An Artificial-Intelligence-Based Omnichannel Blood Supply Chain: A Pathway for Sustainable Development

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Conflicts of interest are described here.

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Abstract

We formulated and tested an innovative omnichannel blood supply chain (OBSC) model based on artificial intelligence (AI) using inputs raised in semistructured interviews conducted with heath care practitioners in a blood supply chain. The proposed AI-based OBSC model addresses the supply and demand imbalance in crucial situations for blood supply chains. A resource dependence theory bottom-up approach was applied to underpin the OBSC model. This model consists of two parts: (a) helping to find the closest and fastest available blood supply (omnichannel perspective) and (b) raising a blood supply request among university students (with the help of the university's IT system) through SMS messaging in case of emergencies or blood shortages (AI perspective). This OBSC model is significant because it contributes to the United Nations' Sustainable Development Goals, specifically the goal 3 to "ensure healthy lives and promote well-being for all at all ages."

Keywords: omnichannel, supply chain management, sustainable development, artificial intelligence, health care

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Perishable items are a crucial part of operations in the health care industry, and ordering, storing, and delivering these items is a constant challenge. Blood is one of the most important medical supplies for ensuring patient health and saving lives. Blood used for medical purposes is mostly obtained through donations, and without adherence to specific measures, stored reserves of blood can quickly become partially or entirely unfit for use. According to the WHO (2020), the number of blood donations and voluntary nonremunerated donors decreases steeply from high-income countries to low-income countries. However, ensuring availability and timely delivery of blood supplies in normal and emergency circumstances is crucial, regardless of the region.

Therefore, we formulated an innovative solution to ensure smooth blood supply in emergencies and blood shortages using an omnichannel blood supply chain (OBSC) model based on artificial intelligence (AI). The term *omnichannel* refers to the combination of all physical and digital channels to create an innovative and unified customer experience (Sealey, 2014). An omnichannel approach offers customers the ability to find alternative or complimentary options to meet their demands. Additionally, this approach has the potential to reduce costs and wasted time and increase efficiency.

AI can optimize several aspects of a blood bank system through automatic processing, such as auto-generating emergency alerts for blood donors, managing inventory and transfers, predicting blood demand using machine-learning algorithms and a data-driven approach, and retaining potential donors. AI can improve the entire blood supply chain, allowing more patients in a variety of conditions to receive blood and decreasing the likelihood of blood scarcity.

The studies on blood supply in disaster situations (e.g., Fahimnia et al., 2017) have recommended using a stochastic biobjective supply chain design model to ensure blood supply in disasters. Osorio et al. (2018) suggested using a new transshipment policy for perishable items that emphasizes the age of the oldest item in the system to improve supply chain performance. Samani and Hosseini-Motlagh (2019) incorporated a two-phase preemptive policy to determine supplementary blood facilities, facilitate cooperation in the production process, and decrease interruptions. Rehmani (2019) presented a robust model of a dynamic emergency blood network design problem. Cheraghi and Hosseini-Motlagh (2020) incorporated three criteria—urgency, fairness, and risk—in their case study to evaluate the blood supply's responsiveness and reliability. Seyfi-Shishavan et al. (2021) proposed a new multiperiod mathematical model that uses fuzzy trapezoidal numbers and spherical membership degrees for blood supply network design. In particular, Goiana-da-Silva et al. (2019) explored how the Portuguese Ministry of Health, along with the Portuguese National Health Service and partners from private media companies, launched three campaigns promoting health and disease prevention on an omnichannel communication platform under a tight budget.

In general, relevant studies on omnichannel health care, such as that by Goiana-da-Silva et al. (2019), are very limited, and this research area is in its nascent phase. An omnichannel approach that involves integrating AI has not been considered or explored in the area of blood supply chain management.

The omnichannel approach proposed in this paper provides new means of service fulfillment and information provision. Regarding the omnichannel approach involving the integration of AI for blood supply chain management, several scholars have acknowledged the importance of attempting to propose a model that integrates all available information about donors, supply, and demand through one outlet to provide an innovative and unified customer experience. Additionally, it is accepted that information on lifesaving commodities must be error free, indicating that AI could be used to facilitate the operation of this model. Furthermore, Clauson et al. (2018) insisted that cutting-edge technologies and innovations should be adopted in the health care industry to move beyond the existing modus operandi. Studies have established the need for a technology-oriented and innovative approach to provide a smooth blood supply (e.g., Cheraghi & Hosseini-Motlagh, 2020; Lee et al. 1997; Zahiri & Pishvaee, 2017), which would solve social issues related to sustainability.

Therefore, the following research questions drive this study: Does an omnichannel integrated AI approach help universities and their students play an integral role in managing the supply and demand of blood? Can such an integrated AI approach lead to sustainability? This study uses the theoretical lens of the resource dependence theory (RDT) and suggests a bottom-up approach and a contingency plan to involve students in meeting the demand and expectation of blood supply in health facilities in certain areas.

To address the aforementioned research questions, we proposed an AI-integrated OBSC model to increase the health care industry's efficiency and effectiveness and to support the end users. This model consists of two parts: (a) helping to find the closest and fastest available supply of blood and (b) raising a blood supply request among university students (with the help of the university's IT system) through SMS messaging in emergencies or blood shortages. The main purpose of this OBSC model is to manage the supply of lifesaving commodities in crucial conditions (e.g., natural disasters). Ultimately, this model may help health institutions reinforce and improve blood supply for normal and emergency scenarios.

We organize the rest of this paper in the following way. In the second section, we discuss the related literature and the research issue in depth and verify the existing knowledge gaps. In the third section, we define our methodology. In the fourth section, we discuss the results of the interviews. In the fifth section, we propose the AI-based OBSC model. In the sixth section, we present our test of this model and discuss the results. In the final sections, we discuss this study's novel contributions and avenues for future research.

Literature Review

Theoretical Background

We applied RDT in this study to explore how outsiders (i.e., university students) can meet hospitals and other health facilities' needs and demand for blood supplies. Pfeffer and Salancik (1978) were the first to propose this theory, suggesting that RDT characterizes organizations as an open system that depends on contingencies in the external environment.

Regarding donation behavior, RDT suggests that an individual's donation behavior is affected by internal and external resources, including human capital (personal characteristics), social capital (social networks), and cultural capital (social assets). For the purposes of this study, blood donation is characterized as an altruistic or prosocial volunteer act and a unique type of gift to other human beings. However, remunerated blood donation (e.g., selling blood) is beyond this paper's scope. Hospitals and other health institutions depend on blood donors to meet their blood supply demand in normal and emergency situations. With universities' mediation, students and health institutions can build an informal partnership to manage the supply and demand of blood.

