Information Technology for Predicting the Course of Climacteric Syndrome

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Abstract

A woman spends almost a third of her life in menopause. This age stage is characterized not only by the end of the reproductive period of a woman's life, but also by complex reactions of the neuroendocrine system, which may manifest as a combination of neurovegetative, psychoemotional, and metabolic-endocrine disorders. Such diseases as atherosclerosis, osteoporosis, cancer, urogenital disorders worsen the quality and life expectancy of a woman. The need for early prognosis of the climacteric syndrome is due to the fact that it makes it possible to carry out preventive and therapeutic measures in time, to prevent the development and complications of diseases. It is important to note that effective management of climacteric syndrome can not only alleviate symptoms but also prevent long-term health problems such as osteoporosis and cardiovascular diseases. Nevertheless, the human body is a complex system, and it's difficult to account for all the factors that impact a woman's health. It's important to consider a woman's overall health, lifestyle, habits, stress levels, and occupational hazards when assessing specific organs or conditions. However, constructing accurate models that take into account all these factors is challenging, especially when qualitative factors are involved. By allowing for imprecise and incomplete descriptions of a system, fuzzy modeling can provide a more accurate representation of the system under study. Fuzzy modeling can be particularly useful in predicting the risk of disorders in hormone-dependent organs and body systems of a menopausal woman, especially when there is uncertainty or imprecision in the available data. The aim of this research is to develop an information technology that can accurately predict the course of climacteric syndrome. The developed information technology demonstrated a high degree of accuracy in predicting the severity of climacteric syndrome. The use of this technology can aid healthcare providers in making better treatment decisions and interventions for menopausal women experiencing climacteric syndrome.

Keywords

Climacteric syndrome, menopause, menopause periods, STRAW, fuzzy logic

1. Introduction

Menopause is an inevitable phase in the life of every woman, and some may experience it with ease, while others may have severe symptoms that negatively impact their daily lives, including work, family, and relationships [1, 2]. Menopause occurs due to the cessation of ovarian function, which leads to the deterioration of the body's organs and systems [3], starting the aging process [4-6]. Symptoms such as hot flashes, insomnia, irritability, tearfulness, anxiety [7-9], sexual dysfunction, and cognitive decline can occur frequently and affect the quality of life [10]. Moreover, if left

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untreated, menopause can lead to atrophy of the urogenital organs' mucous membranes, cardiovascular disorders, bone mineral density loss, and pathological fractures.

Early identification and treatment of climacteric syndrome [11] are crucial to prevent the development of severe symptoms and associated health conditions [12,13]. This underscores the importance of predicting the severity of the climacteric syndrome for gynecologists to provide timely interventions that can improve the quality of life of their patients [14]. In addition, effective management of the climacteric syndrome can reduce the risk of developing conditions such as osteoporosis, cardiovascular diseases [15, 16], and urogenital atrophy. Therefore, healthcare providers must be able to recognize the symptoms and severity of climacteric syndrome and provide appropriate interventions to improve their patients' overall health and well-being.

2. Related works

Menopause and climacteric syndrome have been extensively studied in the scientific community, and there are many scientific papers and studies on this subject. In addition to studying symptoms, developing new treatments, and predicting climacteric syndrome, scientific research has also focused on understanding the underlying biological processes that contribute to this conditions.

The study [17] aimed to investigate the impact of weight at birth and weight and growth trajectory up to age 4 on menstrual statuses among women aged 39-49 years. The research was carried out through a prospective study of two US birth cohorts. The findings suggest that women with low birth weight and who were underweight during infancy are more likely to experience natural menopause or be in the menopausal transition by the age of 39-49 years. The study also found that these associations are not explained by other early-life exposures such as in utero smoke exposure and lower maternal education at birth. The study supports the developmental origins hypothesis, which suggests that the early-life environment can affect follicular development and accelerate ovarian aging, leading to earlier menopause. The findings have important implications as birth weight is inversely associated with the risk of cardiovascular and metabolic diseases but positively associated with breast cancer risk. The study highlights the importance of the intrauterine and early-life environment that influences growth, which may contribute to associations between earlier menopause and chronic disease risk.

The study [18] aimed to investigate the characteristics of menopause transition among different ethnic populations and reflect on the impact of changing patterns of delayed marriage and reproduction. Perimenopause age and duration, menopause age, and hormonal indicators of menopause were examined across 5 ethnicities: Hispanic, Caucasian, Afro-American, Chinese and Japanese. The study found that there was a similar window of menopause age within each population, but no significant difference in perimenopause and menopause age between populations, except for the rate of increase of testosterone and follicle-stimulating hormone in African-Americans and Hispanics during the menopause transition period. The research suggests that menopause is still evolving, given the broad window of variation in age at menopause within the population and the absence of significant differences between populations. Furthermore, the study proposes the mate choice theory of menopause, which suggests that menopause is the result of the accumulation of infertility mutations in older women due to men's preference for younger mates. The study suggests a shifting mate choice-shifting menopause model, which posits that as the age of mate choice/marriage shifts to older ages, so will the age at menopause. The study suggests that menopause is a transient phase of female fertility, and it can de-evolve, be delayed, or even disappear completely. In conclusion, integrated longitudinal menopausal studies linked with genomics and hormonal studies on diverse ethnic populations can provide valuable information for women's health and personalized medicine.

