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Bridging the Gap in Fetal Heart Rate Monitoring: Introduction and Evaluation of an Acoustic-Based Smart Belt for Real-Time, Passive, Mother-Centered Monitoring with Extensive Multicenter Validation

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ABSTRACT

Fetal heart rate (FHR) monitoring facilitates the early detection of pregnancy abnormalities. Current methods, such as cardiotocography (CTG), provide accurate FHR measurements but are neither continuous nor real-time, and require clinical settings. This study presents a smart belt for FHR monitoring utilizing acoustic signal processing without transmitting high-frequency waves. The device is designed for maternal use and features real-time analysis. To evaluate its user-friendliness for mothers and clinical validity endorsed by physicians, questionnaires were administered to 637 individuals and 225 physicians. This follows a multi-year product development and patenting process reported herein. Cronbach's alpha values indicated suitable reliability of the questionnaire items. Results showed that 75.5% of physicians validated the questionnaire data and deemed the recommended usage frequency of the smart belt appropriate at 5-15 times for healthy mothers and 10-15 times for high-risk individuals from fetal heart formation onwards. A decision tree algorithm was employed to identify correlations and relationships among the various variables.

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Introduction

Recent studies indicate that wearable technologies can be valuable in assessing pregnancy complications and bridging the gaps in real-time evaluations. These devices continuously collect maternal health data, such as heart rate and its variability, on a moment-to-moment basis (Feli et al., 2024). Alongside maternal health, precise and timely fetal monitoring is crucial for preventing pregnancy and delivery complications. Fetal phonocardiography (fPCG), or the recording of fetal heart sounds, presents a novel, non-invasive method for assessing fetal well-being, suitable for long-term and remote monitoring (Giordano et al., 2024).

Traditional prenatal care relies on scheduled visits with physicians, providing only transient snapshots of maternal and fetal status. In contrast, continuous remote monitoring offers a more comprehensive approach, enabling the early detection of health status, physiological parameters, abnormal signs, and potential complications (Striker et al., 2024).

Detailed analysis of the Fetal Heart Rate (FHR) pattern reveals that unpredictable factors can instantly transform a low-risk pregnancy into a high-risk one. Consequently, continuous FHR monitoring throughout gestation is essential to identify any anomalies in the FHR pattern that could impact fetal health.

The smart fetal phonocardiography system proposed in this work captures natural acoustic signals (fPCG) using an intelligent monitoring belt. These signals are processed via supporting computer software or a smartphone application. Fetal issues are subsequently identified using local data, after which pattern outputs and analyses are displayed and simultaneously transmitted to the obstetrician.

According to van den Heuvel et al. (2019), remote monitoring represents a promising solution for leveraging e-health technologies in prenatal care. It is a low-cost, passive method that uses a microphone-transducer to record fetal heart sounds and vibrations. This approach is particularly suitable for long-term, at-home monitoring and reduces the need for in-person visits (Barnova et al., 2024).

Numerous studies have explored pregnant individual's experiences with prenatal care. A qualitative study in Iran revealed that expectant mothers are aware of the importance of prenatal care and consider it essential for safeguarding their own health and that of their fetus (Hajizadeh et al., 2023). An experimental intervention study involving 120 pregnant individuals, selected via cluster sampling in 2018 [1397 SH], assessed the effectiveness of SMS-based education on maternal awareness and behaviors regarding pregnancy danger signs (Abbaspour et al., 2020). Participants were randomly assigned to intervention or control groups. The intervention group received 21 daily text messages on common complaints and danger signs, followed by key message reminders over two weeks. Questionnaire data were analyzed using repeated-measures ANOVA, Friedman, and Cochran tests, with a statistical significance level of $p<0.05$.

A review of 15 randomized controlled trials (n=6008 individuals) indicated that home uterine activity monitoring may aid in identifying preterm birth and reduce neonatal intensive care admissions, although it showed limited impact on preterm delivery rates, antepartum mortality, or hospital admissions. It may, however, increase prenatal visits and tocolytic treatments (Khalil et al., 2022). A cross-sectional survey of 357 pregnant individuals attending Al-Zahra Hospital in Ahvaz in 2019 [1398 SH] revealed high rates of online health information seeking among this population (Mirghafouri et al., 2020). Using correlation and regression analysis based on Cochran's formula, researchers noted that while pregnant individuals use the internet to meet their information needs, conflicting information can cause anxiety and adversely affect maternal-fetal health, underscoring the necessity of improving health information literacy during pregnancy. Another study assessed the satisfaction levels of 364 pregnant individuals receiving care at the maternity clinic of Dr. Shariati Hospital in Tehran in 2018 [1397 SH] (Ghabadi et al., 2018). This cross-sectional study, analyzed via Chi-square and multivariate logistic regression using a researcher-designed questionnaire, found 70.2% satisfaction versus 29.8% dissatisfaction. Influencing factors included age and parity, with higher values correlating with lower satisfaction. Crowding, time inefficiency, and lack of parking were cited reasons for dissatisfaction.

Collectively, these studies suggest that developing wearable technologies for continuous maternal and fetal health monitoring can enhance the quality of prenatal care and mitigate associated complications.

