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An intelligent system for blood donation process optimization - smart techniques for minimizing blood wastages

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Abstract
Blood transfusion is a continuous demand, as it is widely required for many medical surgeries and critical operations. Therefore, there is a need to manage the whole process of supplying blood from blood donors to the hospitals and transfusion centers. Many researchers were recently interested in the operations and supply chain management of blood products, they considered the operations and supply chain management of blood products for the purpose of minimizing the blood wastage. As a result of the the inverse relationship between blood donations and blood products demand, more occasional blood shortages can be expected. This research proposes an intelligent system that entails the recruitment of donors that are available to donate blood products on a short notice. The proposed system optimizes the blood donation process by preventing blood shortages and minimizing the wastage of blood units with regards to expiration, and proves promising results. A set of optimization equations have been built for optimizing the process of blood donation to reduce the blood wastage and prevent blood shortage. It considers as well the new insights from the medical literature on the deterioration of stored blood products, as the use of older red blood cells is linked to poorer clinical outcomes.

Keywords Intelligent blood donation · Healthcare management · Intelligent donors · Machine learning · Data mining · Classification algorithms · Internet of health · Optimization

1 Introduction

A critical issue that is carried out globally in many hospitals and medical centers is blood transfusion and storing, as blood is considered a limited resource [1–3]. The availability of blood products in hospitals and medical centers is necessary and these healthcare centers should be fully prepared for any emergency case that needs an urgent blood supply [4–6]. Therefore, the blood donation process becomes significant, and this leads to the urgent need for studying the supply chain management of blood products, and also guarantee a continuous availability of high quality and safety products in the blood banking systems [7–9].

Blood transfusion is the most common procedure conducted in US hospitals [10]. Hospitals and medical centers depend on the availability of compatible blood products. For this, the whole blood is collected from donors, and processed into blood products, such as red blood cells (RBCs), plasma, platelets, and cryoprecipitate. Large players in this field are America's Blood Centers and the American Red Cross (ARC). Stored blood products need to be discarded after exceeding a maximum, regulated shelf-life. This ranges from 5 days for platelets, to 42 days for RBCs, and up to one year for plasma [11]. Consequently, a steady supply is needed to keep inventories up.

As a result of the long blood collection and processing time, the outdating of blood products that have exceeded the maximum shelf-life time is costly, and the expensive products will be considered as wastage. However, the process is complicated by the fact that there are multiple major blood types, and the types of the patients and the

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donors determine whether the blood can be used for transfusion [12].

The operations and supply chain management for blood products should be optimized, since blood products are very often used, and expensive, as well as they are considered as limited resources (especially for a specific blood types). Optimizing the blood wastage in blood donation process has been considered as a significant concept for many researchers. The problem here is the collection of blood products, as it will be very hard to optimize this process during the complex manual donation operations. Hence, in this paper a smart system using recent artificial intelligent techniques has been implemented. This study is illustrating the main findings of previous existing systems developed for managing blood donations and presents some suggestions for addressing the gaps in those systems, as well as provides some prospects for future improvements of such systems. The proposed system is built based on supply and demand concepts via a smart panel. This panel uses a Donors-on-Call procedure with a smart network design for multi sourcing inventory to come-up with an optimized solution.

The main contribution of this paper is develop an intelligent blood donation system that optimize the blood wastage percentage. Specifically, we conducted the following contributions: first, we implemented a smart application as a panel for collecting medical records dataset. Second, we developed smart intelligent system based on donor-on-call approach that ensured the recruitment of donors to smartly donate blood based on short notice. Third, a set of optimization equations have been built for optimizing the process of donation in order to reduce the blood wastage and prevent blood shortage

The remaining of this research is organized as follows. Section 2 reviews the related literature for the medical side at hospitals and the previously applied smart solutions for this problem. In Sect. 3, we highlights the proposed system and the main factors that have been followed to optimize the blood donation process smartly. The achieved results from the proposed intelligent optimization of blood donation process are discussed in Sect. 4. Finally, the work is concluded and the future direction is defined in Sect. 5.

2 Related literature

Over the past decades, a vast body of literature has been produced on the operations and supply chain management of blood products. This area has been studied extensively. We identified two interesting gaps in the current literature, that warrant further investigation. In this section, a comprehensive literature for the current studies that have been employed for optimizing the process of blood donations has been reviewed. The existing approaches that applied machine learning and data mining algorithms for optimizing the process of blood donations smartly are also described in this section.

