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Identifying the Essential Data Elements Set for Creating an Intelligent System to Predict Abortion in Pregnant Mothers: The First Step in Preserving Life

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Abstract

Abortion is a common occurrence during pregnancy. Intelligent technologies can be developed to assist in predicting abortions. This study aims to identify the essential data elements necessary for creating an intelligent system to predict abortion in pregnant women, which represents the first step in the creating of such systems. This descriptive research was conducted in the years 2022-2023. In this study, to access the essential data elements, accredited printed and electronic scientific sources, as well as paper and electronic hospital records, were reviewed. Then, a questionnaire was developed that confirmed its validity by experts, and its reliability was calculated with Cronbach's alpha coefficient, which was 0.83. Then, the questionnaire was distributed among faculty members holding specialty and subspecialty degrees in obstetrics and gynecology, as well as Ph.D.s in health information management and medical informatics. The collected data were analyzed. A total of 19 managerial data elements and 126 clinical data elements were identified across 9 subclasses. Precautionary and preventive measures for pregnant mothers at risk can be provided with the aid of intelligent systems to predict abortion that to develop these systems, the presence of valid and important data elements is required.

Keywords: Essential data elements, Predict, Abortion, Pregnant Mothers, Intelligent System

Introduction

Abortion is one of the most common complications during pregnancy, considered as the termination of pregnancy (Dousti et al., 2021). This event usually occurs before the 20th week of pregnancy (Beckmann et al., 2019) or when the fetus weighs less than 500 grams (Rahmani et al., 2020). In recent decades, abortion has become one of the most severe adverse outcomes of pregnancy (Lu et al., 2022), identified as a cause of infertility and a health and social issue, leading to problems for family and societal health (Rahmani et al., 2020). In recent years, significant lifestyle changes have occurred among women worldwide, and the incidence of spontaneous abortions has increased (Amini et al., 2017). Despite medical advances in the field of women's health and fertility (Maziotis et al., 2022), it is estimated that 23 million abortions occur annually worldwide (Lu et al., 2022). Furthermore, statistics indicate that spontaneous abortion occurs in 10% to 15% of pregnancies (Smith, 2017; Ghazaei et al., 2023), with approximately 80% occurring in the first trimester (Beckmann et al., 2019). Factors causing abortion are divided into two groups. The first category includes factors related to the fetus, among which hereditary and genetic abnormalities can be mentioned. The second category encompasses factors related to the pregnant mother (Makkizadeh and Rashidiboshrabadi, 2021), including uterine problems, endocrine factors, immunological factors, environmental factors to which the pregnant mother is exposed (Beckmann et al., 2019; Shi et al., 2022), and infectious factors (Beckmann et al., 2019). Spontaneous abortion is considered an undesirable phenomenon in the lives of couples and leads to complications for the mother (Amini et al., 2017). These complications include infectious abortion, incomplete uterine evacuation, cervical rupture, disseminated intravascular coagulation, and the post-abortion triad such as low-grade fever, pain, bleeding, accumulation of blood in the uterus (Alves and Rapp, 2021), and septic shock (Sajadi-Ernazarova et al., 2022). Moreover, abortion as a pregnancy complication results in psychiatric disorders such as depression, anxiety, and post-traumatic stress disorders (Mutiso et al., 2019). Abortion also leads to sleep disorders in women (Feizollahi et al., 2020), causing issues in the mother's general health and affecting individual performance (Białek and Malmur ,2020).

Considering that pregnant mothers are recognized as a vulnerable group in society, preserving and enhancing their health level is regarded as the most fundamental pillar of healthcare and treatment in any country (Meraji et al., 2018). Furthermore, given the proven adverse effects of abortion on pregnant mothers, prediction, diagnosis, and the possibility of preventing abortion represent the only solution that can be effective and beneficial in this context and is essential based on standard criteria (Biswas and Shukla, 2022). In pursuit of this objective, given the extensive availability of medical data, artificial intelligence techniques, notably machine learning, can be leveraged for data analysis. As a critical component of artificial intelligence, machine learning boasts broad applicability in the diagnosis and prediction of a wide range of diseases (Bastintakhti and Jahantigh, 2019; Bertini et al., 2022).

Nowadays, machine learning algorithms have been used in various research fields, particularly the health field, to develop models for different purposes, and remarkable results have been obtained. Collecting, storing, analyzing data and ultimately, diseases modeling can provide significant assistance to patients and physicians. (Veisi et al., 2021; Zhang et al., 2022).

