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From the algorithm to the clinical interpretation of childbirth anxiety: analysis and explainability of obstetric predictive models based on psychological indicators

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Abstract Anxiety during pregnancy constitutes a relevant factor that can significantly influence labor development. This study presents a novel approach based on explainable artificial intelligence to predict both the type and duration of labor using psychological indicators of anxiety prior to delivery. Employing data from 235 full-term pregnant women from two Spanish hospitals, we developed a multilayer perceptron model to classify eutocic and dystocic deliveries, achieving a capacity to identify 88% of dystocic deliveries. Additionally, we implemented a regression model that predicts labor time with a mean error of 2 hours, correctly predicting 86% of cases with an error margin of less than 3 hours. The application of explainability techniques to the developed models allows for understanding the specific influence of each anxiety factor on labor development. These results demonstrate the potential of AI models to improve obstetric care and optimize healthcare resource allocation.

Keywords: Anxiety, birth, machine learning, explainable artificial intelligence, labor development prediction, childbirth.

1 Introduction

Childbirth constitutes one of the most significant and complex events in a woman's reproductive life, in which biological, psychological, and sociocultural factors converge to determine its development and outcome 1, 2. For decades, obstetric medicine has focused primarily on the physiological aspects of birth, relegating the emotional and psychological components that influence this process to a secondary place 3, 4. However, recent research has shown that the pregnant woman's emotional state, particularly anxiety levels prior to labor, exerts a significant influence on the development of labor and its perinatal outcomes 5, 6.

Anxiety during pregnancy represents a prevalent health problem that affects approximately 54% of pregnant women at some point during their pregnancy 7. This emotional state not only impacts the mother's psychological well-being, but is also associated with obstetric complications such as premature birth, emergency cesarean sections, instrumental deliveries, and prolongation of labor 8, 9, 2. Previous studies have identified multiple factors that contribute to pre-labor anxiety, including concerns about pain, loss of control, duration of labor, hospital techniques, and the baby's health 10, 11, 12.

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Despite the recognition of this relationship between anxiety and obstetric outcomes, the ability to accurately and systematically predict how psychological factors will influence the specific development of labor remains limited in current clinical practice. Traditional assessment methods are based primarily on clinical experience and physical obstetric indicators, without systematically integrating psychological factors that can be determinants of the process 13.

In this context, artificial intelligence (AI) emerges as a promising tool to address this gap in obstetric care. Recent advances in machine learning have demonstrated their effectiveness in various medical domains, including the prediction of clinical outcomes and treatment personalization 14, 15. However, the application of these technologies at the intersection of perinatal mental health and obstetrics remains relatively unexplored, particularly in predicting labor development based on psychological indicators.

The present study proposes an innovative approach that uses artificial intelligence models to predict both the type of labor (eutocic or dystocic) and its duration, based solely on psychological indicators of anxiety measured before the onset of labor. Additionally, by applying explainable AI techniques, it is possible not only to generate accurate predictions but also to identify which specific anxiety factors have the greatest influence on these outcomes, thereby providing valuable information for clinical practice.

This work is developed in the context of the Spanish health system, using data from 235 full-term pregnant women who gave birth in two public hospitals. The research is based on the hypothesis that anxiety patterns, measured through validated psychometric instruments, contain sufficient predictive information to anticipate key characteristics of labor, which could revolutionize the way obstetric care is planned and managed.

This article is structured as follows. Section 2 presents the state of the art from both a clinical and technological perspective. Section 3 describes the study methodology and the collected dataset. The developed prediction models are presented in Section 4, while the application of explainability techniques is exposed in Section 5. Finally, Section 6 includes a detailed discussion of the obtained results and presents the work conclusions.

2 Background

2.1 Anxiety and Childbirth: Clinical Perspective

The relationship between anxiety and the childbirth process has been the subject of systematic study since the mid-20th century. Dick-Read's pioneering work in 1933 established the theoretical basis of the link between fear, tension, and pain during childbirth, a conceptualization that founded the first prenatal education programs 16.

Contemporary research has deepened this relationship, identifying prenatal anxiety as a multidimensional construct that affects between 15-20% of pregnant women during the third trimester of pregnancy 17, 18. Epidemiological studies reveal that undetected anxiety during the prenatal period can manifest in specific obstetric complications, including a higher incidence of dystocic deliveries (OR = 2.3, 95% CI: 1.8-2.9) and prolongation of labor 19, 20.

A critical factor that conditions the childbirth experience in contemporary society is the so-called "technocratic model of birth", conceptualized by Davis-Floyd 1. This paradigm, dominant in Western health systems, is characterized by the institutionalization of childbirth, the consideration of women as passive patients, and the systematic medicalization of the birth process. According to Davis-Floyd, this model transforms childbirth from a natural physiological event to a "medical-surgical event", where responsibility is transferred from the pregnant woman to the professional team, generating a medical hegemony that can exacerbate anxiety levels in parturients 1, 2.

