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Real-time data acquisition and analysis for predictive modelling of mental healthcare in Indian women with menstrual disorders: unveiling insights and implications from extensive surveys

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ABSTRACT

The consistency and duration of the menstrual cycle exhibit significant associations with specific psychiatric conditions throughout an individual's lifespan. The proposed methodology surveys the relationship between psychiatric disorders and the length or regularity of the menstrual cycle and analyzes the difficulties undergone by the women. A comprehensive dataset is generated and a mathematical model using an exploratory data analytics approach is developed, in order to establish a correlation between these variables. It utilizes a cyclic methodology, leveraging shared menstrual data and a predictive model derived from vehicles to enhance network learning. A decentralized secure learning procedure is implemented to ensure data privacy and security. The transfer learning techniques helps to enhance the ability to learn from diverse data distributions in IoMT (Internet of Medical Things) networks, improve the robustness of the learning process. This approach presents a practical and effective solution for IoMT network learning, allowing each participant to contribute their individual features to collectively extract valuable insights from the data. The decentralization facilitates end-users in accessing their personal medical records while ensuring privacy, irrespective of their location and time. This system also achieves a minimal delay sensitivity of 3.2%, by providing timely access to the required information.

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KEYWORDS
Menstrual cycle; mental disorders; IoMT; blockchain; Deep Learning

1. Introduction

The menstrual cycle is a complex interaction involving the brain, female hormones (estrogen and progesterone) [1], uterus, and ovaries. Any disruption in this interaction can result in an irregular menstrual cycle, affecting approximately 14% to 25% [2] of women worldwide. Around 1.8 billion people menstrual every month across the world (26% of global population) [3]. Most of the women experience their first cycle between the age of 10–16 and lasts up to an average of 50 years. It is experienced by women for about 50% of their average life span. Irregularities and occasional variations in the menstrual cycle are common and differ from woman to woman. Factors such as stress, poor eating habits, hormonal changes, and starting or stopping birth control pills can contribute to these irregularities. While a single missed, delayed, or early period may not be a significant concern, consistent variations should be addressed medically. Consistent variations in the menstrual cycle can have a profound psychological impact on women. This can occur due to pregnancy, hormonal imbalances, Polycystic Ovary Syndrome (PCOS)[4,5,6] or excessive stress [7]. These bodily changes lead to significant mental state alterations, affecting women's daily lives. This not only affects women of reproductive age but also women of all ages. Imbalanced and delayed menstrual cycles can result in increased production of male hormones.

This work focuses on conducting a survey to understand menstrual disorders or irregularities and their impact on women's psychology or mental health [8,9]. The aim is to record the subtle changes that occur in a woman's body throughout the menstrual cycle and explore their correlation, particularly among female students, including those in schools and colleges. IoT-based sensors are utilized to monitor the biological changes in women, and the collected data is processed to determine their mental status.

The remaining sections of the paper are organized as follows. Section 2 presents a comprehensive literature survey, providing an overview of existing research and knowledge relevant to the topic. In Section 3, the methodology is outlined that focuses on the fabrication of sensors for IoMT for data engineering with hyper parameter tuning, explaining the techniques to optimize model performance by novel data-driven modelling and validating using blockchain-driven transfer learning. Section 4 details the implementation and

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the workflow followed. Section 5 presents the results obtained from the implementation and provides an analysis of these results. Finally, the paper concludes with concluding remarks, and suggesting potential future research directions.

2. Literature survey

Kyoko Shimamoto and colleagues [10] conducted a comprehensive investigation on menstrual disorders and their impact on the health-related quality of life (HRQoL) of employed women in Japan. The study employed an index-based approach using a self-reporting questionnaire to establish the correlation between menstrual symptoms and HRQoL. The survey covered a range of demographic variables, including factors such as individuals' age, employment situation, pregnancy and childbirth history, utilization of reproductive healthcare services, associated costs, and menstrual symptoms in terms of timing, duration, characteristics, and their impact on professional work and overall daily activities. The questionnaire design was informed by clinical consultations with patients within the Japanese healthcare system, and the final set of questions was evaluated and validated by the Japan Society of Obstetrics and Gynecology (JSOG). The statistical analysis of health-related aspects was conducted using the EuroQoL 5-dimension 3-level (EQ-5D-3L) instrument.

