	3	0.23175	0.2259	0.53019	0.00011658	0.98963	0.99971	0.37348	0.32717	173,343.7829	416.3457	333.2585	0.99958
	4	0.49827	0.1213	0.044341	0.37469	0.078956	0.076338	0.84056	0.025916	123,519.554	351.4535	295.5338	0.99944
	5	0.11145	0.18245	0.80071	0.91571	0.3337	0.27808	0.999	0.1206	187,904.5992	433.4796	345.0264	0.99973
	6	0.062505	0.13831	0.17654	0.83871	0.55852	0.43634	0.21079	0.072986	133,984.4159	366.0388	304.2886	1
	7	0.12535	0.10758	0.88876	0.99971	0.28039	0.38197	0.99797	0.11452	217,426.4673	466.2901	349.1649	0.99967
	8	0.069619	0.11732	0.22129	0.89167	0.5806	0.5368	0.59439	0.075245	170,350.8234	412.7358	348.6053	0.9999
	9	0.070616	0.15011	0.19064	0.95425	0.4204	0.92513	0.22981	0.082785	119,067.7801	345.062	276.8873	0.99995
	10	0.038819	0.37321	0.098169	0.3057	0.17506	0.19189	0.30862	0.044591	167,675.474	409.482	356.8005	0.99984
Average		**0.1938399**	**0.176338**	**0.3525171**	**0.565536316**	**0.4485842**	**0.4902306**	**0.576866**	**0.1216899**	**159,013.6234**	**396.86867**	**323.83576**	**0.999713**

Table 2. *Cont.*

	Run	Feature Weighting								Performance Metrics			
		W_ (Regular_ Purchases)	W_(Emergency_Purchases)	W_ (Shipping)	W_ (Expired_ Medication)	W_ (Holding)	W_ (Shortage)	W_(BT_ Transaction)	W_(BT_ Installation)	MSE	RMSE	MAE	R^2
FA_ NB	1	0.032531	0.041745	0.08032	0.9808	0.10975	0.18195	1	0.031338	0.02788	0.16697	0.1257	1
	2	0.010457	0.015939	0.033751	0.99143	0.056218	0.05816	0.96678	0.011013	0.016316	0.12773	0.10697	1
	3	0.060931	0.084856	0.18278	0.91442	0.59413	0.3198	0.30078	0.063357	0.01369	0.117	0.096242	1
	4	0.060931	0.084856	0.18278	0.91442	0.59413	0.3198	0.30078	0.063357	0.01369	0.117	0.096242	1
	5	0.029986	0.052286	0.086725	0.99994	0.14185	0.24168	0.31756	0.033475	0.019494	0.13962	0.11491	1
	6	0.015173	0.017665	0.038483	0.99992	0.72279	0.077546	0.22372	0.014434	0.035156	0.1875	0.13605	1
	7	0.032531	0.041745	0.08032	0.9808	0.10975	0.18195	1	0.031338	0.02788	0.16697	0.1257	1
	8	0.010457	0.015939	0.033751	0.99143	0.056218	0.05816	0.96678	0.011013	0.016316	0.12773	0.10697	1
	9	0.060931	0.084856	0.18278	0.91442	0.59413	0.3198	0.30078	0.063357	0.01369	0.117	0.096242	1
	10	0.032531	0.041745	0.08032	0.9808	0.10975	0.18195	1	0.031338	0.02788	0.16697	0.1257	1
Average		**0.0346459**	**0.0481632**	**0.098201**	**0.966838**	**0.3088716**	**0.1940796**	**0.637718**	**0.035402**	**0.0211992**	**0.143449**	**0.1130726**	**1**

Table 3 compares the average of four performance evaluation metrics for each method. In Table 3, FA-DT has the weakest result in terms of all performance metrics (Ave-MSE = 22,980,444.11, Ave-RMSE = 5916.65, Ave-MAE = 3609.44), and R^2 = 0.75, while FA-NB demonstrates robust behaviour with the best average R^2 of 1 and a minimum Ave-MSE = 0.021, Ave-RMSE = 0.143, Ave-MAE = 0.113 among the four methods. Although the averages R^2 values for all methods are acceptable (ranging from 0.757 to 1), the average MSE, RMSE, and MAE values for FA-KNN, FA-DT, and FA-SVM are the worst (ranging from 323.83 to 22,980,444.11). Therefore, the abovementioned metrics indicate that the FA-NB algorithm has better performance for the BT-based PSC cost model than the other proposed algorithms.

