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Prenatal anxiety recognition model integrating multimodal physiological signal

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Anxiety among pregnant women can significantly impact their overall well-being. However, the development of data-driven HCI interventions for this demographic is often hindered by data scarcity and collection challenges. In this study, we leverage the Empatica E4 wristband to gather physiological data from pregnant women in both resting and relaxed states. Additionally, we collect subjective reports on their anxiety levels. We integrate features from signals including Blood Volume Pulse (BVP), Skin Temperature (SKT), and Inter-Beat Interval (IBI). Employing a Support Vector Machine (SVM) algorithm, we construct a model capable of evaluating anxiety levels in pregnant women. Our model attains an emotion recognition accuracy of 69.3%, marking achievements in HCI technology tailored for this specific user group. Furthermore, we introduce conceptual ideas for biofeedback on maternal emotions and its interactive mechanism, shedding light on improved monitoring and timely intervention strategies to enhance the emotional health of pregnant women.

Keywords Pregnant woman, Multimodal physiological signal, Emotion recognition, Feature fusion, Anxiety model

Pregnant women frequently experience emotional instability during pregnancy, which can have adverse effects on both their physiological and psychological well-being. As awareness of maternal mental health grows, there is a heightened focus on the well-being of expectant mothers[1]. The prenatal period is associated with an increased risk of prenatal anxiety and depression, which can result in various negative impacts on the developing fetus[2]. Research has shown that timely attention to maternal emotions and proactive interventions, including emotional support, can positively affect the Physiological and psychological well-being of pregnant women and the overall health of the unborn child[3].

Studies have revealed that specific monitoring and intervention measures can significantly benefit the emotional well-being of pregnant women[4]. For example, monitoring sleep patterns[5] and implementing stress management strategies, such as mindfulness breathing exercises[6], have shown promising results. Some studies have monitored the health status of pregnant women through the measurement of Photoplethysmography (PPG) data[7], while others have employed text mining for sentiment analysis to prevent postpartum depression[8]. Although these studies have contributed to monitoring and enhancing the emotional well-being of pregnant women, research that integrates multiple physiological signals from pregnant women for monitoring purposes is limited. Furthermore, it has been demonstrated that the fusion of multimodal signals enhances emotion recognition accuracy when compared to single-modal signals[9–11].

The limited availability of publicly accessible datasets for pregnant women presents a substantial hurdle for data collection and model development when analyzing pregnancy-related data. Consequently, this scarcity of data resources has led to a relatively small number of data-driven interactive intervention measures designed for the pregnant population.

To achieve more accurate monitoring and identification of the emotional states of pregnant women, this study designed a complete experiment, and utilized the Empatica E4 wristband to measure physiological signal data during the late stages of pregnancy, both during periods of rest and relaxation. Additionally, participants completed questionnaires based on their self-reported feelings at each stage to gather subjective data on their anxiety levels. The relaxation state involved deep breathing exercises guided by a biofeedback system. By fusing

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features extracted from multimodal signals, a model for classifying the relaxation and anxiety states of pregnant women was developed. The results demonstrate that this classification model achieves a best score of 69.3%, effectively assessing the anxiety levels of pregnant women based on their physiological data.

Related work

Emotional well-being during pregnancy and biofeedback intervention methods

From the beginning of pregnancy through its various stages, including the postpartum period, expectant mothers undergo a range of psychological challenges and frequent emotional fluctuations, with the potential for anxiety and depression[12]. Research by Khan et al. has highlighted the risks associated with stress, anxiety, and depressive episodes, which may lead to prenatal and postnatal depression and bipolar disorders[13]. Field and colleagues have investigated the potential long-term harm to the fetus when mothers exhibit high levels of anger and stress during pregnancy[14].

Currently, there are diverse therapeutic approaches to address mental health issues like depression and anxiety, including mindfulness practices that effectively manage emotional variability[15]. Abera et al.summarized the effectiveness of various relaxation interventions, including mindfulness therapy, progressive muscle relaxation, and music therapy[16]. Evans et al.investigated a complex intervention designed to assist pregnant women with mild to moderate anxiety, incorporating cognitive-behavioral therapy (CBT), yoga, mindfulness, and psychoeducation[17]. Furthermore, studies have indicated that activities such as listening to music and singing can contribute to emotional serenity and enhance overall well-being during pregnancy[18].