In the study conducted by Priya Maurya et al. [11], the objective was to explore the relationship between self-reported menstrual irregularities and depressive symptoms in adolescent girls from Uttar Pradesh and Bihar, India. The research utilized data from the UDAYA 2016 survey, which involved a sample size of 12,707 girls aged 10–19 years. Various statistical analyses, including bivariate analysis and multivariable logistic regression models, were employed to examine the association between self-reported menstrual irregularities, depressive symptoms, and other pertinent variables. The findings revealed that 11.22% of the adolescent girls reported experiencing menstrual irregularities, and 11.4% exhibited mild depressive symptoms. The results indicated a positive relationship between depressive symptoms and menstrual irregularities, particularly in girls with moderate to severe symptoms. Furthermore, physical inactivity and the use of inadequate menstrual hygiene practices were associated with a higher likelihood of menstrual irregularities. The study emphasized the need for greater attention to the mental health issues of females with irregular menstrual cycles.

In a study conducted by Elena Toffol et al. [12], the research aimed to investigate the impact of age at menarche and current menstrual irregularities on psychological well-being and psychopathology. The study involved a sample of 4,391 women aged 30 years and older. The relationship between age at menarche and scores on psychological assessment tools such as the Beck Depression Inventory (BDI-21) and General Health Questionnaire-12 (GHQ-12), as well as diagnoses using the Composite International Diagnostic Interview (M-CIDI), were examined. The findings revealed that an earlier age at menarche was associated with an increased risk of recent mental disorders, major depressive episodes, major depressive disorder, and anxiety disorder. Consequently, it is crucial to consider age at menarche and menstrual irregularities in psychiatric evaluations.

In a distinct survey conducted by Mi Yu et al. [13] among adolescents in Korea, it was observed that 32.3% of girls experienced irregular menstrual cycles, while 17.7% had abnormally short or long menstrual periods. The study aimed to assess the participants' mental health by examining psychological stress levels, depressive moods, suicidal thoughts, suicide attempts, and engagement in psychological counselling. Additionally, physical measurements such as body weight, height, BMI, and waist circumference were recorded, and blood samples were analyzed to determine hemoglobin content. The research findings unveiled significant associations between various factors and menstrual irregularities, highlighting the importance of addressing mental health concerns related to menstruation. By addressing these concerns, we have the potential to enhance the overall well-being of adolescent females and potentially reduce the risk of developing related health conditions in the future.

Anna Maijala et al. [14] concluded that monitoring nocturnal skin temperature holds promise for tracking the menstrual cycle in real-life conditions. Wearable technology in the form of Oura rings was utilized to measure skin temperature, while oral temperature measurements were taken upon waking up. By combining these temperature readings, the menstrual cycle was monitored and predictions were made regarding menstruation and ovulation. The study involved 22 volunteer women who wore the Oura rings, underwent urine tests to detect ovulation, and maintained menstrual diaries for an average duration of 114.7 days. The sensitivity of detecting menstruation ranged from 71.9% to 86.5% within a window length of ± 2 to ± 4 days, while the sensitivity of detecting ovulation was 83.3% within a fertile window from -3 to $+2$ days around verified ovulation.

Xinyu Wang et al. [15] identified the potential of menstrual cycle regularity as an indicator of women's physiological health. The study focused on analyzing the characteristics of the menstrual cycle in healthy college women using pulse measurements. Around 120 female pulses were tracked over a period of approximately 3 months, simulating Chinese medicine and personalized care by a family-based physician. Based on these measurements, a predictive model

Table 1. Prior literature works in the field of mental healthcare.