We provide an AI-based omnichannel solution to mitigate supply issues in getting blood to health institutions. This model helps health institutions connect with external institutions and individuals to match the supply and demand of blood and to absorb uncertainty, even in emergency situations. Therefore, in light of RDT, a bottom-up approach was integrated to involve volunteers and to provide the expected blood supply in certain areas. According to Stewart et al. (2015), a bottom-up approach involves a number of individuals working together to achieve a cause. Keefe et al. (2006) explained that many people working together can coordinate volunteer initiatives to achieve specific causes (e.g., blood donation). A bottom-up approach provides goods, services, and information; coordinates and encourages recovery efforts; and enables such groups to access local knowledge, utilize and leverage social capital, and adapt to changing circumstances (e.g., Dahl et al., 2021; Grube, 2020).

Therefore, bottom-up approaches can supply essential lifesaving products and services and can organize reconstruction and recovery efforts because they (a) provide access to local knowledge, (b) can leverage social capital (i.e., social networks), and (c) are adaptable (e.g., Marvi et al., 2021; Storr et al., 2016). In a blood supply chain, RDT depends on the bottom-up approach.

Omnichannel, AI, and Emergency Services

Emergency services, such as police, health care, and fire services, have used the omnichannel approach to increase efficiency in their responses. Although an omnichannel is primarily a retail concept (Ailawadi, 2021), it can be applied to integrate all of the communication channels between two parties and to overcome a multichannel approach's shortcomings (i.e., Piotrowicz & Cuthbertson, 2019; Sun et al. 2020). Specifically, the omnichannel approach has been used in health care for pathway-driven patient activation (e.g., Dahl et al., 2021; Ghosh et al., 2022).

Patient activation is defined as the state in which an individual possesses the knowledge, skills, and confidence to take independent action to manage their health and treatment (e.g., Hibbard et al., 2004). Tovide (2021) proposed developing a mobile design for an emergency service system for deaf people by integrating omnichannel parameters. Al-Warith and Moss (2021) discussed how the Dutch national police force developed the Corporate Newsroom initiative, which provides instant content to support police work, enabling communication between internal and external target groups using social media as their channel strategy. Regarding ambulance management systems, Song et al. (2020) suggested that establishing an ambulance control tower could prompt action on a manager's or operator's mobile device. Additionally, when assigning ambulances, an ambulance dispatcher would first obtain a suggested assignment from a decision support system and then manually adjust the demand based on real-time information regarding ambulance availability. The fire emergency services followed a similar approach, which allowed them to integrate many options or omnichannels with one touch.

Digital trends, such as cloud infrastructure, AI, and the internet of things, are making it possible for all channels to connect and generate new information (e.g., Akhtar et al., 2022; Cordon et al. 2016). AI is usually deployed in mechanical and computing systems to deal with highly sensitive circumstances and to perform given tasks (e.g., Bock et al., 2020; Formosa et al., 2022; Jain et al., 2022), and it has the potential to recognize the demands of a certain entity and to create or bridge relationships between entities (Yang et al., 2020). Many technologies are involved in the deployment of AI, including deep-learning platforms, machine-learning platforms, natural language generation, and speech recognition. Researchers have explored the key drivers of AI adoption, such as quality of life, operational performance enhancement for businesses, and learning (e.g., Augusto & Nugent, 2006; Kamble et al., 2020; Knox, 2020). Loureiro et al. (2020) presented four aspects related to AI and organizations: (a) managing and implementing AI systems in the organization, (b) designing human–machine integrated service strategies, (c) dealing with autonomous systems in social environments, and (d) enabling AI systems to support the development of a sustainable planet. With these aspects, AI can help optimize processes and tasks and reduce completion time.

There is little evidence available regarding the implementation of the omnichannel approach in the health industry (e.g., Clauson et al., 2018; Goiana-da-Silva et al., 2019; Tovide, 2021). We hypothesized that an OBSC model with integrated AI plays a main role in sharing and receiving information from donors and receivers through a multichannel approach. In this context, AI would optimize the supply and demand of blood in a specific geographical location and share up to date information with donors, health institutions, and blood banks.

Blood Supply Chain

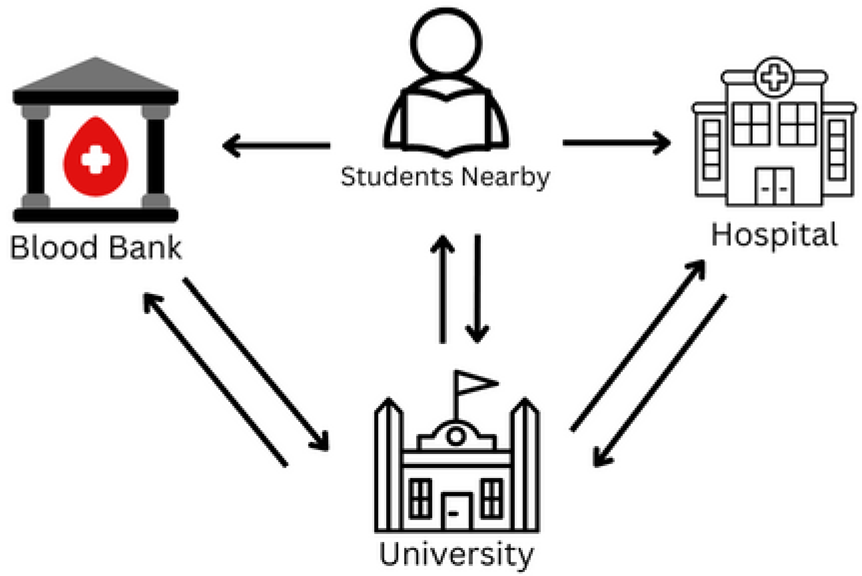
Blood supply plays a crucial role in ensuring health and saving lives (Zhou et al., 2021). Therefore, management of the blood supply chain is considered of the upmost importance (Priporas et al., 2017). Priporas et al. (2017) shared the five echelons of the blood supply chain: donor, mobile collection site, blood center, demand node, and patient. The specific situations and conditions of a society or individual scenarios initiate either a “push” or “pull” blood supply chain strategy. In the push blood supply chain strategy, the blood supply is determined by anticipated customer demand based on daily routines. In the pull supply chain strategy, the supply of blood is determined by actual customer demand based on regular or unexpected events. Demand for blood is constant and can vary in unexpected scenarios. Therefore, the security and distribution of blood supply during and after emergency circumstances depends on efficient management of the blood supply chain (e.g., Beliën & Forcé, 2012; Sheu, 2007).