However, the improvement of effectiveness, efficiency, and quality of health services is largely influenced by accurate, sufficient, and high-quality health information (Meraji et al., 2018). To access such information, the use of essential data elements is required (Darabi et al. ,2016).

Essential data elements, by providing a minimum set of variables related to individuals' health status, including demographic, clinical, and patient care plan data, enable the establishment of beneficial communication between care providers and facilitate timely decision-making (Meraji et al., 2018; Biswas and Shukla, 2022; Bastintakhti and Jahantigh, 2019; Bertini et al., 2022; Veisi et al., 2021; Zhang et al., 2022 and Darabi et al., 2016). Therefore, the minimum data set is advocated as the essential health data requisite for the processes of collection, preservation, and dissemination of health information, establishing a norm, and providing a critical resource for the evaluation of treatments and ongoing monitoring of patient progress and outcomes (Meraji et al., 2018). In recognition of the significance of maternal health and the advantages of possessing a comprehensive suite of vital data elements alongside precise documentation for the creation of an intelligent system aimed at predicting abortions in expectant mothers, researchers initiated this investigation.

Materials and Methods

The current research is a descriptive study conducted in the years 2022-2023 through various stages. Initially, paper and electronic records of pregnant mothers who had experienced abortions in comprehensive urban and rural health centers and university hospitals, including Shahid Beheshti and Ayatollah Taleghani in Abadan city, were examined, and significant data elements were extracted. Then, accredited electronic scientific sources were also reviewed, and data elements not observed in the files were extracted. The study of these sources was conducted using databases such as PubMed, Scholar, ScienceDirect, SID, and Magiran in the fields of fetal health, abortion, pregnant mothers' health, and its relation to machine learning. In the second phase, based on the data obtained from the previous stage, a questionnaire was designed with a 5-point Likert scale including options for very high, high, moderate, low, and very low importance, assigned quantitative values of 5, 4, 3, 2, and 1, respectively. The content validity of the researcher-created questionnaire was confirmed with the assistance of faculty members, including two specialists in obstetrics and gynecology, two with Ph.D. in medical informatics, and two with Ph.D. in health information management. For the reliability of the managerial data elements section of the questionnaire, opinions from ten faculty members with Ph.D. in medical informatics and ten with Ph.D. in health information management were utilized. Similarly,

for the reliability of the clinical data elements section of the questionnaire, feedback from ten specialists in obstetrics and gynecology, who were faculty members, was employed, and finally the questionnaire's reliability was confirmed by calculating Cronbach's alpha coefficient with a value of 0.83. Then, the questionnaire was distributed to survey the importance of the essential set of managerial and clinical data elements among faculty members with Ph.D. in medical informatics, and health information management, as well as specialists and subspecialists in obstetrics and gynecology across university teaching groups in medical sciences nationwide, either in person or via email. The data obtained from the questionnaire were entered into the SPSS software, version 26, and analyzed using descriptive statistical methods such as frequency, percentage, and mean. Any data element considered to be of high or very high importance by at least 50% of the participants, i.e., with an average of 2.5 or more, was determined as a final data element. The results of the data analysis were displayed in a table.

Results

Based on the expert survey and its analysis, out of 245 data elements, which included 19 managerial and 226 clinical data elements, a total of 19 managerial and 126 clinical data elements were validated for predicting abortion in pregnant mothers.

The majority of respondents, 70%, were female, with age groups between 30-40 and 40-50 years old, comprising 37% of the participants. Individuals holding a Ph.D., 67%, in health information management, 47%, participated in completing the questionnaire on essential managerial data elements for predicting abortion in pregnant mothers more than others. Furthermore, the predominant work experience among survey participants ranged from 10 to 15 years, accounting for 37% of respondents that shown in table 1.

Table 1: Characteristics of participants in the essential data elements survey of abortion prediction system in pregnant mothers

Variable	Title	Frequency	Percent
Gender	Female	21	70
	Male	9	30
Age group	<30	1	3
	30-40	11	37
	40-50	11	37
	50,>	7	23
Education level	Specialty	6	20

	Subspecialty	4	13
	Ph.D	20	67
Field of study	Gynecology and Obstetrics	10	33
	Health Information Management	14	47
	Medical Informatics	6	20
Work experience(year)	<5	6	20
	5-10	4	13
	10-15	11	37
	15>	9	30

In the managerial data elements section, the highest average(5) was attributed to the pregnant mother's date of birth, while the lowest average(2.9) was related to the job and education level of the pregnant mother's husband that shown in table 2.