2.1 Blood characteristics

The process of finding a compatible blood type for a patient is called cross-matching demand. After the process of cross-matching and before an operation, an amount of blood products is assigned to the patient, which is larger than the expected amount to be used. This is done, because in case of extra demand in an emergency, extra blood needs to be available immediately, and one cannot wait for the results of a cross-matching procedure. Some days after the operation, left-overs of blood products are returned to the supply for future transfusions. This is prescribed by the cross-matching release policy [13].

Blood products management is part of the general problem management of perishable and aging products. Perishable products here refers to the fact that items might deterioration or become obsolescence during storage. The supply chain and inventory management of perishables is no longer suffices to keep track of the amount of inventory on stock, but the one also needs to store information on the age or the state of deterioration of the products.

An early literature review on the work done on the management of perishable products was done by Nahmias [14] in the early 1980s. More recent literature reviews can by found in Karaesmen et al. [15], Bakker et al. [16], Amorim et al. [17] and Janssen et al. [18]. From a management perspective, it is of interest to integrate constraints of the lifetime of a product during the production and supply chain planning stages. A survey on this can be found in Pahl and Vo [19]. Inventory management for the combination of perishable and non-perishable items together, is studied in Nahmias [20].

2.1.1 Shelf-life

RBCs are the most frequent blood product used in transfusions in the US [11]. After collection, RBCs are stored in special additive solutions and kept refrigerated. Even though, they will degrade progressively during storage, which is referred to as the RBC storage lesion. Because of the degradation, a maximum shelf-life is set, which is in the US regulated to be 42 days.

2.1.2 Older RBC medical impacts

The effect of the aging of RBCs includes a deterioration of the parts in the cells that are important for oxygen transportation. Therefore, doubts have risen on the ability of older RBCs to efficiently and effectively transport oxygen through the body [21]. Over the past two decades, clinical studies have started to suggest that the use of older RBCs correlates with a significant higher mortality and morbidity in certain groups of patients.

Flegel et al. [22] provide an extensive and in-depth literature review of clinical studies into this topic. As they remark, no universal interpretation of fresh and old RBC exists. They conclude that indeed some clinical trials show evidence that some or all patients benefit from fresher RBCs. Whereas some studies show an increased mortality and morbidity in patients receiving old RBCs, other studies fail to show a significant difference.

Lelubre and Vincent [23] concluded based on their analysis of 55 studies, that the heterogeneity among studies is such, that no definite conclusion can be drawn. Therefore, the issue remains a topic of an active debate. Supporting the beneficiality of fresher blood is a meta-analysis by Wang et al. [24], who argued that there is a significant increase of risk of death associated with the use of older stored blood. They indicated the relative risk of death associated with older blood to be 16%.

While the US adheres to an approved maximum shelf-life of 42 days, that is also used in clinical practices [22], other countries have different regulations or practices in place, these range from 21 days for Japan and some blood services in China and Saudi-Arabia, up to 49 days in Germany and Switzerland. It has to be noted that the number of days in some cases also depends on the additive solution used for the storage.

The match between demand and supply will become even more critical than it currently already is. This might give a rise to higher costs, but even worse, more and larger shortages and outdatings might have to be expected. This gives a rise to new challenges at the supply chain level.

2.2 Blood donation organizations

2.2.1 The American Red Cross

The American Red Cross alone, holds more than 145,000 blood drives annually [11], to collect donations of blood. For 2004, a survey report conducted by the United States Department of Health and Human Services found that 135 hospitals have canceled an elective surgery because of blood inventory shortages. This affected 546 patients [10], with a median postponement of 2 days.

The operations and supply chain management for blood products should be optimized, since blood products are very often used and expensive. Therefore, it is important to manage supplies very well. It is estimated that the costs of blood products account for approximately 1% of the costs incurred by hospitals in the US [25]. For the US, it was found that 5.8% of all processed components became outdated before they were used in a transfusion (for 2004, cf. [10]). Therefore, even a marginal improvement in the supply chain can result in high cost savings.

2.2.2 The Australian National Blood Authority

The National Blood Authority's (NBA) core business is to deliver a blood supply system that is responsive to patient needs, built on an evidence based clinical practice and ensures Australia's blood supply is safe, secure, adequate and affordable now and in the future.

NBA is a statutory authority that represents the interests of the Australian and state and territory governments, and sits within the Australian Government's Health portfolio [26].

2.3 Artificial intelligence in health care systems

In the field of healthcare management, many researches address the supply chain management of blood donation by developing systems for blood donation using optimization and classification methods [e.g. [27–33]].

Sundaram and Santhanam classified in [31] the management blood donation supply chain systems by identifying the main stages of a blood plastic bag life cycle as follows: registration of a donor, collecting blood, screening and testing blood, storing blood in inventories, delivering blood units, and using blood units. In contrast, the classification of blood donation supply chain systems performed by Pierskalla in [13] takes into account more issues: the locations of blood centers, the production of blood products, allocating blood to hospitals and medical centers, controlling blood inventory, and delivering blood products. Figure 1 presents the main phases of a blood unit life cycle [34].

