ORIGINAL PAPER

A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

Yussriya Hanaa Doomah[1], Song-Yuan Xu[1], Li-Xia Cao[2], Sheng-Lian Liang[1], Gloria Francisca Nuer-Allornuvor[1,3], Xiao-Yan Ying[1]

[1]Department of Obstetrics and Gynecology, The Second Affiliated Hospital of Nanjing Medical University, Nanjing, Jiangsu Province, China

[2]Department of Obstetrics and Gynecology, Jiangsu Jianyin People's Hospital, Jianyin, Jiangsu Province, China

[3]Department of Obstetrics and Gynecology, Cape Coast Teaching Hospital, Cape Coast, Central Region, Ghana

Corresponding author: Professor Xiao-Yan Ying, Department of Obstetrics and Gynecology, The Second Affiliated Hospital of Nanjing Medical University. No. 262, ZhongShan North Road, Gulou District, Nanjing, Jiangsu Province, China. Phone number: +86 18951762808; E-mail: xiaoyanying_cool@163.com. ORCID ID: http//www.orcid.org/0000-0003-0326-4987.

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ABSTRACT

Introduction: The American College of Obstetricians and Gynecologists (ACOG) defines postpartum hemorrhage (PPH) as a blood loss of >500mL following vaginal delivery or >1000mL following cesarean section. PPH is widely recognized as a common cause of maternal death. However, there is currently no effective method to predict its risk of occurrence. **Aim:** To develop a fuzzy expert system to predict the risk of developing PPH and to evaluate its performance in the clinical setting. **Methods:** This system was developed using MATLAB software. Mamdani inference was used to simulate reasoning of experts in the field. To evaluate the performance of the system, a dataset of 1705 patients admitted at the Labor and Delivery ward of The Second Affiliated Hospital of Nanjing Medical University from 2017-10 to 2018-04, was considered. **Results:** The Negative Predictive value (NPV), Positive Predictive value PPV), Specificity and Sensitivity were calculated and were 99.72%, 18.50%, 87.48% and 92.16% respectively. **Conclusions:** Our findings suggest that the fuzzy expert system can be used to predict PPH in clinical settings and thus decrease maternal mortality rate due to hemorrhage.

Keywords: Postpartum hemorrhage, maternal death, uterine inertia, retained placenta.

1. INTRODUCTION

The American College of Obstetricians and Gynecologists (ACOG) defines postpartum hemorrhage (PPH) as a blood loss of >500mL following vaginal delivery or >1000mL following cesarean section. PPH is widely recognized as a common cause of maternal death. The World Health Organization statistics suggest that hemorrhage is the leading direct cause of maternal death worldwide, representing 27.1% (19.9-36.2) of maternal deaths with more than two thirds of reported hemorrhage deaths being classified as post-partum hemorrhage (1). A practice bulletin from ACOG places the estimate at 140,000 maternal deaths per year or 1 woman every 4 minutes (2). The Royal College of Obstetricians and Gynecologists (RCOG) recommend being aware of both antenatal and postnatal risk factors for PPH and modifying care plans accordingly (3). The risk factors attributed to PPH have been extensively researched and include retained placenta, prolonged duration of third stage of labor, previous cesarean section, and operative vaginal delivery. Other factors such as age, ethnicity (4, 5), emergency cesarean, obesity (6), induction of labor (7), macrosomia (8), sepsis (9), hypertension (10), placental abruption (11), fibroids (12), and multiple pregnancies (5) have been identified as moderate risk factors. However, their impact in combination has not been considered. It is possible that some patients have several low-risk factors or moderate risk factors but when combined could lead to a high risk of PPH (13). Currently, there is no effective method to predict the risk of occurrence of PPH prior to delivery.

Our team has designed an expert system that uses fuzzy logic to predict PPH. The software has the ability to combine several risk factors and thereby generate a risk of developing PPH ranging from low to extremely high. The software also has the ability to predict the possible etiology of PPH.

2. AIM

The present study aims at testing its performance and accuracy in the clinical setting.

3. METHODS

This research is a cross-sectional study conducted in 3 parts:

3.1. Defining the risk factors of PPH

A list of important risk factors was found in medical literature and from previous cases of PPH across eight provinces in China. The risk factors were organized into a questionnaire and divided into five categories namely: a) factors related to present history, b) factors related to past history, c) pregnancy-related diseases, d) complications during pregnancy and e) factors related to delivery.