Apart from health care entities and donors, the OBSC model has few critical actors. Providing information is one of the most crucial activities in the blood supply chain (e.g., Haghjoo et al., 2020; Khalilpourazari et al., 2020), and information regarding lifesaving commodities should be error free (e.g., Hussein & Teruya, 2012; Katsaliaki & Brailsford, 2007). A stable and steady flow of information between partners or stakeholders enhances the management of supply and demand and effective blood distribution. Storage and availability of blood is the second-most important part of the blood supply chain. If blood is transfused and stored properly and is available on demand, patients will receive proper and healthy treatment when needed (e.g., Dzik, 2008; Raat & Ince, 2007). An intermediary entity (i.e., university) is the third integral part in cases of blood unavailability or increased demand due to specific reasons and plays a role in arranging and providing blood to a transfusion and storage facility in emergency situations. Such an intermediary entity should have contact information for potential donors and additional health-related details, such as blood type and illness. To create this list and attract volunteer student donors, universities initiate programs to encourage students to participate in their volunteer program and to donate blood in emergency situations. This may interest and excite the students and motivate them to become potential lifesavers acting on their societal, moral, and ethical values.

Because blood is considered a crucial resource for human life, the supply chain for this resource should be effective, efficient, and systematically integrated among all stakeholders. Figure 1 presents an example of the blood supply chain.

Figure 1

Blood Supply Chain



This study proposes an AI-integrated model consisting of two parts: (a) providing relevant information regarding the existing blood supply using geolocation and (b) helping fulfill requirements in case of emergencies and high demand. In case of emergency blood requirements, the university will inform its volunteer students and ask them to donate.

Methodology

Research Design

The research design is the blueprint that establishes the study's parameters. We used an exploratory research design, which is frequently used during early research stages, when the researchers investigate a research topic to elucidate the "why" component of the phenomenon. Exploratory designs facilitate replication and serve as a mechanism for corroboration across cases (Ghouri et al. 2022; Yin, 1994). This method enables researchers to identify glaring gaps in existing theory and contributes to the advancement of scientific models (Yin, 1994). Furthermore, it entails collecting descriptive data that do not require statistical analysis.

The data collection technique selected in this case is semistructured interviews, which are effective when little to no information is available to answer a research question because they enable the researcher to obtain new information (O'Donoghue, 2018). In this case, the problem area is the Pakistani blood supply chain, which is a largely unexplored phenomenon. This exploratory study is intended to uncover the maximum amount of fresh insight into this phenomenon.

Research Philosophy and Approach

Research philosophy enables the researcher to establish the paradigm within which the research is to be conducted. Considering the existing research, it is necessary to employ an interpretative-based research philosophy, which implies that findings can be inferred by interpreting the thoughts and opinions of individuals who have experienced the relevant phenomenon (Ghouri et al. 2022; O'Donoghue, 2018). We employ an interpretivist approach in this study to achieve the research objectives by considering professionals' opinions and voices and by viewing similar situations or problems from various points of view to gain in-depth and experience-based knowledge.

Like many other emerging-market countries, Pakistan has an inadequate health care system (Anwar & Shamim, 2011; Khalid & Abbasi, 2018), particularly considering the fragmented blood transfusion service (Ali et al., 2021). To deal with this problem, the proposed OBSC model essentially requires managers who have been working in the health care sector for more than five years to share key information related to the mechanisms and problems encountered along the blood supply chain, either directly or indirectly (i.e., from the patients' perspective). Therefore, to achieve our objectives, we employed an interpretivist philosophy. This research philosophy helped us draw conclusions by interpreting the thoughts, opinions, and experiences of relevant professionals working in the blood supply chain (Ghouri et al. 2022; O'Donoghue, 2018; Roulston & Choi, 2018) and helped us establish the OBSC model for Pakistan.

Based on the interpretivist philosophy and the qualitative interview research design we used, we postulated that the selected approach is inductive. The inductive method proposes developing a theory based on data-driven observations (El Sherif et al., 2018; Zhang et al., 2022). We constructed the Pakistani OBSC model by employing an interpretivist philosophy that uses an exploratory research design to explore the blood supply chain and related factors.

According to Mhango (2018), exploratory research design goes hand in hand with interpretivism, paralleling this study's qualitative nature and its methodologies with the aim of answering the research questions. In addition, the qualitative research strategy can be characterized as inductive (Bahari, 2010), and this approach includes constructing a theory as an outcome of empirical data observation (Saunders et al., 2007). Additionally, inductive logic and qualitative methods are generally employed with the goal of understanding a particular phenomenon of interest in its social context (Rocco et al., 2003). Moreover, in qualitative research strategies, the inductive approach is related to theory generation (Bahari, 2010), and in this study, it led to the formation of the OBSC model.

Sampling Method and Size

We primary collected data from interviews with seven participants who work in managerial positions related to blood supply chain operations in the Pakistani health care sector. We selected these individuals because of their valuable experience and insights, which could help us achieve our objectives (Roulston & Choi, 2018). According to Creswell (2003) and Patton (1990), the appropriate sample size should be determined based on the study's purpose and the research questions. The sample size of seven interviewees is justifiable per several researchers' recommendations (i.e., Cresswell, 2013; Polkinghorne, 1989) that a sample size between five and 25 is appropriate for a qualitative study. Another justification is that we used purposive sampling. This type of sampling approach improves the study by better matching the sample to the research aims and objectives and allows researchers to pick the most suitable individuals from the available population (Campbell et al., 2020).

Purposive sampling is a valuable tool for researchers to consider when they plan their studies. Additionally, a purposive-sampling approach better matches the sample to the research aims and objectives, thus enhancing the study's robustness and the trustworthiness of the study-related data and results (Campbell et al., 2020). Furthermore, the researcher determines what needs to be recorded in the data and accordingly sets out to find the appropriate respondents who are able to provide this information on the basis of their knowledge or experience (Bernard, 2002). Usually, researchers use this type of sampling in qualitative research for the identification and selection of information-rich cases to utilize the available resources appropriately (Patton, 2002). Similarly, Cresswell and Clark (2011) claimed that such sampling involves the identification and selection of individuals or groups of individuals who are well informed and proficient in the details of the phenomenon of interest. To sum up, in contrast to convenience sampling, which is based on factors such as easy availability, accessibility, and proximity and is applied in quantitative and qualitative studies, purposive sampling is intended to focus on individuals with specific characteristics who will be able to assist more in the relevant research and is mostly applied in qualitative exploratory studies (Etikan et al., 2016).

Data Collection Method

The data collection was based on semistructured interviews with managers in the blood supply chain. Semistructured interviews were chosen as the data collection method because they allowed us to gain a thorough understanding of the phenomenon under study and to probe in response to the respondents' answers. This method is a very flexible strategy for interviewing people and gathering qualitative data (Peters and Halcomb, 2015). Respondents were contacted and interviewed following recruitment in the manner described in detail in the following section.

Respondents were approached through formal channels to arrange one-on-one interviews. After confirmation was obtained, the respondents were approached at their workplaces, and written informed consent was sought before the formal interview to guarantee that the participants were aware of the aims of the study.

The general steps involved in conducting the interviews were carried out in accordance with Roulston and Choi's (2018) recommendations. The semistructured-interview protocol was created based on the following steps. First, interview questions were developed in line with the research questions. Second, it was ensured that a variety of questions related to each specific research question were available. Third, prompts were added to help elicit as much information as possible after the main pool of questions was determined. Fourth, an expert assessed the interview protocol to ensure the questions' dependability and face validity. Last but not least, a pilot interview was conducted to evaluate the interview protocol's applicability in real-life situations.