Table 3. Performance metrics evaluation for FA combined with four SL algorithms.

	Performance Metrics			
Methods	**Ave_MSE**	**Ave_RMSE**	**Ave_MAE**	**Ave_R^2**
FA_KNN	6,264,931.611	2483.15432	1911.88968	0.930856
FA_DT	**22,980,444.11**	**5916.6525**	**3609.44563**	**0.757411**
FA_SVM	159,013.6234	396.86867	323.83576	0.999713
FA_NB	**0.0211992**	**0.143449**	**0.1130726**	**1**

We also focused on the average of the weights of each cost feature via the FW approach for the FA-KNN, FA-DT, FA-SVM, and FA-NB algorithms, as shown in Table 4. Among these four methods, FA-NB provides the highest average weight for the expired medication cost feature (0.966) and the lowest average weight for the regular purchases cost feature (0.034). The second highest average weight is allocated to the BT installation cost feature by the FA-KNN algorithm (0.849) followed by the holding cost feature by the FA-DT algorithm (0.591). The BT installation cost feature also has the second lowest average weight with FA-SVM (0.121). In addition, the BT transaction cost fluctuates because it has the average weight of 0.576 and 0.278 for FA-SVM and FA-DT, respectively.

Table 4. FW criteria for FA combined with four SL algorithms.

	Feature Weighting	
Methods	**Max_Ave_Weighting**	**Min_ Ave_Weighting**
FA_KNN	W_(BT_Installation) = 0.84988	W_(Expired_Medication) = 0.34659
FA_DT	W_(Holding) = 0.5911684	W_(BT_Transaction) = 0.278396
FA_SVM	W_(BT_Transaction) = 0.576866	W_(BT_Installation) = 0.1216899
FA_NB	**W_(Expired_Medication) = 0.966838**	**W_(Regular_Purchases) = 0.0346459**

5.2. ACO Combined with Four SL Algorithms

In the second step, ACO combined with 4 SL algorithms (ACO -KNN, ACO -DT, ACO -SVM, and ACO -NB) was executed 40 times (each algorithm ran 10 times). Then, the 4 performance metrics and the weights of the 8 cost features were evaluated for the BT-based PSC cost model in the 40 runs. Table 5 illustrates 8 weightings of cost features and performance metrics for 4 algorithms in 10 runs for each algorithm. Table 5 presents the average values of the performance metrics and the average values of the weights of the cost features. Tables 6 and 7 are also derived from the data presented in Table 5.

Table 5. FW and performance evaluation for ACO combined with four SL algorithms in 10 runs for each.