Assessing emotional status in pregnant women

Pregnant women often use self-assessment scales[19] or engage in self-monitoring, health management, and improvement and treatment strategies[20–22]. This approach relies on subjective needs and may exhibit delays. Some research has proposed health monitoring systems for pregnant and postpartum women. However, much of the data and information is largely subjectively provided by pregnant women[20], or it is derived solely from questionnaires and short-term data collection[23,24]. Additionally, some maternal monitoring systems rely on objective data for monitoring[25–28], but they are primarily tailored to address specific health concerns. For instance, mobile applications and wearable electronic devices are used for continuous monitoring of health parameters during and after pregnancy[29,30], often focusing on pregnancy-related issues, such as sleep disorders, physical activity, and hypertension[28,31,32].

Emotion recognition based on multimodal signal fusion

Signals like EDA, HR, and SKT have been widely applied for stress monitoring[33]. Kurniawan et al. assessed stress levels using EDA and speech signals, with SVM demonstrating superior classification performance[34]. E et al. combined features from multiple modalities, including EDA, ECG, PPG, and SKT signals, and applied five machine learning algorithms for emotion prediction, where SVM achieved the highest accuracy[35]. Bornoiu et al. extracted a range of parameters from EDA signal and used a neural network to differentiate between relaxation and stress states[36]. Mokhayeri et al. fused features from pupillary diameter, ECG, and PPG signals for stress detection using a fuzzy SVM[37]. Lee et al. measured changes in heart rate variability and EDA, achieving an emotion recognition accuracy of 80.2% based on neural network algorithms[38]. Pollreisz et al. designed a compact wearable emotion recognition system with an accuracy of 65% in emotion recognition[39]. Gupta et al. conducted emotion recognition on the K-Emocon dataset, achieving the best accuracies for valence and arousal at 91.12% and 62.19%, respectively[40].

However, the unique physiological characteristics of pregnant women render the anxiety assessment models for the general population inapplicable[41]. The development of data-driven HCI interventions tailored to pregnant women faces significant obstacles primarily arising from the limited availability of data and associated challenges in the data collection process.

Biofeedback interventions for pregnancy anxiety management

In the field of biofeedback for regulating emotions in ordinary individuals, researchers have explored various directions. For example, they have visualized physiological stress data through visual feedback, designing systems like AffectiveWall[42]. Bin et al. have employed auditory feedback to sonify real-time heart rate variability for biofeedback training[43]. Some researchers have investigated the application of olfactory biofeedback in emotion regulation[44]. Additionally, some researchers have utilized multi-sensory approaches to provide feedback on emotional states[45]. Moreover, biofeedback techniques have been used to induce relevant emotions, such as in the CPT(Cold Pressor Test), MMST(Mannheim Multicomponent Stress Test), and other stimulation paradigms[46].

However, pregnant women are a more specialised group and require more detailed design considerations. Movalled et al. explored the effects of different types of sound stimuli on pregnant women and their fetuses, indicating that excessive or inappropriate auditory stimulation may have adverse effects on the fetus[47]. Research has also found that pregnant women are more sensitive to odors and should avoid exposure to overly strong smells[48,49]. Studies have also shown that pregnant women's exposure to nature is beneficial to their physical and mental health[50]. Social support is helpful to pregnant women's mood, and this review highlights the significance of supportive environments and interventions in alleviating stress and anxiety during pregnancy[51]. Besides, physiological data collection from pregnant women poses higher challenges in terms of comfort and safety[52]. Therefore, biofeedback interventions applicable to the general population may not necessarily be directly applicable to pregnant women, highlighting the need for further research in this area.

Experimental research

Given the scarcity of data resources available for pregnant women, coupled with the near absence of publicly accessible datasets, it becomes imperative to design a comprehensive experiment aimed at collecting data from pregnant women.

