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Machine learning analysis of the relationships between traumatic childbirth experience with positive and negative fertility motivations in Iran in a community-based sample

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Abstract

Background Psychologically traumatic childbirth leads to short and long-term negative impacts on a woman's health and impacts future reproductive decisions. Considering the importance of fertility growth and strengthening positive fertility motivations in …, this community-based study was conducted to investigate the relationship between traumatic childbirth history and positive and negative fertility motivations.

Methods The present cross-sectional study was conducted on 900 women of reproductive age. Sampling lasted from March 21 to September 23, 2023, using multi-stage and convenient sampling from health-treatment centers in …. History of pregnancy and childbirth, DSM-A criterion, and Miller's questionnaire were used to collect data. For data analysis, Python software was used for machine learning and elastic net analysis was conducted in a nested cross-validation framework.

Results Of the 900 women participating in this study, 387 reported a history of traumatic birth and 513 reported no history of traumatic birth. The positive and negative fertility motivations have a significant relationship with the previous history of traumatic childbirth. Elastic network modeling predicts using RMSE, MAE and R-squared that religious beliefs, married duration, and women's education have the greatest increasing effect on positive fertility motivation. Drug addiction, traumatic childbirth, and abortion history have the greatest effect on increasing negative fertility motivation.

Conclusions Positive and negative fertility motivations are significantly affected by the history of traumatic childbirth. Therefore, in countries that want to grow their population, preventing traumatic childbirth and providing counseling interventions should be placed in the priorities of maternal care.

Keywords Elastic net, Machine learning, Traumatic childbirth, Birth trauma, Fertility motivation

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Plain English Summary

Traumatic birth experiences can lead to significant long-term suffering for women and families. Women with such past experiences may find pregnancy and childbirth particularly challenging due to ongoing physical, psychological, and social repercussions. Machine learning models reveal a significant relationship between fertility motivations and a history of traumatic childbirth. Using elastic net, we found that women with a traumatic childbirth history have significantly lower positive fertility motives and higher negative fertility motives. Traumatic childbirth decreases positive fertility motives while increasing negative ones.

Introduction

Psychological traumatic childbirth is recognized as an unpleasant experience of giving birth in such a way that the mother feels danger or life-threatening for herself or her baby [1], and it usually has negative psychological consequences [2, 3]. Psychologically traumatic childbirth leads to short and long-term negative impacts on a woman's health [4, 5] and impacts future reproductive decisions [6].

Abdollahpour [7] reports approximately one in two women in Iran will experience psychological trauma symptoms from their childbirth. If these symptoms persist, postnatal Post-Traumatic Stress Disorder (PTSD) occurs and women experiencing symptoms are reported as 0.8–26% [8]. Often women, who experience their birth as psychologically traumatic, develop a fear of birth/pregnancy or tokophobia [9]. Often studies report that negative birth experience in mothers leads to their choosing never to embark on another pregnancy described as the horrors of subsequent pregnancies [10, 11] and it directly affects their positive motives for re-pregnancy [12, 13]. Of course, there are contradictory results in this field such as Thompson found a supportive, holistic approach, by a maternity health provider, could provide a pleasant next-birth experience [14].

The fertility rate in Iran has decreased in recent years [15]. The reduced fertility rate and growing increase of the older population in Iran will have led to economic and social consequences [16]. This issue imposes a significant economic burden on the labor force and contributes to a range of chronic non-communicable diseases, economic stagnation, and the closure of the demographic window [17]. In Iran, to boost the fertility rate, policies such as providing welfare benefits for larger families and treating infertility have been implemented [17, 18]. Supporting couples for childbearing requires investigating the factors that increase the positive motivations and reduce the negative motivations for re-pregnancy [19]. Notably, an important group of women who have the greatest potential for pregnancy again are women who have no motivation to have children due to a negative experience from a previous childbirth [20]. Based on this, some studies have recommended supportive interventions for re-pregnancy in women who have experienced a traumatic birth [21, 22]. This study hypothesizes whether machine learning can predict and identify the relationship between a history of traumatic childbirth and fertility motivations and the variables associated with it.