		Feature Weighting								**Performance Metrics**			
	Run	**W_ (Regular_ Purchases)**	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
ACO_ KNN	1	0.35695	0.92549	0.89039	1	0.009856	0.18912	0.47227	0.99903	5,543,172.364	2354.3943	1949.4633	0.92596
	2	1	0.76434	0.43676	0	0.88697	1	0.34671	1	4,695,227.88	2166.8475	1864.3933	0.95763
	3	0.92009	0.62512	0.8734	1	0.76675	0	0.86776	0.84005	4,692,998.943	2166.3331	1818.2033	0.93246
	4	0.70324	0.64935	0.47864	0.021711	0.59772	0.26598	0.36632	0.45778	6,719,708.626	2592.2401	2065.3833	0.89936
	5	1	0.66795	0	0.15666	0.72265	1	0.55566	0.50375	6,928,149.833	2632.1379	2027.5067	0.94752
	6	0.48851	0.97333	0.65892	0	0.30371	1	0.41044	1	6,221,307.472	2494.2549	2142.3833	0.92888
	7	0.45446	0.51932	0.49337	0.38196	0.93485	1	0.34229	0.98086	4,565,317.918	2136.6605	1844.1267	0.94594
	8	0.36326	0.34374	1	0.47294	0.91225	0.4744	0.20598	0.99651	4,394,372.317	2096.2758	1794.3933	0.92742
	9	0.52039	0.70382	0.077738	0	0.69597	0	0.92397	1	10,706,939.15	3272.146	2655.27	0.90856
	10	0.40842	0.36388	0.21883	0.43267	0.95833	1	0.61236	0.72077	5,833,434.956	2415.2505	2088.6967	0.93483
Average		**0.621532**	**0.653634**	**0.5128048**	**0.3465941**	**0.6789056**	**0.59295**	**0.510376**	**0.849875**	**6,030,062.946**	**2432.65406**	**2024.98199**	**0.930856**
		Feature Weighting								**Performance Metrics**			
	Run	**W_ (Regular_ Purchases)**	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
ACO_ DT	1	0.36831	0.65313	0	0	0	1	0.48975	0	27,725,280.24	5265.4801	3918.345	0.8088
	2	0.78548	1	0	0.35183	0	0	0.96679	0.78077	17,268,337.62	4155.5189	3358.6605	0.73903
	3	0.39139	0.30496	0	1	0	0	0	0.078329	20,862,939.19	4567.5967	3543.8508	0.78735
	4	1	0.70817	0	1	0.61945	0.15374	0.36463	0.38276	14,114,845.23	3756.9729	3134.379	0.79848
	5	0.78077	0	0	0.39765	0	0	0	1	22,127,369.33	4703.9738	3421.1334	0.77706
	6	0.11978	0.46586	1	0.43738	0	1	0.86613	0	15,853,729.5	3981.6742	2765.302	0.83271
	7	0.41597	1	0	0	0	1	0	1	13,566,853.1	3683.3209	2900.3703	0.82056
	8	0.72963	0.5107	0	0	0.44327	0	0.58999	1	18,853,360.55	4342.0457	3218.8045	0.80982
	9	0.35453	0	0.50304	0.26006	0.29699	0	0	0.10223	19,129,278.4	4373.7031	3173.7969	0.83869
	10	0.35628	0.37771	0	0.89254	0	0.44445	0	0.27212	23,472,850.57	4844.8788	3620.1248	0.8251
Average		**0.530214**	**0.502053**	**0.150304**	**0.433946**	**0.135971**	**0.359819**	**0.327729**	**0.4616209**	**19297484.37**	**4367.51651**	**3305.47672**	**0.80376**
		Feature Weighting								**Performance Metrics**			
	Run	**W_ (Regular_ Purchases)**	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
ACO_ SVM	1	0.13205	0.17919	0.47213	0.99797	0.41098	0.53424	0.94092	0.16085	214,988.4336	463.6685	372.7033	0.99976
	2	0.98237	0.26347	0.97017	0.0054287	0.65009	0.99563	0.69419	0.52966	118,716.9279	344.5532	291.8931	0.99858
	3	0.36341	0.07529	0.44152	0.94205	1	0.13531	0.35334	0.84212	85,394.6138	292.2236	239.0761	0.99908
	4	0.31839	0.21878	0.80193	0	0.88418	0.86379	0.34368	0.59425	178,499.0214	422.4914	337.9536	0.99957
	5	0.22478	0.99994	0.90923	0.99996	0.68076	0.62322	0.28197	0.23503	79,662.2247	282.245	220.6187	0.99944
	6	0.1891	0.181	0.81952	1	1	0.62985	0.99913	0.17333	282,360.1537	531.3757	415.7638	0.99926
	7	0.15083	0.32986	0.40481	0.99984	0.96917	0.93384	0.98662	0.21624	170,985.299	413.5037	343.692	0.9999
	8	0.97605	0.20016	0.47514	0.9965	0.98931	0.85258	0.99817	0.18793	168,623.3192	410.6377	350.2368	0.99905
	9	0.31839	0.21878	0.80193	0	0.88418	0.86379	0.34368	0.59425	178,499.0214	422.4914	337.9536	0.99957
	10	0.22478	0.99994	0.90923	0.99996	0.68076	0.62322	0.28197	0.23503	79,662.2247	282.245	220.6187	0.99944
Average		**0.388015**	**0.366641**	**0.700561**	**0.69417087**	**0.814943**	**0.705547**	**0.622367**	**0.376869**	**155,739.1239**	**386.54352**	**313.05097**	**0.999365**