In the Spanish context, this model can be defined as "Institutionalized Interventionism", where women must adapt to rigid institutional protocols, which can intensify feelings of loss of control and increase pre-labor anxiety 21, 4. Lang's multidimensional model (1968, 1979) provides a theoretical framework for understanding anxiety responses in the obstetric context, identifying cognitive, physiological, and motor components that interact during the childbirth process 22, 23. This conceptualization has been validated in the Spanish obstetric population, where specific worry factors have been identified that correlate significantly with adverse perinatal outcomes 24, 25. The prevalence of clinically significant anxiety in

Spanish pregnant women is estimated at 19.8%, with variations according to sociodemographic factors and obstetric history 26.

2.2 Artificial Intelligence in Obstetrics

The application of artificial intelligence in obstetrics has experienced exponential growth in the last decade, although its implementation in predicting labor development based on psychological factors remains limited [27]. The first predictive models in obstetrics focused on fetal weight estimation, and prediction of premature labor or obstetric emergencies, mainly using artificial neural networks [28].

Recent studies have demonstrated the efficacy of machine learning algorithms in predicting obstetric complications. A comprehensive meta-analysis by Zhang et al. (2022) of 25 studies found that machine learning models for predicting gestational diabetes achieve an average area under the curve (AUC) of 0.85, with a pooled sensitivity of 0.69 and specificity of 0.75 [29]. Nonlinear models outperformed traditional logistic regression, achieving a pooled AUC of 0.89. The most important variables identified include maternal age, family history of diabetes, BMI and fasting plasma glucose. In the context of emergency cesarean section prediction, machine learning models have been developed using maternal and ultrasonographic parameters during pregnancy. Lee et al. developed a multicenter model that achieved 78% accuracy with an AUC of 0.70 for predicting emergency cesarean sections during active labor [30]. Meyer et al. created a comprehensive model to predict unplanned cesarean sections with features available at admission for labor [31]. However, the integration of psychological variables in all these predictive models has been notably scarce.

Another line of research that has represented a relevant advance in the field of medicine in general, and obstetrics in particular, is the development of explainable models, which not only generate accurate predictions but also provide clinically significant interpretations [32]. In obstetrics, explainability is crucial for clinical adoption, since healthcare professionals need to understand the factors that contribute to predictions in order to integrate them into decision-making [33]. The systematic review developed by [34] evaluated 17 studies on AI models for predicting the mode of delivery. The studies generally demonstrated good to excellent performance (AUC values ranging from 0.61 to 0.932), with ensemble models and advanced ML techniques outperforming traditional logistic regression, especially when interpretability was prioritized.

The present research addresses the development of AI models that use exclusively validated psychometric measures of prenatal anxiety, also applying explainability techniques to identify the most influential factors in obstetric outcomes. This approach represents a significant innovation at the intersection between perinatal mental health and artificial intelligence applied to obstetrics.

3 Methodology

3.1 Participants and Study Design

A single-cohort, longitudinal, observational, analytical study was conducted in two Spanish public hospitals: the University Hospital of Guadalajara and the Rey Juan Carlos Hospital of Móstoles. The final sample included 235 full-term pregnant women, with gestational ages between 36 and 42 weeks, recruited through consecutive sampling. The inclusion criteria were: (1) Spanish-speaking pregnant women who agreed to participate voluntarily, (2) pregnancy included and controlled in the pregnant woman health program according to FAME criteria (Federation of Spanish Midwives Associations) 35, (3) fetuses between 36-42 weeks confirmed by amenorrhea or first trimester ultrasound, and (4) fetuses with appropriate weight for their gestational age according to SEGO standards (Spanish Society of Gynecology and Obstetrics) 36. Pregnant women with uncontrolled pregnancies, and maternal age less than 16 years or greater than 44 years were excluded. The mean age of participants was 31.8 years (SD=4.57), with 64% married and 59.8% employed versus 30.2% unemployed. The study protocol was approved by the Clinical Research Ethics Committees of both hospitals. Obstetric data were collected through a systematic review of medical records by specialized healthcare personnel, following the criteria established by the Spanish Society of Gynecology and Obstetrics 36.