The authors in [19] aimed to summarize the current risk prediction models for natural menopause onset and evaluate their performance. They conducted a systematic review of 14 articles based on 8 unique studies, comprising 9588 women and 3289 natural menopause events. The included studies used onset of natural menopause (ONM) as the outcome, with age, anti-Müllerian hormone, and follicle-stimulating hormone being the most commonly investigated predictors. However, the authors noted that the predictive performance and generalizability of the current prediction models on ONM is limited. This is because the models were generated from studies that were rated at high risk of bias mainly due to methodological concerns related to statistical analysis, and the models were mainly based on specific populations and ethnicities, mainly Caucasian. The estimated C-statistic for the prediction models ranged from 0.62 to 0.95, indicating a variable performance. While the models may be useful in certain settings, efforts to improve their performance are needed as their use becomes more widespread. It is important to note that predicting the onset of menopause is essential for family planning and to ensure prompt intervention in women at risk of developing menopause-related diseases. Therefore, further research is needed to develop more robust and accurate prediction models that can be applied across different populations and ethnicities.

The aim of the review [20] is to provide an overview and comparison of the available tools for climacteric syndrome assessment. The authors identified four holistic questionnaires that are commonly used to assess menopausal symptoms: Kupperman Index (KI), Menopause Rating Scale (MRS), Menopause Specific Quality of Life Questionnaire (MENQOL), and Greene Climacteric Scale. These questionnaires vary in the type of assessment, included symptoms, rating system of severity, weighing of symptoms, resulting total rating score, and validation status. Although these questionnaires are useful, there are several shortcomings that need to be addressed. For example, they do not take into account the ethnic and cultural background of women, which can affect the experience and reporting of menopausal symptoms. Additionally, there are no established thresholds for treatment initiation and monitoring, which can lead to inconsistent and inadequate management of menopausal symptoms. Furthermore, there are other questionnaires available to assess single symptoms or groups of symptoms related to specific aspects of menopause. For example, there are questionnaires that focus on vasomotor symptoms, insomnia, or sexual dysfunction. These questionnaires may be more appropriate for specific populations or situations, but they do not provide a holistic assessment of menopausal symptoms. In summary, the four holistic questionnaires identified in this review are useful tools for assessing menopausal symptoms, but they have limitations that need to be addressed. Healthcare professionals should use these questionnaires as a guide and also take into account the patient's individual needs and preferences when assessing and managing menopausal symptoms.

The objective of the paper [21] is to outline the process of developing an International Classification of Functioning, Disability and Health (ICF) Core Set for Climacteric Syndrome. The process of developing an ICF Core Set for Climacteric Syndrome involves several steps, including a systematic literature review, expert surveys, focus group discussions, and field testing. The literature review aims to identify relevant ICF categories that are frequently reported in the literature and are relevant to climacteric syndrome. Expert surveys are conducted to gather opinions and ratings of the identified ICF categories from various stakeholders, including clinicians, researchers, and women experiencing climacteric syndrome. Focus group discussions are used to further refine the list of ICF categories and to identify additional categories that may have been missed during the literature review. Finally, the ICF Core Set is field-tested to evaluate its feasibility and usefulness in clinical practice.

The development of an ICF Core Set for Climacteric Syndrome is important as it allows for a standardized and comprehensive assessment of the functioning of women experiencing climacteric syndrome. This can help healthcare professionals to identify the most important problems in functioning for each individual woman, and develop personalized treatment plans to improve their quality of life. It also allows for better communication between healthcare providers and researchers, which can lead to more effective and evidence-based care. The ICF Core Set for Climacteric Syndrome can also be used for teaching and training purposes, helping to educate healthcare professionals on the most relevant aspects of functioning in women experiencing climacteric syndrome.

A promising approach for solving complex scientific problems is machine learning methods [22-26]. In particular, the work [27] investigated the effectiveness of machine learning approaches for predicting the risk of osteoporosis in postmenopausal women. Early detection is crucial in the case of osteoporosis, as it is a degenerative condition that is linked to the process of aging after menopause. Osteoporosis, a condition that remains asymptomatic until it results in fragility fractures, can be prevented if diagnosed early. In [27] machine learning models have been developed to predict the risk of osteoporosis, allowing primary care providers to identify women who are at a higher risk of the condition and require further testing. In a study, seven machine learning models were compared, with the artificial neural networks model performing the best, displaying the highest area under the receiver operating characteristic curve (AUROC) value. The application of this model in a clinical environment could assist primary care providers in stratifying osteoporosis patients, improving detection, and early treatment.

The aim of the study [28] was to develop a machine learning-based tool for predicting the risk of osteoporosis in postmenopausal women. A total of 1431 women aged between 40-69 years were included in the study, and 20 features were selected based on their importance in predicting osteoporosis. The features were selected using feature importance and recursive feature elimination techniques. Three machine learning algorithms, Random Forest [26], AdaBoost, and Gradient Boosting, were used to train three different models, A, B, and C. Model A used checkup features, Model B used survey features, and Model C used both checkup and survey features. Among the three models, Model C provided the best results, achieving an accuracy of 0.832 for RF, 0.849 for AdaBoost, and 0.829 for GBM. The AUROC for Model C was 0.919 for RF, 0.921 for AdaBoost, and 0.908 for GBM. The ensemble models developed in this study using multiple feature selection methods achieved an excellent AUROC score of 0.921 with AdaBoost, which was higher than those of the best-performing models in recent studies. The developed model has the potential to be a practical medical tool for early diagnosis of osteoporosis in postmenopausal women.

In the study [29] the analysis of different artificial intelligence methods for the prediction of endometrial intraepithelial neoplasia and endometrial cancer risks was conducted on pre- and postmenopausal women to help in clinical decision-making. The objective was to determine if the application of artificial intelligence could resolve the difficulties posed by traditional statistical and diagnostic tests. The study involved 564 patients, and the collected features were age, menopause status, premenopausal abnormal bleeding and postmenopausal bleeding, obesity, hypertension, diabetes mellitus, smoking, endometrial thickness, and history of breast cancer. Endometrial sampling and biopsy were performed on the women based on certain criteria. Six classification methods, namely Random Forest, Logistic Regression, Multilayer Perceptron, Catboost, Xgboost, and Naive Bayes [26], were used, and the synthetic minority oversampling technique was used to correct the class imbalance in the training sets. A 5-fold cross-validation approach was employed with training sets, with tuning and boosting done to enhance the models' performance. The accuracy of the models was evaluated using various measures. The results revealed an accuracy of 0.94 for predicting precancerous disease, and the precision, recall, and F1 scores for the test group were 0.71, 0.50, and 0.59, respectively. The study concluded that artificial intelligence could effectively identify women at risk of endometrial intraepithelial neoplasia and endometrial cancer, regardless of their menopausal status or symptoms.