Table 5. *Cont.*

	Run	Feature Weighting								Performance Metrics			
		W_ (Regular_ Purchases)	**W_(Emer gency_Pur chases)**	**W_ (Shipping)**	**W_ (Expired_ Medication)**	**W_ (Holding)**	**W_ (Shortage)**	**W_(BT_ Transaction)**	**W_(BT_ Installation)**	**MSE**	**RMSE**	**MAE**	**R^2**
ACO_ NB	1	0.066266	0.083497	0.16188	1	0.22171	0.36769	0.99974	0.064689	0.028975	0.17022	0.12833	1
	2	0.051676	0.076568	0.15739	1	0.39803	0.25806	1	0.055018	0.016852	0.12981	0.10561	1
	3	0.036712	0.055901	0.083755	0.99983	1	0.18925	0.19181	0.041779	0.01459	0.12079	0.092924	1
	4	0.052031	0.0655	0.11217	0.99977	0.32118	0.20282	0.99953	0.047636	0.020784	0.14417	0.12146	1
	5	0.066266	0.083497	0.16188	1	0.22171	0.36769	0.99974	0.064689	0.028975	0.17022	0.12833	1
	6	0.051676	0.076568	0.15739	1	0.39803	0.25806	1	0.055018	0.016852	0.12981	0.10561	1
	7	0.036712	0.055901	0.083755	0.99983	1	0.18925	0.19181	0.041779	0.01459	0.12079	0.092924	1
	8	0.052031	0.0655	0.11217	0.99977	0.32118	0.20282	0.99953	0.047636	0.020784	0.14417	0.12146	1
	9	0.05725	0.07226	0.1489	1	1	0.44111	0.52877	0.058602	0.032984	0.18161	0.1356	1
	10	0.045911	0.080262	0.13201	0.99984	0.23087	0.33649	1	0.053764	0.012642	0.11244	0.098423	1
Average		**0.0516531**	**0.0715454**	**0.13113**	**0.999904**	**0.511271**	**0.281324**	**0.791093**	**0.053061**	**0.0208028**	**0.142403**	**0.1130671**	**1**

Table 6 presents the average values of the performance metrics considered in the evaluation of the proposed ACO combined with four SL algorithms. In Table 6, ACO-DT has the weakest result in terms of all performance metrics (Ave-MSE = 19,297,484.37, Ave-RMSE = 4367.51, Ave-MAE = 3305.47, and R^2 = 0.80), while ACO-NB performs better with an average R^2 of 1 and minimums of Ave-MSE = 0.020, Ave-RMSE = 0.142, and Ave-MAE = 0.113 among the four methods. Although the average R^2 values are acceptable for all methods (ranging from 0.803 to 1), the average MSE, RMSE, and MAE values for ACO-KNN, ACO-DT, and ACO-SVM are the worst (ranging from 313.05 to 19,297,484.37). Therefore, we consider the ACO-NB results to be more reliable than the results obtained by the other proposed methods, all of which are shown in the following table.

Table 6. Performance metrics evaluation for ACO combined with four SL algorithms.