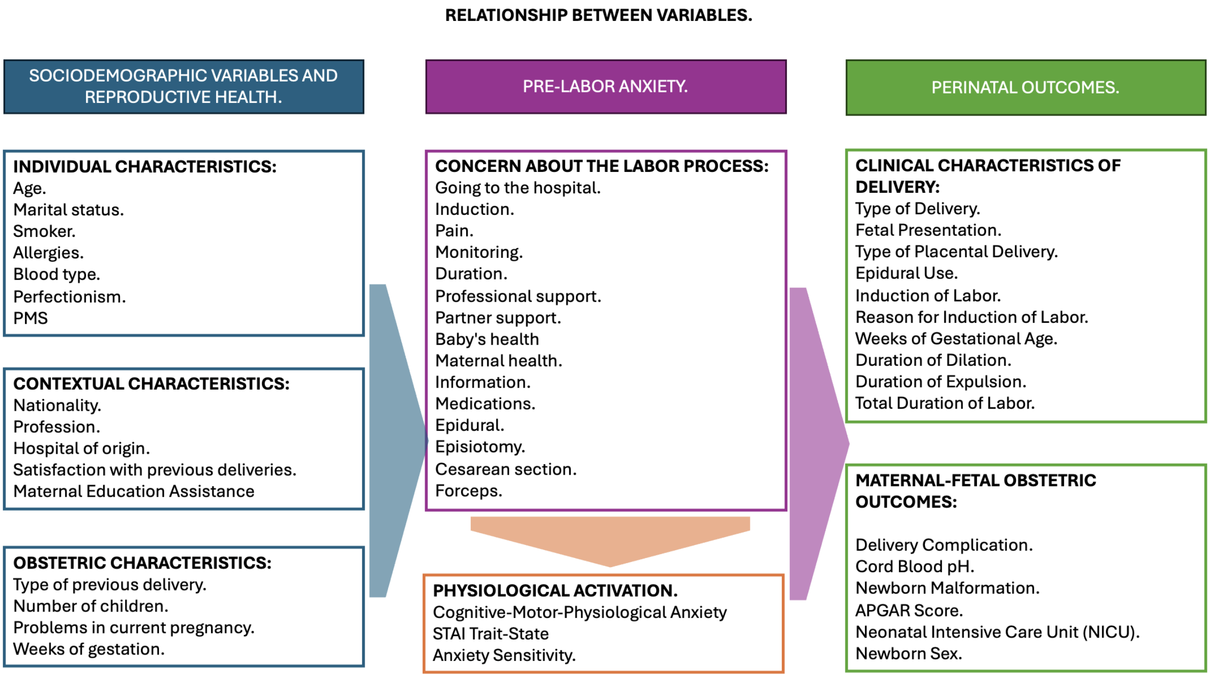


Figure 1: List of variables that compose the study dataset.

3.2 Dataset

For the generation of the study dataset, variables of different natures were collected that are illustrated in Figure 1: (i) sociodemographic and reproductive health variables, (ii) variables about anxiety prior to childbirth, and (iii) perinatal outcomes.

Four validated psychometric instruments were used to collect variables estimating anxiety prior to childbirth. These instruments were selected based on the multidimensional model of anxiety and the technocratic model of birth 37, 1 and described below.

State-Trait Anxiety Inventory (STAI) The State-Trait Anxiety Questionnaire (STAI) by Spielberger et al. 38, is widely used in hospital contexts. This instrument comprises 40 items with four response options that evaluate two independent concepts: anxiety as state (STAI-E), defined as a transitory emotional condition characterized by feelings of apprehension and autonomic hyperactivity, and anxiety as trait (STAI-R), which represents a stable propensity to perceive situations as threatening[1]. The original internal consistency is 0.94, while in our sample, a Cronbach's alpha (α) of 0.73 was obtained.

Inventory of Situations and Responses to Anxiety (ISRA) To measure anxiety from the multidimensional model, the reduced version of the Inventory of Situations and Anxiety Responses (ISRA) by Miguel-Tobal and Cano-Vindel 23 was used. This instrument evaluates anxiety according to four dimensions: social (ISRA-S), cognitive (ISRA-C), physiological (ISRA-F), and motor (ISRA-M). For this study, only the first scale was used, composed of 24 anxiety responses, given that the potentially anxiogenic situation evaluated was specifically the moment prior to childbirth.

[1]We will keep the naming of the Spanish version of tests in Spanish: STAI-E (Estado) and STAI-R (Rasgo)

The internal consistency in our sample was $\alpha = 0.753$ for the total scale, with values of 0.778, 0.765, and 0.728 for the cognitive, physiological, and motor subscales, respectively.

Anxiety Sensitivity Index (ASI) The Spanish version of the Anxiety Sensitivity Index (ASI) validated by Sandín, Chorot and McNally 39 was applied. This multidimensional instrument consists of 16 items with Likert-type responses (0-4) that evaluate the level of sensitivity to suffering anxiety, considered an important risk factor for developing anxiety disorders 40. The ASI measures three components: somatic, cognitive, and social sensitivity, using the total index for our analysis. The original internal consistency is 0.89, obtaining a Cronbach's alpha of 0.754 in our sample.

Survey of Pre-chilbirth Preoccupation factors (PP) To evaluate pre-childbirth worry from the problem-solving perspective 41, a Likert-type scale survey (1-10) was developed based on three validated European scales: the Childbirth and Birth Worry Scale 42, the Cambridge Worry Scale in Pregnancy 43, and the Oxford Worries about Labour Scale 44. The instrument evaluates 16 specific worry factors, organized into three categories according to the technocratic model of birth: factors referring to the clinical process of childbirth (pain, duration, loss of control), factors related to the social phenomenon of childbirth (role change, professional support, information), and worries about hospital techniques (medication, epidural, cesarean section). The internal consistency obtained was $\alpha = 0.908$.

