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ENHANCING FETAL MONITORING THROUGH DIGITAL TWIN TECHNOLOGY AND ENTROPY-BASED FETAL HEART RATE VARIABILITY ANALYSIS

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Abstract. *In fetal healthcare, Digital Twin Technology (DTT) offers a powerful tool for simulating fetal physiological conditions, enabling continuous, real-time monitoring and predictive analysis. This study explores the integration of DTT with entropy-based analysis of fetal heart rate variability (FHRV) to enhance fetal monitoring. Utilizing a dataset of 585 fetal electrocardiogram (ECG) recordings collected via scalp electrode monitoring during delivery, we computed entropy measures such as Markov entropy and multiscale entropy to assess fetal status. The results demonstrate that these entropy measures provide significant information regarding fetal well-being status. Moreover, the calculated entropy values correlate strongly with umbilical cord blood gas parameters. This correlation suggests that entropy-based FHRV analysis, combined with DTT, can serve as an effective and reliable method for improving the accuracy of fetal health monitoring and predicting fetal well-being as delivery approaches.*

Keywords: Fetal heart rate variability, Markov entropy, Multiscale entropy, Correlation, Umbilical cord blood gas parameters, Digital Twin Technology

1. **Introduction.** As Digital Twin Technology (DTT) continues to advance, it is transforming healthcare by integrating real-time data, advanced analytics, and virtual simulations to enhance patient care, predictive analytics, clinical operations, and training [1,2]. By collecting and analyzing extensive patient data from multiple sources, DTT can provide personalized treatment plans tailored to individual characteristics, medical history, and real-time physiological data. Machine learning algorithms enable predictive analytics and preventive interventions, facilitating early detection of health risks and proactive measures [3]. In fetal healthcare, the general architecture of the digital twin based fetal heart rate (FHR) monitoring system consists of three main components. The first component is digital twins monitoring devices such as electrocardiogram (ECG), or ultrasound (US) recordings, that capture and process real-time data, enabling the creation of a digital replica. The second is data analytics component that acts as the bridge

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between the monitoring device and data analytics component facilitating data communication, integration, and management. The final and third component is a developed model simulation component that behaves as a brain of digital twin, uses this data to provide dynamic virtual representations of the fetal [4]. This study aims to enhance fetal monitoring by analyzing the data analytics component from an engineering perspective, offering detailed, real-time insights that enable healthcare professionals to make more accurate decisions during delivery time.

Fetal monitoring during labor is crucial for ensuring the health and safety of both the mother and the baby. One of the key indicators of fetal well-being is fetal heart rate variability (FHRV), which measures the variations in time between consecutive heartbeats by electrocardiogram (ECG) [5,6]. FHRV is considered as an important indicator of cardiovascular function and is primarily controlled by the autonomic nervous system [7,8], providing information to monitor fetal well-being throughout pregnancy [9]. During delivery, the fetal autonomic nervous system, which includes the sympathetic and parasympathetic branches, plays a critical role in regulating heart rate [10,11]. The sympathetic nervous system typically increases heart rate and prepares the body for stress [12], while the parasympathetic nervous system works to slow the heart rate and promote relaxation [13]. Monitoring the balance and interaction between these systems through FHRV can offer valuable insights into the fetus's response to the stresses of labor, ensuring timely and appropriate interventions [14,15].

In addition to FHRV data, umbilical cord blood gas parameters such as pH, pressure of carbon dioxide (PCO_2), pressure of oxygen (PO_2), bicarbonate (HCO_3), and base excess (BE) are critical indicators of fetal respiratory function and acid-base balance [16-18]. These parameters are obtained immediately after delivery by clamping the umbilical cord and taking a blood sample. Analyzing these blood gas parameters can help assess the fetal respiratory status and detect any potential complications [19].

In FHRV research, different entropy methods are used to analyze the complexity and predictability of heart rate signals, providing insights into fetal well-being [20]. Entropy has been widely adopted in various fields, including information theory, biology, and medicine, to quantify the amount of disorder or randomness in a system [21,22]. According to [20], entropy is one of the most applied measures in FHRV analysis. Given that heart rate patterns are inherently non-linear, entropy is particularly more resistant to noise than linear analysis [23]. Integrating entropy with digital twin technology has enhanced the amount of information that can be extracted from FHRV analysis, providing a more comprehensive view of fetal health.