Table 2: Managerial data elements for creating an intelligent system to predict abortion in pregnant mothers

Row	Data element	Mean	Row	Data element	Mean
1	Record Number	4.5	11	Ethnicity	3.4
2	National code	4.5	12	Residence address	4.3
3	First name	3.9	13	Phone number of residence	3.4
4	Last name	3.9	14	Mobile Phone Number	3.8
5	Father' name	3.8	15	Insurance type	4.1
6	Date of birth	5	16	Husband's date of birth	3.2
7	Marital status	3.6	17	Husband's education level	2.9
8	Educational level	3.7	18	Husband's job	2.9
9	Job	4.4	19	Income level	3
10	Nationality	4			

In the clinical data elements class, nine subclasses including previous pregnancy history, current pregnancy history, mother's risky behaviours in current pregnancy, risk factor leading to abortion in current pregnancy, laboratory report, sonography report, medical diagnosis, medical procedure, and physician's profile were identified. In the subclass detailing previous pregnancy history, the abortion history in previous pregnancies received the highest mean score(5), whereas the total number of previous pregnancies was assigned the lowest mean score(2.5). Within the current pregnancy history subclass, the data element concerning the pregnant mother's hard job was

awarded the highest mean score(3.1) and the lowest mean was related to health care status before pregnancy(2.5), pregnant mother's body mass index before pregnancy(2.5), pregnant mother's weight(2.5), pregnant mother's weight in the first trimester of pregnancy(2.5), pregnant mother's weight in the second trimester of pregnancy(2.5), and type of pregnancy(2.5)

In the subclass on mother's risky behaviour in current pregnancy, the data element regarding contact with radioactive material received the highest mean score(4), and the data element on caffeine use and exposed to domestic violence received the lowest mean score(2.5). In the subclass on risk factor leading to abortion in the current pregnancy, the highest mean score (4.7) was attributed to antiphospholipid syndrome and systemic lupus erythematosus. The lowest mean score(2.5) was assigned to data elements related to heart disease, gestational diabetes, thyroid disease, chronic hypertension, gestational hypertension, toxoplasmosis disease, cytomegalovirus infection, chlamydial infection, mycoplasma hominis, listeria monocytogenes, sickle cell anemia, coagulation disorder, genetic disease in the pregnant woman and her husband, as well as fetal hypoxia.

In the laboratory report subclass, the highest mean score(4.1) was assigned to the data element concerning abnormal level of lupus anticoagulant factor. In this subclass, the lowest mean score(2.5), was allocated to data elements representing abnormal BUN(Blood Urea Nitrogen) level, fetal AFP(alpha-fetoprotein) in pregnant mother's blood, abnormal condition of DFI(DNA Fragmentation Index) in pregnant mother's husband, and abnormal sperm chromatin integrity. In the sonography report subclass, the data element concerning the abnormal gestational sac diameter received the highest mean score(4.1). Data elements including abnormal fetal muscles contraction, abnormal fetal nasal septum bone, fetal heart rate increase, and any abnormal finding in fetal heart obtained the lowest mean score(2.5). In subclass of medical diagnosis, the highest mean score(3.2) was related to primary diagnosis and the lowest mean score(2.7) for final diagnosis . In the medical procedure subclass, both data elements of primary and final procedure were accepted with the mean score of 2.8. In the subclass detailing the physician's profile, all data elements were validated with the mean score of 2.5 that shown in table 3.

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers

Main class	Subclass	Row	Data element	Mean
Clinical	Previous pregnancy history	1	Number of previous pregnancies	2.5
		2	Abortion	5
		3	Preeclampsia	2.7
		4	Gestational diabetes	3.6
		5	Premature placental abruption	2.9

		6	Intrauterine fetal growth retardation	3
		7	Preterm delivery	3
		8	Birth of newborn with weight less than 2500 g	3.1
		9	Abnormality in children	2.6
		10	Stillbirth	3.3
		11	Death of newborn due to any abnormality	3.2
		12	Pregnant mother's cervical disability	3.9
	Current pregnancy history	13	Health care status before pregnancy	2.5
		14	Pregnancy under 18 years	2.9
		15	Pregnancy over 35 years	2.7
		16	Pregnant mother's body mass index before pregnancy	2.5
		17	Pregnant mother's weight	2.5
		18	Pregnant mother's weight in the first trimester of pregnancy	2.5
		19	Pregnant mother's weight in the second trimester of pregnancy	2.5
		20	Type of pregnancy	2.5
		21	Pregnant mother's hard job	3.1