The human body is a highly complex system, and when considering the health of a woman, it is essential to take into account various factors that can affect her well-being. This includes the general health of the woman, her lifestyle, bad habits, stress levels, and occupational hazards. Constructing models to manage women's health during climacteric syndrome can be challenging due to the complexity and interdependence of various body systems [30]. Furthermore, qualitative factors such as emotions and subjective experiences can also have a significant impact on a woman's health, making it difficult to apply traditional mathematical tools.

To address these challenges, fuzzy modeling has emerged as a useful tool to deal with incomplete and qualitative data in the study of complex systems. By incorporating fuzzy logic and fuzzy sets, it's possible to construct models that can account for uncertainty, variability, and imprecision in the data, resulting in more accurate predictions and better-informed decision-making.

This is particularly useful when dealing with the complexities of climacteric syndrome prediction and the impact it can have on a woman's health.

An information technology based on fuzzy logic was developed to address the issue of predicting the course of climacteric syndrome. The information technology incorporates expert knowledge in the field to generate accurate predictions.

3. Information Technology for Predicting the Course of Climacteric Syndrome

The proposed information technology is based on the STRAW +10 criteria and uses fuzzy logic. The Stages of Reproductive Aging Workshop (STRAW) criteria [30] is a standardized system developed by a group of experts in reproductive medicine to classify the stages of reproductive aging in women. It uses a combination of menstrual cycle characteristics, hormone levels (in particular follicle-stimulating hormone, FSH), and age to categorize women into various stages, including pre-menopause, early and late menopause transition, menopause, and post-menopause. The STRAW +10 system is an updated version of the original criteria, which provides additional information on menstrual cycle characteristics, hormone levels, and age to improve the accuracy of menopausal staging.

3.1 Menopause Periods and Factors Affecting Women's Health

According to STRAW +10, perimenopause and menopause in a woman's life can be divided into six periods, each of which has specific effects on health (Figure 1).

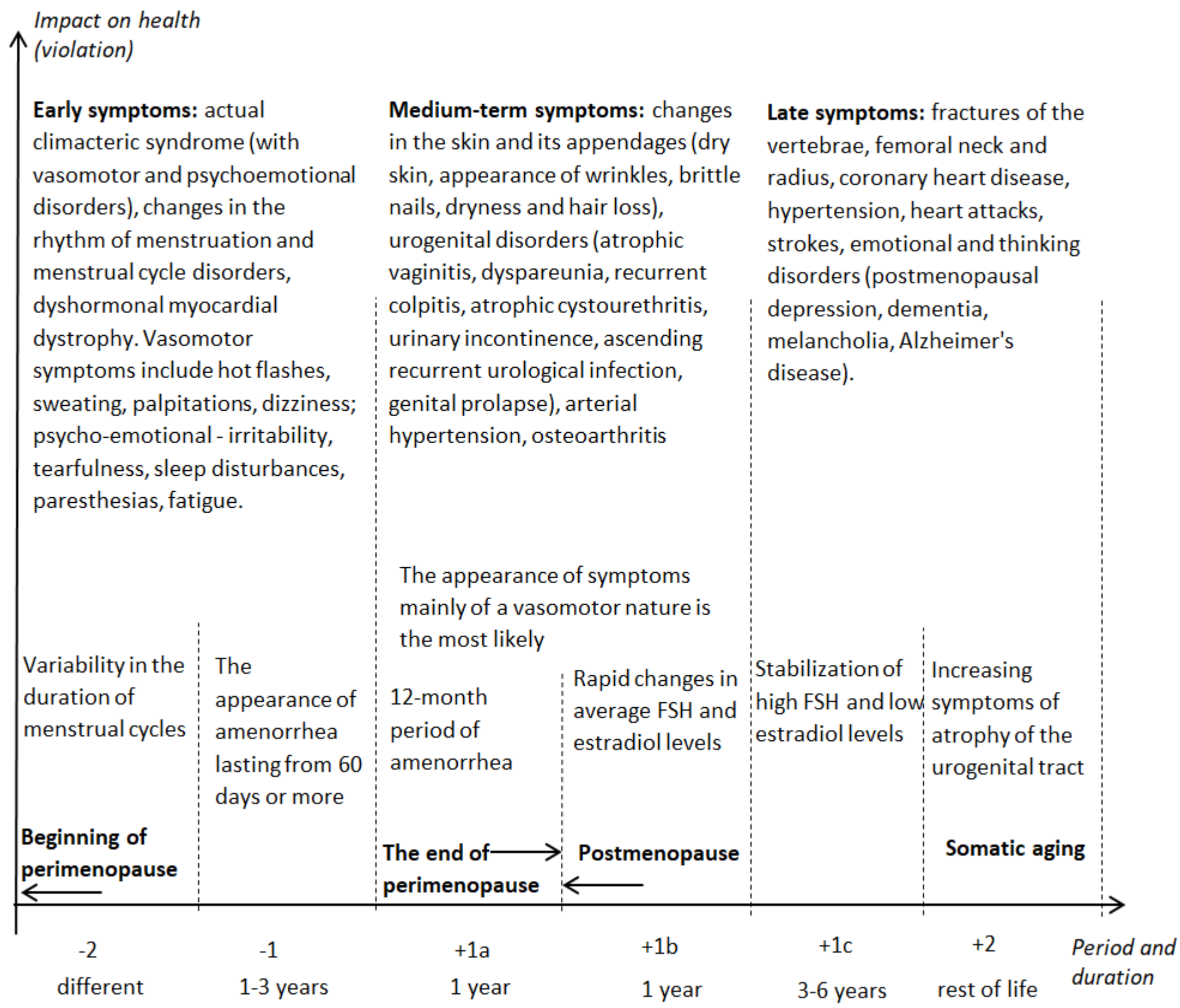

Figure 1: Periods of menopause and features of impact on women's health according to STRAW +10

For effective prediction of menopausal syndrome, it is necessary to use an integrated approach that takes into account various aspects of a woman's condition. The approach involves a three-step model consisting of identifying the stage of menopause, assessing the woman's health status, and forecasting potential health problems in the future.