Therefore, in this study, we aim to analyze FHRV during delivery time data by using Markov entropy and multiscale entropy to enhance fetal monitoring in digital twins. Markov entropy will be employed to examine the probabilistic transitions between different heart rate states [24], providing insights into the predictability and stability of the fetal heart rate during delivery. Meanwhile, multiscale entropy will be utilized to assess the complexity of fetal heart rate signals across various time scales [25], offering a detailed understanding of how these patterns evolve over different periods. By combining these two methods, we aim to capture both the multi-level complexity and the dynamic state transitions of fetal heart rate variability, thereby enhancing the robustness of our analysis. In addition, we partitioned the dataset into downward heartbeats and non-downward heartbeats to focus on the analysis of the parasympathetic and sympathetic nervous systems of the fetal during delivery time. Furthermore, we will explore correlations between the entropy measures and umbilical cord blood gas parameters, aiming to clarify potential associations between fetal heart rate variability characteristics and prenatal metabolic status at birth.

The rest of this paper is composed of three additional sections. Section 2 provides a detailed explanation of the proposed methodology. In Section 3, we present the experimental results, and evaluation of each entropy method. Finally, Section 4 includes the conclusion and suggestions for future work.

2. **Proposed Methodology.** This section outlines the comprehensive methodology adopted for enhancing fetal monitoring through the integration of digital twin technology and entropy-based fetal heart rate variability (FHRV) analysis during delivery. The proposed approach leverages digital twin models to create a virtual representation of the fetal cardiovascular system, enabling advanced analysis and prediction of fetal heart rate pattern.

Figure 1 demonstrates the use of an internal monitoring device to capture fetal heart rate during delivery. The device on the left is used for internal fetal monitoring, where a scalp electrode is attached directly to the fetal scalp, and the output on the right side is a plot showing the fetal heart rate data over time, with the x-axis representing time before delivery in minutes and the y-axis showing the fetal heart rate in beat per minute (bpm). These data were captured during the internal monitoring process at Miyazaki Medical Association Hospital, Miyazaki Prefecture, Japan.

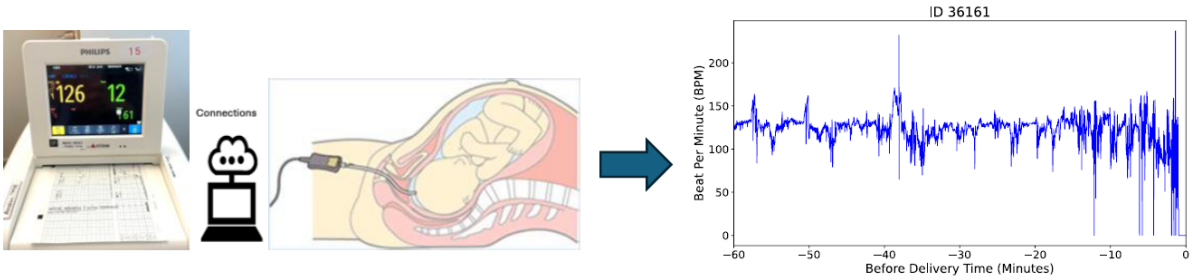

FIGURE 1. The internal monitored beat per minute (bpm) data during delivery time

The overall workflow of the proposed system is shown in Figure 2. The methodology involves the following key steps:

1) Development of the fetal cardiovascular digital twin model (Section 2.1)
2) Preprocessing of recorded fetal heart rate data to eliminate outliers (Section 2.2)
3) Dataset partitioning to separate parasympathetic and sympathetic nervous system components (Section 2.3)
4) Entropy analysis using Markov entropy (Section 2.4) and multiscale entropy (Section 2.5)
5) Correlation testing between entropy measures and clinical outcomes (Section 2.6)