Machine-learning approaches allow for a more thorough identification of association factors that may relate to previous traumatic childbirth and may be the opportunity to confirm previous analyses that implicated childbearing or fertility rate [23]. The research hypothesizes that variables related to traumatic childbirth experiences that are related to fertility motives and can be identified using machine learning.

In other words, to promote effective population growth policies, it is essential to explore both the positive and negative motivations for fertility. Additionally, since traumatic childbirth experiences can diminish the desire to child bear again, this research employs machine learning analysis in a community-based sample with the aim of investigating the relationship between traumatic childbirth experience and positive and negative motivations for fertility in Iranian women.

Methods and materials

Participants and sampling

The present cross-sectional study was conducted on 900 women of reproductive age. Sampling lasted for six months from March 21 to September 23, 2023. The sampling method was community-based and data was collected using multi-stage sampling from health-treatment centers. Health care centers are places where primary health care is provided according to the population covered in different areas of the city. Ten centers were randomly selected from all available health centers and it was ensured that the selected sample could be generalized to a larger population of the target population. Subsequently, among women of reproductive age, sampling continued based on the study's eligibility criteria until the required sample size was achieved. The eligible criteria included women of reproductive age who had experienced at least one delivery (traumatic or non-traumatic) and had the potential for future pregnancy or re-fertilization. Women's cooperation to participate in the study was satisfactory. The sample size was estimated at 900 using the formula N = S2 Z2/d2 according to the study by Irani et al. [24], to achieve the objectives of the study. Demographic information and history of pregnancy and childbirth were obtained from the women. In order to identify the history of traumatic childbirth, the DSM-A criterion was used, and Miller's questionnaire was used to check positive and negative motivations. Incomplete answers to questionnaires led to exclusion from the study. A researcher collected the data from a wide range and separately and privately explained how to answer the questions.

Ethic statements

The proposal of this study was conducted after obtaining the required permit (ID: 4012045) from the Ethics Committee of Mashhad University of Medical Sciences (with the registration code IR.MUMS.NURSE.REC.1401.117). They were assured that participation in the study would be voluntary and information would be kept confidential. Women agreed to participate in the study and all of them provided their informed letter of consent.

Questionnaire

The questionnaires used in this study included Miller's Childbearing Motivation Questionnaire (CMQ), which has two dimensions [25]. The first dimension of positive childbearing motivation (34 items) includes the joy of pregnancy, birth and childhood (6 questions), traditional parenthood (6 questions), satisfaction with parenting (6 questions), feeling of need and survival (5 questions) and instrumental use of the child (11 questions). In the Persian version of this questionnaire, 7 items have been added to the positive motivations of Miller's questionnaire, which are taken from the qualitative study of Khadivzadeh and in line with the adaptation of this questionnaire to Iranian culture [26]. The second dimension is negative childbearing motivation (19 items), which includes the areas of fear of becoming a parent (7 questions), parental stress (8 questions) and child care challenges (4 questions). To score the Childbearing Motivation Questionnaire, a 4-point rating scale ranging from totally disagree (score 1) to totally agree (score 4) was used. Validity and reliability of this questionnaire have been investigated in previous studies in the population of Iranian women [27].

To screen women for traumatic childbirth, a tool aligned with the criteria A of DSM-5 definition of a traumatic event was utilized. This tool assesses the DSM-A through four questions posed to the women. According to this criterion, two fundamental domains of threat (1,2) and emotional (3,4) answer are required for an event to be regarded as a traumatic childbirth. These questions include:

1. Do you think during labor, your life or your baby's life was at risk?
2. Do you think during labor you, or your baby could be physically harmed?
3. Do you think this childbirth was a hard and uncomfortable experience for you?
4. During labor or delivery, did you feel panicked, worried, or helpless?

Traumatic childbirth is indicated by positive responses to one of the first two items and one of the last two items. Thus, two affirmative answers from these four questions mark the childbirth as traumatic [7, 28].