The participants were made aware of the study's purpose and the methodology that would be used to collect and record the information they provided. Following their informed consent, the interview proceeded as designed. An audio recording of each interview was saved on a hard drive along with a few key points that were jotted down during the interview in the form of notes to give the results credibility and validity (King et al., 2018). The interview script was designed to address the main issues and challenges related to the blood supply chain in Pakistan.

Data Analysis Method

In the first step, a verbatim transcription of the audio recordings was made. These transcripts were reviewed in light of the notes taken during the interviews to ensure that no information was missing and no errors were present. Additionally, a soft or hard copy of the relevant written transcript was sent to each respondent for their review in case any mistakes were made during transcription.

Thematic analysis is by far the most frequently used data analysis method for qualitative interviews, and it is based on the descriptive data the participants provide. *Thematic analysis* refers to the process of categorizing and coding data according to recurring patterns of words and phrases. These codes are then grouped together to form themes, from which the results are derived (Terry et al., 2017). In this study, a similar thematic analysis approach was used, and two independent coders coded the data. According to Vaismoradi et al. (2016), this method improves the study's integrity. The themes were developed through a process in which objectives were used to establish the major themes, and data was analyzed to determine the key components in these themes (Terry et al., 2017). The outcome of the thematic analysis addressed the main issues and challenges related to the blood supply chain in Pakistan, with these issues and challenges being used to help design the proposed AI-driven omnichannel blood supply chain.

Additionally, ethical considerations were taken into serious consideration because this study involves primary research. Written informed consent was obtained to ensure that each participant was in agreement with the study's objectives. Respondents' data was not manipulated in any way, and the findings were reported based entirely on the statements of those who were interviewed. We declare no conflicts of interest. Moreover, the data was stored securely on a password-protected device to maintain security. The confidentiality of the participants' personal information was maintained throughout this study (Robertson, 2021).

Results of the Qualitative Phase of the Study

In this section, we describe the results that we obtained after conducting the interviews. We gathered responses from the participants and categorized the results based on coding of themes and subthemes, as detailed above. We used thematic analysis to answer the research questions with respect to the data collected in the interviews and the existing literature on the topic. Terry et al. (2017) stated that thematic analysis is a qualitative data analysis technique that can be used to read sets of data from sources such as in-depth interview transcripts. The emerging themes are as follows.

Theme 1: Lack of Technology-Driven Protocols in the Pakistani Health Care Sector

According to the respondents, the blood supply chain in the Pakistani health care sector is not adequately managed due to various challenges and barriers. The current model followed in Pakistan is a response-oriented model for the management of blood supplies during a disaster, such as a flood or an earthquake. Similar findings were reported by Zaheer and Waheed (2016), who stated that the conventional relief model is followed in Pakistan alongside the response-oriented model. The respondents also mentioned that tertiary hospitals manage their blood supply chain via a quality assurance program whereby internal quality control is conducted on blood products. Standard operating procedures are maintained in the blood supply chain. According to Sultan et al. (2018), standard operating procedures are an indication of an effective supply chain because they minimize errors: "The supply chain has its drawbacks but strengths as well. There are standard procedures for the IQC of blood products. There are regular audits, and the transfusion services are regularly improved by increasing the competency of staff" (p. page).

Blood supply chain management processes depend on supervision, and health care professionals and organizations select the techniques to provide the blood products the patients need. Regarding the management processes in the Pakistani health care sector, Respondent 5 stated,

> Management processes need good leadership and management strategies. The health care sector in Pakistan needs consideration of management practices because the implementation of efficient procedures needs collective efforts of the employees and management staff. Blood supply chain management in the health care sector has been a major issue for decades that needs proper protocols to be followed.

The above response indicates that blood supply chain management issues are very common in the health care sector in Pakistan. Fahimnia et al. (2017) also pointed out the needs of blood supply chain management in the Pakistani health care sector. It has been noted that the health care sector in Pakistan has poor management policies and has failed to maintain the necessary protocols for blood availability (Arshad Ali et al., 2021). In addition, based on the interviews conducted, we also note that several areas of the health care sector in Pakistan need proper health care system protocols and aids so that necessary interventions can be taken, as Anwar and Shamim (2011) determined. The management and maintenance of blood products are based on the proper monitoring of the practices and measures that are required for blood products' stability (Rossaint et al., 2016). To ensure the proper monitoring of practices and measures, tech trends, such as AI and machine learning, should be incorporated to encourage effective people management and optimal decision making (Rathi, 2018). Ernst and Young

(2018) made a similar suggestion when they talked about the great potential of AI-based management applications to increase management efficacy and employee productivity.

Theme 2: Poor Co-ordination Among Actors During Emergencies

This theme is based on the issues that we observed regarding blood supply chain management in the health care sector in Pakistan. We asked the participants questions about challenges and organizational weaknesses in addressing them. Regarding the issues that are faced in managing blood supply during emergency situations, Respondent 3 stated,

> As a manager, I have to deal with such situations on a daily basis. It is very difficult to arrange blood donors during emergencies. Screening of blood and its storage has affected the management of blood supply to a great extent.

The above response highlights that arranging and storing the supply of blood products has impacted supply chain management practices in the health care sector. Researchers have also highlighted the challenges that the health care sector in Pakistan faces (Anwar and Shamim, 2011; Khalid et al., 2018). It has been mentioned that the health care sector cannot manage manmade or natural disasters in Pakistan due to the scarcity of resources and poor management systems. Researchers have found that poor coordination between systems, unavailability of blood stocks, and a lack of blood transfusion management are the main concerns, as Respondent 5 mentioned:

> I have faced the worst consequences due to the shortage of blood in the hospital. A few years back, due to the earthquake, emergencies in the hospital have raised the technical difficulties in managing blood on time. This has resulted in many deaths.

Stanworth et al. (2020) highlighted the same points. Other researchers have also discussed the situation of earthquakes in Pakistan and problematic circumstances in the country

(Mehnaz, 2016). It has been mentioned that natural disasters in the country negatively affect the country's health care sector and economy.

Moreover, it has been shown that the management of the supply chain for blood and drugs is the major concern health care professionals and managers have noted (Abbas et al., 2020). On the other hand, the interview transcripts and recorded responses from the participants show that managers face issues in blood supply chain management due to a lack of resources, storage capacity, storage parameters and maintenance, trained staff, blood supply networks, etc. In other words, in times of disaster, the blood supply to hospitals is a crucial issue in supply chain management (Haghjoo et al., 2020). Regarding the challenges the health care sector faces with respect to the management processes, Respondent 1 stated,

> It is very difficult to manage sudden emergencies and arrangement of resources, specifically blood and drugs for the affected individuals in Pakistan. In comparison, health care sectors in developed countries have strong management plans and strategies that reduce the risks of challenges and support supply chain management.