Hence, this section first reviews the recent and existing studies that use information management systems and optimization approaches in the healthcare domain for supply chain management of blood products. These systems and approaches aim to optimize the process of blood donations, reduce the wastage of blood products, and decrease the unnecessary importation of blood products

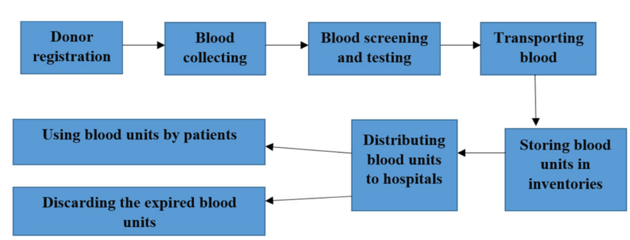

Fig. 1 The Main Phases of the Life Cycle of a Blood Unit

from external sources when blood supply cannot meet the demand. Some of these approaches seek also to predict the future behavior of blood donation.

2.4 Smart blood donation systems

Over the last decades, machine learning, data mining, and optimization algorithms have been extensively applied in different and important domains such as: healthcare management [27, 29–33], natural language processing [35], social media [36–38], business [39, 40], and many other applications [41, 42].

With regards to the healthcare management domain, several optimization methods have been applied to optimize the process of blood donations and manage the task of supplying blood to transfusion centers and hospitals. For example, the study introduced by Olusanya et al. in [27] proposed a model for optimizing the assignment process of blood in blood banking systems based on using the particle swarm optimization (PSO) algorithm [43, 44] on a dataset of blood types. Their study aimed to handle the process of distributing blood effectively among the available blood types and units in blood banks in order to reduce wastages of blood and decrease the need of importing blood units from outside the blood banks. Their approach also combines other two techniques with the PSO optimization algorithm including: multiple knapsack assignment technique and the queuing technique. The first technique is used for matching of blood types with the requests, while the other one is used to track the expiration date of the blood units.

The study introduced by Govender and Ezugwu in [28] applied a symbiotic organisms search (SOS) optimization algorithm for blood assignment policy in blood banks of South Africa [45]. This optimization algorithm aimed to decrease the wastage of blood products, eliminate blood importation, and increase the delivery of blood products to patients in need. The applied optimization algorithm was able to generate accurate percentage bound values for the demand and supply of blood units in each month, where the generated bound values simulate the real-life monthly demand. The authors argued that their approach also minimized the operational costs of the blood transfusion centers.

The approach proposed by Priya et al. in [46] developed a web mobile application of blood donation management system. This optimization system handles and updates information of donors, patients, acceptor, and the donated blood by donors. It also maintains information about the available amount of each blood type. All of these information including the contact details of donors are protected by the system and can be only viewed by authorized users. The approach also integrates geographic information system (GIS) to search for the donors who are available nearby within the required time and during the emergency cases.

Likewise, different studies applied machine learning and data mining algorithms in the healthcare management domain to support the process of blood donation prediction and specify the blood demand, which is increasing by the time, due to accidents, surgeries, and diseases.

For instance, Zabihi et al. applied in [47] a data mining algorithm called fuzzy sequential pattern mining on a dataset of Blood Transfusion Service Center to find a set of rules that predict the future behavior of blood donation. The applied algorithm discovered the relation between the times of blood donating and donating blood in a specific month. The authors argued that their approach helped blood transfusion centers to predict the blood supply and also ensured the availability of a sufficient set of blood units in stock for future demands.

Moreover, the study addressed by Sundaram and Santhanam in [31] applied a classification data mining algorithm, called CART decision tree, on a dataset of blood transfusion in order to classify and discover the future blood donors based on a set of patterns of blood donations. The authors stated that the applied algorithm enabled blood banks to specify the types of donor profiles and manage the demands of blood products by organizing blood donation activities such as recruitment and campaigns for voluntary blood donations.

The study conducted by Darwiche et al. in [32] utilized machine learning algorithms for predicting the future donations of blood. Particularly, the study applied the multilayer perceptrons (MLPs) neural network and support vector machine (SVM) algorithms on a dataset of Blood Transfusion Service Center, taken from the UCI Machine Learning Repository, to identify whether a patient will give his blood or not. Five variables in this dataset have been taken into consideration in the classification done by the algorithms including: months since last donation, months since first donation, total blood donated in c.c., total number of donations, and donation or non-donation in March 2007. The experimental results of the applied algorithms showed promising results.