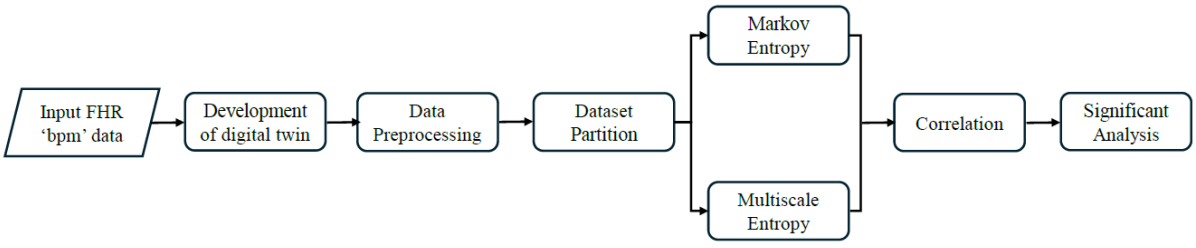

FIGURE 2. The overall flowchart for the proposed system

2.1. **Development of the fetal cardiovascular digital twin model.** The cornerstone of our methodology is the development of a digital twin of the fetal cardiovascular system. A digital twin is a virtual model designed to accurately reflect a physical object or system [26]. In this study, the digital twin simulates fetal heart rate dynamics by integrating physiological data from internal monitoring devices and fetal electrocardiogram (ECG) with computational models.

Data acquisition. We utilized data obtained from internal fetal monitoring during delivery. As shown in Figure 1, a scalp electrode is attached directly to the fetal scalp, providing continuous and precise measurements of the fetal heart rate in beat per minute (bpm). This method offers high-fidelity data crucial for accurate simulation within the digital twin. In addition to bpm data, fetal ECG recordings were used to capture the electrical activity of the fetal heart. ECG provides detailed information on the timing and rhythm of heartbeats, which is essential for modeling the electrical aspects of cardiac function.

2.2. **Preprocessing.** When preprocessing FHRV data in beat per minute (bpm), it typically refers to a method for cleaning the data by removing outliers. This process involves calculating the average (μ) and a measure of variation (σ) of the *bpm data* as shown in Equation (1). This method helps ensure that the analysis focuses on the most representative data points, excluding those that might distort the results due to their extreme values. Importantly, removed data points are omitted and not replaced with any artificial values.

$$\mu - 3\sigma \leq bpm\ data \leq \mu + 3\sigma \tag{1}$$

2.3. **Dataset partition.** The dataset was partitioned into parasympathetic and sympathetic components, represented by downward and non-downward heartbeat data, respectively. This partitioning was achieved by analyzing the differences in consecutive RR intervals in seconds, which were transformed from recorded bpm data using Equation (2). RR intervals, the time between successive heartbeats, serve as a foundational metric for assessing FHRV as shown in Figure 3. To distinguish between parasympathetic and sympathetic activity, we focused on these RR interval changes. Specifically, a decrease in the RR interval was categorized as 'sympathetic' activity [25] or as defined in this study, 'non-downward' heartbeat data, while an increase was categorized as parasympathetic activity [27] or as defined in this study, 'downward' heartbeat data. This novel classification system, specific to our research, aims to enhance the medical decision-making process

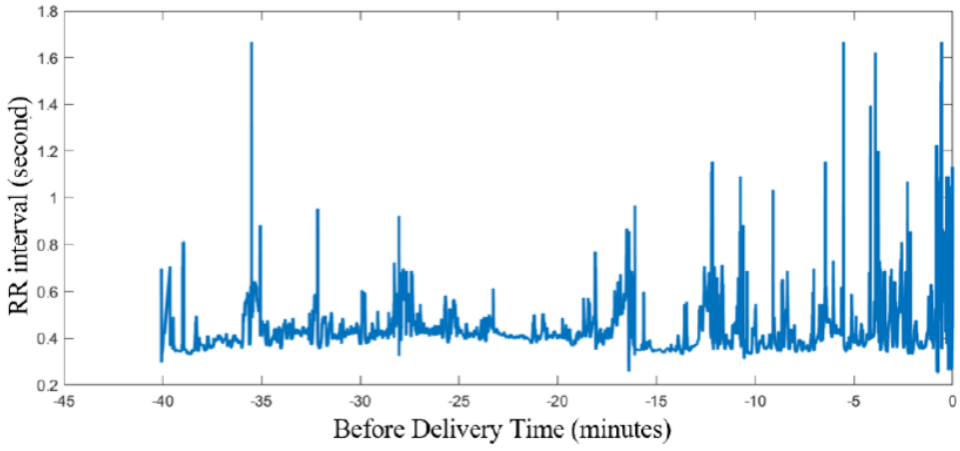

FIGURE 3. RR interval of fetal heart rate of a patient

by providing a more detailed understanding of fetal heart rate variability during delivery time.