The tool for collecting demographic information included questions such as age, education of women and their husbands, place of residence, employment status, drug use by women and their husbands, religious beliefs, level of support from spouses, duration of marriage, and socioeconomic status. Information related to pregnancy and childbirth included questions such as the number of pregnancies, the number of live children, the history of abortion, the history of stillbirth, the number of cesarean sections, and the history of infant hospitalization. These questionnaires were validated by experts and key people after summarizing by the research team. A MSc midwifery explained all three parts of the questionnaires to the women, who then provided their consent and completed the self-report form.

Statistical analyses

The aim of the present study was to build separate predictive models of positive and negative fertility motivation scores in women with a history of traumatic childbirth. Potential predictors are introduced in Table 1. Among the 900 participants, 30 participants did not have a partial response for the positive or negative motivation questionnaire data; missing values were imputed using k = 10 nearest neighbors. To reduce the risk of overfitting and ensure reproducibility, prediction models in nested cross-validation (NCV) were built [29].

Hyper parameterization

K-fold cross-validation is a hyperparameter setting that enhances model validation and generalization. In this study, k was set to 5, meaning the entire dataset was divided into five parts, with each part serving as a test set while the remaining four parts formed the training set. This approach helps mitigate overfitting by ensuring that the model's performance is evaluated on unseen data, thus providing a more reliable estimate of its predictive

Table 1 The results of demographic information and history of pregnancy and childbirth

Quantitative variable	Traumatic childbirth (387)				Non traumatic childbirth (513)				T-S	*P*-Value
	Mean	Std	Max	Min	Mean	Std	Max	Min		
Positive motivation	47.33	13.18	120	34	68.52	27.44	136	34.0	−14.02	0.00
Negative motivation	51.69	14.35	76	19	42.47	14.46	76	10.00	9.50	0.00
Age	34.11	6.46	45	18	34.32	6.51	48	18.00	−0.47	0.64
Previous livebirth	2.09	0.81	4	1	2.10	0.99	12	1.00	−0.11	0.91
Pregnancy number	2.53	1.12	6	1	2.33	1.11	6	1.00	2.64	0.01
Cs number	1.20	1.23	4	0	0.76	1.04	4	0.00	5.91	0.00
Married duration	3.06	1.30	6	1	3.40	1.49	6	1.00	−3.53	0.00

Qualitative variables		Number	Percent	Number	Percent	*P*-value
Women's education	High school	127	32.82	156	30.41	0.02
	diploma	144	37.21	172	33.53	
	Associate Degree	24	6.20	50	9.75	
	Bachelor's degree	74	19.12	112	21.83	
	Master's degree	16	4.13	20	3.90	
	Doctorate	2	0.52	3	0.58	
Drug addiction	No consumption	313	80.88	456	8.89	<0.0001
	hookah	36	9.30	51	9.94	
	cigarettes	25	6.46	4	0.78	
	Opioid	13	3.36	2	0.39	
	Crystal	–	–	–	8.89	
Religious beliefs	Very low	67	17.31	76	14.81	<0.0001
	Low	152	39.28	263	51.27	
	medium	152	39.28	158	30.80	
	High	16	4.13	16	3.12	
Spouse support	Very low	29	7.49	4	0.78	<0.0001
	Low	157	40.57	157	30.60	
	medium	160	41.34	245	47.76	
	High	41	10.59	107	20.86	
Employment status	housewife	326	84.24	412	80.31	0.15
	employed	61	15.76	101	19.69	
place of residence	Village	97	25.06	143	27.88	0.39
	City	290	74.94	370	72.12	
Abortion history	Yes	147	37.98	122	23.78	<0.0001
	No	240	62.02	391	76.22	
Stillbirth history	Yes	41	10.59	29	5.65	0.01
	No	346	89.41	484	94.35	
Infant hospitalization history	Yes	230	59.43	380	74.07	<0.0001
	No	157	40.57	133	25.93	
Last child age	1	42	10.85	58	11.30	0.06
	2	120	31	164	31.96	
	3	90	23.25	113	22	
	4	73	18.86	94	18.32	
	5	39	10	48	9.32	
	6	23	5.94	36	7	

capability. In the outer loop, the dataset was divided as described, while in the inner loop, each training set was used to optimize tuning parameters through standard k-fold cross-validation. The trained models were then used to predict unseen test sets in the outer loop, allowing for the evaluation of model performance. This process was repeated five times, resulting in a total of 25 final models, which facilitated the assessment of variability in model performance and variable selection.