Boonyanusith and Jittamai utilized in [30] an artificial neural network (ANN) and decision tree classification machine learning algorithms for predicting the potential donors to donate blood in the future based on a dataset of individual blood behavior. A set of factors that influence the blood donation decision for an individual have been used in the process of classification. These factors include: knowledge in blood donation, attitudes towards blood donation, perceived risks, altruistic values, and intention to donate blood in the future. The experimental results of evaluating the performance of the two algorithms showed that the performance of ANN outperformed the performance of the J48 decision tree algorithm in terms of the classification accuracy and it helped in managing groups of donors more effectively.

Alajrami et al. proposed in [48] an approach for predicting whether an individual is going to donate blood or not in the future based on using an ANN model. The authors also compared their approach with some other classification machine learning algorithms. The comparison results showed that their approach achieved the best classification results in forecasting the number of blood donors accurately.

The study performed by Ashoori et al. in [29] utilized four different types of decision trees (C5.0, CART, CHAID, and QUEST) for forecasting the blood donor's future behavior in blood transfusion centers. These four data mining algorithms have been applied on a blood donors' data in order to identify the number of blood units that could be provided by the future blood donors in case of emergency. The authors showed that the C5.0 decision tree algorithm has achieved the best accuracy result in the predication process.

Ramachandran, Girija, and Bhuvaneswari in [49] used a classification data mining algorithm to detect the availability of blood groups in the Indian red cross society (IRCS) blood bank hospital. Particularly, they applied the J48 decision tree algorithm, implemented in Weka, on a blood group donor's dataset in order to identify the regular blood donors in the future based on these variables: blood group, sex, weight, and age.

The study introduced by Mostafa in [33] investigated the effects of demographic, cognitive, and psychographic factors on the process of blood donation in Egypt. The classification process in his study was done based on these variables: sex, age, educational level, altruistic values, perceived risks of blood donation, blood donation knowledge, attitudes toward blood donation, and intention to donate blood. The author utilized two variants of artificial neural network (ANN): multi-layer perceptron (MLP) and probabilistic neural network (PNN) to predict the blood donation behavior of donors. Then, he compared these two variants of ANN with the linear discriminant analysis (LDA). The comparison results showed that the two ANN models achieved the best performance results compared to the performance result obtained by the LDA model.

3 Methodology

3.1 The proposed system

In this research, we are proposing an intelligent blood donation system that optimizes the blood wastage percentage. The system users are pre-registered human with different characteristics. Each user information is gathered in a database that has been built using the the implemented panel, which is a smart application for gathering users and selecting donors. A snapshot of the implemented panel is illustrated in Fig. 2.

The collected database will be accessed with every donation request, where a multi-sourcing inventory is considered here for decision making. Modern optimization techniques have been applied with the collected data to come up with an optimal donation process that minimizes the wastage blood and maximizes throughput with acceptable risk management. The remaining of this section explains how the optimization process is applied here. Figure 3 illustrates the proposed intelligent blood donation system.

3.2 Electronic medical records: dataset

The training data that has been tested for validating the proposed system is real. We implemented a smart application as a panel for building the medical records database, for all possible donors, transfusion centers, and people who may need blood transfusion.

The implemented panel has been downloaded on all users devices, and the users classify their collaboration in the proposed system. More information about the implemented panel will be discussed later in this section.

The prepared dataset can be considered as Big Data, as the number of users for this panel may expanded to cover most of the humanity, especially if the application spreaded all over the world.

In the mean time, all users have been contacted in person, by random calls, using booths in shopping centers, and via youth volunteers, convincing them to use the application for this research purpose. Predefined datasets that have been implemented by previous researchers and blood transfusion organizations have been considered as well for validating the proposed intelligent blood donation optimization system.

The dataset includes three main categories (patients, transfusion centers, and donors). Patients and donors must share some information in the application, such as blood type, medical status, age, transfusion location, and availability as a donor. A sample of the collected dataset is illustrated in Fig. 4

3.2.1 Implemented panel of donors on call

A new approach has been proposed in this research to keep the problem of incidental shortages in adequate proportion. A panel of donors is recruited, that are willing to be available to donate on a short notice. We refer to this

