

Development of a Self-Assessment-Based Fertility Estimation System

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Abstract: Infertility is a complex reproductive health issue shaped by biological, psychological, lifestyle-related, and social factors. This research presents the development of a self-assessment-based fertility scoring system that supports fertility awareness without relying on laboratory hormone testing. The system uses questionnaire data on menstrual cycle characteristics, reported symptoms, lifestyle-related and exogenous factors, and timing-related variables to generate structured, non-diagnostic feedback. The methodology is based on a rule-based evaluation framework implemented as a web-based prototype in a Python–Flask environment with modular JSON-based configuration layers. User responses are processed into item-level, domain-level, and overall scores, supported by missing-value handling, category labels, visual feedback, and explanatory notes. The contribution of the system lies in its transparent and reproducible scoring architecture rather than clinical diagnosis. Future work will focus on score calibration, consent-based data collection, clinical validation, and possible machine learning integration after suitable datasets become available.

Keywords: fertility scoring system; self-assessment; reproductive health; fertility awareness

1 Introduction

Infertility is one of the most complex reproductive health challenges today, as it affects not only biological functioning but also psychological well-being, social quality of life, and economic stability [1] [2]. Female fertility is shaped by the interaction of hormonal, lifestyle-related, environmental, psychological, and socio-economic factors. For this reason, fertility preservation cannot be reduced to clinical treatment alone. Early awareness, prevention, and lifestyle-related self-reflection also play an important role in supporting reproductive health [3] [4].

According to the WHO, approximately one in six couples of reproductive age experience some form of fertility difficulty [5]. Although assisted reproductive technologies have developed significantly, treatment is often expensive, physically demanding, and emotionally burdensome, while success is not guaranteed [6] [7].

This highlights the need for accessible tools that can support early recognition and help users understand which personal, behavioural, or health-related factors may be relevant before clinical intervention becomes necessary. Several factors that influence fertility are modifiable, including nutrition, sleep, physical activity, smoking, alcohol consumption, and stress [8]. Digital self-assessment systems can therefore create value by translating these factors into structured feedback. Such systems can improve reproductive awareness, support informed decision-making, and encourage timely consultation with specialists when relevant patterns appear.

At the same time, the current fertility application market shows important limitations. Many widely used menstruation and fertility tracking applications mainly focus on cycle tracking, ovulation prediction, reminders, and user engagement, while their clinical relevance and integration into care remain variable [9] [10]. Sensor-based systems, such as Ava or similar wearable fertility technologies, provide more advanced physiological measurements, but they often require external devices, paid access, or closed algorithmic processing [11]. Educational and awareness-oriented tools can support fertility knowledge and early self-reflection, but their feedback is often static, general, or limited in personalization [12] [13]. In addition, reproductive health applications raise important concerns regarding transparency, data protection, and user privacy [14]. As a result, there is still a gap for a transparent, modular, and scientifically grounded system that gives immediate, interpretable feedback without requiring laboratory hormone testing, external sensors, or paid access.

The present research addresses this gap through the development of a self-assessment-based fertility scoring system. The aim is to create a transparent, rule-based, and non-diagnostic assessment framework that uses structured questionnaire data to support reproductive self-awareness. The system is positioned as an engineering-oriented educational prototype: it applies modular processing logic and interpretable output to help users recognize fertility-related patterns and identify areas where professional consultation may be useful.

2 Methodological framework

The developed fertility scoring system was designed as a self-assessment-based framework that translates user-reported information into structured fertility-related indicators. The methodological starting point was a previous conceptual model that organized female fertility determinants into endogenous and exogenous factors [15]. That earlier model included several hormonal, biochemical and clinical indicators, such as AMH, FSH, TSH, ovarian reserve, ovulatory function and uterine health. These variables are clinically relevant, but they are not suitable for a general self-assessment tool, because most users do not have access to laboratory

values or specialist diagnostic results [16]. For this reason, the present system shifts the focus from hormone-based modelling to questionnaire-based assessment.

The aim of this methodological shift was to create an accessible educational screening logic based on observable or reportable indicators. In the absence of laboratory data, the system uses variables that may indirectly reflect underlying reproductive processes, such as menstrual cycle length, cycle variability, bleeding patterns, pain, diagnosed conditions, lifestyle habits, sleep, stress, body mass index and intercourse timing. These factors cannot provide diagnostic certainty, but they can support early awareness and self-reflection, especially when several less visible risk patterns appear together [4]. In this sense, the system follows the broader logic of fertility-awareness-based approaches, where self-observation is used as a tool for reproductive education and early recognition rather than as a substitute for clinical diagnosis [17].