Ref	Methodology	Problems & Drawbacks
[20]	Deep learning methodologies for mental health diagnosis	Due to increased data dimensionality, it consumes more time to process the data.
[21]	Text mining approach for analyzing the effects of mental health	Limited analysis, and ineffective processing.
[22]	Machine learning model	Lower prediction rate and performance outcomes.
[23]	Random survival forest classifier	Complexity in prediction and lack of efficacy.
[24]	Optimized adaptive CNN model	High error rate and low prediction accuracy.
[25]	Embedded LSTM model	Consumes increased time for disorder prediction and complex training & testing.

was developed to estimate the subsequent physiological period of women. The model achieved an accuracy of 66.7% and 81.8% using two different methods, respectively.

Roberts, et al. [16] conducted a mixed method study for analyzing mental health among women in low income countries. In this study, both qualitative and quantitative analyses have been performed for analyzing the health condition according to the patients' demographic, health and reproductive history. Adjorlolo, et al. [17] aimed to analyze and aid pregnant mothers in Ghana by providing mental health services. As a result of women's more prone to psychological issues throughout pregnancy, accessing and receiving treatment for mental disorders is critical for preserving women who are expecting their emotional and mental health. The present investigation looks on the incidence and correlations of pregnant women and health professionals requesting and receiving mental health services while pregnant. Dar, et al. [18] investigated about the menstrual hygiene related issues in women of their adolescence stage. Uchibori, et al. [19] conducted a cross sectional study to investigate the major factors associated to menstrual disorders. Here, the binomial logistic regression models have been adopted for analyzing the data in order to predict the disorder.

Previous literature has explored numerous approaches for disorder analysis and prediction in smart healthcare. Based on past research (Table 1), it has been concluded that standard approaches are employed to forecast mental disorders. However, it remains difficult to acquire real-time data from the healthcare system for disorder prediction. Other challenges associated with this field include ineffective analysis, a long processing time, and a high processing burden. As a result, the proposed effort intends to analyze menstruation abnormalities and their impact on adolescent women's mental health using a three-phase strategy and a real-time dataset.

3. Methodology

The menstrual cycle, which spans from the onset of one menstrual period to the onset of the next, can vary in length among women. On average, the duration of the menstrual cycle falls within the range of 24–38 days. This variation in cycle length is also observed throughout a woman's reproductive lifespan, from menarche to menopause. On average, the menstrual cycle accounts for approximately one-quarter of a woman's lifetime. During this time, women undergo significant life changes, including environmental factors (such as education, work, and changes in living arrangements), and physical changes (such as puberty, pregnancy, and other health-related modifications), which in turn can lead to psychological changes. These changes are primarily driven by hormonal fluctuations, which influence a woman's mood and psychology. To analyze menstrual disorders and their impact on the mental healthcare of adolescent women, a three-phase approach is adopted. This approach aims to predict, alert, and initiate cautious actions under real-world conditions. The process is viewed as a cyclic process that incorporates a block chain-based dataset-sharing model with incentivization to share big data and data analytics within the Internet of Medical Things (IoMT) network, ultimately improving the accuracy of prediction.

3.1. Proposed system model

The proposed model focuses on the early prediction of menstrual disorders in adolescent girls, with a specific emphasis on mental healthcare for young adult girls in menarche (age $<$ 20) and women experiencing menopause (age $>$ 45). The menstrual cycle serves as a key indicator of overall health for women. The methodology involves deploying an IoMT network that utilizes smart watches and smart phones to acquire various menstrual parameters, including physiological, psychological, metabolic, and biochemical indicators. By collecting near real-time menstrual data, this extensive analysis sheds light on the pathophysiology of menstrual abnormalities in the general population, which is not well understood. The approach utilizes a transfer learning technique for screening menstrual disorder patterns without relying on invasive diagnostic procedures. Furthermore, a decentralized blockchain platform is employed to store and trace historical records of genetic inheritance. Figure 1 provides an overview of the proposed work, illustrating the monitoring of women and the collection of various parameters to build a model that predicts menstrual disorders and associated mental healthcare. The work is divided into three phases for identification and analysis. The section 3.1 discusses about fabrication of sensors to device a IoMT component that can be used in data acquisition process. The section 3.2 speaks about tuning of hyperparameter of the system so that it can be used in transfer learning. The section 3.3 speaks on how transfer learning technique has been used in analyzing the data.