The above responses highlight that blood supply chain management in the Pakistani health care sector is weak compared to the management process in the health care sectors of more developed economies. Kruk et al. (2018) stated that blood availability needs to be increased in developing countries to meet the aging population's needs.

Considering the above factors, artificial intelligence can enhance the ability to manage the blood supply in the case of natural disasters (Kuglitsch et al., 2022). Moreover, it has been stated that the challenges of blood supply chain management can be reduced by using new approaches and the recruitment of trained professionals in the health care sector (Benzidia et al., 2019) or through the use of AI-based management processes. This requires training of new managers to develop their knowledge and become skillful practitioners and can boost not only teamwork but also employee performance (Ernst and Young, 2018).

Theme 3: The Importance of Monitoring and Assessment in Enhancing Efficiency in the Omnichannel Blood Supply Chain

This theme emerged from the participants’ responses based on the questions asked during the interviews. We asked questions regarding OBSC management in the health care sector as well as its importance and significance in today’s context. We collected and analyzed the participants’ responses to observe health care organizations’ perspectives on selecting omnichannel processes for blood supply chains. It may be observed that employees that are engaged in blood supply chain management are responsible for managing inventory and providing products when needed. Respondent 4 stated, “We have trained employees and supervisors who monitor the needs and requirements of blood. Managers have made strict policies for the management of healthcare needs of the patients so that the challenges could be minimized.”

The above response highlights that OBSC management in the health care sector requires proper monitoring and assessment. It also requires appropriate management approaches and practices so that blood shortages will be avoided or reduced. Betcheva et al. (2019) stated that OBSC management is linked with patient care and minimization of medication errors. Managers have to pay significant attention to the status of blood products from donors and to maintaining records in health care systems. Respondent 7 addressed the need for OBSC in the health care sector:

> There are several issues that are faced by both patients and the health care professionals due to unavailability of blood products. As a manager, it is my responsibility to obtain the

best possible measures in order to provide good care to the patients. I think omnichannel blood supply chain management can help in the maintenance of inventories, lowering costs of products, and analysis of patients' and organization needs.

The above response asserts that the presence of an OBSC can help the health care sector work efficiently. Moreover, other research suggests that management should think about the effectiveness of an omnichannel approach for blood supply because it has huge potential to serve health care providers in an affordable way (Kaplan, 2021). For efficient management and to boost all departments' ability to gather and process data and to make preliminary forecasts based on changing conditions, AI technology can be used. AI breaks down and transforms data into a format that is easy to understand using machine learning, which is an advanced form of AI that scans data to identify patterns and modifies program actions accordingly (Ernst and Young 2018; Rathi, 2018).

The themes highlighted in this section are useful for a variety of purposes. First, they enable researchers to gain a thorough understanding of and insights into the existing scenario of blood supply chain operations in Pakistan. Second, it is important to identify the challenges currently faced in blood supply chain management. Third, this helps us develop our model regarding an omnichannel blood supply chain.

Formulation of AI-Based Omnichannel Blood Supply Chain Model

Dataset

The dataset for this study came from a case involving a network of four medical institutions in Karachi, Pakistan. All of these institutions experienced unknown levels of demand due to uncertain variables (e.g., emergency, time, and condition). In the proposed model, a central AI system manages blood inventory requests and optimizes existing blood units by transshipping between multiple hospitals based on each hospital's demand as well as analyzing the demand based on the specific time of day.

We constructed our model based on single blood group unit management, assuming that blood units have an 11-day shelf life from the time they arrive at a hospital from the central blood bank, after which they must be destroyed and designated as outdated (wastage). As a result, each hospital's inventory is defined according to an 11-value array, with each element indicating the number of blood units with a specific remaining shelf life. The input variable space of our modeling issue is 44 dimensional, based on the preceding description of the data, with each set of 11 components representing one of the hospital's current inventory levels. Thus, each hospital's inventory comprises an array based on 11 values, and each array represents the number of blood units available in their inventory based on shelf life. The input variables of demand prediction and transshipments are based on the 11 scale inventory levels of each hospital.

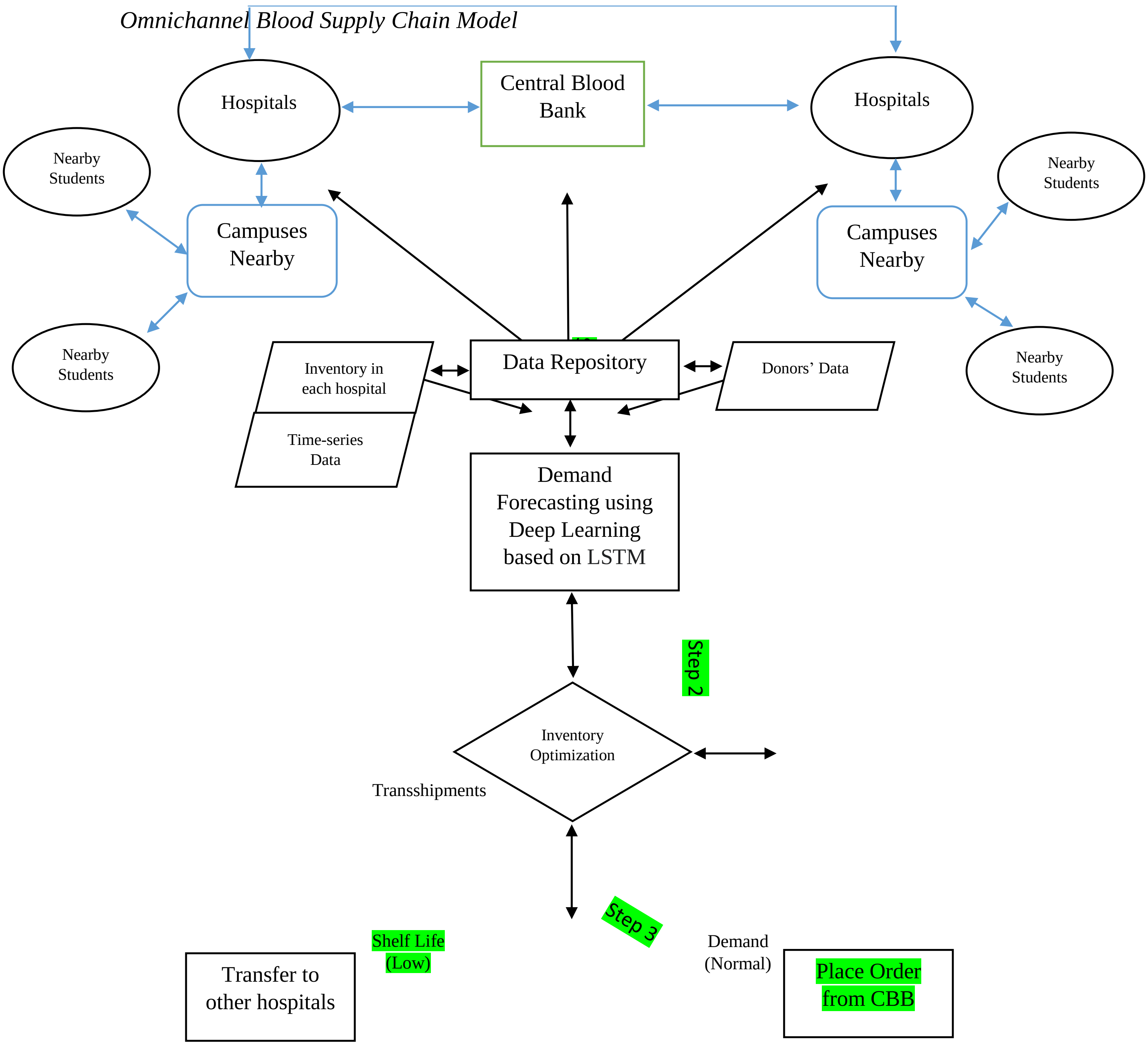
We utilized the two-stage stochastic machine learning AI model Dehghani et al. (2021) proposed to capture the relationship between the blood inventory and the optimization of inventory via transshipment orders. Due to the uncertainty of blood demand, which changes every day for each hospital, the proposed solution is based on zero-inflated negative binomial distribution, which is adopted from Dehghani et al. (2021). Because some hospitals are smaller than others and blood demand fluctuates according to the hospitals' scalability, we used the data in this study to train the AI comprising 44 (11 × 4) input variables based on 4,000 daily occurrences of blood demand.