The first step involves determining the specific stage of menopause that the woman is experiencing. Menopause is generally divided into three stages, including perimenopause, menopause, and postmenopause. Accurately identifying the stage of menopause can help providers make better treatment decisions and predict potential health risks. The second step involves evaluating the woman's overall health status, taking into consideration any pre-existing medical conditions that may impact the severity of climacteric symptoms. Factors such as lifestyle habits, medication use, and family history can also impact a woman's health and the severity of her symptoms. The third step involves forecasting potential health problems that may arise in the future due to climacteric syndrome. By following these three steps, a more holistic approach to redict, managing menopause can be developed and improve the overall health and well-being of women going through menopause.

In order to determine at what period of menopause a woman is, it is necessary to obtain data on variability in the duration of menstrual cycles, the onset of amenorrhea and the period of the last menstruation. The variable x_0 indicates how many years amenorrhea lasts, according to this value it is possible to determine at what period of menopause a woman is (Table 1).

The next step is to determine the state of health of the woman at the time of the examination and to establish the presence of health disorders, if any. For this purpose, a cognitive map was created, which identifies the factors that affect a woman's health, and how strong this influence is (Figure 2). In order to establish the presence of violations in the health of a woman, it is necessary to analyze the questionnaire that the doctor fills out during the examination.

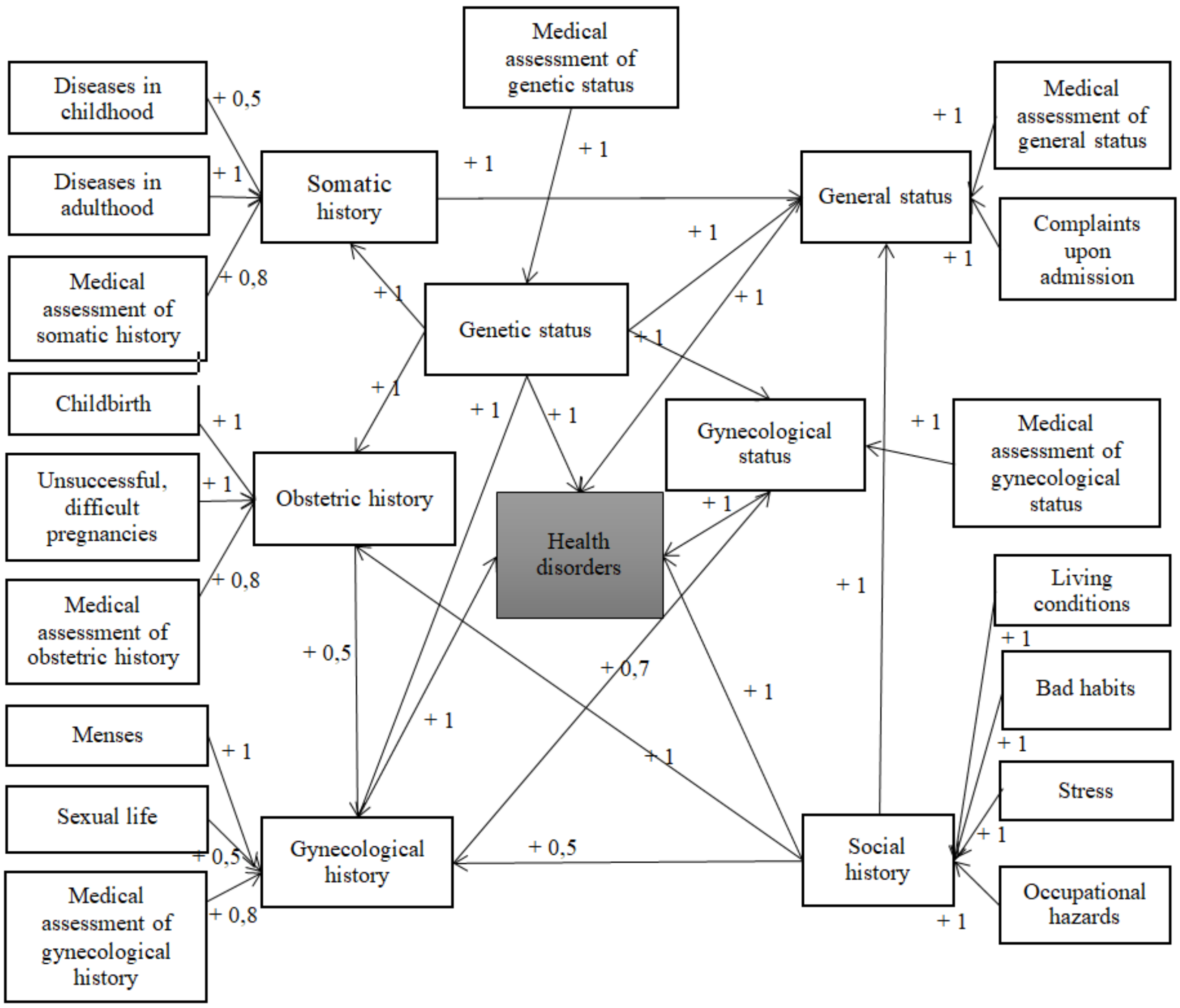

Figure 2: Cognitive map of the influence of factors on health disorders

By creating a cognitive map, many factors were identified that characterize the state of a woman's health (Table 2).