The questionnaire was reviewed and completed by domain experts who were asked to assign suitable weight to the factors based on their significance in the risk of developing PPH. According to the completed questionnaires, 46 substantial risk factors with the highest weight were selected. A list of the risk factors is shown in Table 1.

3.2. Designing the fuzzy expert system

In order to predict the risk of PPH, fuzzy set theory was applied in this study. A rule-based fuzzy expert system has been developed which uses the selected risk factors to predict PPH. The basic structure of the system includes four main components:

- A fuzzifier that interprets crisp input (classical numbers) into fuzzy values;
- An inference engine that uses a fuzzy reasoning function to take a fuzzy output (Mamdani inference);
- A knowledge base that includes a set of fuzzy rules and a set of membership functions displaying the fuzzy sets of linguistic variables;
- A defuzzifier that interprets fuzzy output into crisp values (14, 15);

The basic architecture of a fuzzy logic system is shown in Figure 1.

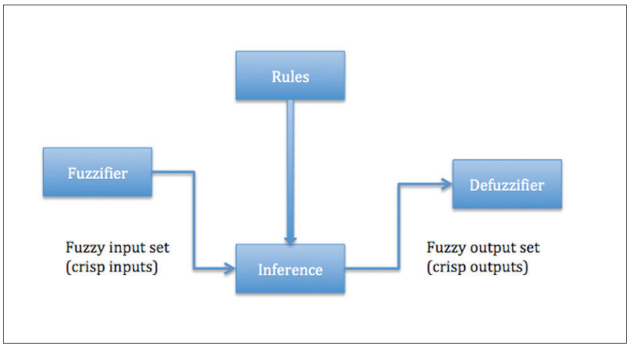

Figure 1. Fuzzy logic system

The first step of designing a fuzzy expert system is to determine the input and output variables (16). There are 46 input variables (shown in Table 1) and 1 output variable (risk of PPH). Secondly, the membership functions of all variables have to be designed. These membership functions specify the membership of objects to fuzzy sets. Membership functions were used for input variables according to both the literature review and domain expert opinions. Subsequently, the inference engine performs the decision process using rules contained in the knowledge base. The knowledge base is the principal section in the fuzzy inference system and its performance is dependent on fuzzy rules (17). These rules determine the relationship between the fuzzy input and output. The formula to a fuzzy rule is; if antecedent, then consequent. Fuzzy operators express the antecedent, and the outcome is an expression that administers fuzzy values to the output variables. The inference process evaluates all rules in the knowledge base and combines the weighted consequence of all relevant rules into a single output fuzzy set (Mamdani model). The fuzzy output set is then replaced by a "crisp" output value obtained by a process called defuzzification (15). Figure 2 shows the Mamdani fuzzy model for variables categorized as "pregnancy complications.

The detailed description of input variables, output variables, and membership functions are displayed in Table 2. To make all variables homogeneous, we performed normalization of all variables in the range of 0 to +1 by using the appropriate formula in MATLAB. Since there were 46 input variables in this study, combination of

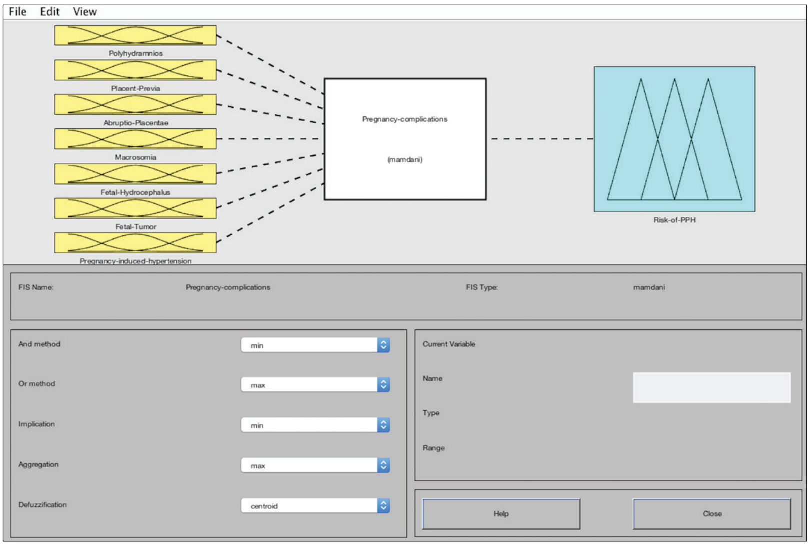

Figure 2. Mamdani fuzzy model of "pregnancy complications" variables that can lead to the development of PPH