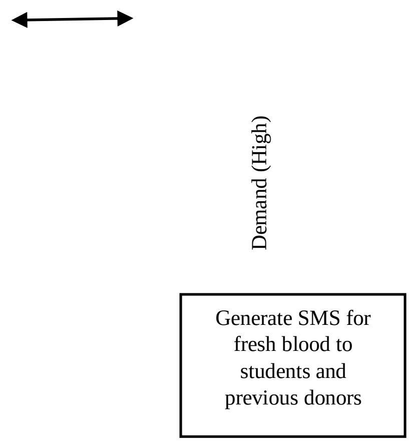
Moreover, we created a dataset repository comprising donors' information and blood inventory demand (daily, weekly) to capture time series data to reinforce the learning method and resolve uncertain constraints, such as emergency (pandemic), time conditions (transshipment delays), and quality (shelf life).

Figure 2 shows the AI-based OBSC model. In line with Loureiro et al. (2020), it represents the first dimension related to AI, whereby organizations manage and implement AI systems in their organizations.

Figure 2

Omnichannel Blood Supply Chain Model





Potential Donors (Students)

The targeted donors in this study were university students, mainly because of the healthiness of young blood. The students’ relevant data (name, address, and phone number) were integrated with the main AI to track and match the addresses of nearby universities and their students who lived near hospitals where blood is needed. From this information, the AI system predicts the demand for blood in nearby hospitals and notifies the donors (students) via SMS to prompt voluntary blood donations. Loureiro et al. (2020) proposed a second dimension related to AI and organizations: designing human–machine integrated service strategies.

Prediction Model and Machine Learning

Machine-learning methods use data sets to train machine-learning algorithms to predict unknown outcomes or future events. Most machine learning algorithms utilize one of three methods of model training: semisupervised learning, supervised learning, or unsupervised learning. However, in blood demand prediction, the level of demand is uncertain due to factors such as emergencies (e.g., a pandemic), time conditions (e.g., transshipment delays), and quality (e.g., shelf life). Therefore, the input data have to be updated regularly to avoid issues with obsolete information, which can result in inaccurate predictions. To address this problem, we utilized a transfer learning approach in this case to support the AI in updating and learning. This method removes obsolete data while new data are continuously added.

The transfer-learning method consists of using a model produced for one activity as a starting point for training on a different task. This is a common strategy in deep learning, where a previously trained model is utilized as a starting point to avoid wasting a large amount of time and resources on training a new model for a new task and instead leverage an existing model's knowledge. Yosinski et al. (2014) discussed the way the lower layers of machine-learning models operate as tools for the extraction of conventional computer-learning features, such as edge detection, while the upper layers strive towards the task-related function. Using transfer learning, Kocer and Arsalan (2012) devised a system for routing traveling pathways based on traffic density; depending on previous experiences, such models can quickly adjust their routing. In addition, Meng and Xu (2022) and Sharma et al. (2017) used machine learning to estimate product prices.

In blood demand prediction, an accurate prediction system is required to cope with future occurrences; in this case, the requirement is to predict upcoming blood demand and to notify students. Therefore, machine learning is applied to the processing of sample data to enhance performance. After collecting data from hospitals and the central blood bank, we must anticipate the total blood required by calculating hospitals' demand based on previous data, with this data being fed into AI classifiers to begin training the model. Therefore, we can anticipate the number of blood units each hospital requires. We may also predict blood demand required in a given week in case of emergencies, such as an epidemic that spreads in a specific period and necessitates additional blood supply. Every week, input data are processed for overall demand projection, based on current inventory, demand prediction, and shelf life. This exemplifies the integration of the third dimension related to AI and organizations Loureiro et al. (2020) proposed: People deal with autonomous systems in social environments.

Table 1 shows several examples of input data (the identifiers given here are connected to the hospital, universities, and students' data).

Table 1

Sample Input Data for Training Models to Make Predictions

Week	Hospital	Current Inventory	Demand Prediction	Shelf Life
1	CBB	Normal (0)	High (1)	Normal (0)
1	H01	High (1)	Low (−1)	Low (−1)
1	H02	Low (−1)	Low (−1)	Very low (−2)
2	H03	Low (−1)	Very High (+2)	High (1)

In this example, we forecasted the number of units a certain hospital requires for a given week of the year. The algorithm may also be able to forecast requirements based on geographic information as the address is captured, along with weekly-demand predictions. The trained machine-learning model predicts the output (demand) for a particular input (week and hospital), relying on its knowledge throughout this prediction. The test prediction finishes by estimating the shelf life and blood inventory of each hospital based on previous weeks and makes a comparison to evaluate the model's success. As a result, 89% of demand predictions were fully accurate, 4% were inaccurate in one hospital, 5% were inaccurate in two hospitals, and 2% were completely inaccurate.

Inventory Optimization Model and Machine Learning

For inventory optimization using the transshipment process, we trained and compared several machine-learning models to produce outputs for the stochastic optimization model on the basis of input parameters extracted from the model to train accurate inventory optimization models. In the two-stage stochastic optimization model, first-stage decisions are instantly actionable; however, the second stage (indexed scenario) judgments assist in establishing knowledge of robustness but are not crucial to immediate action. Therefore, we trained the machine-learning model to compute and generate actionable decisions in the stochastic optimization mode via the transshipping process.