	Feature Weighting			
Methods	**Ave_MSE**	**Ave_RMSE**	**Ave_ MAE**	**Ave_R^2**
ACO_KNN	6,030,062.946	2432.65406	2024.98199	0.930856
ACO_DT	**19,297,484.37**	**4367.51651**	**3305.47672**	**0.80376**
ACO_SVM	155,739.1239	386.54352	313.05097	0.999365
ACO_NB	**0.0208028**	**0.142403**	**0.1130671**	**1**

We also investigated the average weights of each cost feature via the FW approach in the ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB algorithms (see Table 7). For the ACO-NB algorithm, the maximum average weight of 0.999 is allocated to the expired medication cost feature, and the minimum average weight of 0.051 is obtained for the regular purchases cost feature. For the ACO-KNN algorithm, the second maximum average weight is obtained for the BT installation cost feature (0.849) followed by the holding cost feature (0.814) obtained by ACO-SVM (see Table 7). Accordingly, the ACO-SVM algorithm gives the second lowest average weight of 0.135 for the holding cost feature. In addition, a variation in the average weight of the expired medication cost feature is observed, which is obtained as 0.346 and 0.999 by ACO-KNN and ACO-NB, respectively. Similarly, the holding cost feature weight varies as 0.135 and 0.814 obtained by ACO-DT and ACO-SVM, respectively.

Table 7. FW criteria for ACO combined with four SL algorithms.

	Feature Weighting	
Methods	**Max_Ave_Weighting**	**Min_Ave_Weighting**
ACO_KNN	W_(BT_Installation) = 0.849875	W_(Expired_Medication) = 0.3465941
ACO_DT	W_(Regular_Purchases) = 0.530214	W_(Holding) = 0.135971
ACO_SVM	W_(Holding) = 0.814943	W_(Emergency_Purchases) = 0.366641
ACO_NB	**W_(Expired_Medication) = 0.999904**	**W_(Regular_Purchases) = 0.0516531**

5.3. Determining Reliable Algorithms for BT-Based PSC Cost Model

Table 8 summarises the TRS of eight algorithms based on the obtained Ave-MSE, Ave-RMSE, Ave-MAE, and Ave-R^2 values. In TRS, the lowest Ave-MSE, Ave-RMSE, and Ave-MAE receive the highest scores, and the highest Ave-R^2 obtains the highest score (and vice versa). Overall, the ACO-NB algorithm outperforms the other compared algorithms and achieves the first position among all the algorithms (a TRS of 32), followed by FA-NB with a TRS of 29, ACO-SVM with a TRS of 24, and FA-SVM with a TRS of 22. FA-DT and ACO-DT achieve the worst scores of 6 (rank 8th) and 10 (rank 7th), respectively.

Table 8. Ranking of eight selected algorithms based on TRS scores using performance metrics.

		Performance Metrics					
Methods		**Ave_MSE**	**Ave_RMSE**	**Ave_MAE**	**Ave_R^2**	**TRS**	**Rank**
FA_KNN		6,264,931.611	2483.15432	1911.88968	0.930856		
FA_DT		**22,980,444.11**	**5916.6525**	**3609.44563**	**0.757411**		
FA_SVM		159,013.6234	396.86867	323.83576	0.999713		
FA_NB		**0.0211992**	**0.143449**	**0.1130726**	**1**		
ACO_KNN		6,030,062.946	2432.65406	2024.98199	0.930856		
ACO_DT		**19,297,484.37**	**4367.51651**	**3305.47672**	**0.80376**		
ACO_SVM		155,739.1239	386.54352	313.05097	0.999365		
ACO_NB		**0.0208028**	**0.142403**	**0.1130671**	**1**		
Ranking Score	FA_KNN	3	3	4	5	15	6
	FA_DT	**1**	**1**	**1**	**3**	**6**	**8**
	FA_SVM	5	5	5	7	22	4
	FA_NB	**7**	**7**	**7**	**8**	**29**	**2**
	ACO_KNN	4	4	3	5	16	5
	ACO_DT	**2**	**2**	**2**	**4**	**10**	**7**
	ACO_SVM	6	6	6	6	24	3
	ACO_NB	**8**	**8**	**8**	**8**	**32**	**1**