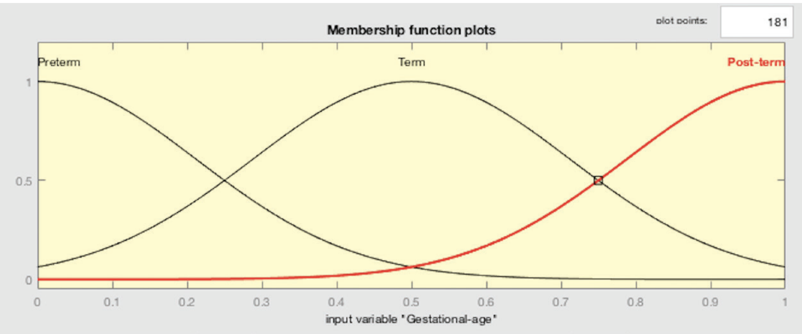

Figure 3. Membership function plot for input variable "Gestational Age"

all possible inputs led to the construction of many rules. Therefore, to increase efficiency only relevant rules were considered based on expert opinion. The knowledge used in the proposed system was collected based on the experts' interviews and other scientific references such as books and websites. Sum was the aggregation method used in this research; meanwhile, in order to defuzzify, centroid method was applied. MATLAB software was used to build the model and the graphical user interface was designed by Visual Studio and C# programming language to increase the user friendliness of the software.

3.3. Evaluation

To evaluate the performance of the developed fuzzy expert system, a list of medical records of patients, hospitalized at The Second Affiliated Hospital of Nanjing Medical University from October 2017 to April 2018, was reviewed. Information about the patients was input in the expert system and a prediction for PPH was made. The predicted risks were then analyzed to compare the outcome of the system and the results in medical records. The specificity, sensitivity, positive predictive value (PPV), negative predictive value (NPV) of the predictive model was determined based on the analyzed data. The diagnosis of postpartum hemorrhage was made according to the ACOG definition and patients were managed according to WHO guidelines [http://apps.who.int/iris/bitstream/handle/10665/44171/9789241598514_eng.pdf;sequence=1].

4. RESULTS

The fuzzy set related to the linguistic input variable "Gestational age" is shown in Figure 3. Membership degree indicates that the input belongs to the set. Figure 4 shows the membership plot of the output variable "risk of PPH". Figure 5 shows the graphical user interface of the system. In order to validate the efficiency of the system, a total number of 1705 patients were included in this study among which 51 (2.99%) developed PPH. 757 (44.40%) patients underwent a Cesarean section while 948 (55.60%) delivered normally. For the patients who were diagnosed with PPH, the mean volume of blood loss was 989.21±484.75 mL and the most common cause was attributed to uterine atony (60.78%).

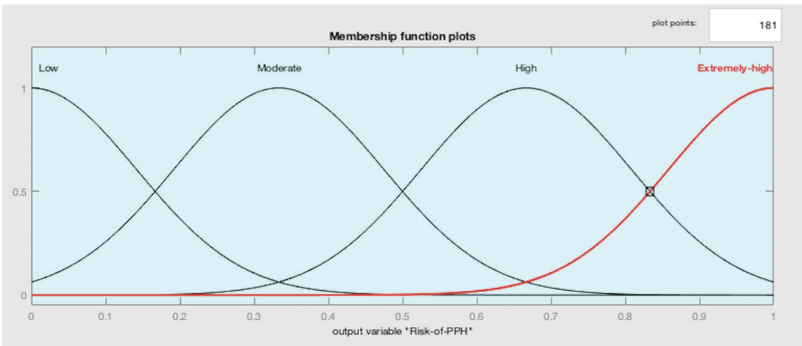

Figure 4. Membership function plot for the output variable "Risk of PPH"

The true positive (TP), false positive (FP), false negative (FN) and true negative (TN) values obtained after prediction are shown in Table 3. The Negative Predictive value (NPV), Positive Predictive value PPV), Specificity and Sensitivity were