The selection of these instruments allows a comprehensive evaluation of the pre-childbirth anxiety construct, integrating the dimensional, situational, and anxiety sensitivity perspectives, fundamental for the development of accurate and clinically relevant predictive models.

From the third group of variables referring to perinatal outcomes, only two target variables were defined due to their special relevance:

Type of childbirth: Binary categorical variable that classifies births as *Eutocic*: childbirth that begins and ends naturally and spontaneously, without medical intervention; and *Dystocic*: childbirth that requires maneuvers or surgical interventions for its completion.

Labor time: Continuous variable that measures the total duration of labor in hours, from the start of active labor to birth.

4 Prediction models

The generated dataset represents a significant advance in research on psychological factors in childbirth, managing to collect data from 235 pregnant women with multiple psychological variables related to anxiety. For both the task of classifying childbirth type and estimating labor time, various models, including neural networks, decision trees, and statistical models, were evaluated. Finally, the models that reported the best performance for both tasks were the *multi-layer perceptron* (MLP) classifier and the *extreme gradient boosting* (XGB) regressor as described in this section.

4.1 Classification of Childbirth Type

There are numerous state-of-the-art classification techniques that can be applied to the dataset described in the previous section. Therefore, the most popular approaches were implemented and evaluated to identify the model that offers the best performance for classifying childbirth type.

A critical challenge in this problem was the inherent imbalance in the class distribution: 161 eutocic cases (68.5%) versus 74 dystocic cases (31.5%). To address this imbalance, the SMOTE (Synthetic Minority Over-sampling Technique) technique was applied before training, generating synthetic instances of the minority class by interpolating existing cases. This strategy balanced the training set to 161 cases per class, preserving the original distribution in the test set for a realistic performance evaluation. The data division followed a 75%-25% scheme for training and testing, respectively, with stratification to maintain consistent class proportions. Preprocessing included one-hot encoding for categorical variables

Model		Dystocic		Eutocic	
	F1	Precision	Recall	Precision	Recall
MLP	.81	.82	.88	.80	.73
Gaussian Process	.78	.83	.81	.74	.76
XGBoost	.75	.82	.75	.68	.76
Nearest Neighbors	.70	.76	.77	.66	.64
AdaBoost	.70	.79	.69	.62	.73
Linear SVM	.69	.77	.69	.61	.70
Decision Tree	.68	.71	.83	.68	.52
Random Forest	.65	.79	.56	.55	.79
Neural Net	.63	.74	.58	.53	.70
Naive Bayes	.54	.64	1.0	1.0	.18
QDA	.50	.92	.23	.46	.97
RBF SVM	.44	1.0	.15	.45	1.0

Table 1: Performance in terms of F1, precision, and recall of different machine learning models for childbirth type classification.

(*hospital, pregnancy problems, induction, smoking, epidural*) and standardization of continuous features to optimize model convergence.

The performance comparison of the evaluated models is shown in Table 1. As can be observed, the best results are obtained through the multilayer perceptron (MLP). This classifier was implemented through hyperparameter optimization. The resulting configuration was: logistic activation function (sigmoid), a single layer with 50 neurons, Adam optimizer with initial learning rate of 0.0001, and Alpha Regularization = 0.0001. The resulting multilayer perceptron model for childbirth type classification demonstrated outstanding performance on the test set, achieving an F1-score of 81%, indicating an adequate balance between precision and recall across both classes. Specifically, the model obtained a precision of 82% and a recall of 88% for dystocic deliveries ($F1 = 0.85$), while for eutocic deliveries it achieved a precision of 80% with a recall of 73% ($F1 = 0.76$).

Here, it is necessary to highlight that in this specific domain, we must prioritize the recall of dystocic deliveries as a critical evaluation metric, as it reflects the model's capacity to avoid false negatives (that is, dystocic deliveries not predicted as eutocic). In this way, the identification of dystocic deliveries is maximized as these cases require specialized medical intervention and an anticipated allocation of hospital resources. On the contrary, false positives in this class would mean the activation of resources for deliveries that will ultimately be eutocic, which does not entail risk for pregnant women. Thus, the recall result for dystocic deliveries indicates that the model can identify 88% of deliveries that pose a risk to the pregnant woman.

4.2 Regression of Labor Time

Analogously to classification, different regression models have been implemented and evaluated to estimate labor time. In this case, the analysis focused exclusively on eutocic deliveries (150 cases), with labor time ranging from 2 to 20 hours, thereby eliminating outliers that could distort predictions. Data preprocessing for this model included filtering of cases to include only eutocic deliveries with a duration between 2 and 20 hours, one-hot encoding for categorical variables (*hospital, pregnancy problems, induction, smoking, epidural*), MinMaxScaler normalization for continuous variables, scaling all features to the range [0,1], and 75%-25% division for training and testing sets.