Model

In this study Elastic Net regularization was employed as the model-building algorithm because of its effective feature selection capabilities. This approach is particularly valuable for its ability to discern relevant predictors from complex datasets. Its strength lies in handling correlated variables, making it well-suited for studies focused on intricate factors like fertility motivations [30]. Elastic Net is a combination of two well-known methods, Ridge and Lasso, each with its own advantages and limitations. Ridge works effectively with data that has many features by controlling regression coefficients and reducing the risk of overfitting, but it cannot completely eliminate some unnecessary features. On the other hand, Lasso excels in simplifying models and selecting relevant variables due to its ability to fully eliminate certain predictors. However, it encounters challenges when features are highly correlated. By combining these two approaches, Elastic Net creates a balance between model simplicity and prediction accuracy. In situations where some variables are highly correlated, Elastic Net performs well, identifying and retaining multiple related variables, while Lasso retains only one and discards the others. This capability is particularly valuable for the current study, which aims to identify complex factors such as positive and negative fertility motivations. Another strength of Elastic Net is its use of two tuning parameters, α (alpha) and λ (lambda), which allow control over the model's behavior. The parameter α, ranging from 0 to 1, governs the similarity of Elastic Net to Ridge and Lasso methods. This flexibility enables researchers to establish a balance between these two approaches according to the study's needs. The parameter λ serves as a penalty factor, determining how simple or complex the model should be [31]. In this study, Elastic Net was used as a tool to create a reliable predictive model, demonstrating strong performance in both accuracy and interpretability of results. The 1-SE method was employed to select optimal parameters, ensuring that the final model strikes an appropriate balance between predictive accuracy and model complexity. Additionally, the significance of the models was statistically assessed through permutation testing, highlighting the high capability of Elastic Net in providing reliable results. Overall, Elastic Net is utilized in this study as a robust and suitable method due to its feature selection power, balance between accuracy and simplicity, and ability to control complexities within the data, resulting in statistically meaningful and high-performing models.

Accuracy measures

The metrics used in this study include R-squared (R^2), which measures the proportion of variance in the dependent variable explained by the independent variables, with values close to 1 indicating optimal model performance. Mean Absolute Error (MAE) calculates the average absolute differences between predicted and actual values, where lower MAE values signify higher accuracy. Root Mean Square Error (RMSE) computes the average magnitude of errors while giving more weight to larger errors, with lower RMSE values reflecting a better model fit to the data. In this process, model parameters are selected based on those closest to the minimum RMSE (the best accuracy). However, increasing model complexity may lead to a slight increase in RMSE values. This balance between accuracy and simplicity is achieved through the determination of optimal parameters, with the combination of parameters evaluated for each training set in the inner loop. Initially, a linear regression model was created using the Elastic Net to determine the regression coefficients for each variable [32].

Then, by changing the values of these coefficients, 25 different models were created. If the mean values of the standard errors (SE) of the regression coefficients were positive or negative (i.e., non-zero coefficients), that model was selected as the predictor. The selected models were evaluated using accuracy measures such as R-squared, MAE and RMSE. To ascertain the significance of models and errors, a permutation test was performed. In this study, pregnancy motivation scores were randomly shuffled and models were retrained using the predictive matrix. This operation was repeated 1000 times [33]. It should be noted that two dependent variables (positive and negative fertility motivations) have been investigated separately and the entire analysis has been performed independently for each.

All analyzes were performed using Python version 3 [34], using pandas, numpy, scipy, sklearn, statsmodels, seaborn and matplotlib libraries. A summary of the used libraries is provided at the end of the study in the Abbreviations section.