Table 1
Determination of the period of menopause

Variable value	Menopause period number	Period name
$x_0 < 0{,}2$	1	-2
$0{,}2 \le x_0 < 1$	2	-1
$1 \le x_0 < 2$	3	+1a
$2 \le x_0 < 3$	4	+1b
$3 \le x_0 < 9$	5	+1c
$x_0 \ge 9$	6	+2

3.2 Subsystems of Information Technology for Predicting the Course of Climacteric Syndrome

The occurrence of disorders in hormone-dependent organs and body systems of a woman of menopausal age depends on 17 main input parameters, $x_1 - x_{17}$. These parameters can be attributed to 7 subsystems.

Table 2
Linguistic variables

Variable	Designation	Variable type
Complaints upon admission	x_1	Input
Medical assessment of general status	x_2	
Living conditions	x_3	
Bad habits	x_4	
Stress	x_5	
Occupational hazards	x_6	
Medical assessment of gynecological status	x_7	
Medical assessment of genetic status	x_8	
Diseases in childhood	x_9	
Diseases in adulthood	x_{10}	
Medical assessment of somatic history	x_{11}	
Childbirth	x_{12}	
Unsuccessful, difficult pregnancies	x_{13}	
Medical assessment of obstetric history	x_{14}	
Menses	x_{15}	
Sexual life	x_{16}	
Medical assessment of the gynecological history	x_{17}	
General status	p_1	Intermediate
Social history	p_2	
Gynecological status	p_3	
Genetic status	p_4	
Somatic history	p_5	
Obstetric history	p_6	
Gynecological history	p_7	
Health disorder	v	Output

Subsystem "General status" describes an initial evaluation of a patient's overall health and well-being. This evaluation is based on various factors, including the patient's medical history, physical examination, and subjective complaints or symptoms. "General status" subsystem takes into account complaints reported by a woman upon admission to a healthcare facility, as well as an assessment of her general feeling. This may involve asking the woman about any symptoms she is experiencing, such as pain, fatigue, or nausea, and assessing her level of distress or discomfort. It may also involve a physical examination to check for any signs of illness or disease.

Overall, the purpose of the "General status" subsystem is to provide an initial impression of a patient's overall health and well-being, which can then be used to guide further assessment and treatment:

$$p_1 = f(x_1, x_2, p_2, p_4, p_5). \tag{1}$$

The subsystem "Social history" includes an assessment of various social and environmental factors that can impact a woman's health, such as living conditions, bad habits, stress, and occupational hazards. These factors can provide valuable information about the total indicator of the influence of conditions and lifestyle on a woman's health. Living conditions, for example, can have a significant impact on a woman's health. Poor housing quality, lack of access to clean water and sanitation can all contribute to a range of health problems, from infectious diseases to chronic conditions such as asthma. Bad habits such as tobacco and alcohol use, poor diet, and lack of exercise can also have a significant impact on a woman's health. These lifestyle factors are associated with a range of health problems, including heart disease, cancer, and diabetes. Stress is another factor that can have a significant impact on a woman's health. Chronic stress has been linked to a range of health problems, including high blood pressure, heart disease, and depression. Occupational hazards, such as exposure to chemicals, noise, or physical strain, can also impact a woman's health. These hazards can cause a range of health problems, from musculoskeletal disorders to respiratory diseases.

By assessing these and other social and environmental factors, healthcare providers can gain a more complete understanding of a woman's health status. Thus, the subsystem "Social history" determines the total indicator of the influence of conditions and lifestyle on a woman's health:

$$p_2 = f(x_3, x_4, x_5, x_6). \tag{2}$$

The subsystem "Gynecological status" is an important aspect of a woman's overall health assessment, and it includes several key components. The first component is the genetic status of a woman. This involves assessing any potential genetic risk factors for gynecological conditions such as breast or ovarian cancer. The second component is a medical assessment of a woman's gynecological status. This involves a physical examination to assess the health of the reproductive organs, including the uterus, ovaries, and fallopian tubes. The healthcare provider may also perform a Pap smear or other tests to screen for cervical cancer or other gynecological conditions. The third component is a gynecological history, which involves gathering information about a woman's menstrual cycle, pregnancy history, and any gynecological conditions she has experienced in the past. This information can provide valuable insight into a woman's gynecological health and help identify any potential issues that may require further assessment or treatment.

The subsystem "Gynecological status" can be defined as follows:

$$p_3 = f(x_7, p_4, p_7). \tag{3}$$

The "Genetic status" subsystem is based on a medical assessment of the genetic status and takes into account genetic diseases in the family:

$$p_4 = f(x_8). \tag{4}$$

The subsystem "Somatic history" involves evaluating woman's overall medical history and any concomitant diseases that may impact her health. The first component of the somatic history is an assessment of any diseases a woman may have experienced during childhood, as well as any chronic conditions that may have developed during childhood. The second component is an assessment of any diseases a woman may have experienced during adulthood. This can include chronic conditions such as hypertension or heart disease, as well as acute illnesses such as the flu or pneumonia. The third component is a medical assessment of a woman's somatic history, which involves gathering information about any medical treatments she may have received, such as surgeries, hospitalizations, or medications. The fourth component is an assessment of a woman's genetic status, which involves evaluating any potential genetic risk factors for certain medical conditions. This may involve genetic testing in some cases.