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	**Subclass**	**Row**	**Data element**	**Mean**
Clinical	Mother's risky	22	Smoking	3.5

	behaviour in current pregnancy	23	Number of cigarettes use	3.6
		24	Hookah use	3.4
		25	Number of hookah use	3.5
		26	Caffeine use	2.5
		27	Number of caffeine use	3
		28	Alcohol use	2.9
		29	Number of alcohol use	3.4
		30	Traditional drug use	3.1
		31	Number of traditional drug use	2.7
		32	Industrial drug use	2.7
		33	Number of industrial drug use	2.7
		34	Contact with radioactive material	4
		35	Contact with chemicals material	2.9
		36	Exposed to injury	2.7
		37	Exposed to domestic violence	2.5

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	**Subclass**	**Row**	**Data element**	**Mean**
Clinical	Risk factor leading to abortion in	38	Heart disease	2.5
		39	Diabetes disease	3.1

	current pregnancy	40	Gestational diabetes	2.5
		41	Thyroid disease	2.5
		42	Connective tissue disease	3.4
		43	Chronic hypertension	2.5
		44	Gestational hypertension	2.5
		45	Chemotherapy	2.8
		46	Radiation therapy	2.9
		47	Toxoplasmosis disease	2.5
		48	Cytomegalovirus infection	2.5
		49	Chlamydial infection	2.5
		50	Mycoplasma hominis	2.5
		51	Listeria monocytogenes	2.5
		52	Autoimmune disease	3.6
		53	Antiphospholipid syndrome	4.7
		54	Sickle cell anemia	2.5
		55	Coagulation disorder	2.5
		56	Thrombophilia	4.5
		57	Thromboembolism	3.5
		58	Genetic disease	2.5

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	Subclass	Row	Data element	Mean
Clinical	Risk factor leading to abortion in current pregnancy	59	Husband's genetic disease	2.5
		60	Pregnant mother's reproductive system abnormality	3.1
		61	Uterine septum	4.3
		62	Unicornuate uterus	4.3
		63	Bicornuate uterus	3.9
		64	Double uterus	4.3
		65	Polycystic ovary syndrome	2.7
		66	Ectopic pregnancy	2.6
		67	Placental abruption	2.8
		68	Systemic lupus erythematosus	4.7
		69	Asherman syndrome	4
		70	Luteal phase defect	2.6
		71	Fetal hypoxia	2.5

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	Subclass	Row	Data element	Mean
Clinical	Laboratory report	72	Abnormal fasting blood sugar level	3.3

		73	Abnormal blood sugar level after breakfast	3.6
		74	Abnormal blood sugar level after lunch	3.2
		75	Abnormal HbA1C level in the first trimester of pregnancy	3.7
		76	Abnormal HbA1C level in the second trimester of pregnancy	3.2
		77	Abnormal indirect coombs rate	3.2
		78	Abnormal BUN level	2.5
		79	Abnormal creatinine level	2.9
		80	Abnormal TSH level	3.1
		81	Fetal AFP in pregnant mother's blood	2.5
		82	Abnormal level of anti-cardiolipin antibodies	3.6
		83	Abnormal level of glycoprotein antibodies	3.6
		84	Abnormal level of lupus anticoagulant factor	4.1
		85	Abnormal condition of DFI in pregnant mother’s husband	2.5
		86	Abnormal sperm chromatin integrity	2.5
		87	Abnormal sperm morphology	3.1

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	**Subclass**	**Row**	**Data element**	**Mean**
Clinical	Sonography report	88	Abnormal cervical length size	2.6
		89	Abnormal gestational sac diameter	4.1

		90	Abnormal yolk sac diameter	3.7
		91	Any abnormal condition in placenta	3.5
		92	Number of fetus	3.4
		93	Abnormal fetal umbilical artery blood flow	3.1
		94	Abnormal maternal uterine artery blood flow	3.1
		95	Abnormal fetal crown-rump length size	3
		96	Abnormal fetal cerebral artery blood flow	2.6
		97	Abnormal fetal muscles contraction	2.5
		98	Difference mean gestational sac diameter (mGSD) to crown-rump length (CRL) less than 5 mm	3.5
		99	Abnormal fetal nuchal fold thickness	3
		100	Abnormal fetal nasal septum bone	2.5
		101	Fetal heart rate reduction	3.3
		102	Fetal heart rate increase	2.5
		103	Any abnormal finding in fetal heart	2.5
		104	Any abnormal finding in other fetal organs	2.9
		105	Fetal pericardial effusion	3
		106	Fetal pleural effusion	3
		107	Fetal ascites	3
		108	Fetal hydrops	3.4

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	Subclass	Row	Data element	Mean
Clinical	Sonography report	109	Fetal implantation disorder	3.5
		110	Any fetal abnormalities	3.9
		111	Intrauterine growth retardation	3
		112	Disruption of chromosome 13	3.7
		113	Disruption of chromosome 18	3.7
		114	Disruption of chromosome 21	3.6
		115	Polyhydramnios	3.4
		116	Oligohydramnios	3.4
		117	Chorioamnionitis	3.2
		118	Abnormal ductus venosus blood flow	3.4

Table 3: Clinical data elements for creating an intelligent system to predict abortion in pregnant mothers
Continued...