Results

Of the 900 women participating in this study, 387 reported a history of traumatic birth and 513 reported no history of traumatic birth. The average age of women with traumatic and non-traumatic childbirth was 34.11 ± 6.46 and 34.32 ± 6.51, respectively. The average positive childbearing motivations for pregnancy in the group of women with a history of traumatic and non-traumatic childbirth were 47.33 ± 13.18 and 68.52 ± 27.44, respectively. The average negative childbearing motivations for pregnancy in the group of women with a history of traumatic and non-traumatic childbirth were 51.69 ± 14.35 and 42.47 ± 14.46, respectively. A summary of demographic information and pregnancy and childbirth histories, classified by traumatic and non-traumatic childbirth history, is shown in Table 1. As shown in the Table, the positive and negative fertility motivations have a significant relationship with the previous history of traumatic childbirth. In other words, in women who have had a history of traumatic childbirth, the positive motivation for re-pregnancy is less compared to women who have not had a history of traumatic childbirth. Also, these women have more negative fertility motives than women who do not mention any history of traumatic childbirth, and this difference is statistically significant. In this study, the average of married duration in mothers who had a history of traumatic childbirth was less and significant. Also, the number of pregnancies in this group of women was significantly higher. It is noteworthy that in women who experienced traumatic childbirth, they had more number of previous cesarean section and this rate was statistically significant. Also, in this study, women's lower level of education, history of drug addiction, and level of support from their husbands were related to the history of traumatic childbirth, and this relationship was statistically significant. Also, the level of religious beliefs was significantly lower in women who had a history of traumatic childbirth. In this study, the history of abortion, stillbirth, and the history of hospitalization of the baby had a significant relationship with the history of traumatic birth. Figure 1 shows a summary of the above results.

Table 2 presents the performance metrics for the Elastic Net algorithm, evaluating RMSE, MAE, and R-squared for both positive and negative fertility