Data acquisition

We signed a scientific research cooperation project with the hospital. The user study was approved by the Affiliated People's Hospital of Ningbo University. All experiments were performed in accordance with the hospital's guidelines and regulations, and we confirmed that informed consent was obtained from all participants.

The doctor enrolled 20 pregnant women in their late stages of pregnancy (average gestational age = 35.2 ± 3.2 weeks), aged between 20 and 35 years (M = 29.125, SD = 3.6). The hospital signed an ethical agreement with each pregnant woman, who consented to the experiment content and noticed the potential risks. Referring to the methods adopted by previous studies[53], we designed the experimental environment to simulate the real environment as much as possible, reducing other interferences, so as to better control variables and draw valid conclusions.As depicted in Fig. 1, pregnant women are left alone in a quiet and undisturbed room (the experimental environment is controllable and there is no interference from others), and the wrist is worn with Empatica E4 bracelet, which is used to accurately measure various physiological signals such as BVP, SKT and IBI of the experimenter. Empatica E4 has been verified by researchers to measure physiological data effectively and accurately[54].Considering that the anxiety state is a relatively subjective and personalized indicator, following the method of previous studies[55,56], in the first stage of the test, we tested the baseline data of each experimenter.

The specific test process is as follows: In the first phase, participants were in a resting state for 3 min to establish baseline physiological data. They were then asked to complete the RRS and STAI questionnaires to subjectively assess their anxiety and relaxation levels. In the second phase, participants engaged in two 8-minute deep breathing relaxation exercises guided by a biofeedback system while their physiological data was measured. Following each deep breathing exercise, participants once again completed the RRS and STAI questionnaires.

Data preprocessing and label setting

The entire experimental procedure is depicted in Fig. 2.

The physiological signals, including BVP, SKT and IBI, were measured using the Empatica E4 wristband with sampling frequencies of 64 Hz, 4 Hz and 1 Hz, respectively. To prepare the data for analysis, initial preprocessing steps included cleaning the raw data to address anomalies and missing values. Once this cleaning was completed, the signals from each participant were synchronized.

Given that the physiological data collected in this experiment lacked intrinsic emotional labels, we implemented a labeling method as follows. After each phase, participants completed the STAI questionnaire, providing their subjective assessments. Prior studies have established a well-documented correlation between STAI scores and varying anxiety levels in pregnant women[57]. Leveraging this correlation, we aligned the labels for the physiological data with participants' self-reported STAI scores. Data with STAI scores below 28 were classified as indicative of a relatively relaxed state, scores between 28 and 40 were considered to signify a moderate level of anxiety, and scores exceeding 40 were categorized as representing a high degree of anxiety[57].

According to the above classification criteria, pregnant women's emotions are divided into relaxed state (label = 0), mild anxiety (label = 1) and severe anxiety (label = 2). According to the statistics of experimental

Fig. 1. Experimental data collection scene diagram.

Fig. 2. Research experiment workflow diagram.

data, there are 31 data labeled as 0,8 data labeled as 1 and 11 data labeled as 2. Details are shown in the Table 4 in the appendix.

Feature engineering

Utilizing the PyTeap library (https://github.com/cheulyop/PyTEAP/tree/master), a total of 17 BVP features, 6 SKT features were extracted. The IBI data underwent analysis using Kubios software (https://www.kubios.com/), from which 6 features were extracted. The extracted features are detailed in Table 1.

Pearson correlation analysis was employed for feature selection to identify the most strongly correlated features with emotional states. This method is used to measure the linear relationship between two continuous variables. The value of R falls within the range of [− 1, 1], where an R-value closer to 1, either positive or negative, signifies a stronger correlation, while values closer to 0 indicate a weaker correlation[58]. This approach aids in model analysis by reducing feature dimensions and enhancing model performance[59]. In this experiment, we utilized Pearson correlation analysis to select the 7 features with the strongest and most significant correlations. The selected features are arranged in descending order according to their R-values, and their corresponding significance values are also presented in Table 2 .