Bengio et al. (2021) examined developments in the areas of operations and machine learning to utilize machine learning to address combinatorial optimization challenges. Machine-learning algorithms can produce optimized or close-to-optimized outputs for a single subset or all subsets of decision-making variables in a combinatorial challenge (Larsen et al., 2021). In the proposed model, the inventory was optimized using the transshipment process and automating the decision-making process for the transshipment of blood inventory and blood unit processing.

Sustainable development requires performing the correct tasks using an efficient and effective attitude and approach; therefore, this aspect is integrated into the fourth dimension related to AI and organizations Loureiro et al. (2020) mentioned: Systems support the development of a sustainable planet.

Main AI Modeling and Classifier Testing

We obtained the characteristics of the proposed machine-learning model during training of the model whereas hyperparameters are often discovered explicitly or based on prior information about the data set. However, numerous published works have provided searching techniques for determining the optimal value of hyperparameters (e.g., Cawley & Talbot, 2007;

Tsamardinos et al., 2018; Zhang et al., 2020). For this paper, we used a grid-search cross-validation approach to fine tune the critical hyperparameters of our machine learning models. A grid search creates a comprehensive factorial design for conducting trials based on the hyperparameters provided. We used cross-validation throughout the full training data set to evaluate the model's performance through each node of the grid. According to Stone (1974), the cross-validation approach is widely employed in statistical and machine-learning modeling and significantly affects the way available data are divided to ensure appropriate generalization of estimated parameters. A cross-validation approach is useful when the training data set is inadequate or suffers from bias when comparing the generalization capacity of multiple machine-learning models (Burden et al., 1997). We used a fivefold cross-validation setup with 30 repetitions in this experiment. This approach implies that in each iteration, the entire data set was randomly partitioned into five parts and the model was iteratively trained using four parts (i.e., 80% of the data) and tested using the remaining part (i.e., 20% of the data); therefore, all data were tested only once. To eliminate bias, this procedure was performed 30 times to classify the test data, build a model, and retrieve the structure of the training data; many techniques, such as LSTM, random forests, classification and regression tree (CART), and k-nearest neighbors (K-NN) can be utilized for this process. However, we used and compared multiple classifiers. The next four subsections describe the classifiers used in the comparison of machine-learning models.

LSTM Classifier

The LSTM algorithm has received much interest because of its ability to capture nonlinear trends and relationships. The initial investigation showed that LSTM outperformed classic decline curve analysis approaches when numerous parameters were considered at the same time. However, various flaws arose in the consideration of a single AI model, such as outlier effects, poor convergence, local minima, and temporal loss. To address these issues, significant hybrid models are proposed, such as an approach utilized in optimization techniques that employs each component of the model to its advantage to improve prediction accuracy and model performance.

Random Forest Classifier

The random forests method is an ensemble learning approach for classification, regression, and other tasks that works by building a large number of decision trees during training. For classification problems, the random forest output is the class chosen by the majority of trees. The mean forecast of the individual trees is returned for regression tasks. Random decision forests compensate for decision trees' tendency to overfit their training set. Random forests outperform decision trees in general although their accuracy is lower than that of gradient-enhanced trees. However, the data's characteristics can hinder their performance.

CART Classifier

CART is a predictive model that describes the way the values of one outcome variable may be predicted based on the values of other variables. Each fork in a predictor variable is segmented in a CART output, and each end node comprises a prediction for the outcome variable. The optimal maximum depth value of the tree for a particular problem is found using the grid-search cross-validation technique to create a suitable decision tree using the CART algorithm and prevent overfitting. The mean squared error across the full data set is adopted as the splitting criteria, which is a suitable option for issues that arise in regression.

K-NN Classifier

In k-NN classification, the output is returned based on class membership. An item is categorized based on a simple majority of its neighbors, with the object allocated to the most common class among its k-nearest neighbors. The k-NN model was implemented using the normalized Euclidean distance. The k-NN classification with $k = 7$ was built as the final K-NN model based on cross-validated grid-search results for the optimal number of nearest neighbors.

Evaluation

This phase involves performance evaluation of the results. To perform a fair comparison between several classifiers, we utilized the standard evaluation measures, such as normalized discounted cumulative gain at 5 (nDCG@5), precision at 5 (P@5), and mean reciprocal rank (MRR). Additionally, nDCG@5 is considered the main metric for performance evaluation of the classifiers' comparison. Moreover, for demand prediction, we utilized mean absolute error (MAE) and root mean squared error (RMSE) matrices to measure the quality of the predictions. We describe these evaluation measures in Table 2.

Table 2

Evaluation Measures

Measure	Description	References
NDCG@5	A calculation that employs a gain multiplier to consider the role in which each relevant result was returned as well as its relevance score.	(Gao & Liang, 2012)
P@5	P@5 relates to the fraction of related scores within the top five results.	(Rajendran et al., 2020)

MRR	MRR measures the reciprocal rank in the ranking of the original corresponding document.	(Shi et al., 2012)
MAE	MAE is used to calculate the magnitude of an error, which is the average of the difference between expected and actual values.	(Wang & Lu, 2018; Willmott & Matsuura, 2005)
RMSE	RMSE calculates the quadratic mean of the discrepancies between predicted and actual values. It can have a value between 0 and infinity, and it is based on penalizing significant errors; therefore, values closer to 0 are preferable to larger values.	(Wang & Lu, 2018; Willmott & Matsuura, 2005)

Discussion

Three themes emerged from the in-depth interviews conducted with practitioners. Theme 1 relates to the lack of technology-driven protocols in the health care sector. This finding is in line with the literature, such as Ernst and Young (2018) and Rathi (2018), who explained that health care protocols in the health sector are not adequate and do not align with newly available technologies. This inadequacy forces health care providers to follow outdated models to manage the supply and demand of blood in Pakistan, which is unsustainable. Other studies on emerging market economies have also depicted similar situations (e.g., Haddad et al., 2018; Kuruppu, 2010; Nouhjah & Jahanfar, 2020).

Theme 2 demonstrates poor coordination among actors during emergencies, and this outcome corresponds to literature that has posited that the availability of blood becomes a challenge at crucial times due to a lack of coordination (Khalid et al., 2018). Unavailability and inaccessibility of donors, storage capacity, and delivery of blood to the hospital are a few of the major reasons for blood scarcity at crucial times (e.g., Diks et al., 2019; Khalilpourazari & Doulabi, 2022; Nisingizwe et al., 2022).

Theme 3 confirms that monitoring and assessment is key to enhancing efficiency in an omnichannel blood supply chain, in accordance with Kaplan (2021) and Leo et al. (2022), who posited that efficacy and effectiveness can be enhanced in the health care sector, specifically in the blood supply chain, to provide blood resources to patients on time.