The questionnaire was built around five assessment domains: cycle and ovulation, lifestyle and exogenous factors, pain and symptoms, demographics and medical history, and timing/partner-related factors. These domains were not created as arbitrary categories. They reflect the main functional areas through which fertility may be influenced in a self-assessment context. The cycle and ovulation domain represents the most direct observable proxy of hormonal and ovulatory function, because ovulation, cycle regularity and luteal phase adequacy are central biological conditions of conception [18]. The lifestyle and exogenous domain captures modifiable behavioural and environmental factors, such as BMI, sleep, stress, smoking, alcohol consumption and environmental exposures, which may influence hormonal balance, metabolic function and reproductive outcomes [8] [19]. The pain and symptoms domain collects signs that may indicate reproductive or endocrine disorders, including endometriosis, PCOS, thyroid dysfunction and hyperprolactinaemia [20] [21]. The demographics and medical history domain covers background factors, such as age, previous pregnancy, trying time and family history, which strongly shape reproductive probability but are only partly modifiable [22] [23]. Finally, the timing and partner-related domain reflects behavioural and relational conditions that may affect the chance of conception, especially intercourse frequency and timing during the fertile window [24] [25].

The questionnaire items were selected from the literature according to three practical criteria. First, the factor had to be relevant to female fertility or fertility-related awareness. Second, it had to be answerable by a non-clinical user without laboratory testing. Third, the answer had to be transformable into a transparent scoring rule. This means that the system does not ask for every possible medical detail, but focuses on variables that can be interpreted in a structured and reproducible way. For example, cycle length, luteal phase length, BMI, sleep duration and age can be handled as scale variables, while smoking status, diet type, diagnosed conditions and ovulation tracking can be handled as categorical variables. This design supports both usability and methodological clarity. The five-domain structure also serves an engineering purpose. It separates heterogeneous

information into smaller, interpretable modules. Instead of producing only one overall score, the system first evaluates each domain separately. This makes it possible to show which area contributes most strongly to the result. It also avoids the main weakness of a single undifferentiated score: the loss of information. For example, a low score caused by irregular cycles has a different meaning from a low score caused by smoking and sleep deprivation, even if the numerical value is similar. Domain-level evaluation therefore improves interpretability and supports more targeted educational feedback.

Overall, the methodological framework should be understood as a non-diagnostic, literature-based decision-support structure. Its purpose is to organize self-reported information and highlight potentially relevant patterns, not to replace gynecological, endocrinological or reproductive medical evaluation.

3 Scoring and evaluation logic

The scoring logic was developed to convert heterogeneous questionnaire answers into comparable, interpretable indicators. Since primary clinical data were not available, the scoring rules were derived from published literature and from the relative biological relevance of each factor. The aim was not to define exact medical probabilities, but to create a transparent relative ordering of responses within each question or smaller question group, while using domain weights and cap rules to reduce the limitations of simple numerical averaging. In this logic, an answer receives a higher score when it is closer to the fertility-related optimum described in the literature, and a lower score when it represents a less favourable or more concerning pattern.

Each item was evaluated on a 0–100 scale. The maximum value indicates the most favourable category within the given question, while lower values indicate increasing deviation from the expected optimum. The size of the reduction depends on the reported importance of the factor, the seriousness of the deviation and the likely reversibility of the condition. For example, a mild lifestyle deviation receives a smaller reduction than a diagnosed reproductive disorder, because its biological effect is usually less direct and more modifiable. By contrast, a very short luteal phase receives a stronger reduction because luteal phase insufficiency may affect endometrial preparation and implantation [26] [27]. Severe BMI deviation is also scored more strictly, because both underweight and obesity are linked to impaired reproductive function [28]. Similarly, diagnosed endometriosis receives a strong reduction because it may affect fertility through inflammatory, anatomical and endometrial mechanisms [29].

The system uses different scoring patterns depending on the nature of the variable. Some items are scored as nominal categories, such as diet type or smoking status.