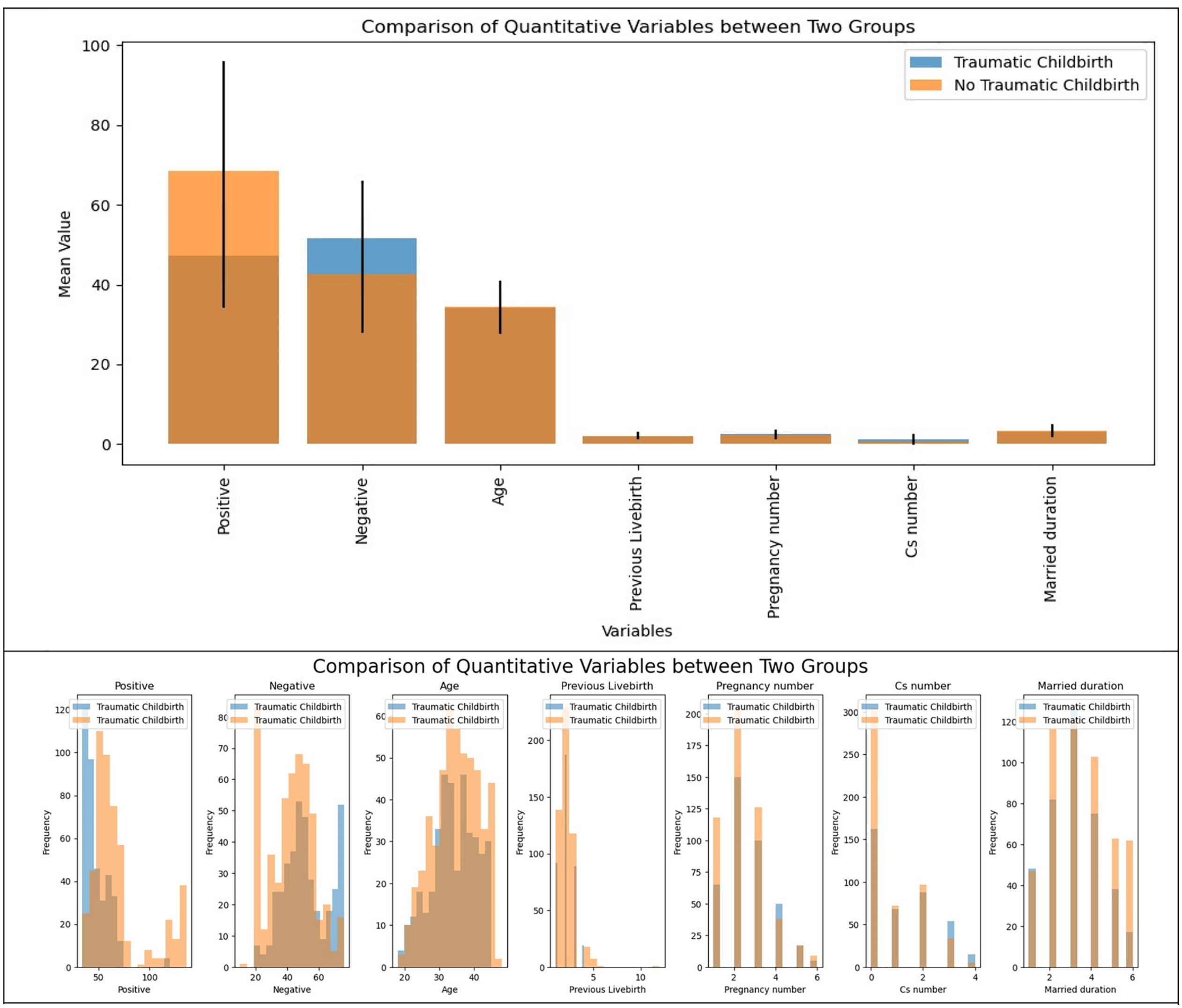

Fig. 1 Comparison of Quantitative Variables between Two Groups—Traumatic and None Traumatic Childbirth

Table 2 Elastic network for evaluating the performance of two models of positive and negative motivations

Model	RMSE			R-squared			MAE		
	Mean ± sd	Mean ± sd	*P* value	Mean ± sd	Mean ± sd	*P* value	Mean ± sd	Mean ± sd	*P* value
	Train	Test		Train	Test		Train	Test	
Positive motivation	0.77 ± 9.9	0.81 ± 1.4	<0.05	0.40 ± 4.96	0.381 ± 0.01	<0.05	0.54 ± 7	0.547 ± 4.02	<0.05
Negative Motivation	0.78 ± 0.001	0.82 ± 4.9	<0.001	0.38 ± 4.96	0.32 ± 8.9	<0.05	0.60 ± 7	0.65 ± 7	<0.05

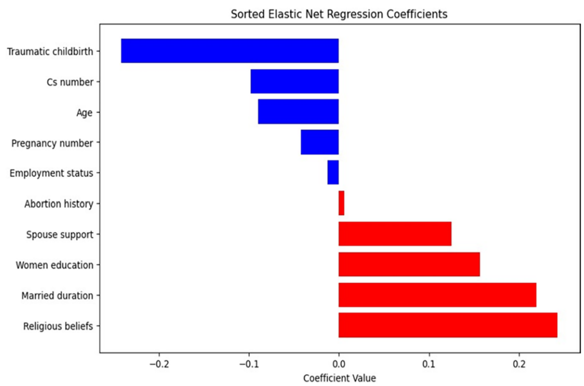

Fig. 2 Elastic Net Regression Coefficients for positive fertility motivation

Table 3 Elastic Net Regression Coefficients for Positive and Negative fertility motivation

Positive fertility motivation		Negative fertility motivation	
Feature	Coefficient	Feature	Coefficient
Religious beliefs	0.243205	Drug addiction	0.089844
Married duration	0.219431	Traumatic childbirth	0.083277
Women education	0.156925	Abortion history	0.068699
Spouse support	0.125077	Cs number	0.054592
Abortion history	0.006077	Age	0.037240
Employment status	−0.012396	Last child age	0.037132
Pregnancy number	−0.042491	place of residence	0.023994
Age	−0.089437	Previous Livebirth	0.018725
Cs number	−0.098196	Women education	−0.095552
Traumatic childbirth	−0.241987	Spouse support	−0.135544
–	–	Married duration	−0.204513
–	–	Religious beliefs	−0.326040