$$RR\ interval\ (second) = 60/bpm\ data \tag{2}$$

2.4. **Markov entropy.** Markov entropy, derived from the principles of Markov processes, quantifies the uncertainty or predictability of transitions between discrete states over time. This is the combination of Markov process and Shannon entropy from information theory [28]. Table 1 presents a sample of the recorded data after applying the differencing method. The first column, Timestamp (ms), indicates the exact time each heart rate measurement was recorded, providing the temporal resolution necessary for heart rate variability analysis. In this study, we exclusively used data labeled with the FHR mode fetal electrocardiogram (FECG) to ensure the highest data quality and reliability for our analyses.

Table 1. Differencing bpm data for a patient

Timestamp (ms)	**FHR mode**	**Heart rate (bpm)**	**Differences (bpm)**
2596750	FECG	171	0
2597000	FECG	171	0
2597250	FECG	171	0
2597500	FECG	171	−2
2597750	FECG	169	4
2598000	FECG	173	0
2598250	FECG	173	0
2598500	FECG	173	−3
2598750	FECG	170	3
2599000	FECG	173	0
2599250	FECG	173	0

Moreover, the computed difference values between two consecutive bpm data points are presented in the "Differences (bpm)" column of Table 1. These values are calculated using Equation (3) and represent the change in heart rate between successive measurements. Positive values indicate an increase in heart rate, while negative values indicate a decrease. Analyzing these differences is crucial for assessing fetal heart rate variability (FHRV), as they reflect the dynamic changes in the fetal autonomic nervous system.

$$Differences = bpm_{t+1} - bpm_t, \quad t = 1, 2, \ldots, n \tag{3}$$

Subsequently, we defined classes based on the resulting differences of bpm data, as illustrated in Table 2 to analyze the transitions between these defined classes for the Markov process.

Table 2. Assigning classes according to the differences results of bpm data

Class	**Condition**
Decrease (D)	$Differences < 0$
Stable (S)	$Differences = 0$
Increase (I)	$Differences > 0$

To facilitate this analysis, we constructed a co-occurrence matrix in Table 3 that captures the frequency of transitions between each pair of defined classes. Let $c(i, j)$ be the number of transition pairs of defined classes for $i, j = 1, 2, 3$. This matrix serves as

TABLE 3. Co-occurrence matrix from transition of defined classes

Classes	**D**	**S**	**I**
D	$c(1,1)$	$c(1,2)$	$c(1,3)$
S	$c(2,1)$	$c(2,2)$	$c(2,3)$
I	$c(3,1)$	$c(3,2)$	$c(3,3)$

the basis for calculating transition probabilities, which are essential for determining the Markov entropy. By examining these transition probabilities, we can better understand the dynamic behavior of fetal heart rate variability during delivery.

Then, we obtained the 3×3 probability transition matrix (P) by calculating each index of the co-occurrence matrix using Equation (4). Subsequently, we adjusted the matrix (P) to be stationary. In this context, a stationary matrix refers to a transition matrix (P) that satisfies Equation (5) for the stationary distribution (π). This means that after transitions, the distribution π remains unchanged, indicating a long-term stable state in the Markov process.

$$a_{ij} = \frac{c_{ij}}{\sum_{j=1}^{3} c_{ij}} \text{ for } i = 1, 2, 3 \tag{4}$$

$$\pi P = \pi \tag{5}$$

Finally, we compute the Markov entropy for FHRV data during delivery time by using Equation (6).

$$\text{Markov entropy} = -\sum_{i,j=1}^{3} \pi_i a_{ij} \log_2 a_{ij} \tag{6}$$

2.5. **Multiscale entropy.** Multiscale entropy (MSE) is an extension of sample entropy that provides a more comprehensive analysis of time series data by evaluating the complexity of signals across multiple temporal scales. The calculation of MSE involves two main steps: (i) a coarse-graining process to obtain representations of the original time series at different time scales, and (ii) the sample entropy procedure to quantify the regularities of the coarse-grained time series [29].