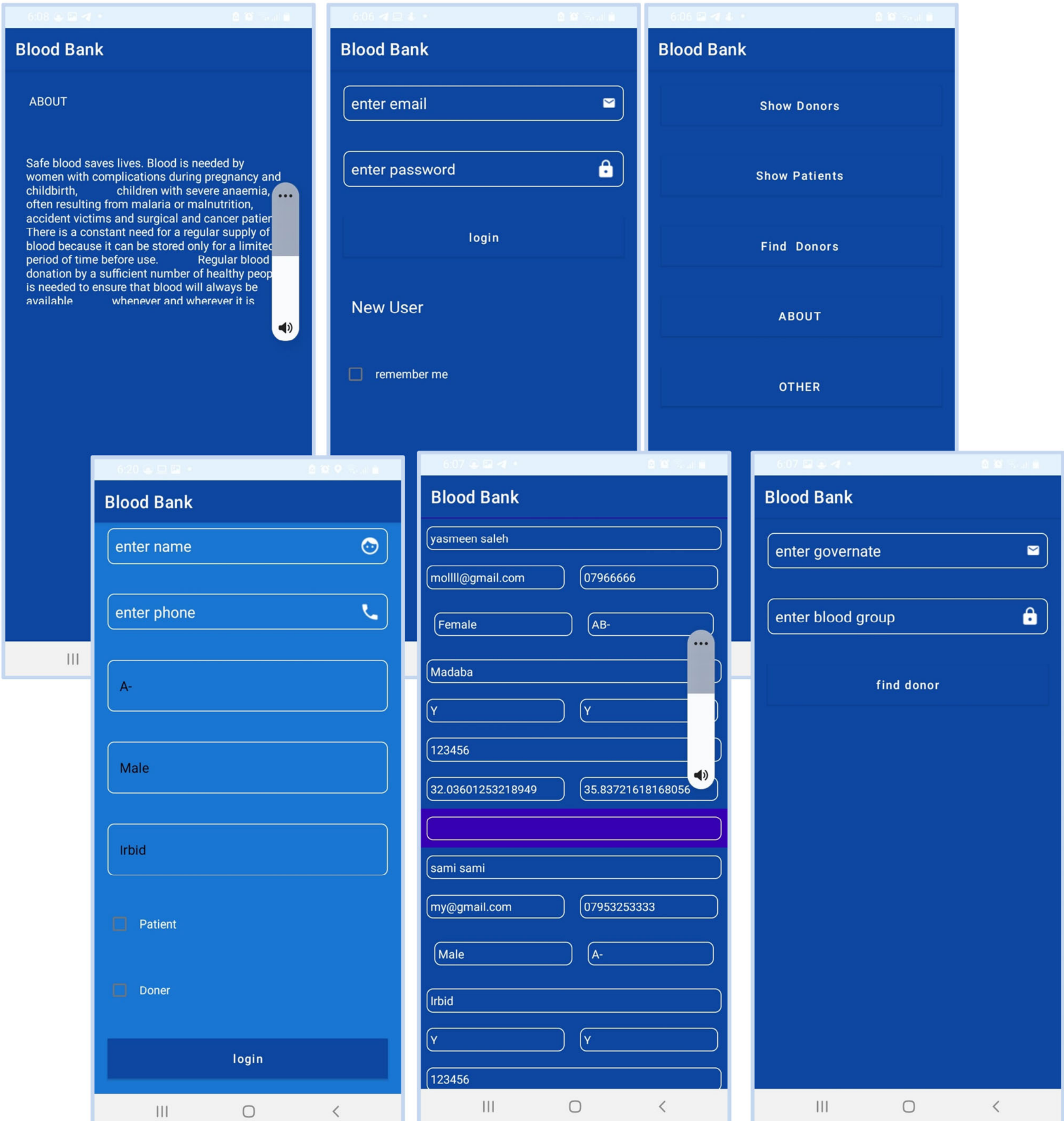

Fig. 2 The implemented panel

approach as having 'donors-on-call', i.e., when one of these donors is approached, then he/she will be asked to donate blood in the same day or in the upcoming days. This donation could be for whole blood or specific blood products. This option of having a donor available on a short notice will only be used when inventories are dropping precautionary low. The donors that are part of this panel, have been screened beforehand, and their blood group is known. Hence, in case of a shortage for a certain blood type, the donors with this type of blood can be specifically targeted.

3.2.2 Selecting donors

In this work, flexible donors are the ones that are willing to move between panels in order to 'donate the right product