The results are shown in Table 2, where the Gradient Boosting Regressor model shows the best performance with a mean absolute error (MAE) of 2.03 hours, followed very closely by the Voting Regressor (MAE 2.07) and Random Forest Regressor (MAE 2.08). These three models also present the best coefficients of determination (R^2), with values of 0.25, 0.31, and 0.27, respectively, indicating that approximately one quarter to one third of the variability in labor time can be explained through the

Model	MAE	RMSE	R^2
GradientBoostingRegressor	2.03	2.73	0.25
VotingRegressor	2.07	2.61	0.31
RandomForestRegressor	2.08	2.70	0.27
BaggingRegressor	2.16	2.91	0.15
LassoLars	2.22	2.98	0.11
XGBRegressor	2.25	2.94	0.13
PoissonRegressor	2.32	2.85	0.18
StackingRegressor	2.40	3.11	0.03
ElasticNet	2.40	3.10	0.03
Ridge	2.40	3.09	0.04
LinearRegression	2.40	3.10	0.03
TweedieRegressor	2.40	2.99	0.10
HistGradientBoostingRegressor	2.77	3.41	-0.17
MLPRegressor	2.95	3.52	-0.25

Table 2: Performance in terms of absolute error (MAE) and quadratic error (RMSE) in hours, together with the R^2 value of different machine learning models for estimating labor time.

analyzed psychological factors. It is notable that ensemble-based methods (such as Gradient Boosting, Voting Regressor, and Random Forest) considerably outperform traditional linear models and neural networks (MLPRegressor), which shows the worst performance with a negative R^2, suggesting that the psychological factors of anxiety have a nonlinear but modelable relationship with labor duration.

Gradient Boosting algorithms obtain the best results in the comparison. This model demonstrated notable performance in predicting labor time, with a mean absolute error of 2.03 hours. A detailed analysis of prediction errors (presented in Figure 2) revealed that 86% of predictions had errors of less than 3 hours, providing valuable information for hospital resource planning and the management of pregnant women's expectations.

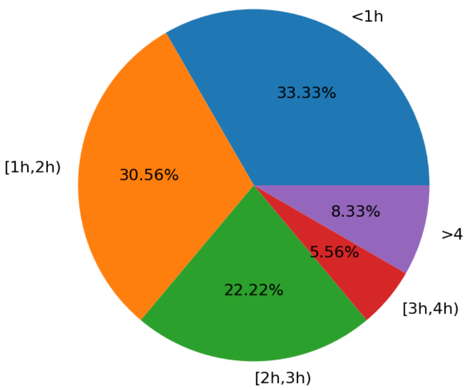
5 Explainable Artificial Intelligence

Despite the effectiveness demonstrated by machine learning models, particularly the Gradient Boosting Regressor and the Multi-Layer Perceptron Classifier, these systems function as "black boxes" where internal decisions remain opaque to users. In the medical context of labor time prediction and eutocic/dystocic delivery classification, this lack of transparency is especially problematic [33, 34]. To address this limitation, we employ Explainable Artificial Intelligence (XAI) techniques that allow us to inspect and understand the internal behavior of the developed models.

For the classifier, we will use two complementary approaches: SHAP (SHapley Additive exPlanations) analysis, which assigns contribution values to each feature for a specific prediction based on game theory [45], and ALE (Accumulated Local Effects), which shows how the model's prediction changes when a feature varies while the others remain constant, avoiding the problems of dependence between variables [46]. In the case of the regression model, SHAP analysis will allow us to identify relationships between psychological indicators of anxiety and labor duration. These techniques will not only increase confidence in the models, but will also provide valuable information for healthcare professionals about which psychological factors significantly influence the development of the childbirth process.

5.1 Interpretation of the Classification Model

The application of Explainable Artificial Intelligence techniques allows us to unravel the internal functioning of our classifier model, revealing significant patterns in the relationship between psychological factors and the type of childbirth.



Prediction Margin	% predictions	% cumulative
$< 1h$	33.33	33.33
$[1h, 2h)$	30.56	63.89
$[2h, 3h)$	22.22	86.11
$[3h, 4h)$	5.56	91.67
$\geq 4h$	8.33	100

Figure 2: Detailed analysis of the percentage of errors in the prediction times of the Gradient Boosting model

The SHAP analysis shown in Figure 3 identifies the variables that exert the greatest influence on the prediction of childbirth type, although they do not indicate the direction of such influence (toward eutocic or dystocic delivery). The five variables with the greatest impact are: ISRA-S (anxiety in social situations), ASI (anxiety sensitivity index), STAI-E (state anxiety), ISRA-C (cognitive anxiety responses), and Childbirth Worry. This distribution of importance confirms that psychological aspects of anxiety, both in their cognitive and social dimension, play a crucial role in childbirth development. It is also especially noteworthy that the hospital where gestation and childbirth took place has no impact on the prediction, since in the study data were collected equitably from a hospital in an urban area and another from a much more rural area.