Table 9 shows the ranking of the average weights of eight costs features, namely, regular purchases, emergency purchases, shipping, expired medication, holding, shortage, BT transaction, and BT installation for the FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB algorithms. This table assigns an appropriate weight to each cost feature to show their importance. The average weight with higher TRS receives a higher priority in the TRS process (and vice versa). Overall, the Shortage cost obtains the best TRS of 46 for the average weight followed by the holding cost with a TRS of 45 and the expired medication cost with a TRS of 43. The minimum TRS for the average weight is allocated to the emergency purchases cost (TRS = 28) followed by both the regular purchases cost and the shipping cost, which have the same rank of 5th with TRS = 30.

Table 9. FW ranking based on TRS scores for eight selected algorithms.

	Methods									
Ave_FW	**FA_ KNN**	**FA_DT**	**FA_ SVM**	**FA_NB**	**ACO_ KNN**	**ACO_ DT**	**ACO_ SVM**	**ACO_ NB**	**TRS**	**Rank**
W_(Regular_Purchases)	0.430661	0.4915424	0.1938399	0.0346459	0.621532	0.530214	0.388015	0.0516531		
W_(Emergency_Purchases)	0.411784	0.437994	0.176338	0.0481632	0.653634	0.502053	0.366641	0.0715454		
W_(Shipping)	0.5084726	0.41217	0.3525171	0.098201	0.5128048	0.150304	0.700561	0.13113		
W_(Expired_Medication)	0.63562	0.427483	0.56553631	0.966838	0.3465941	0.433946	0.69417087	0.999904		
W_(Holding)	0.501085	0.5911684	0.4485842	0.3088716	0.6789056	0.135971	0.814943	0.511271		
W_(Shortage)	0.750703	0.524643	0.4902306	0.1940796	0.59295	0.359819	0.705547	0.281324		
W_(BT_Transaction)	0.408787	0.278396	0.576866	0.637718	0.510376	0.327729	0.622367	0.791093		
W_(BT_Installation)	0.640878	0.487918	0.1216899	0.035402	0.849875	0.4616209	0.376869	0.053061		

Table 9. *Cont.*

Ave_FW		Methods									
		FA_ KNN	FA_DT	FA_ SVM	FA_NB	ACO_ KNN	ACO_ DT	ACO_ SVM	ACO_ NB	TRS	Rank
Ranking Score	W_(Regular_ Purchases)	**3**	**6**	**3**	**1**	**5**	**8**	**3**	**1**	**30**	**5**
	W_(Emergency_ Purchases)	**2**	**4**	**2**	**3**	**6**	**7**	**1**	**3**	**28**	**6**
	W_(Shipping)	**5**	**2**	**4**	**4**	**3**	**2**	**6**	**4**	**30**	**5**
	W_(Expired_ Medication)	**6**	**3**	**7**	**8**	**1**	**5**	**5**	**8**	**43**	**3**
	W_(Holding)	**4**	**8**	**5**	**6**	**7**	**1**	**8**	**6**	**45**	**2**
	W_(Shortage)	**8**	**7**	**6**	**5**	**4**	**4**	**7**	**5**	**46**	**1**
	W_(BT_Transaction)	1	1	8	7	2	3	4	7	33	4
	W_(BT_Installation)	7	5	1	2	8	6	2	2	33	4