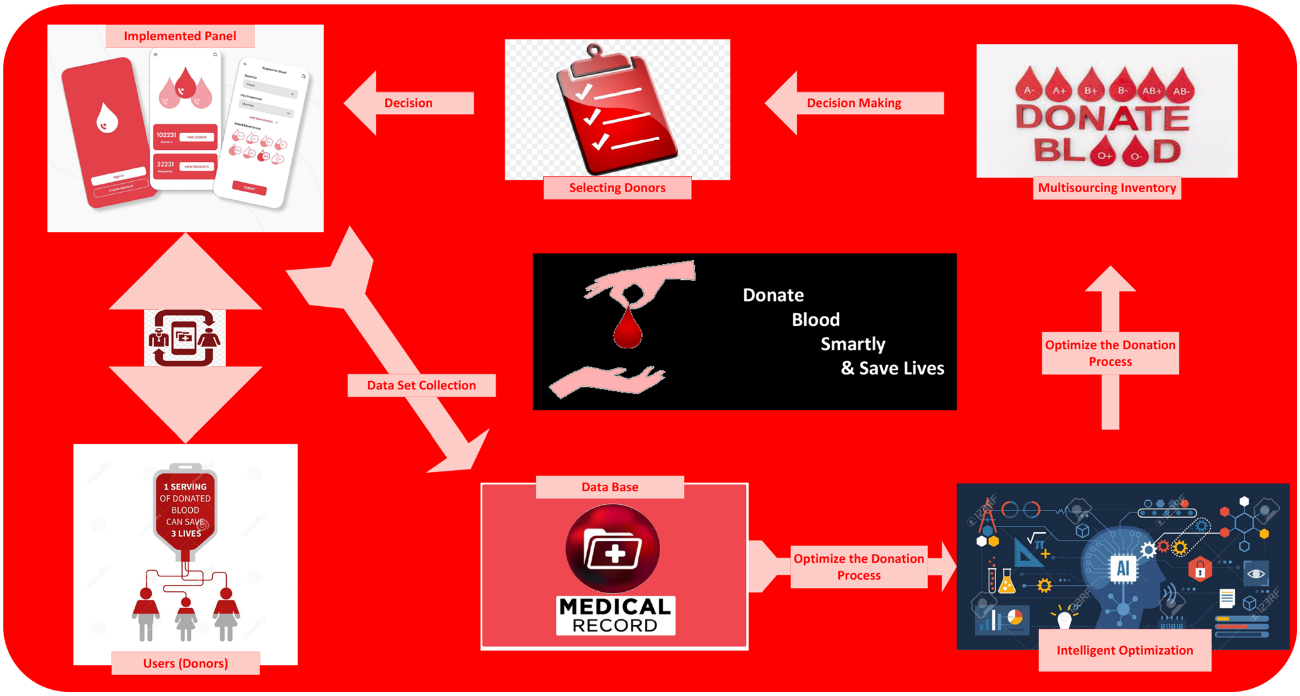

Fig. 3 The proposed intelligent blood donation system

email	uname	mobile	password	gender	bloodgroup	governate	patient	donor	lon	lat
aliali@ali.com	ali ali	0794444	123456	Male	O-	Madaba	Y	N	35.84378671364934	32.020907470193045
dooo@dooo@gmail.co	dodo dodo	09399393	123456	Male	A-	Irbid	Y	Y	0.0	0.0
mail@gmaill.com	mohammmmm	089999	123456	Male	A-	Irbid	Y	Y	0.0	0.0
mailco gmail.com	mariam ali	079766	123456	Female	O+	Karak	Y	Y	0.0	0.0
mohammed@gmail.com	mohammed	0790000000	111111	Male	A-	Irbid	N	N	35.86587688406362	31.975749750306825
molll@gmail.com	yasmeen saleh	07966666	123456	Female	AB-	Madaba	Y	Y	32.03601253218949	35.83721618168056
my@gmail.com	sami sami	07953253333	123456	Male	A-	Irbid	Y	Y	35.85341043340668	31.975749750306825
other@gmail.com	malek soud	22234444	123456	Male	AB+	Aqaba	N	Y	32.3	32.3
shahd@gmail.com	shahd shahd	079123456	123456	Female	A-	Zarqa	Y	Y	35.85341043340668	32.020907470193045
some@gmail.com	juman jameel	9399393	123456	Female	A-	Ajloun	Y	Y	32.3	32.3
youuu@ggg.com	sameer ahmed	0796555	123456	Female	B+	Irbid	Y	Y	0.0	0.0

Fig. 4 Subsection from the collected dataset

at the right time'. While this work includes the idea of exibility, the timing aspect has not been taken into account. The proposed approach is aimed at having the panel of donors available within a short time frame for a donation. It is especially this time aspect that creates an extra layer of exibility on the supply side when (expected) shortages are upcoming. In this way, a better match between supply and demand can be created. This reduces wastages in times of oversupply, and reduces shortages in times over under-supply. What makes this approach even more interesting, is that it also considers the location of the user. That is, when there is a request for a certain type of blood, the system locates donors that are physically present nearby a donation site at that time.