Others are ordinal, such as perceived stress level or pain severity. Scale variables, such as age, BMI, cycle length, sleep duration and luteal phase length, are scored according to biologically meaningful ranges. In several cases, the relationship is not linear. BMI requires a U-shaped interpretation, because both very low and very high BMI values may be unfavourable for reproductive function [28]. Age also requires non-linear interpretation, because fertility decline becomes stronger after specific reproductive age thresholds [22] [30]. This approach makes the model more flexible than a simple linear point system.

Domain scores are calculated from the item scores belonging to the same domain. The result expresses how close the user's responses are to the favourable range within that area. The final score is then calculated from weighted domain scores. The weights reflect the relative importance of each domain in fertility-related assessment. The cycle and ovulation domain received the highest weight, 0.30, because ovulation, cycle regularity and luteal phase adequacy are among the most direct functional indicators of female fertility [18]. The lifestyle and exogenous domain received a weight of 0.25, because modifiable factors such as BMI, sleep, stress, smoking, alcohol consumption and environmental exposures can affect hormonal balance, metabolic function and reproductive outcomes [8] [19]. The pain and symptoms domain received a weight of 0.20, because symptoms and diagnosed conditions may indicate clinically relevant disorders, although their effect depends on severity, diagnosis and individual context [20] [21]. The demographics and medical history domain received a weight of 0.15, because age, previous pregnancy and family history are important but partly static factors [22] [23]. The timing and partner-related domain received a weight of 0.10, because it mainly represents behavioural and relational conditions rather than female biological function, but it can still modify the probability of conception [24] [31].

The weighting scheme was designed as a transparent compromise between biological relevance and educational usefulness. An equal distribution of weights would not have reflected the stronger reproductive role of ovulation and cycle function. At the same time, giving excessive weight to pain and symptoms could have distorted the overall result, because some symptoms are important warning signs but do not affect every user in the same way. The final distribution therefore preserves the dominant role of cycle and ovulation indicators, while still giving meaningful weight to lifestyle, symptoms, background factors and timing behaviour.

Missing values are handled separately from unfavourable answers. If a user does not know an answer, or if a question is not applicable, the system does not automatically treat this as a negative fertility indicator. Instead, missing items are excluded from the relevant score calculation and reflected in a completeness indicator. This prevents the final result from being distorted by unavailable information. At the same time, the completeness value tells the user how much of the model could actually be evaluated. This is important because a high score with low completeness is less informative than a high score based on a more complete

response profile. The domain and overall scores are interpreted through broad score bands. Scores of 80 or above indicate a high category, scores between 65 and 79 indicate a medium category, and scores below 65 indicate a low category. These categories should not be read as diagnostic labels. They are interpretive bands that help users understand the result more easily. Their main function is to support communication and visualization, not to define strict medical thresholds.

In addition to ordinary scoring, the system applies override and cap rules. These rules are necessary because some fertility-related situations cannot be represented accurately by simple averaging. In a purely additive model, several favourable answers could compensate for a clinically important warning sign. This would be misleading in cases where the biological limitation is strong or threshold-like. For example, hysterectomy requires a strict cap because the anatomical basis of natural gestation is absent [32]. Very long cycles or very few menstrual periods require strong limitation because they may indicate amenorrhoea or severe ovulatory dysfunction. Advanced reproductive age and extreme BMI values also require cap logic, because they are linked to sharp declines or disruptions in reproductive function [22] [25] [33] [34]. Diagnosed endocrine or inflammatory conditions may also limit the maximum score when they indicate specific reproductive risk patterns [35] [36] [37] [29].

The purpose of the cap logic is to preserve biological plausibility. If a factor indicates a strong functional limitation, the score should not remain high simply because other domains are favourable. Similarly, some combined patterns may be stronger than the sum of their individual components, such as high stress with very short sleep [38], smoking with frequent alcohol consumption [39] [40], or irregular cycles with androgenic symptoms. These rules reduce the risk of misleading compensation effects. The override system also supports educational feedback. Some rules do not only reduce or cap the score, but also trigger explanatory notes. These notes help the user understand why a specific pattern may be relevant and when medical consultation may be reasonable. In this way, the scoring logic is not a black-box prediction mechanism. It is a transparent evaluation framework in which each score, cap and comment can be traced back to a predefined rule and a fertility-related rationale.

4 System architecture and implementation

To make the scoring logic operational, the fertility scoring system was implemented as a modular web-based prototype using a Python–Flask backend and a lightweight HTML–JavaScript frontend. The architecture follows a layered logic in which the questionnaire interface, configuration files, validation layer, scoring engine, and result presentation are separated. This structure was selected because the system functions both as a user-facing tool and as a research prototype. Therefore, the

technical design had to remain simple, auditable, and easy to modify. A more complex cloud-based or microservice architecture would have introduced unnecessary dependencies at this development stage.