Main class	Subclass	Row	Data element	Mean

Clinical	Medical diagnosis	119	Primary diagnosis	3.2
		120	Final diagnosis	2.7
	Medical procedure	121	Primary procedure	2.8
		122	Final procedure	2.8
	physician's profile	123	First name	2.5
		124	Last name	2.5
		125	Medical council number	2.5
		126	Phone number	2.5

Discussion

The essential set of data elements for creating an intelligent system to predict abortion in pregnant mothers was compiled into two main sections, comprising 19 managerial data elements and 126 clinical data elements.

A study aimed at designing an artificial neural network to predict pregnancy outcomes in lupus mothers in Iran was conducted. Sixteen variables impacting the prediction of pregnancy outcomes in pregnant lupus mothers were identified (Akbarian et al., 2015). The variable of anti-cardiolipin antibodies present in this research was similar to the current work. Another research pointed at integrating machine learning techniques and physiological variables based on fetal heart rate for fetal monitoring was carried out. In this study, variables such as maternal age, fetal weight based on cardiotocography, number of weeks of pregnancy, newborn's weight at birth, fetal gender, Apgar score, delivery type, and variables related to fetal heart rate were used (Signorini et al., 2020). The variables of maternal age and fetal heart rate were similar to those in the present study.

A study aimed at designing an abortion prediction system using machine learning techniques was conducted. This research utilized ten effective features for predicting abortion, where five aspects, namely unique identifier, maternal age, body mass index, number of previous abortions, and blood pressure (Biswas et al., 2022), were consistent with the current work. Another research pointed at developing a nomogram model to predict macrosomia in pregnant women with gestational diabetes was carried out. Features such as the pregnant woman's age, pre-pregnancy body mass index, weight during pregnancy, and

fasting glucose levels were used in this research (Zou et al., 2021), which showed similarities with the present study.

A study aimed at developing a wearable system based on the Internet of Things with an accelerometer and machine learning techniques for the automatic monitoring of fetal movements was conducted (Marques et al., 2020). In this research, the data elements of fetal heart rate and maternal blood pressure were consistent with the current work. Another research pointed at pre-birth detection of cleft lip and palate using deep neural networks was carried out. Thirty-six variables were used for model design. In this study, data elements related to the mother, including abortion history, smoking habits, frequency of smoking, drug use, alcohol consumption, diabetes, hypertension, and income level (Shafi et al., 2020), were common with the present research.

A study was conducted to compare logistic regression with machine learning methods for predicting fetal growth abnormalities. The data elements of this research, including maternal age, marital status, income level, pre-pregnancy body mass index, chronic hypertension history, diabetes history, gestational diabetes history, history of giving birth to a newborn weighing less than 2500 grams, preterm delivery history, smoking during pregnancy, drug use during pregnancy, and pregnancy-induced hypertension, (Kuhle et al., 2018) were identical to those in the current work.

A research was carried out with the objective of predicting fetal health status based on the mother's clinical history using machine learning techniques. Twenty-three data elements were utilized in this research to predict the fetal condition, including variables such as maternal age, type of pregnancy, number of previous pregnancies, abortion history, diabetes history, abnormalities history in previous children, smoking, and alcohol use, (Akbulut et al., 2018) which were similar to the present study.

Conclusions

The incidence of abortion in Iran and globally is on the rise due to various reasons, and given the significance of maternal and fetal health, there is a felt need for solutions to reduce abortions, prevent them, and minimize their resultant complications. Achieving these goals necessitates a system capable of predicting abortions in pregnant mothers using artificial intelligence algorithms, which hold special importance. The first step in creating an intelligent predictive system for abortions involves collecting a comprehensive and high-quality data elements, which can assist physicians in predicting abortions and, where possible, taking timely action to prevent them.

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Authors Contribution

Elham Aalipour and Fourogh Baratzadeh were involved in the execution of all the work and data analysis; Elham Aalipour, Fourogh Baratzadeh, Farideh Moramezi, and Shahram Tahmasebian were provided the research guidance and manuscript editing. All authors have read and approved the final manuscript before its submission.

Conflicts of Interests

None to declare.

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