While sample entropy (SampEn) measures the irregularity of a time series at a single scale, multiscale entropy expands this concept by assessing entropy over various scales [30]. Given with a one-dimensional discrete time series bpm data, $[x_1, \ldots, x_i, \ldots, x_n]$, we generate consecutive coarse-grained time series based on a scale factor k. The process begins by segmenting the original time series into non-overlapping windows of length k. Next, we calculate the average of the data points within each window by using Equation (7).

$$y_j^{(k)} = \frac{1}{k} \sum_{i=(j-1)k+1}^{jk} x_i, \quad 1 \le j \le \frac{N}{k} \tag{7}$$

where y_j represents the data point in the newly constructed time series, x_i represents the data point in the original time series. N is the length of the original time series. Furthermore, sample entropy (SampEn) was calculated as follows: Let $x = \{x_1, x_2, \ldots, x_N\}$ represent an FHRV bpm time series of length N. In this study, we used an embedded dimension (m) of 2 and set r as 0.2 times standard deviation (σ). We then define a sequence of vectors by constructing

$$x_i^m = [u(t_i), u(t_{i+1}), \ldots, u(t_{i+m-1})] \tag{8}$$

Then, calculate the Chebyshev distance by

$$d[x(i), x(j)] = \max\left(\left|u(t_{i+k-1}) - u(t_{j+k-1})\right|, 1 \leq k \leq m\right) \tag{9}$$

Then, for each i, $1 \leq i \leq N - m + 1$,

$$C_i^m(r) = \frac{\text{number of } j \text{ such that } d[x(i), x(j)] < r}{N - m + 1}, \quad i \neq j \tag{10}$$

Next, we will calculate

$$\Phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} \log C_i^m(r) \tag{11}$$

Finally, sample entropy (SampEn) is defined as

$$SampEn(m, r, N) = -\ln \frac{C^m(r)}{C^{m+1}(r)} \tag{12}$$

As described in the conventional MSE algorithm proposed by [31], MSE at a scale factor k is defined as the SampEn of the first coarse-grained time series, as shown in Equation (13).

$$MSE(x, k, m, r) = SampEn\left(y_1^{(k)}, m, r\right) \tag{13}$$

2.6. **Correlation.** After calculating the entropy values, we will determine the correlation between these entropy values and post-delivery blood gas parameters by employing the correlation Equation (14). This approach allows us to quantitatively assess the relationship between the complexity of fetal heart rate variability, as indicated by entropy, and the fetal health status, reflected by blood gas measures.

$$\hat{r} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{14}$$

where $\hat{r}$ is correlation coefficient, x_i and $\bar{x}$ represent the calculated Markov and multiscale entropy values and their averages, respectively. Additionally, y_i and $\bar{y}$ represent the indices of umbilical cord blood gas parameters and their corresponding averages.

3. **Experimental Results and Discussion.** In this section, we present the dataset, results, and discussion of our experimental analysis. The results highlight the effectiveness of our methods in distinguishing between parasympathetic and sympathetic activity, followed by an in-depth discussion of the findings and their implications for fetal monitoring.

3.1. **Dataset.** In this study, we used a dataset comprising 585 fetal heart rate bpm data of ECG recordings, gathered through internal monitoring methods. The data were preprocessed to remove noise and outliers, ensuring high-quality and reliable input for analysis. Additionally, the recordings were segmented into 10-minute intervals during delivery time to facilitate a detailed examination of heart rate variability across different periods.

3.2. **Results.** Markov entropy values from Figure 4 show a variable trend as delivery approaches, with some instances of decrease. This indicates fluctuations in heart rate variability, suggesting that as the body prepares for delivery, downward bpm FHRV, undergoes dynamic changes. This variability could reflect the body's efforts to maintain stability and readiness for the upcoming stress of delivery. Nevertheless, Markov entropy values for non-downward category are not always consistent; some values are similar to those of the downward heartbeat condition, reflecting an overlap in the autonomic responses.