Method

Questionnaire information collection

Given the critical importance of maternal-fetal health monitoring and prior studies on health information-seeking behaviors and maternal satisfaction with prenatal services, this study investigates the acceptance and utilization of a self-monitoring phonocardiography belt for continuous fetal heart rate monitoring among pregnant individuals in Tehran. Employing a field-based methodology with structured questionnaires, the research evaluates user satisfaction, implementation challenges, and factors influencing the adoption of this novel technology. The findings are positioned to enhance fetal monitoring protocols and improve the quality of prenatal care. Data mining-based methods were further employed to identify relationships between key variables.

From a total of 637 participants, 269 questionnaires were collected from private clinics and 368 from hospitals. Geographic distribution of participants showed highest engagement in Central Tehran (32%, n=88), followed by North and South Tehran (25% each, n=65 and n=68 respectively). Western Tehran contributed 11% (n=30), while Eastern Tehran had the lowest participation (6%, n=18). Hospitals with the highest recruitment included Pasargad, Kashani, Mofarah, Feyzebanesh, Hedayat, Shahid-e Tajrish, Iranmehr, and Shariati.

Table 1) Part of the table for calculating the proposed statistics of 637 pregnant individuals in hospitals and medical centers of Tehran

Districts of Tehran	Fetal diseases	Parental medical history	Cost of pregnancy routine visiting physicians	Num. of visiting physicians	Num. of times used	Maximum cost of analysis (rent)	Maximum cost of analysis (purchase)	Method of Device Usage	Maximum cost	Num. of Pregnancies	Num. of children	Father's age	Mother's age	Num	Sign
C= Center	0	0	700000	10	5--15	30	30	B) Rent	400-600	2	2	34	29	…213	c
	0	Gestational diabetes	1500000	20	50	10	20	B) Rent	400-600	1	1	27	20	214	c
	0	Gestational diabetes	1800000	30	30--50	20	30	A) Purchase	800-1200	1	1	33	27	215	c
S= South	None	Abortion	7000000	20	30--50	30	20	A) Purchase	1200-1600	2	1	35	29	…362	s
	None	None	3000000	10	5--15	20	10	A) Purchase	400-600	1	1	22	25	363	s
	None	Abortion	6000000	15	30--50	30	20	B) Rent	1200-1600	3	2	42	38	364	s
	None	None	2000000	10	5--15	10	10	B) Rent	400-600	1	1	29	27	365	s
N=North	None	None	2000000	40	5--15	20	20	B) Rent	400-600	1	1	29	22	…366	N
	None	None	3500000	25	50	30	10	B) Rent	800-1200	2	2	42	34	…478	N
	None	Abortion	6000000	9	30--50	50	10	B) Rent	600-800	4	3	40	34	479	N
	None	Gestational diabetes	4000000	15	30--50	40	20	B) Rent	600-800	1	1	36	29	480	N
W=West	None	None	4000000	30	30--50	50	50	A)Purchase	1200-1600	1	1	30	30	…481	W
	None	None	800000	10	15--30	50	50	B) Rent	800-1200	3	3	40	38	…594	W
	None	None	2500000	12	5--15	50	30	B) Rent	600-800	1	1	25	23	595	W
	None	None	4000000	12	30--50	20	30	B) Rent	400-600	1	1	32	32	596	W
E=East	None	None	100000	15	5--15	10	20	B) Rent	400-600	2	2	42	37	597	E
	None	Abortion	5000000	15	5--15	30	30	B) Rent	600-800	6	2	40	35	…634	E
	None	None	1700000	10	5--15	10	10	B) Rent	400-600	1	1	22	23	635	E
	None	None	500000	11	5--15	30	10	A)Purchase	400-600	1	1	31	27	636	E
			2087169.5	12.58268		28.930818	23.861852			1.744113	1.579278	34.3585	30.04874	Mean	Mean
			2351085.75	8.40		13.43	13.37			0.94	0.77	6.27	5.94	Standard Deviation	Standard Deviation
			1000000	10		30	10			1	1	35	28	Mode	Mode

Statistical Analysis

The mean values, which reflect the central tendency and distribution of the data across specific age groups, facilitate the identification of age segments that are more inclined to use the device and support the analysis of potential consumer behavior. In addition, the standard deviation was used to assess the degree of variability and homogeneity within the age groups of mothers and fathers. A smaller standard deviation indicates lower dispersion and greater homogeneity of the data.

The mean ages of mothers and fathers were 30.5 and 34.5 years, respectively, while the standard deviations were 14.7 for mothers and 47.97 for fathers. The mean number of children and the mean number of pregnancies were both equal to 1, with corresponding standard deviations of 58.7 and 75.9, respectively. The data were organized in grouped form and are presented in the frequency distribution shown in Table 2.

Table 2) Grouped data of the statistical table

Age range (years)	Number of pregnant individuals (abundance)
18-22	50
23-27	165
28-32	215
33-37	142
38-42	56
43-47	6
48-52	3
Total	637

The mode is calculated based on the following Equation:

$$\delta = L + \left(\frac{(f_m - f_{m-1})}{(f_m - f_{m-1}) + (f_m - f_{m+1})}\right) \times h \tag{1}$$

where L denotes the lower boundary of the modal class, f_m represents the frequency of the modal class, f_{m-1} is the frequency of the class preceding the modal class, f_{m+1} is the frequency of the class following the modal class, and h is the class interval width.