A central design decision was the use of JSON-based configuration files for both the questionnaire structure and the scoring rules. The questionnaire schema defines the questions, answer types, response options, domains, and input constraints, while the scoring configuration stores score ranges, domain weights, and override rules. This separates the model logic from the application code. As a result, new questions, modified score ranges, or updated override rules can be introduced at the configuration level without rewriting the backend or frontend logic. From an engineering perspective, this supports maintainability and version control; from a methodological perspective, it makes the rule set inspectable.

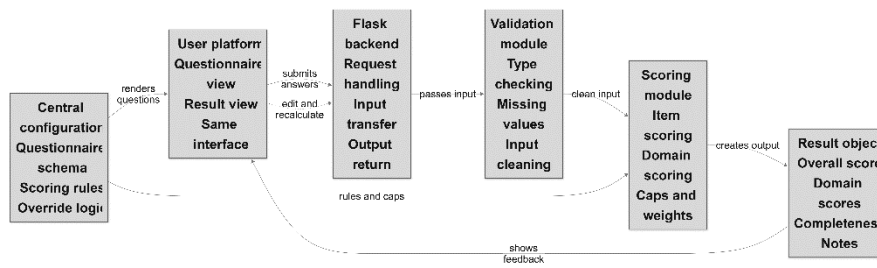


Figure 1
System architecture – data flow

The questionnaire is automatically rendered from the central configuration layer. The user interface is therefore not manually hard-coded question by question, but generated from the same structured source that defines the assessment logic. This reduces the risk of inconsistency between the displayed questionnaire and the variables used by the scoring model. It also supports later extension, because changes in the questionnaire schema can be reflected in the interface without restructuring the whole application. The data flow of the system is shown in Figure 1.

The backend was implemented in Python with Flask because this combination is lightweight, readable, and appropriate for a research-oriented prototype. Python supports the implementation of validation, scoring, and data-processing logic, while Flask provides simple endpoints for loading the questionnaire and calculating the score. In the current version, the backend acts as a controlled communication layer between the frontend, the validation process, and the scoring engine, rather than as a large-scale commercial application framework. After submission, the validation layer checks type compatibility, expected input ranges, and missing-value markers before passing a cleaned response object to the scoring engine. This step ensures that the scoring engine receives structured and processable input. It also separates input validation from score calculation, which makes the system easier to test and maintain.

The scoring engine is the computational core of the system. It reads the scoring configuration, calculates item-level values, aggregates them into domain scores, applies domain weights, and executes the predefined override and cap rules. The calculation is deterministic: identical input under the same configuration version produces identical output. This was chosen deliberately, because the current research phase does not yet include a clinically validated dataset that would justify machine learning-based prediction. A rule-based engine is therefore more appropriate at this stage, as it remains explainable and controllable. The result is returned as a structured output object containing the overall score, domain scores, completeness values, category labels, and explanatory notes. This output is displayed on the same user platform where the questionnaire was completed. The circular data flow supports usability, because the user does not leave the interface after submission. It also supports the educational function of the system, since answers can be modified and recalculated, allowing the user to observe how changes in selected variables influence the output.

The current implementation operates as a local and stateless prototype. Submitted answers are processed only for score calculation and are not stored by default. This design was selected because fertility-related data are sensitive and because the primary aim of the prototype is to test the model logic rather than to collect user data. Future versions may introduce online deployment and data storage, but this would require a separate consent and data-protection framework.

5 User feedback and interpretability

The user feedback layer was designed to make the fertility scoring logic understandable, not only visible. Since the system has an educational purpose, the interface cannot simply display a numerical result. It must help the user understand what the result means, which domain influenced it, and why certain answers may be relevant. For this reason, the output combines an overall score, domain-level scores, category labels, completeness information, visual representation, and explanatory notes.