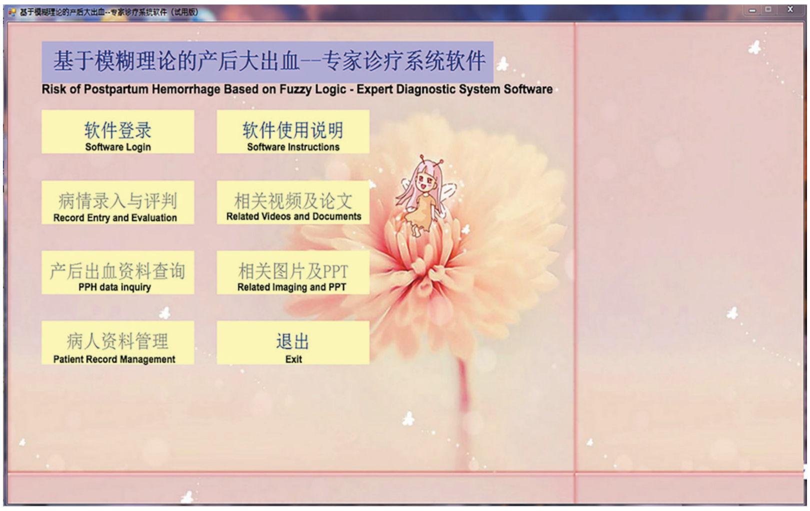

Figure 5. Graphical User Interface of the PPH predictive system

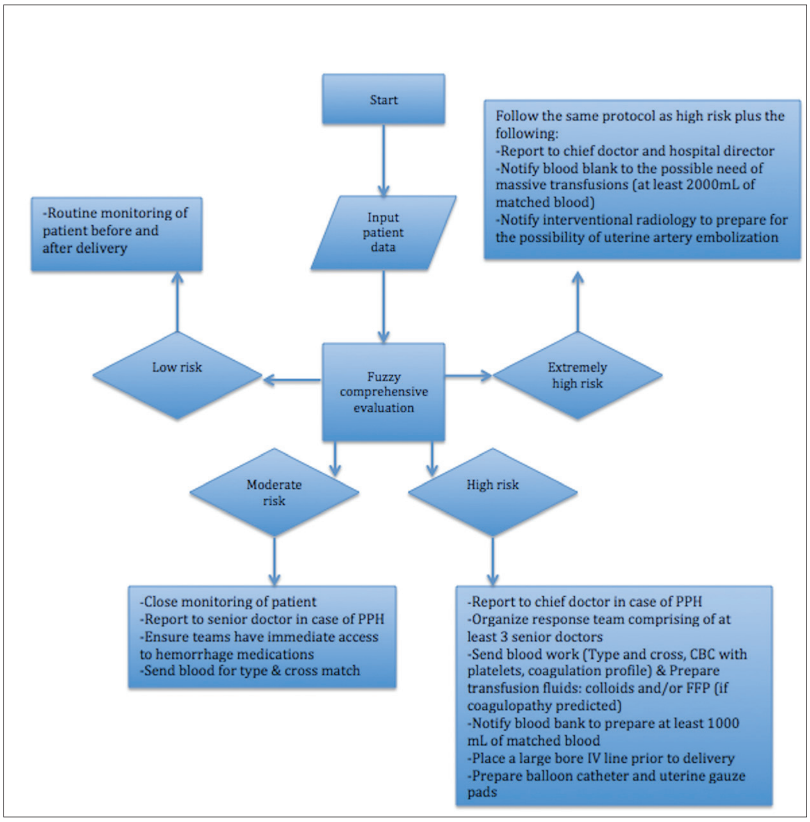

Figure 6. Flowchart proposing a management protocol following the risk stratification by the fuzzy expert system

calculated and were 99.72%, 18.50%, 87.48% and 92.16% respectively.

Another feature of the software is its ability to predict the cause of PPH according to the four T's; tissue (placenta), thrombin (coagulopathy), trauma (soft birth canal injury) and tone (uterine atony). Analysis of the results shows that there is no statistically significant difference between the predicted cause and the actual cause.

5. DISCUSSION

Our data shows that this fuzzy expert system is a reliable tool to predict PPH and its corresponding cause. The software has the ability to combine and analyze all the risk factors of PPH together by using the fuzzy comprehensive evaluation method and thus generate a risk of developing PPH. Furthermore it can predict the right cause of PPH.