The modal class is defined as the interval containing the highest number of pregnant individuals (i.e., the highest frequency). According to the frequency table, the modal class corresponds to the age range of 28–32 years, with a frequency of 215. Accordingly, the mode was calculated as follows:

$$f_m - f_{m-1} = 215 - 142 = 73$$
$$f_m - f_{m+1} = 215 - 165 = 50$$
$$(f_m - f_{m-1}) + (f_m - f_{m+1}) = 123$$
$$\left(\frac{(f_m - f_{m-1})}{(f_m - f_{m-1}) + (f_m - f_{m+1})}\right) = \frac{73}{123} = 0.59,$$
$$0.59 \times 4 = 2.3 \implies \delta = L + 2.3 = 28 + 2.3 = 30.3$$

Therefore, the mode—or the most prevalent age of pregnant individuals —was estimated to be 30.3 years. This calculation indicates that although the highest frequency occurs within the 28–32-year age interval, the more precise modal age is approximately 30.3 years. This indicator facilitates a more refined analysis of age-related preferences among pregnant individuals.

To identify the acceptable price, range from the consumer perspective, Table (3) was constructed to illustrate mothers' financial acceptance of the device purchase scenario. The "Price (IRR)" column represents the maximum amount each group was willing to pay. The "Number of approvals" column indicates the number of participants who accepted purchasing the device within each price range, while the “Acceptance percentage” column reports the proportion of acceptance relative to the total sample. The price range of 400,000–600,000 IRR demonstrated the highest level of acceptance at 54.11%, and was therefore identified as the optimal pricing range for device offering. Formula (2) presents the mathematical calculation of the proposed device price as follows:

$$P = \frac{\sum_{i=1}^{n}(x_i \times m_i)}{N} \quad (2)$$

Where P denotes the proposed device price, x_i represents the number of respondents who agreed within price range i, and m_i is the midpoint of price range i (for example, for the range of 400–600 thousand tomans, m_i=500). N indicates the total number of respondents (637 participants). Accordingly, the weighted mean—or proposed price—based on parental preferences was calculated using the data presented in the table as follows:

$$P = \frac{(500)(342) + (700)(133) + (1000)(73) + (1400)(88)}{637} \cong 722 \text{ One thousand tomans}$$

This price reflects a relative equilibrium among the number of positive responses across different price ranges and is aligned with the parents’ willingness and ability to pay. Finally, the acceptance rate was calculated using Formula (3), where θ denotes the acceptance percentage, x_i is the number of approvals within a given price range, and X_t represents the total number of participants.

$$\theta = \left(\frac{x_i}{X_t}\right) \times 100 \quad (3)$$

Subsequently, Table (3) was constructed to present the financial acceptance of pregnant individuals with respect to the device purchase scenario.

Table 3) Maximum rate for the device

Acceptance Rate	**Num. of Agreements**	**Amount (Toman)**
(٪٠)	1	Free
(% 53/69)	342	400-600
(% 20/88)	133	600-800
(% 11/46)	73	800-1200
(% 13/81)	88	1200-1600
	637	

In this study, the mean, standard deviation, and mode of the number of physician visits were 12, 8, and 10, respectively. For the number of physician visits, Figure 1 illustrates the frequency distribution across different visit intervals.

Medical service costs during pregnancy are also considered a key study indicator, as they help identify the financial status of families. The mean cost represents the average amount paid by pregnant individuals for medical services during this period. The standard deviation reflects variability in family expenditures and contributes to a better understanding of economic differences across groups. The mode indicates the most frequently occurring cost paid by the majority of individuals. Together, these statistical measures enable more effective targeting of strategies aimed at reducing the financial burden on families.

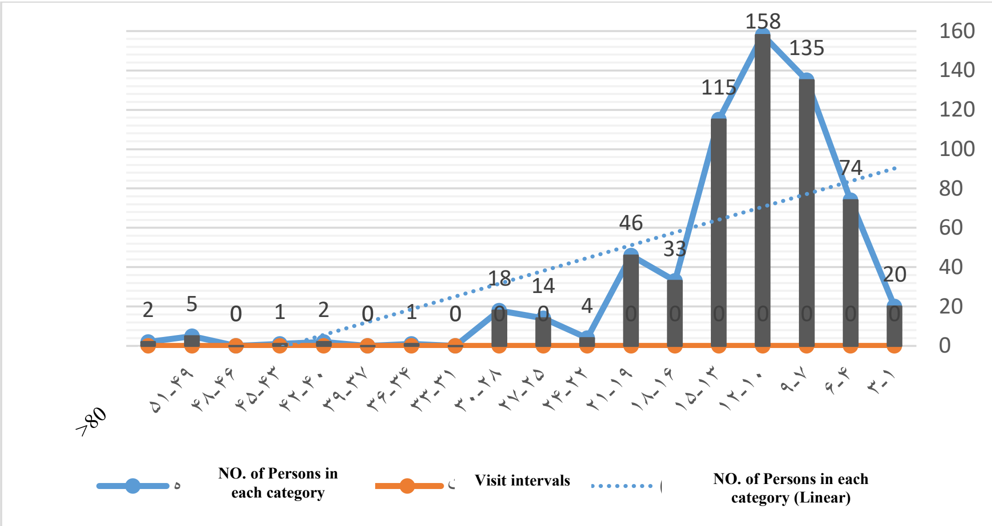


Figure 1) Frequency of physician visits and the number of pregnant individuals in each category

The mean, standard deviation, and mode of physician-related costs were 2,087,169, 2,351,085, and 1,000,000 Iranian Tomans, respectively. Histogram (Figure 2) demonstrates how pregnancy-related medical costs are distributed across different cost intervals. The distribution is right-skewed, indicating that most observations fall within lower cost ranges, while a smaller number of cases incurred very high expenses. The majority of individuals paid between 1,000,000 and 2,000,000 Tomans. Some intervals exhibited low frequencies, which may warrant further investigation to determine whether these ranges correspond to specific or specialized medical services.