Thus, the subsystem "Somatic history" takes into account all concomitant diseases:

$$p_5 = f(x_9, x_{10}, x_{11}, p_4). \tag{5}$$

The subsystem "Obstetric history" involves evaluating a woman's pregnancy and childbirth history, as well as any related medical, social, and genetic factors. The first component of obstetric history is an assessment of all pregnancies and childbirths a woman has experienced. This includes information about the number of pregnancies, the gestational age at delivery, any complications during pregnancy or delivery. The second component is an assessment of any unsuccessful or difficult pregnancies a woman may have experienced, such as miscarriages, stillbirths, or ectopic pregnancies. The third component is a medical assessment of a woman's obstetric history, which involves gathering information about any medical treatments or interventions she may have received during pregnancy or childbirth.

The subsystem "Obstetric history" takes into account also social history and genetic status:

$$p_6 = f(x_{12},\ x_{13}, x_{14}, p_2, p_4). \tag{6}$$

The subsystem "Gynecological history" involves evaluating a woman's gynecological history and related medical, social, and genetic factors. The first component of gynecological history is an assessment of a woman's menstrual history. This includes information about the regularity, length, and severity of her periods, as well as any related symptoms such as cramping or bloating. The second component is an assessment of a woman's sexual history, including the age at which she became sexually active, the number of sexual partners she has had, and any history of sexually transmitted infections. The third component is a medical assessment of a woman's gynecological history, which involves gathering information about any medical treatments or interventions she may have received for gynecological conditions, such as pelvic inflammatory disease or endometriosis.

The subsystem "Gynecological history" can be defined as follows:

$$p_7 = f(x_{15}, x_{16}, x_{17}, p_2, p_4, p_6). \tag{7}$$

The presence of disorders in hormone-dependent organs and body systems of a woman of menopausal age is defined as a total indicator of the initial parameters of the described subsystems:

$$v = f(\ p_1, p_2, p_3, p_4, p_7). \tag{8}$$

The predicted value of possible disorders in hormone-dependent organs and systems of the body of a woman of menopausal age is determined as follows:

$$z_{n+1} = f(P_{n+1}, z_n), \tag{9}$$

where n is the period of menopause in which the woman is,
$z_n = v$ – the level of health disorders of a woman in period n,
z_{n+1} – predicted level of health disorders in period $n + 1$,
P_{n+1} – intermediate variables that affect the value of violations of the period $n + 1$ (Table 3).

Table 3
The influence of variables on each period and their importance

Menopause period	n	P_n	Weights of variables
-1	2	p_2	0.8
+1a	3	p_2, p_3	0.8, 0.7
+1b	4	p_2, p_3	0.85, 0,8
+1c	5	p_2, p_4, p_5	0.9, 0.8, 0,7
+2	6	p_2, p_4, p_5	0.95, 0.95, 0,75

To calculate the assessment of violations in each period, it is necessary for each indicator to set an assessment of the weight $w_i \in [0; 1]$, $i = \overline{1,7}$ and obtain the value of the variable under study. For example, an assessment of violations in the current period can be obtained as follows:

$$v = \sum_{i=1}^{7} p_i \cdot \beta_i, \tag{10}$$

where β_i is the weight coefficient characterizing the relative importance of the indicators, which can be calculated as follows:

$$\beta_i = \frac{w_i}{\sum_{i=1}^{7} w_i}, \quad \sum_{i=1}^{7} \beta_i = 1. \tag{11}$$

Similarly, weighting factors are set for all variables.

A feature of a system based on fuzzy logic is that such a system contains a decision-making mechanism based on expert information. Based on the knowledge and experience of experts in the studied subject area, the importance of each linguistic variable was determined (Table 4).

Table 4
The importance of linguistic variables

Variable	Weight	Variable	Weight	Variable	Weight	Variable	Weight
x_1	1	x_9	0,5	x_{17}	0,8	p_5	1
x_2	1	x_{10}	1	p_1	1	p_6	0,5
x_3	1	x_{11}	0,8	$p_2 \rightarrow v$	1	p_7	1
x_4	1	x_{12}	1	$p_2 \rightarrow p_1$	1	z_1	1
x_5	1	x_{13}	1	$p_2 \rightarrow p_6$	0,7	z_2	1
x_6	1	x_{14}	0,8	$p_2 \rightarrow p_7$	0,5	z_3	1
x_7	1	x_{15}	1	p_3	1	z_4	1
x_8	1	x_{16}	0,5	p_4	1	z_5	1

3.3 Definition of Linguistic Variables

The development of a fuzzy model involves defining the basic term set T and the domain of definition X for all linguistic variables. Table 5 summarizes these definitions. In addition to these definitions, graphs of the membership functions for each linguistic variable are constructed (Figures 3-5).

The membership function is used to specify the degree to which each value in the domain of definition belongs to each term in the basic term set. The graphs of these functions provide a visual representation of the degree of membership for each linguistic variable, which is used to make predictions and decisions in the fuzzy model.

Thus, seventeen input linguistic variables, seven intermediate and six output variables have been selected and described, and graphs of membership functions have been constructed for them.

Table 5
Definition of linguistic variables

Variable	Variable type	Scope of X	Basic term set T
x_1	Input	[0; 1]	{low, medium, high}
x_2			{positive, medium, negative}
x_3			{good, medium, bad}
x_4			{low, medium, high}
x_5			
x_6			
x_7			{positive, medium, negative}
x_8			
x_9			{normal, high}
x_{10}			
x_{11}			{positive, medium, negative}
x_{12}		[0; 4]	{decrease, steady, increase}
x_{13}			{normal, high}
x_{14}		[0; 1]	{positive, medium, negative}
x_{15}		[12; 17]	{decrease, steady, increase}
x_{16}		[0; 50]	{decrease, steady, increase}
x_{17}		[0; 1]	{positive, medium, negative}
p_1	Intermediate	[0; 1]	{normal, medium, heavy}
p_2			
p_3			
p_4			
p_5			
p_6			
p_7			
v	Output	[0; 1]	{low, medium, high}
z_{n+1}			