Additionally, the ALE graphs shown in Figure 4 allow us to interpret the effect (positive or negative) regarding childbirth development of these variables. The most relevant results from this figure are the following:

- STAI-E (State Anxiety): Low values increase the probability of eutocic delivery, confirming the initial hypothesis that reduced levels of situational anxiety favor normal physiological childbirth.
- ISRA-S and ISRA-C: Surprisingly, high values in social anxiety (ISRA-S) and cognitive anxiety responses (ISRA-C) are associated with a higher probability of eutocic delivery. This apparent contradiction could be explained by compensatory coping mechanisms: pregnant women with greater awareness of their anxiety (cognitive component) and concern about the social environment could develop more effective strategies for prenatal preparation, communication with healthcare professionals, and active seeking of support, factors that contribute positively to the physiological development of childbirth.
- ASI and ISRA-F: Conversely, elevated values in anxiety sensitivity (ASI) and physiological anxiety responses (ISRA-F) slightly increase classification as dystocic delivery. This suggests that the physiological response to anxiety (tachycardia, hyperventilation, muscle tension) and sensitivity to these bodily sensations directly interfere with the physiological mechanisms of childbirth, hindering its normal progress. The correlation between physical anxiety responses and obstetric complications could reflect the interaction between stress neuroendocrine systems and hormonal dynamics of childbirth.

These findings suggest a psychophysiological model of childbirth where not all dimensions of anxiety negatively influence the process. While anxious physiological activation (ISRA-F) and hypersensitivity to bodily sensations (ASI) hinder normal progress, the cognitive and social components of anxiety could stimulate adaptive behaviors that favor eutocic delivery. This interpretation has important implications

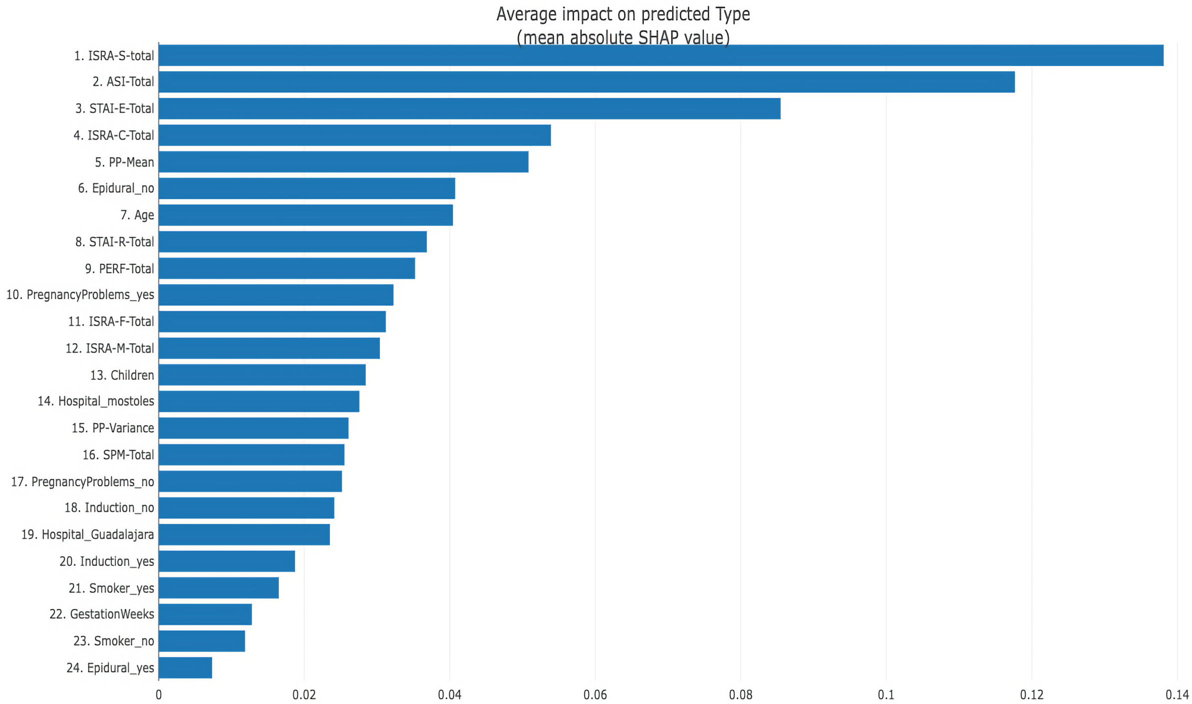


Figure 3: SHAP analysis of the classification model

for prenatal interventions, suggesting that instead of addressing "anxiety" as a unitary construct, professionals should specifically assess and manage physiological activation and anxiety sensitivity, while enhancing cognitive coping strategies.