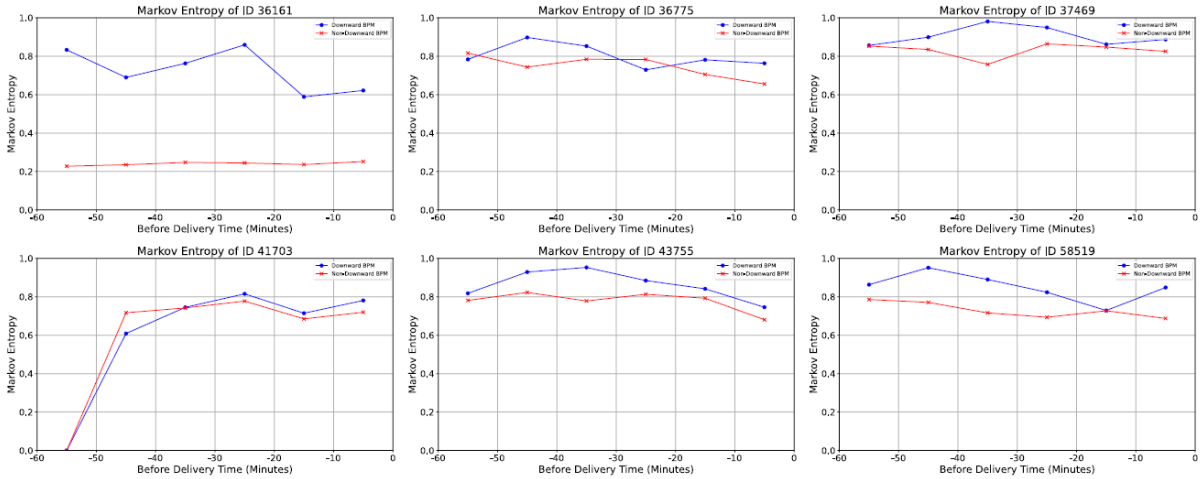

FIGURE 4. Markov entropy values of FHRV for some patients ID

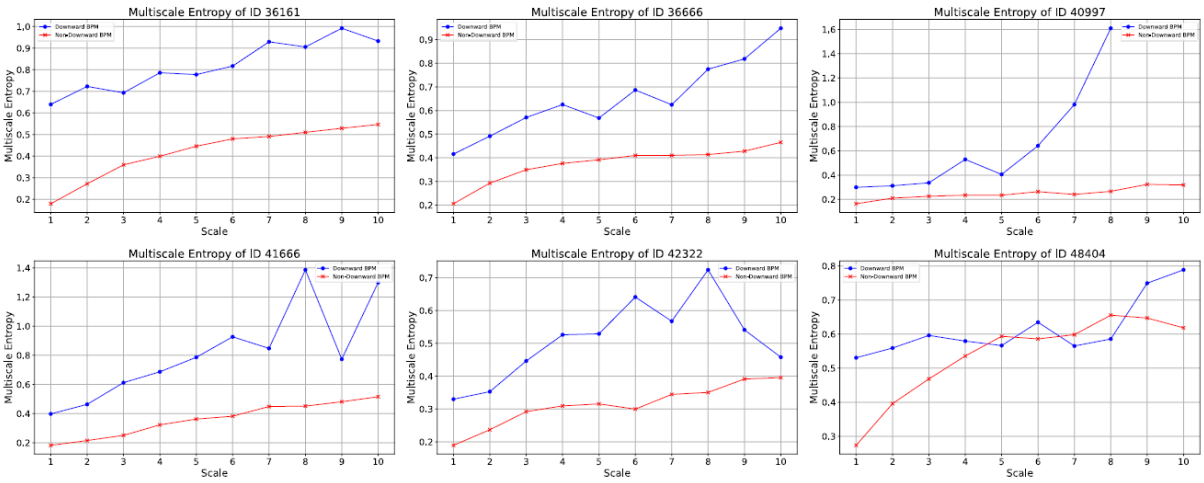

FIGURE 5. Multiscale entropy (MSE) values of FHRV for some patients ID

Further analysis shows that the downward heartbeat for parasympathetic condition often displays higher Markov entropy values initially, which then fluctuate and sometimes stabilize closer to the delivery time. The eventual stabilization of entropy values might reflect a state of readiness, where the body has optimized its autonomic functions to handle the stress of delivery.