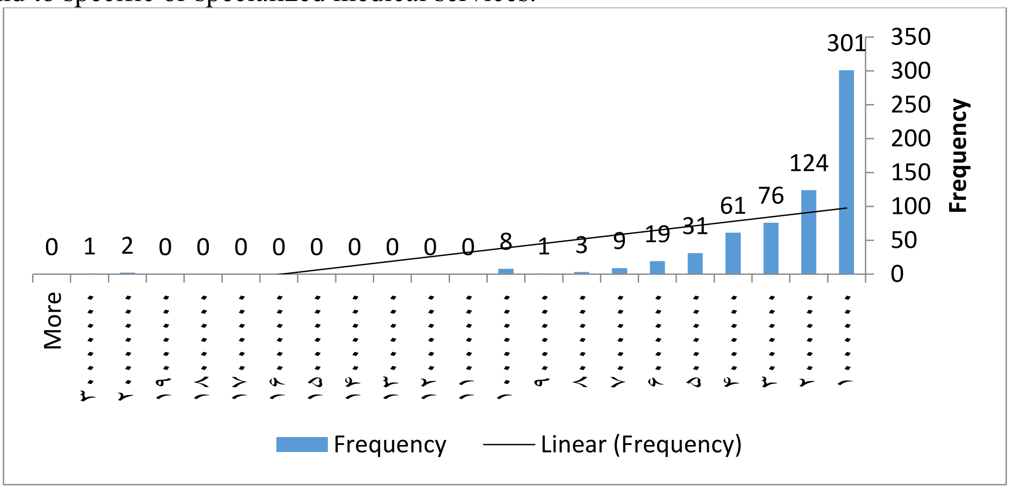


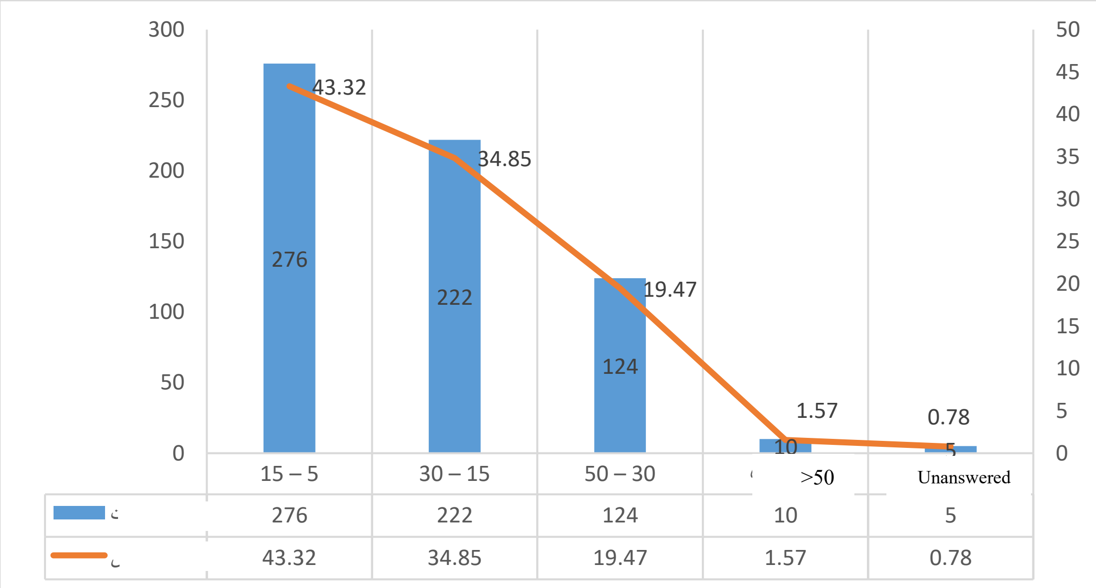
Figure 2) Distribution of expenses during pregnancy

A total of 215 respondents opted to purchase the device, 407 preferred renting it, and 15 did not provide a response, indicating a clear need for pricing flexibility and installment-based payment models. Based on these analyses, a scientific estimate of the expected per usage cost can be derived for both the purchase and rental scenarios. According to Table (4), the mean cost per usage in the rental scenario was 28.93 thousand tomans, which is slightly higher than that of the purchase scenario (23.86 thousand tomans). The difference in the mode between the two scenarios (10 for purchase and 30 for rental) reflects distinct behavioral patterns, potentially driven by user preferences regarding payment methods or device utilization. These findings can serve as a basis for pricing policy formulation and the optimization of service delivery strategies.