Based on the themes raised in the interviews, we developed a machine-learning model by translating the data into five data values (very low: −2; low: −1; normal: 0; high: 1, very high: 2), along with hospital data, such as ID, location, and date. The data set was based on 4,000 records, and the prediction accuracy was 89%, with an LSTM classifier for all three variables (current inventory, demand, and shelf life).

We have compared LSTM-based models with classifiers such as random forest, CART, and K-NN; the performance comparison indicated that the proposed approach works best with LSTM, including prediction of abrupt changes in demand. Via the integration of AI with university student data, the system notifies student donors with addresses matching nearby hospitals where blood is in high demand. As Table 3 shows, the results indicated that LSTM outperformed random forest, CART, and K-NN classifiers by significant margins in all measures tested; random forest and CART also showed slight differences in performance whereas K-NN scored the lowest.

Table 3

Results and Comparison of the Utilized Classifiers Along With MAE and RMSE Scores in Shortage, Normal, and Abrupt-Change Scenarios

Model	MRR	P@5	NCDG@5	MAE			RMSE		
				Shortage	Normal	Abrupt Change	Shortage	Normal	Abrupt Change
LSTM	0.686	0.697	0.624	78.57	53.18	99.13	78.12	85.06	99.23
Random Forest	0.638	0.659	0.579	83.91	81.77	105.29	83.58	103.64	114.39
8	0.650	0.648	0.566	83.26	79.03	105.81	81.91	104.18	128.52
K-NN	0.632	0.629	0.502	94.03	97.82	138.06	93.19	112.56	134.11

Unexpected emergencies can unbalance a system and actors within it and force the system into a bottleneck. This disruption leads to technological, economic, and social instability.

Many health care operators have begun to use omnichannel retailing to connect and enhance customer experience (Dahl et al., 2021; Kraus et al., 2021).

Our OBSC model is a premier addition to this concept in the health care industry. Kochan et al. (2018) suggested that health care supply chains should be able to deliver supplies in the right quantity, at the right quality, at the right place, at the right price, and at the right time. Our model addresses these challenges by integrating omnichannel blood supply chains driven by AI, resulting in resource efficiency, saving lives, and delivering social sustainability.

Implications of the Study

Academic and Practical Implications

We formulated and tested the OBSC model with the integration of RDT. RDT suggests that university students can constitute a healthy resource to meet the demand for blood during crises on a necessity basis. Students can help meet the blood requirements by creating informal partnerships with mediation of their universities with hospitals and other health institutions in normal and emergency situations. Under the assumptions of RDT, the OBSC model uses a bottom-up approach to involve the volunteers and thereby meet the demand and expectation of blood supply in certain areas. This is an academic contribution of this study because it links RDT and an IT-based solution.

Regarding the model’s practical implications, governments can adopt the OBSC model to manage the blood supply chain in hospitals and disseminate and integrate supply among all hospitals. Private networks of hospitals and health institutions can also benefit from the OBSC model. Further, they can create a network to manage the supply and demand of blood using this model. Other industries and business stakeholders (e.g., agriculture, farming, warehousing, and food-processing businesses) could also utilize the OBSC model to manage their inventory.

OBSC can help increase donor engagement by allowing for appointment scheduling, blood-drive event management, and donor and donation tracking.

Social Implications

The proposed OBSC model also contributes to sustainable development because sustainable development requires performing the correct tasks with efficient and effective attitudes and approaches to minimize resource utilization. The OBSC model provides cost-effective connectivity between health institutions and university students to contribute to the blood supply chain with an environmentally friendly approach that serves society. Ultimately, OBSC enhances local partnerships for sustainable development, complemented by multiple stakeholder partnerships that mobilize and share blood resources, serve existing and future communities, promote patients' well-being, and initiate social cohesion and inclusion. The proposed model provides the solution to the social issue of blood shortages and overcomes such shortages in crisis and normal situations. The OBSC model enables two entities in society (universities and young, healthy individuals) to interact and benefit mutually.

Further, this model integrates four important entities in society (i.e., hospitals, blood banks, universities, and students). The main stakeholders among these entities are hospitals, from which demand will be gauged. Therefore, hospital staff must understand how to manage the OBSC app interface to highlight demand or send other messages. Blood bank personnel should also know how to operate this app. Universities, for their part, act as an agent between blood donors (students) and hospitals or blood banks. The government can play a role in supporting and disseminating this system to enhance citizens' quality of life, health services, and standard of living.

The OBSC model developed here assumes significance in the literature because it is aligned with two of the United Nations' Sustainable Development Goals, Goal 9 and Goal 12. Goal 9 is to "ensure healthy lives and promote well-being for all at all ages," and the OBSC model is designed to help patients in the difficult situation of blood shortages. Under this model, the supply and demand of blood would be managed efficiently, according to need. Additionally, Goal 12 is to "ensure sustainable consumption and production patterns." This model provides the easiest way to fulfill the demand for blood with minimal effects on the environment by conserving energy and natural resources when finding donors and available current blood inventory. The OBSC model strengthens the country's scientific and technological capacity to move toward patterns of consumption and management of blood resources that are more sustainable.

Conclusions

The responses from participants and the data that we have reviewed from prior studies have highlighted that the omnichannel approach could very efficiently reduce blood supply issues in the health care sector. In addition, managers in the health care sector in Pakistan currently face several issues and challenges due to limited resources and the unavailability of trained professionals. The interview sessions highlighted many important aspects that are linked with blood supply chain management and the strategies that are needed to make the health care sector run smoothly. Furthermore, it has been noted that Pakistan-based health care organizations should implement OBSC management strategies so that on-time treatment of patients can be achieved. Availability of resources is very important in the health care sector because of the life-threatening parameters that exist in health care systems. This study proposes an AI-based OBSC model to address this.

This model provides a system that supports individual blood needs and seamless experiences of blood availability, demand, and supply. The proposed model could play a lifesaving role in crucial conditions and unexpected events (e.g., natural disasters). This is the first omnichannel model proposed in the health care industry that integrates hospitals, health institutions, and blood banks along with universities and their students.

Limitations and Future Research Directions

This study has a number of limitations that provide opportunities for future research. First, when we formulated and tested the model, data availability was limited; for instance, only four hospitals shared their data sets. Therefore, in future, the same OBSC model could be tested on large-scale data sets from larger health care institutions. Second, we tested the OBSC on four machine-learning approaches; researchers may employ multiple new or existing machine-learning models to test the proposed model and arrive at new insights (e.g., MARS, QSAR, or SVR). Another future research avenue involves the retraining of the model on updated data from the health care industry over longer periods or following emergency situations, such as a pandemic. This would increase the prediction's accuracy. One issue with the model proposed here is that retraining the model and updating the data takes a significant amount of time. Therefore, researchers should provide a way forward to reduce the retraining time of the proposed model. Finally, the suggested model could be adapted in future studies to help hospitals integrate with each other to manage the supply and demand of other resources (e.g., medicine and equipment).

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