5.2 Interpretation of the Regression Model

In contrast to the classification model, the SHAP analysis of the labor time regressor shows less precise but still revealing results. As we can observe in Figure 5, the variable with the greatest predictive impact turns out to be the number of previous children, which confirms well-established findings in obstetric literature on the progressive reduction in labor duration in multiparous women. This biological-obstetric factor outweighs psychological variables in importance, suggesting that although psychological factors influence labor duration, obstetric history retains a predominant role.

Among psychological variables, the Anxiety Sensitivity Index (ASI), cognitive anxiety responses (ISRA-C), and trait anxiety (STAI-R) stand out in order of importance. These correlations suggest that more stable and lasting psychological factors (trait anxiety and cognitive processing of anxiety) have a greater impact on labor duration than transitory emotional states, possibly because they influence long-term expectations and prenatal preparation. Anxiety sensitivity (ASI), by representing fear of bodily sensations, could have a direct relationship with pain perception and physiological responses during labor, thus affecting its temporal progression. As an additional result, we can also observe that according to this prediction model, the pregnant woman's age does not appear to have an impact on labor time.

6 Discussion and conclusions

The results of this research reveal a significant relationship between psychological factors of anxiety and childbirth development, mainly in its typology, although also in its duration. The classification model has demonstrated 88% predictive accuracy in identifying dystocic deliveries, while the regression model can predict labor time with a mean error of approximately 2 hours. These predictive capacities represent

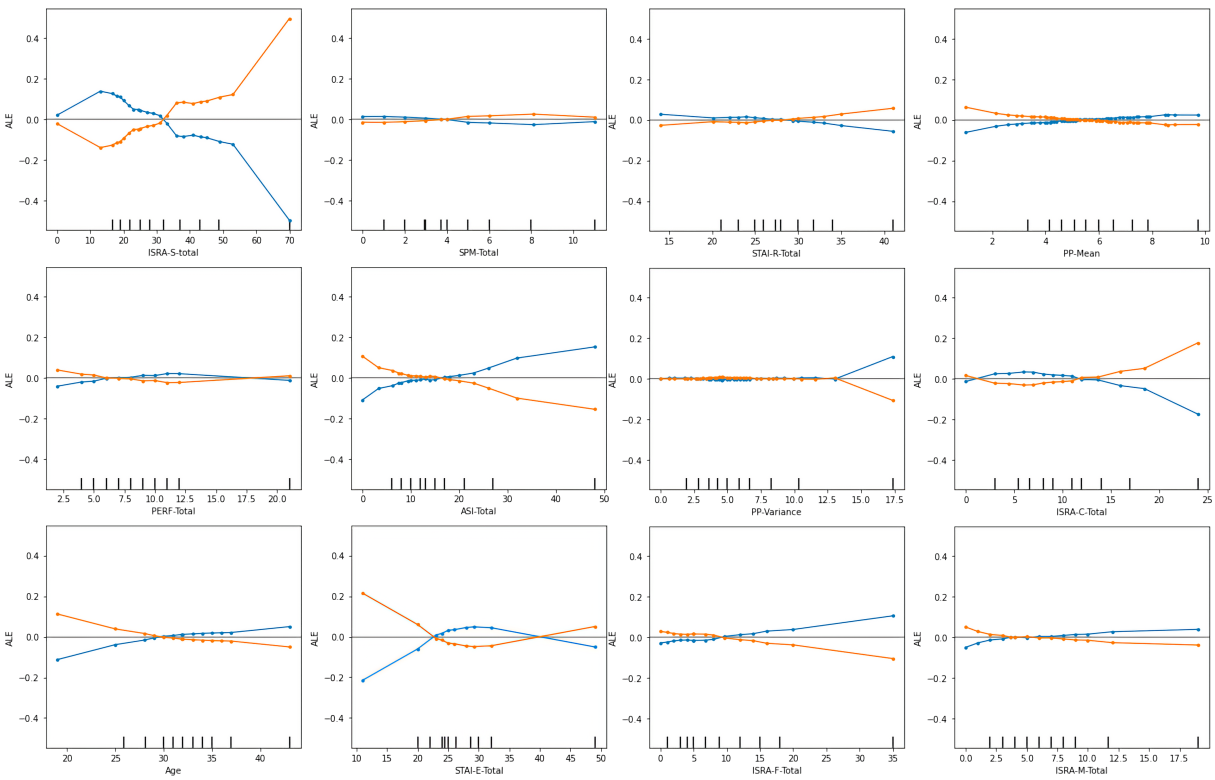


Figure 4: Main results of ALE analysis. Orange: eutocic delivery, Blue: dystocic delivery. The graph indicates how the impact of said variable on classification in each of the classes increases or decreases (y-axis) as its value varies (x-axis)

an important advance in understanding the influence of psychological factors on the physiological process of childbirth.