Table 4) Maximum Cost of Analysis per Device Usage for Purchase and Rental Scenarios

	The mean of the maximum cost of analysis per usage in purchase scenario	The mean of the maximum cost of analysis per usage in rental scenario
Mean	24000 Tomans	29000 Tomans
Standard Deviation	13.37	13.43
Mode	10000 Tomans	30000 Tomans

To evaluate pregnant individual's willingness to use the belt during pregnancy, different usage intervals were examined, and the acceptance percentage for each interval was calculated. This evaluation helps obtain accurate information about consumer behavior and allows pricing to be adjusted based on real demand. Figure 3 represents the usage intervals and the corresponding number of approvals for each interval, illustrating the distribution of individuals willingness to use the device during pregnancy. According to Figure 3, the highest acceptance percentage corresponds to intervals with lower usage frequencies, meaning that many individuals may prefer to use the device in a limited and specific manner. This could be due to various reasons, including concerns about cost, lower perceived need for usage or confidence in the device's effectiveness. On the other hand, acceptance in higher usage intervals may indicate potential challenges in promoting continuous use of the device. These results clearly highlight the need to design promotional strategies based on usage intervals. To calculate the acceptance percentage, the following formula can be used, where θ represents the acceptance percentage, x_i is the number of approvals in a given interval, and X_t is the total number of participants: $\theta = \left(\frac{x_i}{X_t}\right) \times 100$.



	15 – 5	30 – 15	50 – 30	>50	Unanswered
Number of approvals	276	222	124	10	5
Acceptance rate	43.32	34.85	19.47	1.57	0.78

Figure 3) Combo hybrid model showing the number of agreements and the acceptance percentage of pregnant individuals per device usage

Based on the collected data and using Equation (4), the proposed price of the device was estimated by

$$Q = \frac{\sum_{i=1}^{n}(y_i \times k_i)}{N} \quad (4)$$

where Q represents the mean number of device usage, y_i denotes the number of respondents who agreed with usage interval *i*, k_i indicates the midpoint of usage interval *i* (for example, for the interval of 15–30 usage, k_i=22.5), and *N* represents the total number of respondents. Based on these parameters, the average number of device usage according to parental preferences was estimated to be 21 usages. This calculation contributes to more accurate pricing decisions and provides valuable insights into user behavior and the level of device acceptance across different time intervals.

Common maternal conditions during pregnancy included prenatal depression and stress (31 cases), cardiovascular diseases and hypertension (10 cases), thyroid disorders (27 cases), gestational diabetes (56 cases), gestational diabetes combined with a history of miscarriage (12 cases), and a history of miscarriage alone (51 cases). Other conditions, such as renal and respiratory disorders, seizures, epilepsy, abnormal bleeding, and thalassemia, were reported less frequently. Overall, 48.50% of mothers (309 individuals) were healthy and reported no medical conditions during pregnancy, while 13.81% of participants did not respond to the health-related questions.

The most prevalent fetal conditions were miscarriage (51 cases, 8%) and neonatal jaundice (15 cases, 2%). Other conditions, including favism (3 cases), fetal growth restriction and insufficiency, neonatal reflux, allergies, nuchal cord, thrombocytopenia, and asthma (each reported in 2 cases), were less common. Additional conditions such as chromosomal abnormalities, hypothyroidism, epilepsy, and others accounted for a very small proportion of the total cases. Notably, 414 fetuses were reported to be free of any disease, while 131 individuals did not respond to the questions related to fetal conditions. These analyses highlight the most prevalent conditions that require immediate attention and more precise planning. Moreover, percentage-based calculations provide valuable insights into the target population, such as mothers with healthy fetuses versus those requiring early disease monitoring.

If the sales strategy is based on providing the device free of charge and charging only for data analysis, the expected revenue from each device during pregnancy can be estimated according to Equation (5) as follows:

$$R_1 = (C \pm \sigma_C) \times \bar{n} \tag{5}$$

Where (C) represents the mean cost of data analysis per device usage under the rental model, σ_C denotes the standard deviation of the analysis cost, $\bar{n}$ is the average number of device usage, and R_1 indicates the expected revenue under the rental strategy (including upper and lower bounds based on the standard deviation of the cost). Accordingly, the expected revenue for the strategy of providing the device free of charge and charging for analysis is calculated as follows:

$$R_1 = (28.93 \pm 13.43) \times 21 = 607.53 \pm 282.03 \quad \text{Thousands of Tomans}$$

The inclusion of the standard deviation in this formulation reflects the uncertainty in analysis costs and can be used to evaluate different revenue scenarios. If the strategy involves an initial device sale followed by paid analysis services, the expected revenue per device can be estimated according to Equation (6) as follows:

$$R_2 = P_{sale} + \left[\mu_n \times \left(P_{analysis} \pm \sigma_{P_{analysis}}\right)\right] \tag{6}$$

Where P_{sale} denotes the initial sale price of the device, μ_n represents the mean number of device usage, $P_{analysis}$ is the cost of data analysis per usage, $\pm\sigma_{P_{analysis}}$ indicates the standard deviation of the analysis cost, and R_2 refers to the total revenue generated under this strategy. Accordingly, the expected revenue for the strategy involving an initial device sale followed by paid analysis services is calculated as follows:

$$R_2 = 722 + [21(23.86 \pm 13.37)] = 722 + (501.06 \pm 280.77) = 1223.06 \pm 1002.77 \text{ Thousands of Tomans}$$

Therefore, it is possible to estimate the revenue generated by each device over the course of pregnancy. In terms of value creation, presenting the potential revenue from data analysis alongside device sales provides an economic justification for the product and supports its attractiveness to investors.