3.2.3 Multi-sourcing inventory

From a supply chain point of view, a blood bank, which is supplied by regular donations and by donations from the proposed 'donors-on-call' panel, can be seen as a multi-sourcing inventory system. The supply of blood from regular donations can be interpreted as one source of supply, while the new stream of supply from the standby donors used in cases of (predicted) shortages is another source. We note that supply from this second stream clearly has a shorter lead time, however, it is to be expected that this is a more costly option to acquire blood products. Therefore, this option should only be preferred when inventories are running low.

Only a random amount of the invitations sent to the donor panel will indeed result in blood donations. People might not always be available or willing to donate on a short notice, even though registered in the panel. Therefore, almost surely not everyone invited to donate will (be able to) show up. This results in a high yield uncertainty. In a general setting of multi-sourcing inventory models, yield uncertainty has been considered in this research.

It might be expected that because of the higher cost of collection, blood banks might increase the price set for hospitals for blood products collected in this way. This might effect the demand from the hospitals, as they will only restock at the higher price if necessary. We further note that in hospital blood banks, cross-matched blood products, that have been reserved for a particular patient, and of which a part will be released again after a few days, make the inventory model, especially when a new emergency supply source is added, even more interesting and challenging.

4 Results and discussion

First, to validate that the panel can be successfully recruited, the benefits of it should be assessed. Therefore, the proposed work has been tested for a small system, consisting of, e.g., one hospital (virtual) and one blood bank (virtual) only. After that, the model could be expanded to include a larger system of blood banks.

For a small setting, initially stylized mathematical models could be used. For this, it is important that decision rules have been considered, and the optimization equation must answer the following questions to minimize the amount of wastage blood.

- At which inventory levels are the donors called? (INV_LEV)
- How many donors in the panel receive a call? (NO_TRGT_DNR)
- Donors with which blood type are called? (DNR_BLD_TYP)
- What is the time frame to which they are requested to donate blood? (TIME)
- What is the impact of the duration of this time frame? (TIME_IMPCT)
- Should the request be canceled once enough blood or blood products have been collected? (CNCL_TIME)
- What percentage of the donors will indeed show up for donation? (DNR_PRCTG)
- What is the optimal amount of blood requested for this stage? (OPTML_RQST_BLD)

Since it would be infeasible to come up with optimal inventory rules, the goal should be to heuristically or approximately optimize the parameters of the policy. The ideal results would be to see a decrease in the shortage rates. The question is how this decrease depends on the decisions taken. It would also be of interest to see whether the extra cost incurred for using donations from donors in the panel, could be quantified. Equations 1 and 2 show the initial optimized wastage by answering the previous questions.

$$OPTML\_RQST\_BLD = \frac{DNR\_PRCTG \times INV\_LEV}{NO\_TRGT\_DNR \times TIME\_IMPCT} \tag{1}$$

$$TIME\_IMPCT = \int_{1}^{NO\_TRGT\_DNR} \frac{CNCL\_TIME}{TIME} \tag{2}$$

In any case, the goal is to relate the benefits with the inputs, such as the size of the panel, the blood types present within the panel, the willingness (and ability) of donors to show up for donation on a short call, the time frame set to them. Equation 3 shows the impact of these factors on the wastage optimization.

Another important aspect is how donors for the panel should be recruited, how they should best be approached, and how high their response rate would be to the calls for donation. The following questions have been considered to modify the general issue of recruiting and retaining blood donors to the optimization process.

- How people prefer to be approached? (ACCSS)
- What an acceptable time frame they consider? (ACPT_TIME)
- Which days of the week and which times of the day, they would be available? (AVL_TIME)
- How often at most they would like to be approached? (FREQ)
- What is the response rate to calls? (RSPNS_RT)

$$OPTML\_EXPCT\_BLD = OPTML\_RQST\_BLD \times RSPNS\_RT \tag{3}$$

where, (OPTML_EXPCT_BLD) is the optimized expected amount of required blood type, (PNL_SIZE) presents the size of the panel, (PRST_DNR_BLD_TYP) presents the blood types within the panel, (WLNG) presents the willingness rate of donors to show up for donation on a short call, it could be any number [0-10], and (RSPNS_RT) is the response rate for donors, which is calculated in equation 4.

$$RSPNS\_RT = \left(\frac{PRST\_DNR\_BLD\_TYP}{PNL\_SIZE}\right)^{WLNG} \tag{4}$$

where,

$$WLNG = \frac{ACCSS^{FREQ}}{ACPT\_TIME \times AVL\_TIME} \tag{5}$$

A simulated study has been conducted with the available dataset that has been built using the implemented system. Figure 5 illustrates the current distribution of discards of blood donations by reason [50].