Classification methods and results

Numerous previous studies have demonstrated that SVM is the most commonly used and highly accurate emotion classification algorithm[35,40]. The SVM model is well-suited for small sample sets with multiple dimensions. Grid search involves an exhaustive search within a specified range of hyperparameter combinations, evaluating the performance of each combination[60].

In this experiment, the SVM algorithm was used for modeling and analysis of the selected features. We set appropriate penalty coefficients (C) and kernel function ranges. The optimal hyperparameter configuration for the best model performance was found through grid search, and the performance of the model was evaluated through leave-one-subject-out cross-validation. Finally, the accuracy of the model reached 69.3%.

For the three physiological signals collected above, we trained the models of single-mode, dual-mode and multi-mode signal characteristics respectively, and compared the effects of the models. As shown in Table 3, we can find that the F1 score of the model is higher after the three physiological signals are fused, so the fusion of multi-mode signal characteristics is meaningful and the model performance is effectively improved.

Discussion

Constructing an SVM-based anxiety model for women during pregnancy offers significant benefits for HCI interventions. It enables more accurate and tailored monitoring of anxiety levels, facilitating timely and personalized interventions to improve maternal well-being. In HCI domain, this contributes to the development

Signals	No.	Features extracted
Blood volume pulse (BVP) (64 Hz)	17	Mean, Std, Multiscale entropy (MSE), Spectral power of low/medium/high frequency bands, spectral power ratio, Tachogram's spectral values and ratio
Skin temperature (SKT) (4 Hz)	6	Mean, Std, Kurtosis, skewness, spectral power
Inter-beat interval (IBI) (1 Hz)	6	Mean HR, SDNN, LF/HF ratio, RMSSD, PNS Index, SNS Index

Table 1. Collected signals and extracted features.

Feature	Statistical significance	|R-value|
Spectral power of medium frequency bands (BVP)	0.000	0.682
Spectral power 0001 (BVP)	0.000	0.633
Spectral power 0102 (BVP)	0.000	0.586
SDNN (IBI)	0.000	0.555
Spectral power 0203 (BVP)	0.003	0.526
LF/HF ratio (IBI)	0.011	0.441
Skewness (SKT)	0.041	0.382

Table 2. Features arranged in descending order by R-Values with significance.

Signal	BVP	SKT	IBI	BVP+SKT	BVP+IBI	SKT+IBI	Multimodal
F1 score	61.9%	50.1%	48.4%	56.0%	64.2%	53.0%	69.3%

Table 3. F1 score among modalities.

of specialized, data-driven technologies that address the unique needs of special user groups, advancing the precision and effectiveness of health monitoring systems.

From previous works, we found that research on visualizing feedback for anxiety in pregnant women is limited, highlighting the potential for further exploration. Below, "Empowering data-driven design interventions for pregnancy well-being and "Methods of providing intervention through the intimate relationship of pregnant women" outline potential design interventions. "Empowering data-driven design interventions for pregnancy well-being" proposes a design for visualizing emotional feedback in pregnant women. "Methods of providing intervention through the intimate relationship of pregnant women" explores how intimate relationships, such as partners, can provide more effective interventions when anxiety arises in pregnant women.

Empowering data-driven design interventions for pregnancy well-being

In this pioneering study, we introduce a groundbreaking model designed to assess and manage anxiety levels in pregnant women, significantly advancing the field of HCI. We delve into the creation of a visual feedback mode that not only evaluates emotional states but also facilitates timely intervention and emotional adjustment. For instance, Robert Plutchik's "Plutchik Wheel" model, often referred to as emotional fingerprints[61], can be used to create Plutchik flowers, with each petal's size reflecting the prevalence of specific emotions in a given corpus. By integrating this innovative visual feedback mode for pregnant women, we unlock new dimensions for monitoring and supporting emotional states, ultimately contributing to more effective and empathetic interactions in the realm of healthcare and well-being.