6. Discussion

This section discusses the results for the proposed eight algorithms that minimise the prediction errors of the BT-based PSC cost model. The proposed algorithms aim to answer the three research questions mentioned in the Introduction. As stated in Section 3, there are eight components in the BT-based PSC cost model: the regular purchases cost, the emergency purchases cost, the shipping cost, the expired medication cost, the holding cost, the shortage cost, the BT transaction cost, and the BT installation cost. This provides the answer to our first research question. Regarding the second research question, among the eight examined algorithms, we select some algorithms that demonstrate better performance in minimising the prediction errors of the BT-based PSC cost model. Figure 2 is derived from the data presented in Table 8 and shows the TRSs for all eight studied algorithms (FA-KNN, FA-DT, FA-SVM, FA-NB, ACO-KNN, ACO-DT, ACO-SVM, and ACO-NB). Four performance metrics (MSE, RMSE, MAE, and R^2) evaluate the algorithm efficiency. The overall results of this study show that both ACO-NB (first position) and FA-NB (second position) algorithms outperform the other algorithms. This means that NB combined with either the FA or ACO is considered to be the most effective in performing the regression. The EC algorithms (FA and ACO) also play a significant role in optimizing the hyperparameters of the selected SL algorithms. Moreover, the SVM algorithm, combined with the FA and ACO, shows the second position with respect to TRS. The DT algorithm, combined with the FA and ACO, cannot predict the costs of the BT-based PSC model well. Thus, we have determined the most reliable predictive algorithms for our cost model using TRS and the four performance metrics.

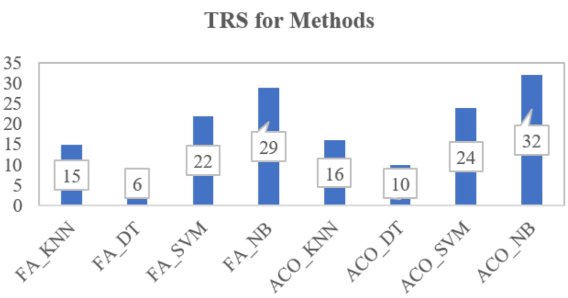

Figure 2. TRS of all algorithms.

The third research question is to determine the significant cost components of the model. The FW approach measures the importance of the features and assigns an appropriate weight to each feature. Figure 3 is derived from Table 9 and shows the TRS for the weights of all cost components (features) of the BT-based PSC model. These weights estimate the degree of relevance that each feature has for extracting the cost prediction. The shortage cost, the holding cost, and the expired medication cost strongly influence the cost model. The remaining five cost features have relatively the same position based on the weights (regular purchases cost, emergency purchases cost, shipping cost, BT transaction cost, and BT installation cost).

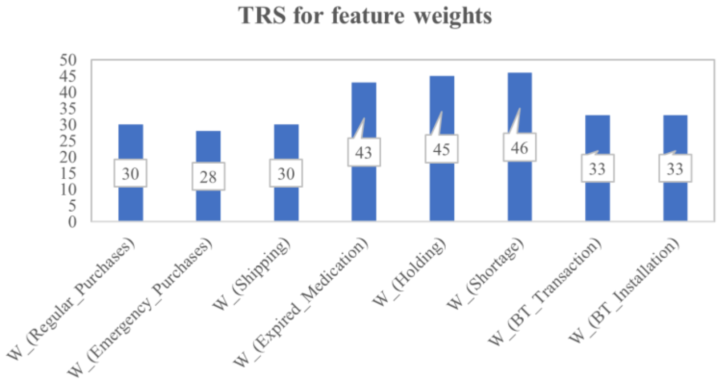

Figure 3. TRS for feature weights.

Compared to previous work that modelled the costs of PSC, this study developed a new mathematical cost model called the BT-based PSC that includes BT transaction cost and BT installation cost. Researchers in other fields can also use BT cost formulation (BT transaction cost and BT installation cost) in their mathematical models to estimate the SC costs integrated with BT. The practical significance of the study lies in providing the most reliable predictive algorithms for the BT-based PSC cost model, the cost components of the model, the degree of relevance of each component to the cost model, and the components of BT in the SC model.