3.2. Fabrication of sensors to configure IoMT for data engineering

- Acquiring and measuring the real-time data necessities going for fabricating the sensors for sleep efficiency and sweat categorization as per the requisites because the sensors readily available in the market does not fit our handy decentralized application (DApp).
- The smart watch is designed based on the parameters to be sensed.
- The smart phone is designed to be the edge node for lightweight communication to arrive at the correlated parameters.

3.3. Hyperparameter / model tuning

- Profiling the menstrual data and arriving at a correlation equation or matrix for mental healthcare and recording on the dataset.
- Transfer learning provides an opportunity to train a model on one specific data domain and then apply that knowledge to make predictions in different areas of future data. It allows the model to leverage its learned features and patterns from the source domain to enhance its performance and adaptability in the target domain.
- However, predictive and preventive analysis is more effective and efficient when the process involves a comprehensive and diverse dataset. A rich set of data provides a broader range of information and patterns, enabling the analysis to uncover more accurate insights and make better predictions. The inclusion of diverse data sources enhances the model's ability to identify complex relationships, detect anomalies, and anticipate future trends or events, ultimately improving the effectiveness of predictive and preventive analysis.

3.4. Validating novel data-driven modelling with blockchain-driven transfer learning

To minimize the time and expenses involved in training models that predict menstrual disorders and related mental healthcare, we employ blockchain-powered transfer learning and validate it on new data-driven modelling.

- IoMT Intelligence: Real-time estimation of fertility state by applying the predictive model to the onboard smart device that consequently adopts the preventive measures with over-the-air updates.
- Configuring an IoMT network environment that boosts node cooperation with incentivization based on a block chain-powered dataset/model sharing model. A pegged side chain in planned to be implemented on the Ethereum base to avoid overloading on the core chain. The side chain updates the global predictive model to the core chain.
- Incentivization in terms of Ethers is introduced based on the model/data shared among the peers.

The provided figure offers visual representations that clearly depict the three phases of work being conducted. These visuals effectively demonstrate the use of blockchain-based transfer learning to validate new data-driven models, which aim to minimize training time and costs involved in predicting menstrual disorders and related mental healthcare. The figures serve as explanatory tools, highlighting the implementation and benefits of this approach.

Algorithm: LaDApp Algorithm

Input:

D: Set of different physical readings collected from Smart Health Care System

Output:

- App: Interactive application integrated with a predictive model enhanced through blockchain-based transfer learning, providing users with personalized health insights and recommendations.

Procedure:

(1) D←CollectPhysicalReadings() // Collect various physical readings in real-time
(2) M←ConstructPredictiveModel(D) // Construct a predictive model using the collected data
(3) M′←BlockchainTransferLearning(M) // Implement blockchain-based transfer learning to enhance the model
(4) App←CreateApplication(M′) // Create an application for users to interact with the system using the updated model

3.4.1. Fabrication of sensors to configure IoMT for data engineering

Utilizing a combination of multi-sensor wearable devices and smart phones, a highly sensitive network can be established to capture various physiological features related to women's health research. The smart watch is employed to monitor sleep patterns and associated physiological changes, while also tracking self-reported daily functioning and symptoms throughout both regular, healthy menstrual cycles and irregular periods. This comprehensive approach enables the collection of valuable data for studying women's health and understanding the impact of menstrual cycle variations on various aspects of well-being.