Data Classification

In this section, the results obtained from the k-means clustering, decision tree, and random forest methods applied to a dataset of 637 pregnant individuals, comprising 14 different features, are presented. These features include maternal age, paternal age, number of children, number of pregnancies, maximum purchase amount, device usage method, maximum analysis cost (purchase scenario), maximum analysis cost (rental scenario), number of device usage, physician visits, medical costs during pregnancy, parental medical history, fetal conditions, and region (five districts of Tehran).

The decision tree was trained using both Gini and entropy criteria. To prevent overfitting, the maximum tree depth was set to 5. Table 5 presents the features ranked according to their importance. Subsequently, a hierarchical tree was constructed, with the main branch representing the regions of Tehran. Decision tree models were extracted separately for each region. To build a combined version of the decision tree, advanced visualization techniques using Graphviz were employed to customize the tree structure. This approach ensures that all features are displayed, even if their importance is zero.

Table 5) Importance of features

Feature Name	Importance
Num. of Pregnancies	0.357555
Fetal diseases	0.115384
Mother's age	0.113723
Maximum cost of analysis (purchase)	0.084029
Cost of pregnancy routine visiting physicians	0.067059
Num. of visiting physicians	0.060165
Num. of children	0.046647
Father's age	0.042850
Maximum Cost	0.035105
Parental medical history	0.034199
Num. of times used	0.028483
Method of Device Usage	0.010755
Maximum cost of analysis (rent)	0.004027

The most important features in the central district included the maximum analysis cost (purchase scenario), number of children, number of device usage, number of pregnancies, maximum analysis cost (rental scenario), maximum purchase amount, paternal age, fetal conditions, maternal age, physician visits, and parental medical history. Features with low or zero importance included the device usage method and medical costs during pregnancy. Therefore, in this district, the utilization of medical services and related purchases (particularly analysis and purchase amounts) are the primary determinants.

In the southern district, the key features were, in order: number of children, paternal age, maternal age, number of pregnancies, device usage method, maximum purchase amount, and medical costs during pregnancy. Features with zero importance included fetal conditions, parental medical history, physician visits, number of device usage, maximum analysis cost (rental scenario), and maximum analysis cost (purchase scenario). Thus, in the southern district, family-related factors (number of children, parental ages, and number of pregnancies) play the main role. Unlike the central district, financial or medical analysis–related features (e.g., purchase or analysis amounts) have little or no effect. It appears that purchasing patterns in the southern district are more strongly influenced by respondents' family characteristics rather than economic or healthcare factors.

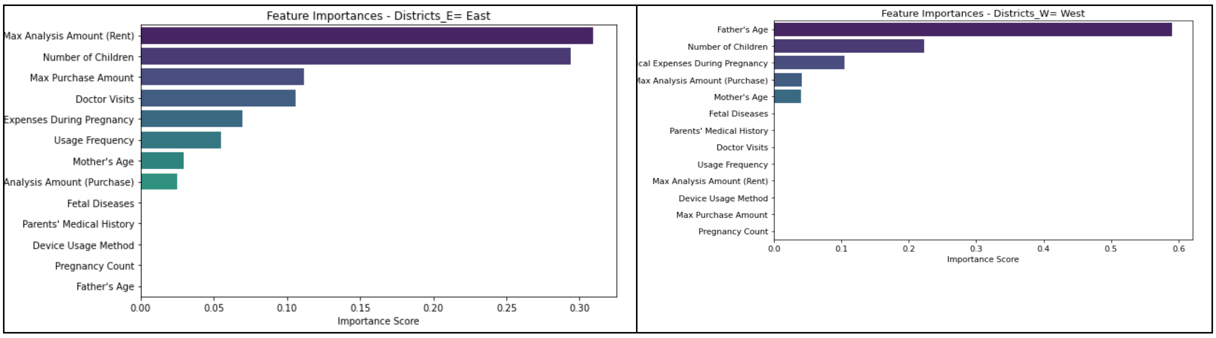
In the northern district, the most important features included the maximum analysis cost (purchase scenario), fetal conditions, maternal age, paternal age, number of pregnancies, physician visits, medical costs during pregnancy, number of children, number of device usage, maximum analysis cost (rental scenario), and maximum purchase amount. Features with low importance included device usage method and medical costs during pregnancy. The northern district exhibits more diverse behavioral patterns and family conditions. Unlike the southern or central districts, fetal conditions play a prominent role here. This may indicate higher parental attention or sensitivity to fetal health in this region, or possibly easier access to medical services.

In the western district, the most important features were paternal age, number of children, medical costs during pregnancy, maximum payable amount (purchase scenario), and maternal age. Features with low or zero importance included fetal conditions, parental medical history, physician visits, number of device usage, maximum analysis cost (rental scenario), device usage method, maximum purchase amount, and number of pregnancies. Unlike other regions such as the north, where medical factors played a stronger role, in the western district demographic factors (e.g., number of children, paternal age) were the primary differentiators. Features that were highly important in other regions—such as number of pregnancies, fetal conditions, and physician visits—had no apparent effect here. This may be due to incomplete data access or could reflect a genuinely lower influence of these factors. Overall, clustering in this district appears to be driven more by family structure and parental age rather than medical or financial conditions.