PPH is considered to be a highly unpredictable event in the clinical setting. Existing guidelines by the Royal Australian and New Zealand College of Obstetricians and Gynecologists (RANZOG), the Society of Obstetricians and Gynecologists of Canada (SOGC) and RCOG all promote the prevention of PPH through active management of third stage of labor (AMTSL) with the use of uterotonics as first line management. However, there are no specific recommendations discussed in any of the guidelines with regard to PPH prevention strategies prior to the onset of the third stage of labor. Our software shows that with the use of new tools and technology, PPH risk can be predicted well before the onset of the third stage of labor and appropriate management can start at an earlier stage.

Currently, risk factors for PPH can be divided into 3 major categories: 1) pre-existing factors such as a history of PPH, preeclampsia, over-distended uterus, anemia, high-parity, fibroids and obesity; 2) placental factors such as placental abruption, placenta previa, fundal placenta, retained placenta and abnormal placentation; 3) intrapartum factors such as prolonged labor, augmented labor, rapid labor, operative labor, induction of labor amongst others (18). All existing guidelines recognize that women with suspected or proven placental abruption, placenta previa or those with a history of cesarean section represent the highest risk for developing PPH and are advised to undergo delivery in a consultant-led facility. However, the combined effects of multiple risk factors have not been considered. Our proposed software analyses the effect of multiple minor risk factors that when add up can lead to previously undetected risk of PPH.

Category	Risk factors
1.Present Gestation	General condition
	Mental status
	Age
	Gestational age
	Vaginal discharge before uterine contractions
	Vaginal bleeding
	Endometritis
	Uterine status
	Uterine malformations
	Uterine fibroid
2.Past History	Number of abortions
	Number of delivery
	Previous uterine surgery
	>5cm fibroid surgery
	Cervical surgery
3.Pregnancy-related diseases	Anemia
	Aplastic anemia
	Diabetes
	Idiopathic Thrombocytopenic Purpura
	Leukemia
	Kidney disease
	Liver disease
4.Complications of pregnancy	Polyhydramnios
	Placenta previa
	Abruptio placentae
	Number of fetus
	Fetal position
	Macrosomia
	Fetal hydrocephalus
	Fetal tumor
	Pregnancy-induced hypertension
5.Factors related to delivery	First stage of labor
	Second stage of labor
	Third stage of labor
	Dystocia
	Method of delivery
	Use of tocolytics
	Use of anesthetics before delivery
	Operative delivery
	Cervical laceration
	Perineal laceration
	Uterine rupture
	Incarcerated placenta/residual placenta
	Placenta accreta
	Succenturiate placenta

Table 1. Risk factors causing PPH according to Chinese domain experts.

Having a risk assessment tool allows obstetricians to anticipate PPH and thus provide considerations for what might be required to manage PPH. Those with a predicted low risk should be monitored and treated as a normal patient and receive the routine 10 units IM Oxytocin during AMTSL. For those stratified as medium risk, a hemorrhage cart with supplies and resuscitation fluids should be ready and teams should have prompt access to PPH medications. Then those deemed to be a high risk should have ready access to crossed matched blood and transfusion fluids. In addition a response team should be in place comprising of at least 3 senior doctors; one action doctor to perform the delivery, one circulating doctor to communicate with other departments if necessary such as blood blank, advanced gynecologic surgery, operating theatre, anesthesiologists and interventional radiologist whilst another one should manage the whole procedure. In the case of extremely high risk, patients should be delivered by experienced obstetricians, in a unit with prompt access to gynecological theater equipment, embolization, blood blank and vascular surgeon availability. Figure 6 shows a protocol on the effective use of the software in different situations. Health facilities in the rural or remote areas often struggle with a shortage of human resources and life-saving commodities, training resources and health infrastructure, which limit the early identification and effective management of PPH. When applied in those settings, recognizing women at high-risk or extremely high risk can lead to the timely transfer to a tertiary care center or unit with rapid access to blood products or an intensive care unit. The management of each patient can further be individualized based on the predicted cause of PPH. In cases where coagulopathy causes have been predicted, prompt coagulation panel should be sent during delivery and provisions should be made for FFP. For those who are at risk of lacerations, patients could be advised to undergo cesarean section instead of vaginal delivery to minimize injury to the soft birth canal. This software is a first in the field of obstetrics and could represent the cornerstone of PPH prediction and management.