The expected blood wastage in Jordan will be very low compared to the meantime status, as no smart solutions are used for minimizing the wastage blood, where the blood donation process is executed via volunteer campaigns. Figure 6 illustrates the distribution vision of discards of blood donations by reason in Jordan after applying the proposed system.

It can be noticed from Figs. 5 and 6 that the proposed system proves that the it can reduce the blood wastage, that has been lost due to expiry date passing, all over the country, and many benefits can be gained. The total discards in blood due to the expiry data can be reduced from 33 to 22%. Hence, the total amount of discarded blood is reduced. using the proposed system, we can facilitate the donation process with less cost and effort, and in a healthiest procedure. This would save lives, money, and meet the vision of the automated future in all human needs including healthcare system.

5 Conclusion and future work

Blood transfusion guarantees a continuous blood supply to meet the hospitals' demands and save lives. This study proposed a smart intelligent system that ensured the recruitment of donors to smartly donate blood based on a short notice. A panel was implemented which uses a donor-on-call procedure. The proposed system is built based on supply and demand concepts. The proposed system proved that it can minimize the blood wastage all over the country. It facilitated the donation process with less cost and effort, and in a healthiest procedure. This would save lives, money, and meet the vision of the automated future in all human needs including healthcare system.

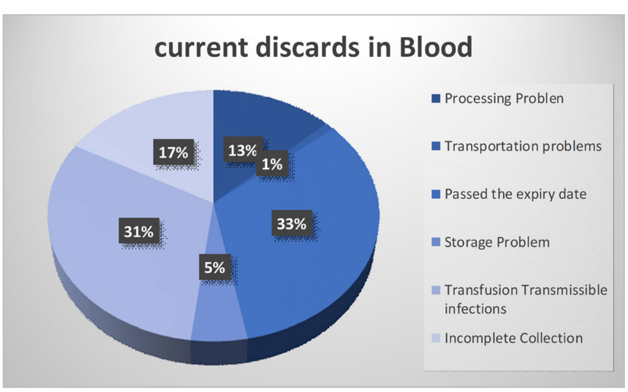

Fig. 5 The current distribution of discards of blood donations by reason (from the WHO)

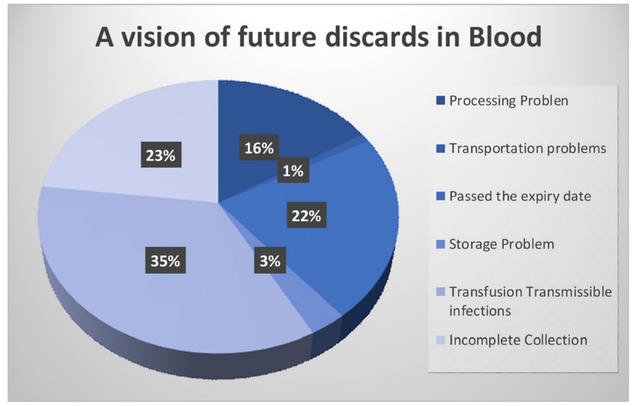

Fig. 6 The distribution vision of discards of blood donations by reason in Jordan after applying the proposed system

Based on the intelligent operation research conducted in this paper, five equations have been implemented and applied with the collected dataset. The five implemented equations have been employed with the Donors-on-Call panel to optimize the donation process by selection the best donor. This is based on multi-sourcing inventory, blood type, donors location, Timing, and the donors desire to donate. The main contribution of this paper is develop an intelligent blood donation system that optimize the blood wastage percentage. Specifically, we conducted the following contributions: first, we implemented a smart application as a panel for collecting medical records dataset. Second, we developed smart intelligent system based on donor-on-call approach that ensured the recruitment of donors to smartly donate blood based on short notice. Third, a set of optimization equations have been built for optimizing the process of donation in order to reduce the blood wastage and prevent blood shortage

As machine learning techniques have been widely applied to support the blood donation process, one of the future prospective is to apply machine learning for predicting the behaviour of the proposed intelligent blood donation system. Such as, predicting the number of donors who are likely to donate, locations of donors, timing of the future blood donation requests and compare between them.

Author Contributions All Three Authors worked in an equivalent load at all stages to produce this research

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Data availability The data set used in the work will be available upon request

Declaration

Informed consent I have read and I understand the journal information and have agreed to all mentioned terms and conditions.

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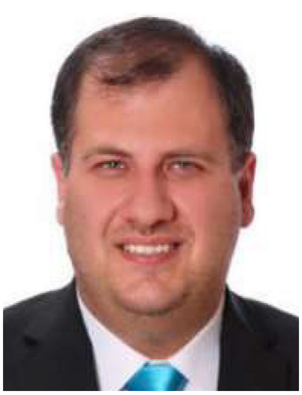

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