In the eastern district, the key features included maximum analysis cost (rental scenario), number of children, maximum purchase amount, physician visits, medical costs during pregnancy, number of device usage, maternal age, and maximum analysis cost (purchase scenario). Features with low importance included fetal conditions, parental medical history, device usage method, number of pregnancies, and paternal age. Therefore, in this district, individuals with low maximum analysis costs (rental scenario) but high physician visits are likely to exhibit attentive health behaviors, sensitivity to fetal health, and controlled utilization patterns.

Overall, in central Tehran, there were high-consumption families with a larger number of children and high spending on medical services and purchases. The most determinant features were the maximum analysis cost (purchase scenario) and number of pregnancies. In northern Tehran, families tended to have fewer children, higher purchase and maximum analysis costs (rental scenario), but lower physician visits. This region exhibits higher socioeconomic status and greater behavioral diversity. Southern Tehran consisted of households with more children, relatively high medical expenses, and notable analytical consumption patterns. Key factors in this region included number of children and medical costs during pregnancy. In western Tehran, behavioral patterns were primarily influenced by parental age, number of children, and medical expenses during pregnancy, reflecting traditional family structures with a high level of care. Eastern Tehran households were relatively proactive regarding medical care, with frequent physician visits and high rental analysis costs. Distinct differences in medical and expenditure behaviors were observed between the two main subgroups.

Figure 4 presents the feature importance charts for each region, while Figure 5 shows a portion of the decision tree obtained for the northern and western districts.



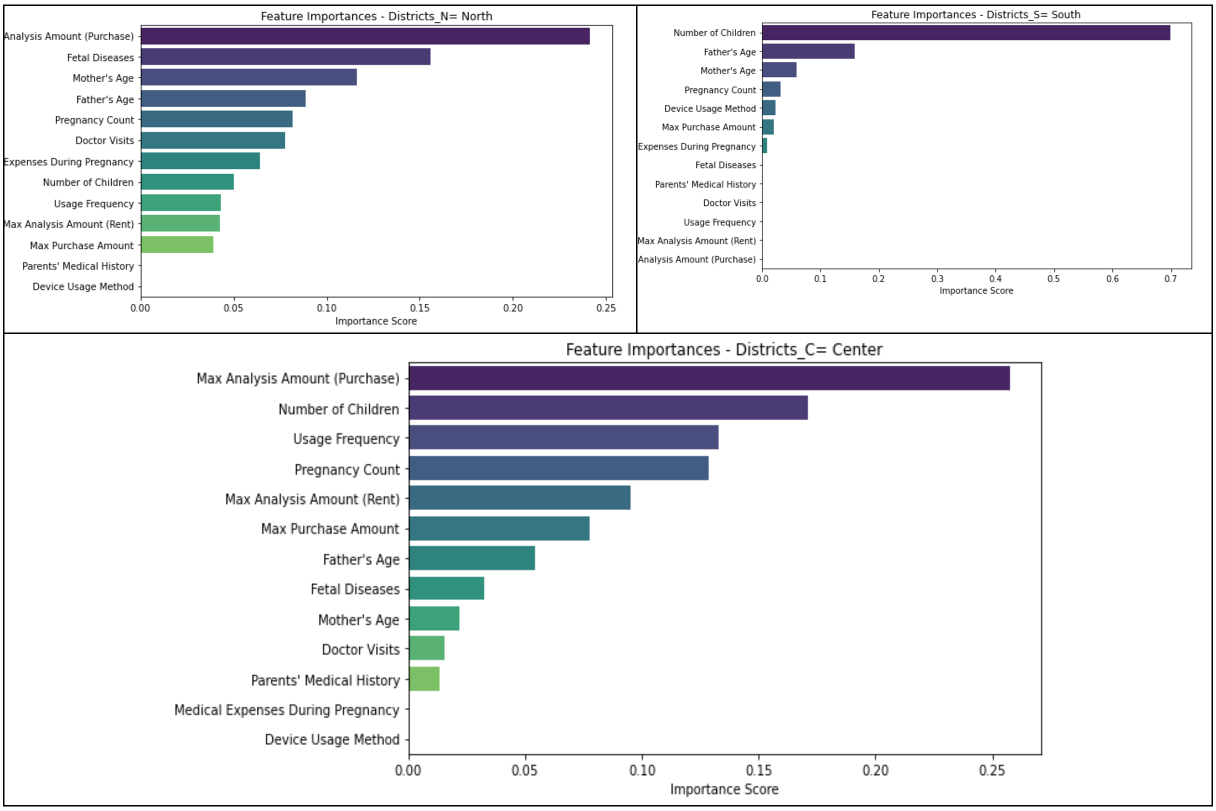
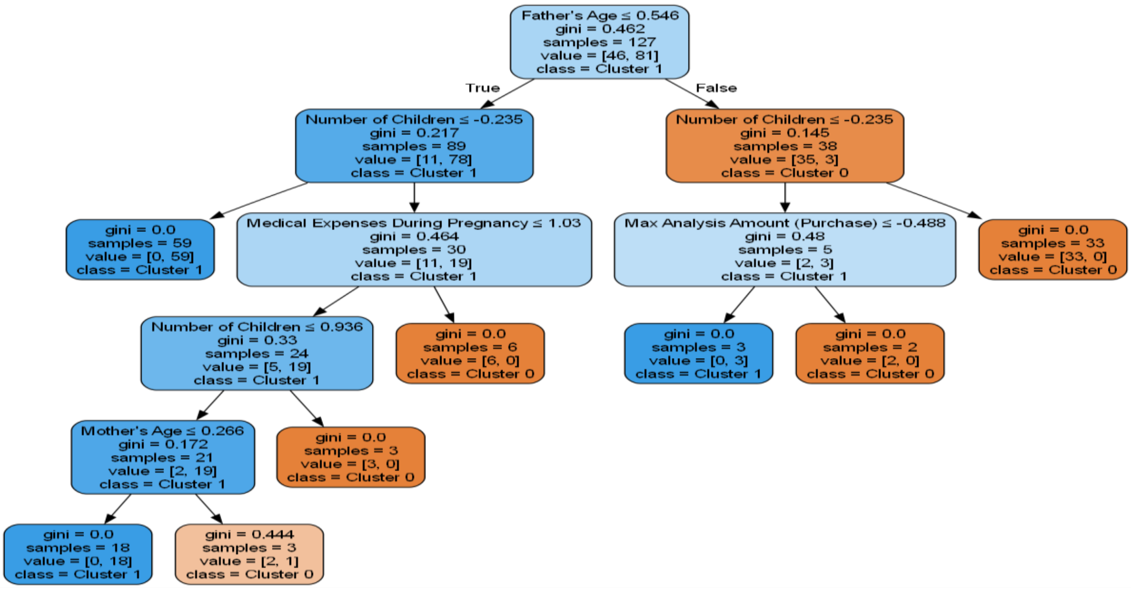