Our software also consists of a database providing instructions about the proper rescue measures that can be adopted for each patient. It consists of 1) relevant literature on PPH; 2) updated guidelines and protocols on PPH management; and 3) videos on several procedures used to manage PPH such as insertion of balloon catheter and compression, all of which can be used by the obstetricians to update their knowledge on PPH.

In recent years, the use of computer-based predictive model in medicine has gained more popularity. In 2016 Scheer et al. proposed a computer-based preoperative predictive model for proximal junction failure in the field of orthopedics. Their model showed 86% accuracy at predicting the complication (19). The use of fuzzy models in pediatrics is quite common. A study by Safdari et

Category	Variable	Variable Value	Actual Range of Variable	Membership Function
Input				
1.Present Gestation	General condition	Fair	0	Guassmf
		Poor	1	Guassmf
	Mental status	Normal	0	Guassmf
		Abnormal	1	Guassmf
	Age	Young	<18	Guassmf
		Normal	18-35	Guassmf
		Old	>35	Guassmf
	Gestational age	Preterm	<37	Guassmf
		Term	37-42	Guassmf
		Post-term	>42	Guassmf
	Vaginal discharge before uterine contractions	No	0	Guassmf
		Yes	1	Guassmf
	Vaginal bleeding	None	0	Guassmf
		Less than menses	<80ml	Guassmf
		More than menses	≥80ml	Guassmf
	Endometritis	No	0	Guassmf
		Yes	1	Guassmf
	Uterine status	Good	0	Guassmf
		Poor	1	Guassmf
	Uterine malformations	No	0	Guassmf
		Yes	1	Guassmf
	Uterine fibroids	None	0	Guassmf
		Small	<5cm	Guassmf
		Big	5cm	Guassmf
2.Past History	Number of abortions	None	0	Guassmf
		At least once	1-2 times	Guassmf
		More than twice	>2 times	Guassmf
	Number of delivery	None	0	Guassmf
		Once	1	Guassmf
		More than once	>1	Guassmf
	Previous uterine surgery	None	0	Guassmf
		Within past 2 years	<2 years	Guassmf
		More than 2 years ago	≥2 years	Guassmf
	> 5cm fibroid surgery	None	0	Guassmf
		Within past 2 years	<2 years	Guassmf
		More than 2 years ago	≥2 years	Guassmf
	Cervical surgery	No	0	Guassmf
		Yes	1	Guassmf
3.Pregnancy-related diseases	Anemia	No	≥11.0mg/dL	Guassmf
		Mild	10-10.9mg/dL	Guassmf
		Moderate	7-10mg/dL	Guassmf
		Severe	<7mg/dL	Guassmf
	Aplastic anemia	No	0	Guassmf
		Yes	1	Guassmf
	Diabetes	No	0	Guassmf
		Yes	1	Guassmf
	Idiopathic Thrombocytopenic Purpura	No	0	Guassmf
		Yes	1	Guassmf
	Leukemia	No	0	Guassmf
		Yes	1	Guassmf
	Kidney disease	No	0	Guassmf
		Yes	1	Guassmf
	Liver disease	No	0	Guassmf
		Yes	1	Guassmf