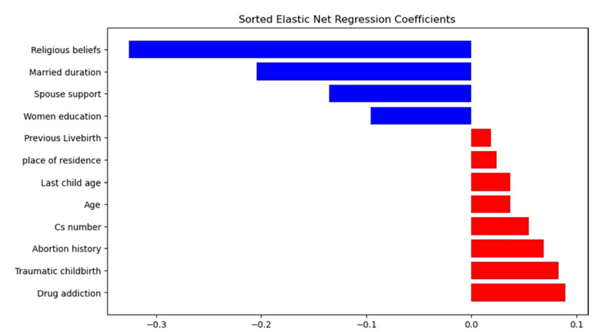

Fig. 3 Elastic Net Regression Coefficients for negative fertility motivation

motivation models. The results compare the performance on training and test datasets, highlighting the predictive accuracy of each model. Statistical indicators, such as *p*-values, confirm the significance of the findings. Lower RMSE and MAE values, along with higher R-squared scores, demonstrate strong model performance, with the positive motivation model showing better results than the negative. The permutation test confirmed the statistical significance ($p < 0.05$) of all metrics (RMSE, MAE, and R-squared) for the Elastic Net model. This modeling identified key variables influencing positive fertility motivations, with regression coefficients calculated for both positive and negative motives. As shown in Table 2 and Fig. 2, the model identifies variables with the greatest and least impact on increasing positive motivations for re-pregnancy.

So, respectively, the variables Religious beliefs (0.24), Married duration (0.22) and Women's education (0.15) have the greatest increasing effect, and the variables Traumatic childbirth (−0.24), Cs number (−0.090), Age (−0.09) have the greatest decreasing effect on positive motives. The history of traumatic childbirth with the greatest reducing effect among other variables can reduce the positive motives of pregnancy.

Also, elastic network modeling to predict the negative fertility motivations identified the influencing variable. On the other hand, the negative fertility motives increase and decrease under the influence of other variables. As shown in Table 3 and Fig. 3, variables such as Drug addiction (0.09), Traumatic childbirth (0.055), and Abortion history (0.054) have the greatest effect on increasing negative motivations, or in other words, these are variables that reduce re-pregnancy. The variables Religious beliefs (−0.32), Married duration (−0.20), and Spouse support (−0.13) have the greatest effect of reducing negative motivations and can play a role in increasing women's motivation to get pregnant again by reducing negative motivations.

Discussion

Our findings show a significant relationship between positive and negative fertility motivations with the history of traumatic childbirth, which was carried out using machine learning models. Using elastic net, we identified that in women who had a history of traumatic childbirth, the amount of positive fertility motives is significantly lower and the amount of negative fertility motives is significantly higher. In other words, traumatic childbirth has a decreasing effect on the positive fertility motives and an increasing effect on the negative fertility motives. The results of other studies have confirmed this finding. For example, the results of Mirzaei's study show that high-risk pregnancies, had the most significant effect on childbearing desire [35].

Certainly, mothers who go through high-risk pregnancies have experienced difficult and traumatic childbirth from a psychological point of view, and their motivation to get pregnant again decreases. Women who experienced high-risk pregnancies struggle with many physical, psychological, social and economic complications [36, 37]. In this way, a qualitative study showed that women who have a history of traumatic childbirth, conveyed their lack of positive fertility motivation for re-pregnancies, in spite of their previous family plans [38]. Traumatic childbirth experiences are found to be related to a decrease in the number of subsequent pregnancies [39]. In contrast, satisfactory experiences of childbirth were among the factors that motivated women to re-pregnant [40]. Shorey's study in a systematic review observed positive associations between prior negative childbirth experiences and decisions to not have another child, or delay a subsequent birth or maternal requests for cesarean section in subsequent pregnancies [41].

Another result of this study is that, traumatic childbirth is significantly related to the number of pregnancies, duration of marriage, number of cesarean sections, woman's education, spouse's support, drug use, religious beliefs, and history of abortion/stillbirth. In line with these results, Ghazanfarpour study showed that the couple's childbearing was influenced by educational level, participation of couples in childbearing, religious level [42]. Also, Mirzaei's study showed that the history of cesarean section can decrease significantly childbearing desire [35]. Of course, the emergency cesarean section is considered as a risk factor for the formation of traumatic birth [43].