The system presents domain-level scores in addition to the overall score. This design allows the user to see whether the result is mainly influenced by cycle and ovulation patterns, lifestyle-related factors, pain and symptoms, demographic or medical background, or timing-related behaviour. This is important because two users may receive similar overall scores for very different reasons. By showing the domain profile, the system makes the output more specific and prevents the interpretation of fertility-related status as one homogeneous number. Each domain score is assigned to a broad category: high, medium, or low. These categories are not diagnostic labels, but communication tools. Their role is to reduce cognitive load and make the numerical output easier to interpret. In a self-assessment context,

users may not know whether a score such as 72 or 84 is meaningful. Category labels provide a first layer of interpretation, while the detailed numerical scores preserve transparency. The completeness indicator shows how much of the questionnaire could be evaluated based on the submitted answers. This helps users interpret the reliability of the output. A high score based on nearly complete information is more informative than a high score based on many missing answers. By displaying completeness separately, the system makes the limits of the result visible without treating unknown information as an unfavourable fertility-related factor.

The radar chart was selected as the main visual output because it represents the five-domain profile in a compact form. This is useful in a short educational report, where the goal is not to present complex statistical results, but to show balance or imbalance between functional areas. The chart allows users to see whether the profile is evenly strong or whether one domain is clearly weaker than the others. In this way, the visual output seen in Figure 2. connects the numerical score to concrete areas of reproductive health.

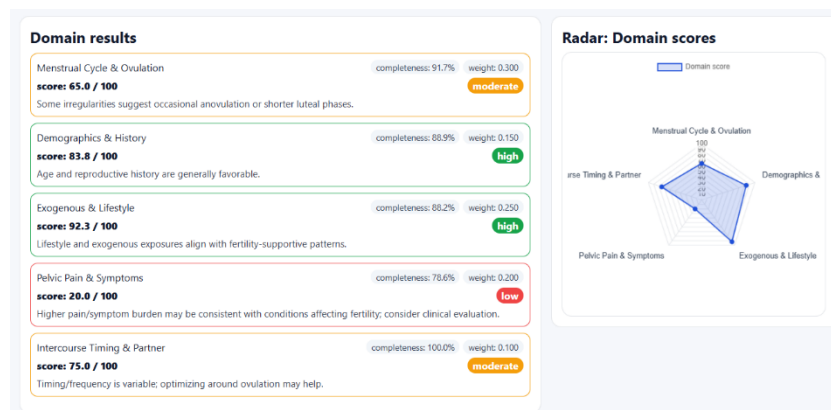


Figure 2
Visualisation of the domain results

The interface was also designed to keep the questionnaire and the result on the same platform. This is important because the system is not only a calculator, but a learning environment. If the result appeared in a separate document or disconnected report, the user would be less able to connect the output to the original answers. By keeping the questionnaire, result cards, chart, and explanatory notes in one interface, the system supports immediate comparison between input and output. This also enables recalculation: the user can change an answer and observe how the result changes. This interactive mechanism strengthens self-reflection and makes the scoring model more understandable.

Explanatory notes connect the score to the scientific logic behind it. When a response or response combination activates a relevant rule, the system can display a short explanation of why the factor matters. For example, notes may be triggered

by very short or long cycles, low or high BMI, short sleep, high stress, severe menstrual pain, diagnosed PCOS, endometriosis, or prolonged trying time. Their purpose is to make the scoring logic traceable and to help users recognize when professional consultation may be reasonable.

Overall, the feedback layer turns the scoring result into an interpretable educational output. The user can see the domain structure, the numerical values, the completeness of the input, the visual profile, and the explanatory comments. This makes the system more suitable for educational, research, and awareness-raising use than a single unexplained fertility score.

6 Discussion and limitations

The developed fertility scoring system occupies a specific position among existing fertility-related digital tools. Many commercial applications focus mainly on cycle tracking, ovulation prediction, reminders, community functions, or user engagement. Sensor-based systems can provide more advanced physiological input, but they often require additional hardware, paid access, or closed algorithmic processing. Educational tools support fertility awareness, but their feedback is often static or only weakly personalized [12] [13]. In contrast, the developed system combines an educational purpose with an interactive and rule-based scoring architecture. Its main contribution is not clinical prediction accuracy, but the creation of a transparent framework that converts self-reported fertility-related information into structured and interpretable feedback.

The system creates value through accessibility, transparency, and modularity. It does not require laboratory hormone values, wearable sensors, registration, or paid access, which makes it suitable for early-awareness and educational contexts. Its logic is also explicitly documented: the questionnaire items, domain structure, scoring rules, domain weights, missing-value handling, and override rules are stored in a modular configuration layer. This means that the assumptions behind the output are visible and can be reviewed, updated, or tested. From an engineering perspective, this supports maintainability and reproducibility. From an educational perspective, it helps users understand that the output is not a hidden prediction, but the result of predefined, interpretable evaluation logic.