4.Complications of pregnancy	Polyhydramnios	No	0	Guassmf
		Yes	1	Guassmf
	Placenta previa	No	0	Guassmf
		Yes	1	Guassmf
	Abruptio Placentae	No	0	Guassmf
		Yes	1	Guassmf
	Number of fetus	Singleton	1	Guassmf
		Twins	2	Guassmf
		Multiple	>2	Guassmf
	Fetal position	Occiput	0	Guassmf
		Breech/Transverse	1	Guassmf
	Macrosomia	No	0	Guassmf
		Yes	1	Guassmf
	Fetal hydrocephalus	No	0	Guassmf
		Yes	1	Guassmf
	Fetal tumor	No	0	Guassmf
		Yes	1	Guassmf
	Pregnancy-induced hypertension	No	<140/90mmHg	Guassmf
		Mild	140/90-160/110mmHg	Guassmf
		Severe	≥160/110mmHg	Guassmf
5.Factors related to delivery	First stage of labor	Normal	0	Guassmf
		Prolonged/Arrested	1	Guassmf
	Second stage of labor	Normal	0	Guassmf
		Prolonged/Arrested	1	Guassmf
	Thirds stage of labor	Normal	0	Guassmf
		Prolonged	1	Guassmf
	Dystocia	None	0	Guassmf
		Strong/uncoordinated/weak	1	Guassmf
	Method of delivery	Vaginal	0	Guassmf
		Cesarean	1	Guassmf
	Use of tocolytics	No	0	Guassmf
		Yes	1	Guassmf
	Use of anesthetics before delivery	No	0	Guassmf
		Epidural/Intravenous	1	Guassmf
	Operative delivery	No	0	Guassmf
		Vacuum/Forceps	1	Guassmf
	Cervical laceration	No	0	Guassmf
		Yes	1	Guassmf
	Perineal laceration	No	0	Guassmf
		Yes	1	Guassmf
	Uterine rupture	No	0	Guassmf
		Yes	1	Guassmf
	Residual placenta	No	0	Guassmf
		Yes	1	Guassmf
	Placenta accreta	No	0	Guassmf
		Yes	1	Guassmf
	Succenturiate placenta	No	0	Guassmf
		Yes	1	Guassmf
Output				
Risk of PPH		Low	0-20	Guassmf
		Moderate	20-25	Guassmf
		High	25-33	Guassmf
		Extremely	>33	Guassmf

Table 2. Input and output variables, variable values and membership functions.

Predicted Risk	PPH	No PPH
Positive Test Result	47 (TP)	207 (FP)
Negative Test Result	4 (FN)	1447 (TN)
Total	51	1654

Table 3. The predictions by the Fuzzy expert system; TP: True positive; FP: False positive; FN: False negative; TN: true negative

al. using fuzzy expert system has been able to predict the risk of neonatal death with an accuracy of 90% (15). Similarly, this model was used to diagnose cystic fibrosis with the authors reporting an accuracy of 92.86% (17). However, the use of this technology in obstetrics is still in its infancy and instead studies related to the use of scoring models are more common. In 2017, Sittiparn et al. described a risk score for the prediction of PPH in patients undergoing normal labor having a sensitivity of 81.3% and a specificity of 50.8% (20). In another scoring model designed by Lee et al., the authors found that a score of 5/10 had a sensitivity of 81% and a specificity of 77% for predicting massive postpartum bleeding (21). However, the above-mentioned studies are limited to a pre-defined population group namely normal delivery and placenta previa patients respectively. Thus, they cannot be used for all pregnant patients. Similarly, a recent study by Dunkerton et al. proposed a new tool for predicting PPH in patients undergoing cesarean section (The Leicester PPH predict tool). In their study, the reliability testing showed an intra-class correlation of 0.98 and mean absolute error of 239.8 mL with the actual outcome (13). While this could represent a valuable asset in the prediction of PPH, the study only takes into account cesarean section (CS) patients. In contrast, our proposed model can predict the risk of PPH in both CS and vaginal delivery and is therefore more versatile. Our fuzzy expert system shows great promise for the field of obstetrics and should be further tested so that it can be implemented in clinical settings. Its use in the global setting should also be explored as a means to reduce maternal mortality rates due to PPH.

However, our study design has some limitations, as it is a single-centered study and the amount of PPH patients was limited. The use of this software in a larger full-scale prospective research should be undertaken across the country. The software also provides the management option whereby it can dictate the treatment protocol that should be adopted for each patient in the case of PPH. Nevertheless, the reliability of this function is yet to be assessed. Another disadvantage of the software is that it is currently available in Chinese. This could restrict its use to Chinese doctors only. Efforts should be made to design the software in English to explore its use on a global level.

6. CONCLUSION

Our findings suggest that the software is reliable for the prediction PPH and its corresponding cause. The proposed system can be used as a means to anticipate PPH and thus be better prepared to manage it. Further researches are needed to perfect its algorithm before its use can be considered on a global scale.

- **Authors' contributions:** SLL and XYY designed the original study. YHD and SYX collected the data. YHD analyzed the data and drafted the manuscript. LXC also helped in the analysis of data. GFA critically revised the article and provided intellectual input. XYY substantially revised the manuscript. All authors provided critical input to the paper. All authors have read and approved the final manuscript.
- **Competing interests:** Authors have not competing interests.

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