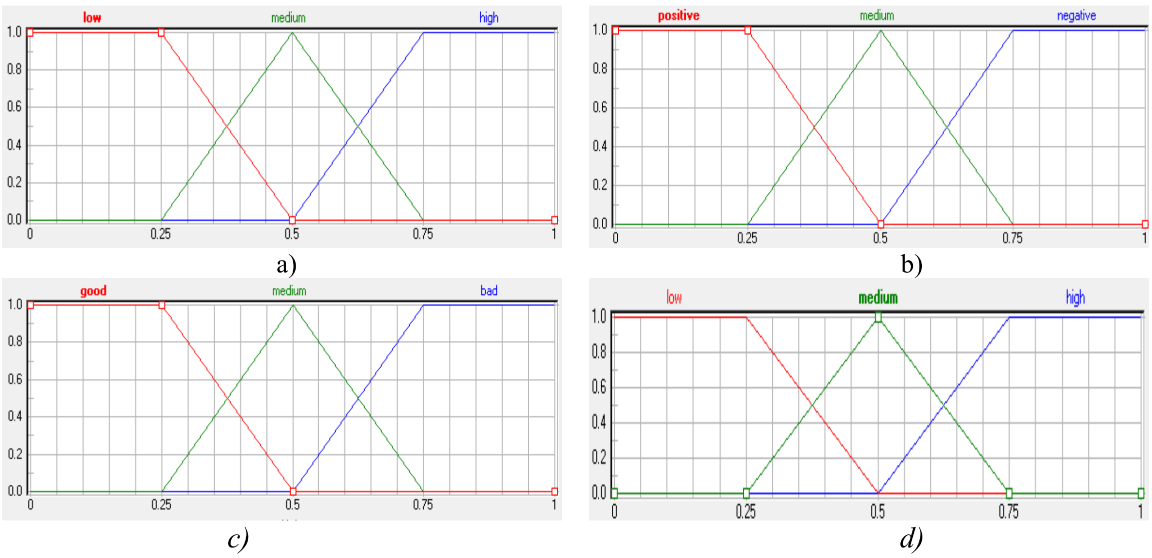

Figure 3: Membership functions graph of input variables: a) x_1, x_4; b) x_2, x_7; c) x_3; d) x_5

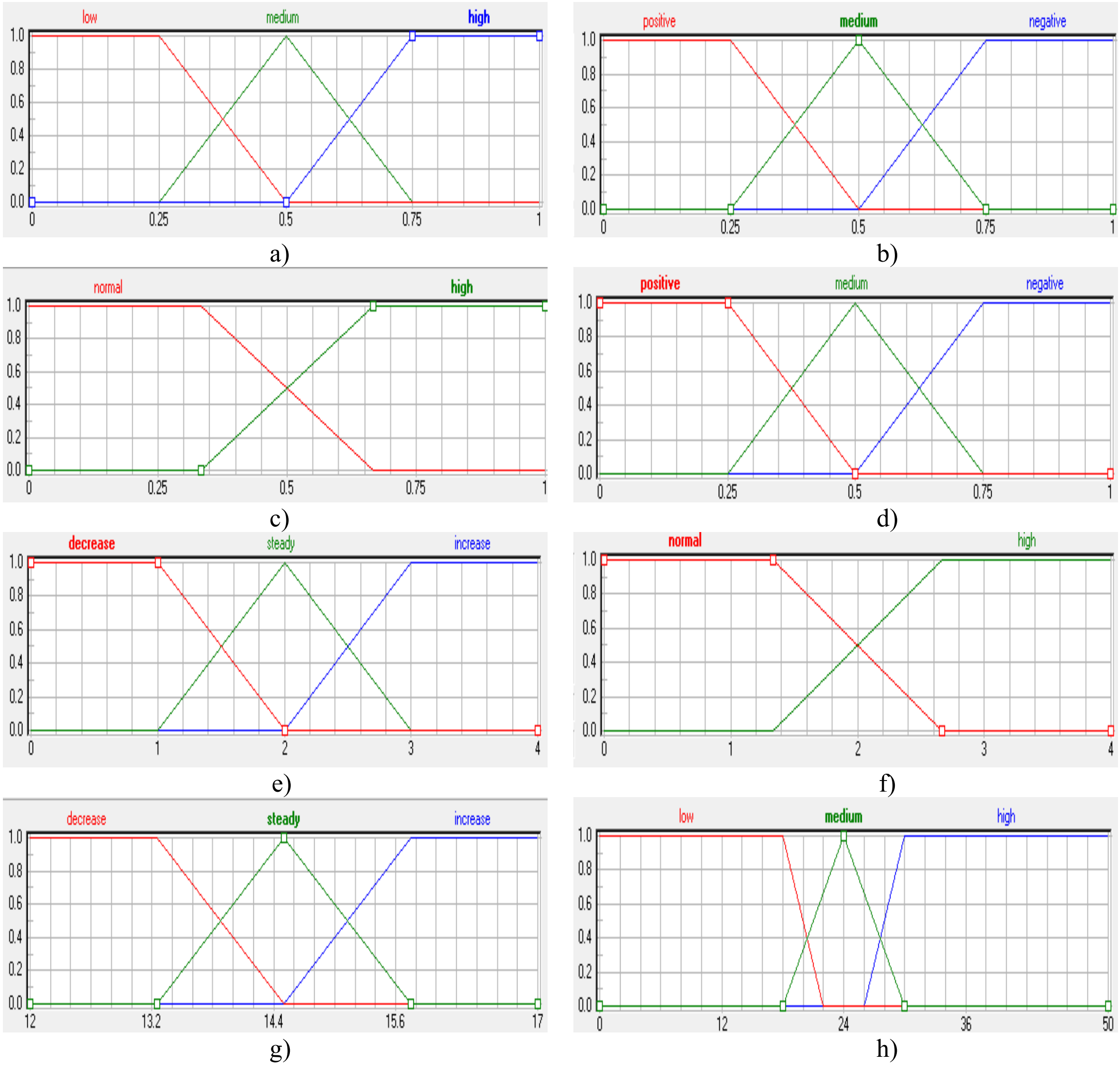

Figure 4: Membership functions graph of input variables: a) x_6; b) x_8, x_{14}, x_{17}; c) x_9, x_{10}; d) x_{11}; e) x_{12}; f) x_{13}; g) x_{15}; h) x_{16}