However, similarly to the other studies, this research is subject to two limitations. The first significant limitation is the inaccessibility of real data because the use of BT in the PSC is a new area of research. Therefore, the eight algorithms studied in this work applied the generated data to validate the proposed BT-based PSC cost model. The use of generated data, rather than real data, may influence the outcomes and conclusions of the research. The second limitation is related to the model design. To design the cost model, we first selected some parts of the mathematical model inspired by other papers and then added BT costs. This means that the study may not cover some cost components of a real case, hindering the comparison of the results of this research with the results of other studies.

Finally, future research may extend the BT-based PSC cost model to a multi-objective model, which, for example, includes the uncertainty demand in PSCs. Another promising direction is to use other EC algorithms to enhance the performance of the SL algorithms or to test different SL algorithms to predict costs. The use of Feature Selection (instead of FW) is another direction that should be investigated to compare the optimization process of this model. The last potential future research direction is to determine the cost components of the private BT and formulate the private BT instead of the public BT used in the current study.

7. Conclusions

The BT-based PSC enables traceability and transparency of the drugs' movement and of the stakeholders in the supply chain and can affect medication quality and final patient outcomes. This paper presents a mathematical cost model for a BT-based PSC system to estimate the costs of the model. This study is important because it provides a PSC system with BT (BT transaction cost and BT installation cost) that can improve the safety, performance, and transparency of medical information sharing in a healthcare system. One of the main contributions of this research is to formulate this cost problem and apply a combination of EC (ACO and FA) and SL (KNN, DT, SVM, and NB) algorithms and use four performance metrics (MSE, RMSE, MAE, and R^2) to evaluate the efficiency of the proposed algorithms. This combination of EC and SL algorithms provides eight algorithms (as the regression producer), reducing prediction errors and improving the SL results. Overall, the ACO-

NB and FA-NB algorithms outperform the other six algorithms in estimating the costs of the model with lower errors. ACO-DT and FA-DT show the worst performance for this comparison, showing that the DT algorithm is not an appropriate predictive approach for the current cost model. The findings also show that the shortage cost, the holding cost, and the expired medication cost strongly influence the cost model more than the other cost components that have almost the same effect on the model (regular purchases cost, emergency purchases cost, shipping cost, BT tansaction cost, and BT installation cost). This selection of components is derived from the allocation of an appropriate weight to each cost feature to show their importance using the FW approach. Therefore, the statistical outcomes on the generated dataset show that some of the proposed algorithms can obtain satisfactory results and assign appropriate feature weights. In the real world, managers in the field of healthcare services can use this model practically to control financial resources, stay within the budget, analyse information, and identify unnecessary costs, particularly if they decide to use BT in the system. The important contribution of this research is to provide a PSC system with BT. Selected SL algorithms can also help managers estimate costs with the minimum prediction errors and correctly decide whether the new system benefits their organisation. As the cost factor is important to managers, this study also determines and measures the importance of each cost component of the BT-based PSC model.

Author Contributions: Conceptualization, H.H. and T.-M.D.; methodology, H.H., T.W. and T.-M.D.; software, H.H. and T.W.; validation, H.H. and T.-M.D.; formal analysis, H.H. and T.W.; investigation, H.H.; resources, H.H.; data curation, H.H. and T.W.; writing—original draft preparation, H.H.; writing—review and editing, H.H., T.W. and T.-M.D.; visualization, T.-M.D.; supervision, T.W. and T.-M.D.; project administration, T.-M.D.; funding acquisition, T.-M.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data that support the findings of this study are openly available in https://data.mendeley.com/datasets/jxv5jrydnc (accessed on 1 November 2022). This sentence was stated in Section 3 of the manuscript to show data availability: "5000 series of the generated raw data for all eight components of the BT-based PSC cost model and the total cost were uploaded to https://data.mendeley.com/datasets/jxv5jrydnc (accessed on 1 November 2022)".

Conflicts of Interest: The authors declare no conflict of interest.

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