The MSE values from Figure 5 for most datasets exhibit an exponential increase as the scale increases from 1 to 10. This pattern indicates that heart rate complexity grows with larger time scales, reflecting more intricate and varied autonomic responses as the observation period lengthens. The exponential rise in MSE suggests that the fetal heart rate dynamics become more complex and less predictable over longer time intervals, which is characteristic of a healthy and adaptive autonomic nervous system (ANS). However, in a few instances, the MSE values for the parasympathetic condition show a decrease from scale 8. This drop in MSE at the higher scales might indicate changes in fetal heart rate dynamics at these larger temporal scales. Such a pattern could reflect specific adjustments occurring closer to the delivery time. These findings provide a detailed understanding of how autonomic regulation evolves over different time scales during delivery time.

Figures 4 and 5 represent the Markov entropy and multiscale entropy values, respectively, for six selected patients from our dataset of 585 patients. These patients were not randomly selected; rather, they were deliberately chosen to represent the diversity of patterns observed in the FHRV analyses. While many patients exhibited similar entropy patterns, these six patients display distinct trends and features in their heart rate variability.

Moreover, we investigated Markov entropy and MSE and their correlations with umbilical cord blood gas parameters. Before proceeding with the analysis, it is important to note that for MSE we focused on scale 10, as it exhibited the most significant correlations with blood gas parameters among other scales. Table 4 summarizes the correlation coefficients for Markov entropy and MSE at scale 10.

TABLE 4. Correlation indices with entropies and blood gas parameters

Method	**pH**	**PCO_2**	**PO_2**	**HCO_3**	**BE**
Markov entropy (downward)	0.09	−0.12	0.06	−0.04	0.03
Markov entropy (non-downward)	0.07	−0.14	−0.01	−0.03	0.02
Multiscale entropy (downward)	0.11	−0.15	0.14	−0.09	0.16
Multiscale entropy (non-downward)	0.18	−0.13	0.11	−0.07	0.12

For both downward (parasympathetic) and non-downward (sympathetic) categories in Markov entropy, the correlations with blood gas parameters indicate meaningful associations. In the downward (parasympathetic) condition, there are positive correlations with pH and PO_2, indicating increased heart rate complexity with higher pH and oxygen levels. Negative correlations with PCO_2 and HCO_3 suggest decreased complexity with higher carbon dioxide and bicarbonate levels. Notably, the correlation coefficient between Markov entropy (non-downward) and PO_2 is -0.01, indicating an almost negligible negative linear relationship. This suggests no significant association between non-downward heartbeat entropy and the partial pressure of oxygen; the negative value reflects a lack of correlation rather than a meaningful inverse relationship. On the other hand, in non-downward (sympathetic) conditions, similar trends are observed with positive correlations for pH and negative correlations for PCO_2.

Multiscale entropy (MSE) shows notably significant correlations with blood gas parameters. In both categories, at scale 10, there are positive correlations with pH, PO_2, and BE, indicating increased heart rate complexity with higher pH, PO_2, and BE. Negative correlations with PCO_2 and HCO_3 suggest decreased complexity with higher carbon dioxide and bicarbonate levels. These significant correlations highlight how changes in blood gas parameters may reflect adaptations in autonomic nervous system function, influencing heart rate dynamics and the overall physiological readiness of the fetal.

This kind of analysis result will be helpful for medical professions in interpreting FHRV patterns. Understanding the correlations between heart rate entropy measures and blood gas parameters can enhance the interpretation of fetal monitoring. By integrating these insights into digital twin technology, medical professionals can gain more precise and timely assessments of fetal health, improving diagnostic capabilities and potentially leading to better outcomes in obstetric care.

4. **Conclusion.** This study leveraged Markov entropy and MSE to analyze FHRV during delivery time, showing dynamic changes in ANS activity. Incorporating Markov entropy and MSE analysis into digital twin technology enhances our understanding of FHRV during delivery. This integration of digital health innovations with traditional fetal monitoring significantly enhances prenatal care, offering valuable insights for healthcare

professionals. It promises developments in fetal health predictions and interventions, while paving the way for future enhancements, such as integrating advanced image processing technologies to further transform digital healthcare systems.

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