A central methodological issue is that the current scoring model is based on literature-supported relative ordering rather than clinically calibrated probability estimation. The score assigned to an answer indicates that one response category is more or less favourable than another within a given question or domain. However, the exact numerical distance between two scores should not be interpreted as a precise biomedical measurement. For example, the difference between 80 and 65 does not necessarily have the same meaning in cycle length, BMI, sleep duration,

pain severity, or diagnosed endometriosis. The system can justify why one category is placed below another, but it cannot yet fully justify whether a specific deduction should be 5, 10, or 15 points. This is an important limitation of the current prototype.

This limitation is especially relevant because the model operates in a heterogeneous factor space. The questionnaire combines biological, behavioural, demographic, symptomatic, medical-history, and timing-related variables. These variables differ in measurability, reversibility, clinical seriousness, and causal proximity to fertility. A lifestyle factor such as moderate caffeine intake is not methodologically equivalent to a diagnosed condition such as endometriosis, even if both are represented numerically. Similarly, a missing ovulation-tracking answer has a different meaning from a missing diagnosis-related answer. For this reason, the system cannot rely on simple averaging alone.

The use of domain weights, completeness indicators, and override rules is an attempt to manage this heterogeneity. Domain weights ensure that more direct biological indicators, especially cycle and ovulation variables, have a stronger influence on the overall score. Completeness values prevent missing information from being treated as an unfavourable answer. Override and cap rules protect the result from biologically implausible compensation effects, where favourable answers in one area would otherwise hide a clinically important warning pattern in another. For example, healthy lifestyle responses should not fully compensate for amenorrhoea, premature ovarian insufficiency, hysterectomy, or strong symptom combinations suggesting a reproductive disorder. In this sense, the system already moves beyond a simple relative scoring table and applies a more structured evaluation logic. Nevertheless, the current system should be interpreted as a first-stage educational prototype. It has not yet been clinically validated, and its scoring rules are based on literature review and logical modelling rather than empirical calibration. The output should therefore not be read as a medically confirmed probability of infertility. It is more appropriate to interpret the result as a structured awareness profile that highlights potentially relevant fertility-related patterns. This distinction is essential, because self-reported questionnaire data can be incomplete, uncertain, or misunderstood. The completeness indicator helps communicate this uncertainty, but it cannot fully eliminate the limitations of self-reporting. Future development should therefore focus on strengthening the scoring structure and testing the model's behaviour. Sensitivity analysis could show how strongly each question, domain, and override rule influences the final output. Synthetic scenario testing could help identify whether the system behaves plausibly in typical, borderline, and extreme cases. The current relative scoring logic should also be complemented by clearer impact categories, such as low-impact, moderate-impact, high-impact, and critical factors. This would make the model less dependent on small numerical differences and easier to defend scientifically.

A further development direction is consent-based data collection. The current prototype does not store user responses, which is appropriate for privacy protection during the initial phase, especially because fertility-related data are sensitive.

However, empirical validation requires structured data collection, ethical approval, a clear consent form, and GDPR-compliant data handling. Online deployment would also require secure hosting, database design, anonymization procedures, and user-rights management. Only after such data are available would machine learning integration become methodologically justified. Even then, data-driven models should not replace the current interpretability logic, but should support score refinement, calibration, and comparison between rule-based and empirical patterns.

Conclusions

This research presented the development of a self-assessment-based fertility scoring system designed to support reproductive awareness through structured and interpretable feedback. The system translates questionnaire data on cycle patterns, lifestyle and exogenous factors, pain and symptoms, demographic and medical history, and timing-related behaviour into domain-level and overall scores. Its contribution lies in the transparent architecture of the scoring framework: questionnaire items, scoring rules, domain weights, missing-value handling, and override logic are organized in a modular and reproducible way. The system should be understood as an educational prototype rather than a clinical diagnostic tool. Its current scoring logic provides literature-supported relative ordering, while future work should focus on score calibration, validation, and consent-based data collection.

Overall, the fertility scoring system offers a scalable and transparent approach to digital fertility awareness. By combining accessibility, modularity, and interpretability, it can support users in recognizing relevant reproductive patterns and can serve as a basis for future research-oriented and clinically validated reproductive health tools.

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