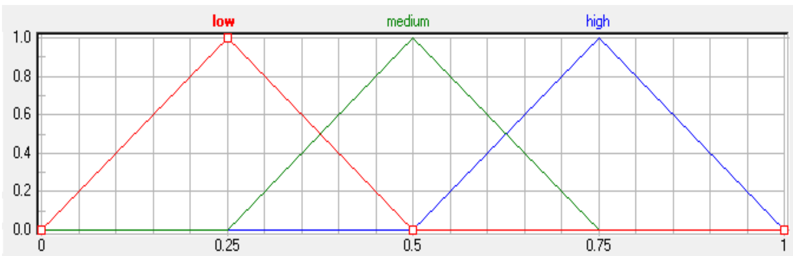

Figure 5: Membership functions graph of the output variables $z_1 - z_6$

3.4 Building the Rule Base

To implement the information technology, a rule base was built, consisting of 13 blocks of rules. The rule base provides a way to model the complex interactions between the input, intermediate variables and the output variable, and can be used to make predictions about a woman's health status based on her individual characteristics and medical history.

For each term of the input variables, there is at least one rule in which this term is used as a precondition. Each rule has a set of preconditions (IF statements) that define the conditions under which the rule applies, and a conclusion (THEN statement) that specifies the value of the output variable.

The preconditions and conclusions are expressed using fuzzy terms, which allow for imprecision and uncertainty in the input variables and output variable.

For example, the block of rules for variable z_1 consists of 243 rules. Examples of fuzzy rules are:

- IF the general status is normal, AND the social history is normal, AND the gynecological status is medium, AND the genetic status is medium, AND the gynecological history is normal, THEN health disorders are low;
- IF the general status is normal, AND the social history is medium, AND the gynecological status is heavy, AND the genetic status is normal, AND the gynecological history is medium, THEN the health disorders are medium;
- IF the general status is medium, AND the social history is heavy, AND the gynecological status is normal, AND the genetic status is heavy, AND the gynecological history is heavy, THEN health disorders are high.

The example rules given illustrate how the intermediate variables are used to determine the level of health disorders. For example, the first rule suggests that if the general status, social history, and gynecological history are normal, and the gynecological status and genetic status are medium, then the level of health disorders is low. This rule reflects the idea that if a woman has a generally good health status and no significant risk factors, she is likely to have few health problems. The second rule suggests that if the social history is medium and the gynecological status is heavy, then the level of health disorders is medium, even if the general status and genetic status are normal, and the gynecological history is medium. This rule reflects the idea that certain risk factors, such as heavy gynecological problems, can have a significant impact on health outcomes. The third rule suggests that if the social history, genetic status, and gynecological history are heavy, and the general status and gynecological status are medium, then the level of health disorders is high. This rule reflects the idea that a combination of multiple risk factors can significantly increase the likelihood of health problems.

Together, the set of fuzzy rules in the rule base allows for a flexible and nuanced assessment of a woman's health status, taking into account multiple factors and their interactions.

4. Experiments

To assess the effectiveness of the developed information technology, a retrospective analysis of the data of 112 women who sought help from the Khmelnitsky city perinatal center in the period from 2015 to 2020 for various gynecological problems and had a normal menstrual cycle was carried out. All women were over the age of 45. To make a prognosis, after obtaining the informed consent of patients, personal data of patients were collected using specially designed questionnaires. With the help of the developed information technology, the collected data were analyzed in order to obtain a forecast of the course of menopause. When women reach menopausal age, the predicted results of the course of menopause were compared with the actual observations of the patients.

The results of the experiments are presented in Table 6, which includes the true positive (TP), true negative (TN), false positive (FP), false negative (FN), accuracy (ACC), Precision (PR) and Recall (REC) for each predicted severity of climacteric syndrome (high, medium, and low). The results show that the accuracy of the predictions was high, with an ACC of 0.9196 for both high and medium severity, and 0.9821 for low severity. The precision and recall rates were also high for all three severities, indicating that the developed information technology can accurately predict the severity of climacteric syndrome.

Therefore, based on the results presented in Table 6, the developed information technology is considered to be effective in predicting the severity of climacteric syndrome, both moderate and severe. It provides doctors with valuable data that can be used for preventive measures against predicted disorders.

Table 6
Comparison of the results of predicting the course of the menopause with its real course

Severity of climacteric syndrome	Predicted result (%)	Actual result (%)	TP	TN	FP	FN	ACC	PR	REC
high	34	31	28	75,00	6	3	0,9196	0,8235	0,9032
medium	75	76	68	35,00	7	2	0,9196	0,9067	0,9714
low	3	5	2	108,00	1	1	0,9821	0,6667	0,6667

5. Conclusions

In summary, diagnosing and predicting menopause and climacteric syndrome can be challenging due to the wide variability in symptoms and factors that can influence them. The aim of this research was to develop an information technology that takes into account various health factors to predict the course of climacteric syndrome accurately. The technology demonstrated a high degree of accuracy and can aid healthcare providers in making better treatment decisions and interventions for menopausal women experiencing climacteric syndrome. Early prognosis is crucial for preventing disease development and complications. This information technology can provide personalized health advice and identify women who may need closer medical monitoring or intervention.

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