A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

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Original Paper / Acta Inform Med. 2019 Dec 27(5): 318-326

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.

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
A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

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%).

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...
A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

The risk factors of PPH 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 (AMTS) 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, fundal placenta, retained placenta and abnormal placentation;
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 | Risk factors |
|----------|-------------|
| Present Gestation | General condition, Mental status, Age, Gestational age, Vaginal discharge before uterine contractions, Vaginal bleeding, Endometritis, Uterine status, Uterine malformations, Uterine fibroid |
| Past History | Number of abortions, Number of delivery, Previous uterine surgery, 5cm fibroid surgery, Cervical surgery |
| Pregnancy-related diseases | Anemia, Aplastic anemia, Diabetes, Idiopathic Thrombocytopenic Purpura, Leukemia, Kidney disease, Liver disease, Polyhydramnios, Placenta previa, Abruptio placenta, Number of fetus, Fetal position, Macrosomia, Fetal hydrocephalus, Fetal tumor, Pregnancy-induced hypertension |
| Complications of pregnancy | 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 |
| Factors related to delivery | Table 1. Risk factors causing PPH according to Chinese domain experts. |
A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

| Category | Variable | Variable Value | Actual Range of Variable | Membership Function |
|----------|----------|----------------|--------------------------|---------------------|
| Input    |          |                |                          |                     |
|          | General condition |                  |                          |                     |
|          | Mental status     |                  |                          |                     |
|          | Age               |                  |                          |                     |
|          | Gestational age   |                  |                          |                     |
|          | Vaginal discharge before uterine contractions |                  |                          |                     |
|          | Vaginal bleeding  |                  |                          |                     |
|          | Endometritis      |                  |                          |                     |
|          | Uterine status    |                  |                          |                     |
|          | Uterine malformations |              |                          |                     |
|          | Uterine fibroids  |                  |                          |                     |
|          | Number of abortions |               | At least once 1-2 times | Guassmf             |
|          | Number of delivery |                | None 0 Guassmf           |                     |
|          | Previous uterine surgery |       | Within past 2 years <2 years Guassmf |                     |
|          | > 5cm fibroid surgery |            | Within past 2 years <2 years Guassmf |                     |
|          | Cervical surgery  |                  | None 0 Guassmf           |                     |
|          | Anemia            |                  | No ≥11.0mg/dL Guassmf    |                     |
|          | Aplastic anemia   |                  | No 0 Guassmf             |                     |
|          | Diabetes          |                  | Yes 1 Guassmf            |                     |
|          | Idiopathic Thrombocytopenic Purpura |           | No 0 Guassmf             |                     |
|          | Leukemia          |                  | Yes 1 Guassmf            |                     |
|          | Kidney disease    |                  | No 0 Guassmf             |                     |
|          | Liver disease     |                  | Yes 1 Guassmf            |                     |

1. Present Gestation

2. Past History

3. Pregnancy-related diseases
A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

4. Complications of pregnancy

| Variable                      | Value         | Membership Function |
|-------------------------------|---------------|---------------------|
| Polyhydramnios                | No            | 0                   |
|                               | Yes           | 1                   |
| Placenta previa               | No            | 0                   |
|                               | Yes           | 1                   |
| Abruptio Placentae           | No            | 0                   |
|                               | Yes           | 1                   |
| Number of fetus               | Singleton     | 1                   |
|                               | Twins         | 2                   |
|                               | Multiple      | >2                  |
| Fetal position                | Occiput       | 0                   |
|                               | Breech/Transverse | 1          |
| Macrosomia                    | No            | 0                   |
|                               | Yes           | 1                   |
| Fetal hydrocephalus           | No            | 0                   |
|                               | Yes           | 1                   |
| Fetal tumor                   | No            | 0                   |
|                               | Yes           | 1                   |
| Pregnancy-induced hypertension| No <140/90mmHg | Guassmf           |
|                               | 140/90-160/110mmHg | Guassmf     |
|                               | ≥160/110mmHg   | Guassmf            |
| First stage of labor          | Normal        | 0                   |
|                               | Prolonged/Arested | 1          |
| Second stage of labor         | Normal        | 0                   |
|                               | Prolonged/Arested | 1          |
| Thirds stage of labor         | Normal        | 0                   |
|                               | Prolonged     | 1                   |
| Dystocia                      | None          | 0                   |
|                               | Strong/uncoordinated/weak | 1          |
| Method of delivery            | Vaginal       | 0                   |
|                               | Cesarean      | 1                   |
| Use of tocolytics             | No            | 0                   |
|                               | Yes           | 1                   |
| Use of anesthetics before delivery | Epidural/Intravenous | 1          |
|                               | No            | 0                   |
|                               | Vacuum/Forceps | 1                   |
| Cervical laceration           | No            | 0                   |
|                               | Yes           | 1                   |
| Perineal laceration           | No            | 0                   |
|                               | Yes           | 1                   |
| Uterine rupture               | No            | 0                   |
|                               | Yes           | 1                   |
| Residual placenta             | No            | 0                   |
|                               | Yes           | 1                   |
| Placenta accreta              | No            | 0                   |
|                               | Yes           | 1                   |
| Succenturiate placenta        | No            | 0                   |
|                               | Yes           | 1                   |

5. Factors related to delivery

| Variable                      | Value         | Membership Function |
|-------------------------------|---------------|---------------------|
| Operative delivery            | No            | 0                   |
|                               | Vacuum/Forceps | 1                   |
| Cervical laceration           | No            | 0                   |
|                               | Yes           | 1                   |
| Perineal laceration           | No            | 0                   |
|                               | Yes           | 1                   |
| Uterine rupture               | No            | 0                   |
|                               | Yes           | 1                   |
| Residual placenta             | No            | 0                   |
|                               | Yes           | 1                   |
| Placenta accreta              | No            | 0                   |
|                               | Yes           | 1                   |
| Succenturiate placenta        | Yes           | 1                   |

Output

| Risk of PPH        | Membership Function |
|--------------------|---------------------|
| Low                | 0-20                |
| Moderate           | 20-25               |
| High               | 25-33               |
| Extremely          | >33                 |

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

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

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

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A Fuzzy Expert System to Predict the Risk of Postpartum Hemorrhage

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