The interpretation of models through Explainable Artificial Intelligence techniques has revealed complex patterns that challenge the traditional conception of anxiety as a unitary construct with uniformly negative effects on childbirth. We have identified that different dimensions of anxiety influence differently: while physiological anxiety (ISRA-F) and anxiety sensitivity (ASI) tend to favor dystocic deliveries, surprisingly, the cognitive (ISRA-C) and social (ISRA-S) components of anxiety appear to be associated with a higher probability of eutocic deliveries. This finding suggests that certain cognitive coping processes could have protective effects, possibly by stimulating adaptive strategies for preparation and seeking support. Regarding labor duration, results confirm the primordial importance of obstetric factors such as parity (number of previous children), while highlighting the additional influence of stable psychological traits such as trait anxiety (STAI-R) and anxiety sensitivity (ASI). This suggests that more lasting psychological characteristics have a greater impact on labor time than transitory emotional states.

From a clinical perspective, these findings have important implications for improving care for pregnant women. First, they underscore the importance of prenatal psychological assessment that goes beyond general anxiety measures, differentiating between its cognitive, physiological, and social components. Second, they suggest that psychological interventions during pregnancy could benefit from a differential approach: specifically, reducing anxious physiological activation and sensitivity to bodily sensations, while enhancing adaptive cognitive coping strategies.

Healthcare professionals could implement childbirth preparation programs that include specific techniques for managing physiological anxiety responses (such as breathing and muscle relaxation techniques), while promoting adaptive cognitive processes (cognitive restructuring, positive visualization) and strengthening social support networks. This personalized approach could significantly improve the childbirth experience, reduce obstetric complications, and optimize healthcare resources.

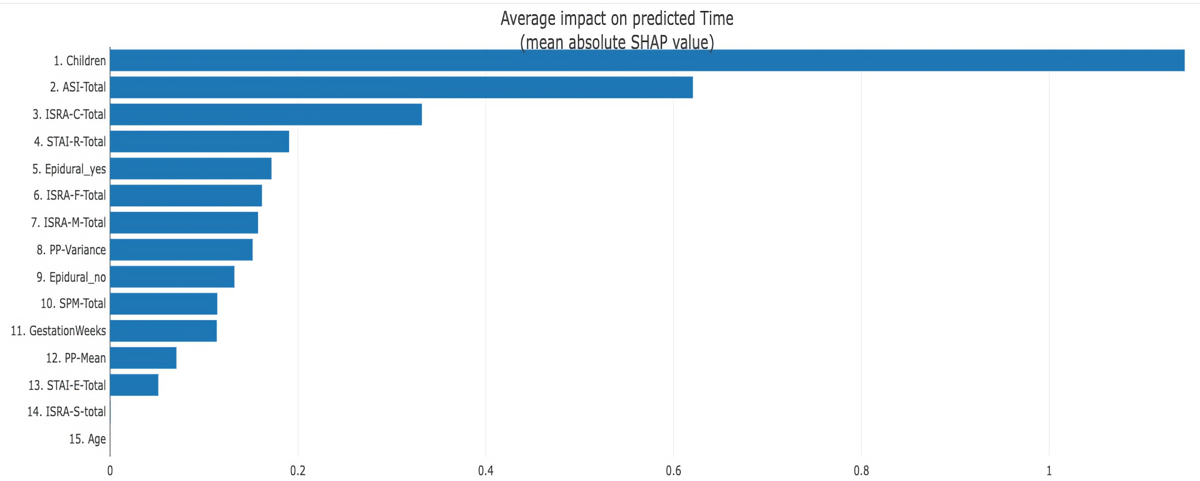


Figure 5: SHAP analysis of the regression model

The capacity of the presented models to classify childbirth types and estimate their duration also represents a valuable contribution to hospital management and care resource planning. Early prediction of potentially dystocic deliveries would allow healthcare centers to optimize the allocation of specialized personnel, operating rooms, and neonatal intensive care units. Likewise, estimating labor time with an error margin of approximately 2 hours would facilitate a more efficient distribution of beds in dilation rooms, better scheduling of healthcare personnel shifts, and a reduction in waiting times for pregnant women. This type of predictive tool could be integrated into hospital management systems to develop dynamic resource allocation models that adapt in real time to anticipated care demand, improving the quality of care and potentially reducing operational costs in obstetrics services.

This research is based on a dataset of 235 participants, possibly the only study of this nature in Spain that relates detailed psychological factors to obstetric outcomes. Data collection took place over four years across two hospitals, yielding a sufficiently robust sample to train effective machine learning models. This database provides a unique platform for understanding the psychological reality of pregnant Spanish women, although its size, significant for research of this type, does not reach the volumes necessary to implement complex deep learning models. Future work could expand this valuable base with multicenter collaborations, incorporate biomarkers to establish more precise psychobiological correlations, and develop specific prenatal interventions at the national level based on identified patterns.

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