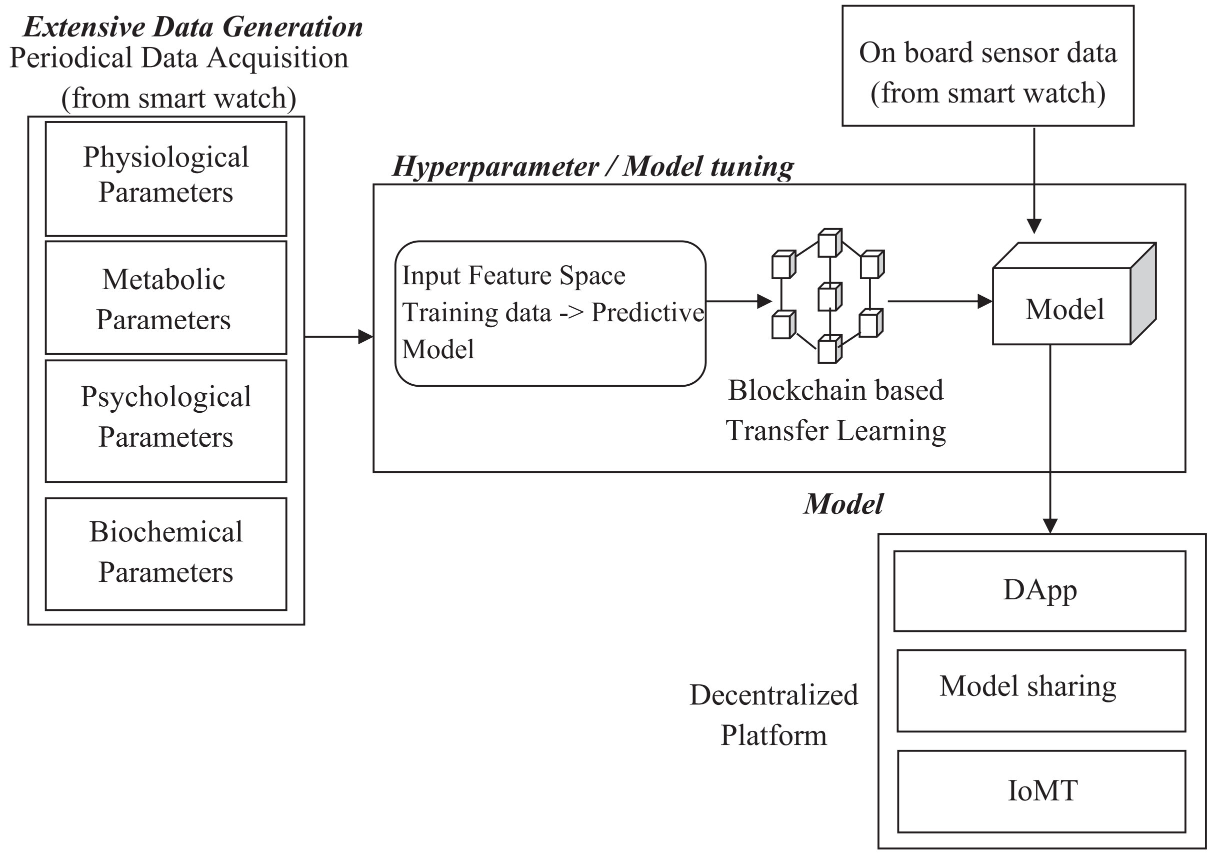

Figure 1. Overview of the proposed work.

Figure 2. Extensive dataset generation by real-time monitoring with near real-time experience.

Figure 2 illustrates the inclusion of various sensors within a wearable device and the corresponding parameters they capture. Detailed information regarding the acquired parameters and the embedded sensors can be found in Tables 2–4. In order to effectively monitor the physical state of the subject or sample being studied, specific sensors are employed to capture relevant physiological parameters [26]. To account for body

Table 2. Physiological parameters.

	Parameters	Embedded devices
1.	Basal body temperature	Basal body thermometer
2.	Sleep sensing	Biochemical sensor: Sleep (fabricated)
3.	Sweat monitoring	Biochemical sensor: Sweat (fabricated)
4.	Whole body thermo flow	Heat flux sensor
5.	• Sleep posture • Physical activity	3-axis accelerometer sensors
6.	• Stress sensing from saliva • Galvanic skin response	Electrodermal activity sensor
7.	To sense blood oxygen level	Pulse oximeter

Table 3. Metabolic parameters.

	Parameters	Embedded devices
1.	Stress level (Threshold fixation) Computation at edge-node (smart phone)	Electrodermal sensor actuates stress level monitor
2.	• Total energy expenditure • Active energy expenditure	Calorie burnt calculation from 3-axis accelerometer
3.	Sleep efficiency	3-axis accelerometer

Table 4. Psychological parameters.