In our quest to offer comprehensive emotional support for pregnant women, we've devised an innovative system that harnesses the power of visualization. Drawing from research demonstrating the therapeutic benefits of tending to plant growth[62], we introduce a concept that intertwines the emotional state of expectant mothers with the flourishing of virtual trees, providing a tangible and visually intuitive means of tracking their well-being.

In our ongoing research, we aim to refine this system further by customizing the leaves' characteristics, color, and growth trajectory to mirror the pregnant woman's emotional state. For instance, vibrant green leaves symbolize a positive mood, while the presence of yellow leaves hints at a less optimal emotional state. When emotions remain stable over time, virtual trees thrive and flourish, culminating in lush, vibrant forests. However, prolonged anxiety can manifest in the slowing or stalling of tree growth, serving as a poignant signal that family members should extend their support and care, as illustrated in Fig. 3.

Furthermore, we envision enhancing the system's hardware design to incorporate features that extend beyond emotional support. These additions may include capabilities such as radiation absorption and carbon dioxide reduction, delivering broader well-being benefits to pregnant women. This holistic approach signifies a pioneering leap in the landscape of maternal care and emotional well-being.

By means of this decorative physical installation, we can offer real-time feedback on the pregnant woman's anxiety, thereby alerting her and those around her to pay timely attention. However, the physical installation can only be used in specific settings. Therefore, we can provide online feedback through an app, allowing users to monitor the emotional state linked to the plant's condition. Pregnant women can set this as aesthetically

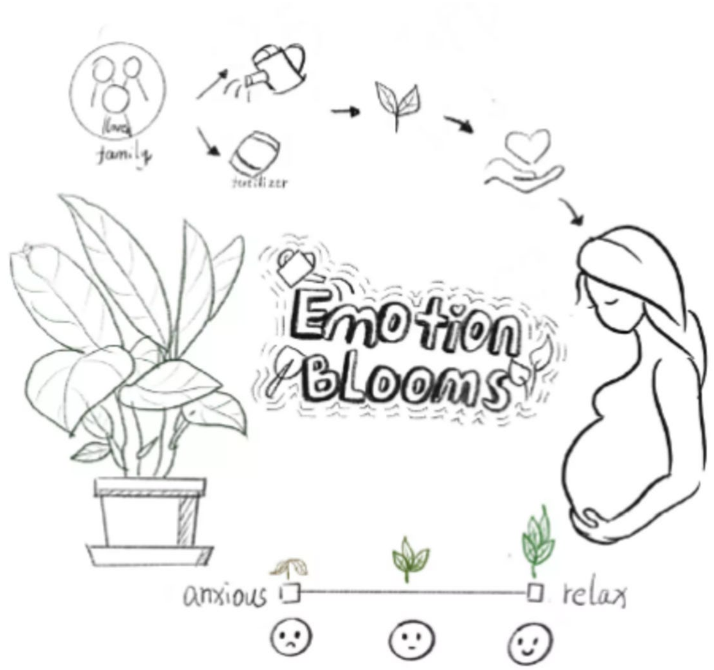

Fig. 3. Emotional feedback interactive device.

dynamic wallpaper or a screen widget, and configure threshold-based notification actions to easily and promptly understand their emotional state.

Methods of providing intervention through the intimate relationship of pregnant women

From a social psychology perspective, pregnancy can be seen as a specific and highly emotional state, and during a wife's pregnancy[63], the husband may be influenced by the partner's negative emotions, possibly leading to "couvade syndrome", characterized by symptoms like loss of appetite, irritability, and sleep disturbances[64,65]. Offering emotional support can improve the quality of the childbirth experience, as pregnant women require more social and partner support during this period[66].

To foster interaction, we can provide a means for pregnant women's partners or family members to pay attention and offer care. For instance, the husband can water and nurture the plant installation, symbolizing that the process of nurturing an embryo is not the sole responsibility of the pregnant woman. It can involve the active participation of the husband and family members, thereby sharing the burdens of pregnancy. Considering practical limitations, we also offer a partner and family interface within the app, enabling them to understand and intervene in the pregnant woman's emotions in the same manner.