Figure 4) Importance of features across different regions



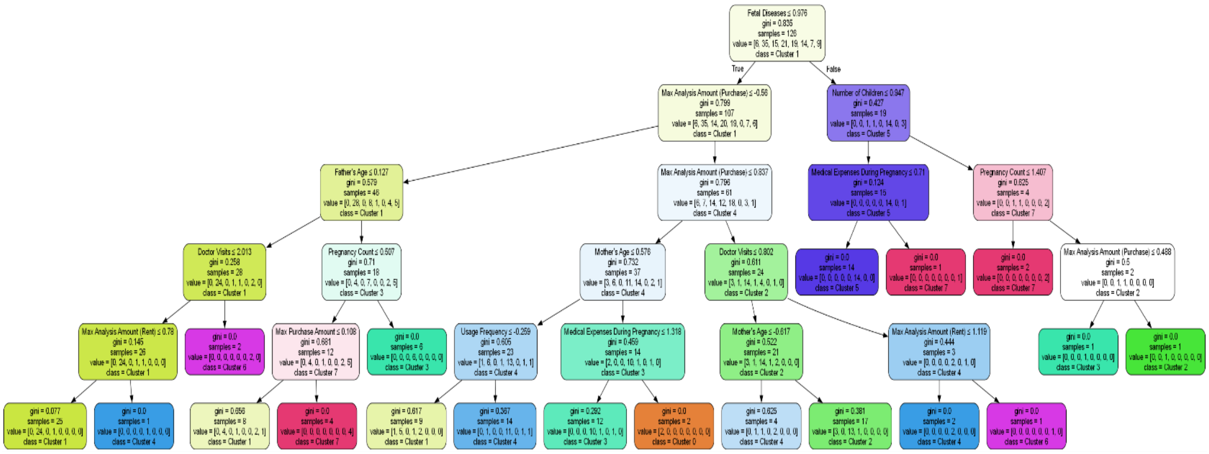


Figure 5) Extracted decision tree for the northern and western regions

Conclusion

This study examined economic, behavioral, and geographical differences in the acceptance of fetal heart monitoring devices among pregnant individuals in Tehran and demonstrated that maternal needs and financial capacity are significantly shaped by regional location and socio-economic characteristics. The application of a hybrid clustering–classification decision tree algorithm enabled a detailed exploration of non-linear behavioral patterns and consumption trends across different districts of the city.

The findings revealed distinct technology adoption patterns across Tehran's five major regions. In central Tehran, larger families with higher medical expenditures and a greater number of pregnancies exhibited a stronger inclination toward purchasing the device. Conversely, northern Tehran—characterized by lower fertility rates and higher levels of economic welfare—displayed a more balanced pattern of purchasing and renting. Southern Tehran, marked by a concentration of larger households and substantial medical costs, and eastern Tehran, associated with frequent physician visits and high rental expenses, highlighted structural differences in maternal priorities. In western Tehran, traditional families placing greater emphasis on prenatal care demonstrated a distinctive behavioral pattern.

Beyond geographical variations, key factors including ease of use, data accuracy, home usability, and stress reduction were identified as primary drivers of device adoption. Nevertheless, limitations such as reliance on outdated data and the absence of analysis regarding physicians' roles in recommending the device underscore the need for future prospective studies that incorporate key stakeholders.

To mitigate inequalities in access, the development of more affordable devices through collaboration with charitable organizations is essential, alongside strengthening maternal education via targeted awareness campaigns. Moreover, integrating machine learning–based analyses with field studies can offer practical strategies for narrowing access gaps to health technologies, particularly in metropolitan areas like Tehran where socio-economic heterogeneity is pronounced. Such an approach not only supports policymakers in designing equity-oriented interventions but also provides a framework for advancing user-centered technologies in maternal and child health.

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