One of the important variables in increasing positive motivations and also reducing negative motivations is the husband's support for the woman. In this regard, other studies [44, 45] have found the effect of social networks such as spouse support to be effective in a woman's motivation to get pregnant again, because in cases where the spouse's support decreases, the probability of a psychologically traumatic birth increases, and the positive motivation is reduced. Also, Khadivzadeh's study showed that the quality of marital relations has a significant relationship with the positive fertility motivations in women and their husbands [46].

In this study, the role of history of traumatic childbirth was significantly related to the level of religious beliefs, and in elastic net, religious beliefs had an increasing effect on positive motives and a decreasing effect on negative motives of pregnancy. In this regard, the study of Khadivzadeh et al. indicates that religion plays a significant role in the formation of fertility preferences of couples [47].

One of the important results of this study was that increasing women's education has a significant role in reducing traumatic childbirth. This variable can have an increasing effect on the positive fertility motives. In other words, if the level of education of women is higher, the traumatic childbirth will be less and the positive motives for having children will increase. These results are in line with the systematic review conducted by Ghahremani, and potentially women's education contribute to population growth [48]. In this study, women's employment status was one of the factors that reduced the positive fertility motives. In this regard, Amini and colleagues stated that employment and education have made women reluctant to have children [49], of course, the results of this study are excluded from women's education. This controversy can be justified by the fact that in his study, religious orientation had an effect on women's education and employment status, and in this study, the use of elastic net models has clearly distinguished the two in the analysis.

One of the elastic net results of this study was the reverse reduction effect of the number of pregnancies on the positive motives of pregnancy, in this regard, the study of Irani et al. [24] showed that women with higher-positive motivation and lower-negative motivation scores have higher ideal number of children.

It is suggested to use the data available in health centers and childbearing counseling centers for modeling. Also, it is suggested that other machine learning algorithms be investigated by other researchers and the use of longitudinal research designs can help clarify the clinical significance of these findings. It is recommended to research the effect of counseling interventions in women who have had a history of psychologically traumatic childbirth on fertility motivation in the population of Iranian women.

Conclusion

Our findings indicate a strong link between positive and negative fertility motivations and the history of traumatic childbirth, analyzed through machine learning models. In Iran, where health polices focus is on increasing fertility rates, prioritizing the prevention of traumatic childbirth is essential to increase positive fertility motivation. If prevention is not feasible, counseling interventions should be implemented to address its complications and help maintain an appropriate fertility motivation. This study's results are generalizable for effective planning and interventions in countries facing declining fertility and an aging population. Therefore, the results of this community-based study can be generalized in the reproductive age population, where the improvement of fertility motivation is targeted.

Limitations

One of the strong points of this study is the large sample size based on the community, the results of which can be helpful in facilitating and advancing population incentive policies in Iran. A limitation of this research is that the data collection relied on mothers' self-reports, which may not accurately recall birth experiences over time.

Abbreviations

NCV	Nested Cross-Validation
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R^2	R-squared
SE	Standard Errors
Pandas (pd)	A library for data manipulation and analysis, providing data structures like DataFrames
NumPy (np)	A fundamental package for numerical computing in Python
SciPy (SP)	A library used for scientific and technical computing, offering modules for optimization, integration, and statistics
Scikit-learn (sklearn)	A machine learning library that provides tools for model training, and performing cross-validation, and evaluating performance metrics
Statsmodels (sm)	Statistical modeling tools for regression analysis and hypothesis testing
Seaborn (sns)	Data visualization library for creating informative statistical graphics, particularly for model results and distributions
Matplotlib (plt)	Foundational plotting library for creating various types of visualizations, essential for presenting results clearly

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Author contributions

SA conceived the study. SA and MSh developed the study protocol. All authors were involved in data gathering. MA and TKh analyzed the data and SA and MA interpreted the data. SA wrote the draft manuscript. All authors read and approved the final version of the manuscript.

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Availability of data and material

The Data could be available upon a reasonable request to the Abdollahpour with abdollahpourts2@yahoo.com and with the permission of the Mashhad University of Medical Science ethical committee.

Declarations

Ethics approval and consent to participate

This project was approved with the code (IR.MUMS.NURSE.REC.1401.117) in the ethics committee of Mashhad University of Medical Sciences.

Consent for publication

None.

Competing interests

The authors declare no competing interests.

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