	Parameters	Embedded devices
1.	Eating style (frequency of swallowing)	3-axis accelerometer (Pre-requisite: Subject should wear the watch in her dominant hand)
2.	Sleeping pattern	Pattern matched embedded in the edge device
3.	Biphasic body temperature	Differential computation from readings of basal body thermometer and heat flux

Table 5. Biochemical parameters.

	Parameters	Embedded devices
1.	Fine lines in the skin	Skin tensiometric sensor
2.	Prolactin mensuration	Ionophore-based optical sensor

temperature, the wearable device incorporates a basal body thermometer for measuring basal body temperature, as well as a heat flux sensor to monitor overall body heat flow. For assessing blood oxygen levels, a pulse oximeter sensor is integrated. Additionally, specialized biochemical sensors are developed to track sleep patterns and sweating of the subject. To monitor sleep posture and daily physical activity, a 3-axis accelerometer sensor is utilized. Furthermore, the stress experienced by the subject and their galvanic skin response are measured using an electrodermal activity sensor.

The active human is characterized by their healthy metabolic activities like workout, amount of calories burnt, steps taken, etc. The *electrodermal sensor* mentioned earlier is used in analyzing the stress level with a fixed threshold and the computation with respect to threshold is done in the smart phone. The previously mentioned *3-axis accelerometer sensor* is used in computing the total energy expenditure and the active energy expenditure. It is also used in monitoring the sleep efficiency.

The earlier measured parameter directly affects a subject's physical and metabolic activities but also indirectly affects her psychology (mental state). The measurement of the following sensors provides fruitful truth about how the menstrual stress affects the subject's mind. The frequency in swallowing of food is measured by the *3-axis accelerometer sensor*. The subject must wear the sensor embedded device (smart watch) in her dominant hand while eating. The sleeping pattern is matched with the patterns in the edge device (smart phone). The biphasic body temperature is computed by the difference between the readings of the *basal body thermometer* and the *heat flux sensor*.

To monitor the biochemical parameters (Table 5), *skin tensiometric sensor* and *ionophore-based optical sensor* are used. The skin tensiometric sensor is used in analyzing the fine lines in the skin. The ionophore-based optical sensor is used in monitoring the prolactin mensuration.

3.5. Hyperparameter / model tuning

The designed transfer learning model shown in Figure 3 is specifically tailored for the identification of menstrual disorders in women. Data acquisition is performed using the aforementioned sensors embedded in smart watches, and the collected data is then utilized in the transfer learning process. The block chain-based model sharing model is employed for predictive analysis, enabling the effective sharing and utilization of models for accurate predictions of menstrual disorders. This approach leverages the power of transfer learning and blockchain technology to improve the accuracy and efficiency of identifying and predicting menstrual disorders in women.