Additionally, researchers have demonstrated that prenatal yoga and spending time in nature significantly benefit pregnant women's physical and mental health[67]. To further develop a more comprehensive plant-based system, the following functionalities can be expanded: using plant movements, such as swaying, to guide pregnant women through appropriate yoga poses, thereby achieving emotional relief and intervention effects.

Limitations and future work

This paper uses the SVM training model. Because for some high-dimensional small sample data sets, SVM can exhibit good performance and model interpretability[68]. Moreover, due to the limited sample data size, we have used the regularization method that has been proven effective in previous studies to reduce the risk of overfitting[69,70]. In addition, deep learning is also very useful in dealing with complex nonlinear and other issues. We consider exploring deep learning methods when expanding our data set in future research.

The data in this paper is collected in an experimental environment. The laboratory environment may not be able to fully simulate the stress and environmental factors that pregnant women experience in daily life. In future work, we will conduct field research to address the current limitations and continuously update the model to cope with the complex and changeable scenarios in real life.

In previous studies, researchers have utilized various physiological signals from the general population, such as pupillary diameter, BVP, and EDA, to construct models using techniques like SVM and decision trees. These efforts have yielded high accuracy rates[71–73]. However, our model's accuracy still offers potential for improvement. In our forthcoming research, we plan to explore ensemble methods at the decision layer, such as weighted averaging or voting, to amalgamate results from multiple algorithms. This approach aims to enhance the model's reliability and robustness[74,75].

Furthermore, due to the limited dataset size, there is a critical requirement for the acquisition of a more extensive dataset derived from pregnant women in various physiological states. This expanded dataset will play a pivotal role in refining model training and subsequently improving the overall performance of this study.

Conclusion

In this research, physiological data from pregnant women were collected using Empatica E4 wristbands during both rest and relaxed states. Subjective feedback regarding anxiety levels was gathered through questionnaires. After preprocessing the raw physiological data and conducting feature engineering, features from five modalities, including BVP, SKT, and IBI, were integrated. Employing the SVM algorithm, we successfully constructed an anxiety recognition model that assesses the anxiety levels of pregnant women, achieving an accuracy of 69.3%. This study contributes to the HCI field by demonstrating the feasibility of developing tailored, data-driven interventions for specific user groups, such as pregnant women. The introduction of conceptual ideas for visual feedback design on maternal emotions and interactive devices lays the groundwork for future research. It enhances the potential for more precise and effective monitoring of maternal emotional health, ultimately contributing to improved well-being through innovative HCI technologies.

Data availability

The datasets generated and analysed during the current study are not publicly available due to privacy concerns for protecting the special user group of our study but are available from the corresponding author on reasonable request.

Appendix

See Table 4.

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Participants	STAI_Base	Label (STAI_Base)	STAI_Back	Label (STAI_Back)	STAI_Forward	Label (STAI_Forward)
No.1	29	1	27	0	24	0
No.2	42	2	31	1	30	1
No.3	35	1	21	0	20	0
No.4	48	2	44	2	44	2
No.5	29	1	20	0	20	0
No.6	40	2	25	0	26	0
No.7	33	1	26	0	21	0
No.8	47	2	28	0	31	1
No.9	41	2	42	2	44	2
No.10	34	1	23	0	22	0
No..11	39	1	26	0	23	0
No.12	21	0	20	0	20	0
No.13	40	2	33	1	29	1
No.14	23	0	20	0	20	0
No.15	31	1	27	0	21	0
No.16	35	1	34	1	36	1
No.17	23	0	20	0	20	0
No.18	31	1	26	0	22	0
No.19	26	0	20	0	20	0
No.20	41	2	32	1	29	1

Table 4. STAI values and corresponding label values of the participants at three different stages.

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Author contributions
Y.B., J.G., Y.C., and S.W. analyzed the results, and Y.B. wrote the manuscript. M.X. supervised and revised the manuscript. M.X., J.W., and B.Y. designed the user study and conceived the experiment. P.F. was in charge of recruiting participants from the hospital and collecting the consent forms. All authors reviewed the manuscript.

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