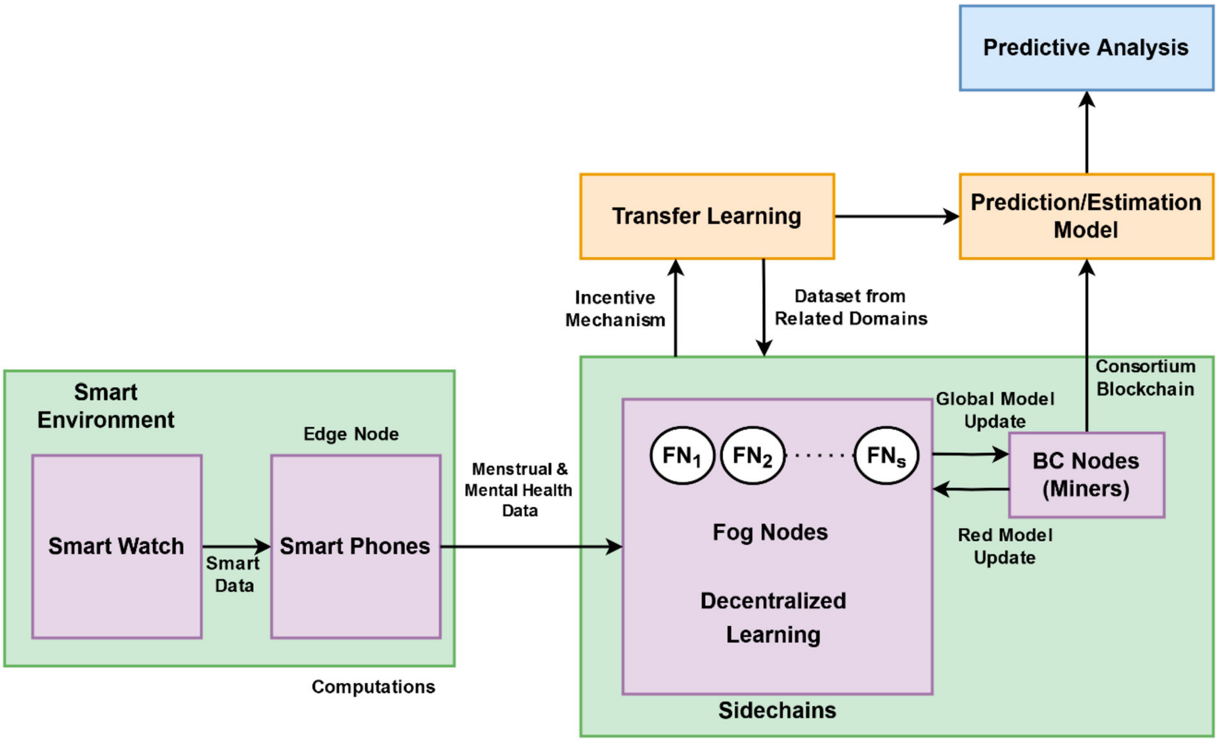

Figure 3. Mathematical modelling of correlation between menstrual disorder and mental health (Blockchain based Transfer learning).

3.5.1. *Focusing and validating on novel data-driven modelling*

In a collaborative Internet of Medical Things (IoMT) environment, a decentralized block chain-based smart data/model sharing model is proposed. This model eliminates the need for extensive datasets to achieve more accurate predictive models. For women with similar demographics and medical conditions, pre-trained models that are readily available can be shared, bypassing the training phase and reducing associated costs. This system is utilized to predict menstrual disorders using data collected from onboard multi-sensor devices. Figure 4 provides a visual representation of the learning process in the transfer learning model, highlighting the interaction between the entities involved. The ResNet 50 CNN (Convolutional Neural Network) is employed in the transfer learning process. ResNet 50 is a specific type of CNN consisting of 48 convolutional layers, one max pooling layer, and one average pooling layer. It is chosen for its deep architecture and the ability to address the vanishing gradient problem through the use of short connections. By skipping certain layers, ResNet 50 transforms a regular network into a residual network, enhancing its learning capabilities in the context of predicting menstrual disorders.

4. Implementation

4.1. *Hardware and software requirements*

Hardware components like basal body thermometer, biochemical sensor, heat flux sensor, 3-axis accelerometer sensor, electrodermal activity sensor, pulse oximeter, skin tensiometric sensor, ionophore-based optical sensor have been embedded into the smart device for monitoring the physical condition of the subjects in real time (daily day life). The software requirements are Python environment for implementation of the transfer learning and the block chain for understanding the relation among the physical and psychological condition of the subjects under study.

4.2. *Real-time data acquisition*

The physical condition of the subjects is monitored and the data acquisition is done by using the questionnaire. The drafted questionnaire is distributed among the girls and the statistics on the psychological factors are analyzed. Table 6 shows the questions included in the questionnaire. The questions are categorized as the general and the psychological, metabolic, and physiological parameter interrogation. The general includes the questions related to the subject's age,

4.3. *Exploring insights and implications from comprehensive surveys*

The data collection process involved administering a survey questionnaire to the subjects to gather their responses. The responses are collected from more than 30 female candidates belong different age groups with different professions such as students, working women

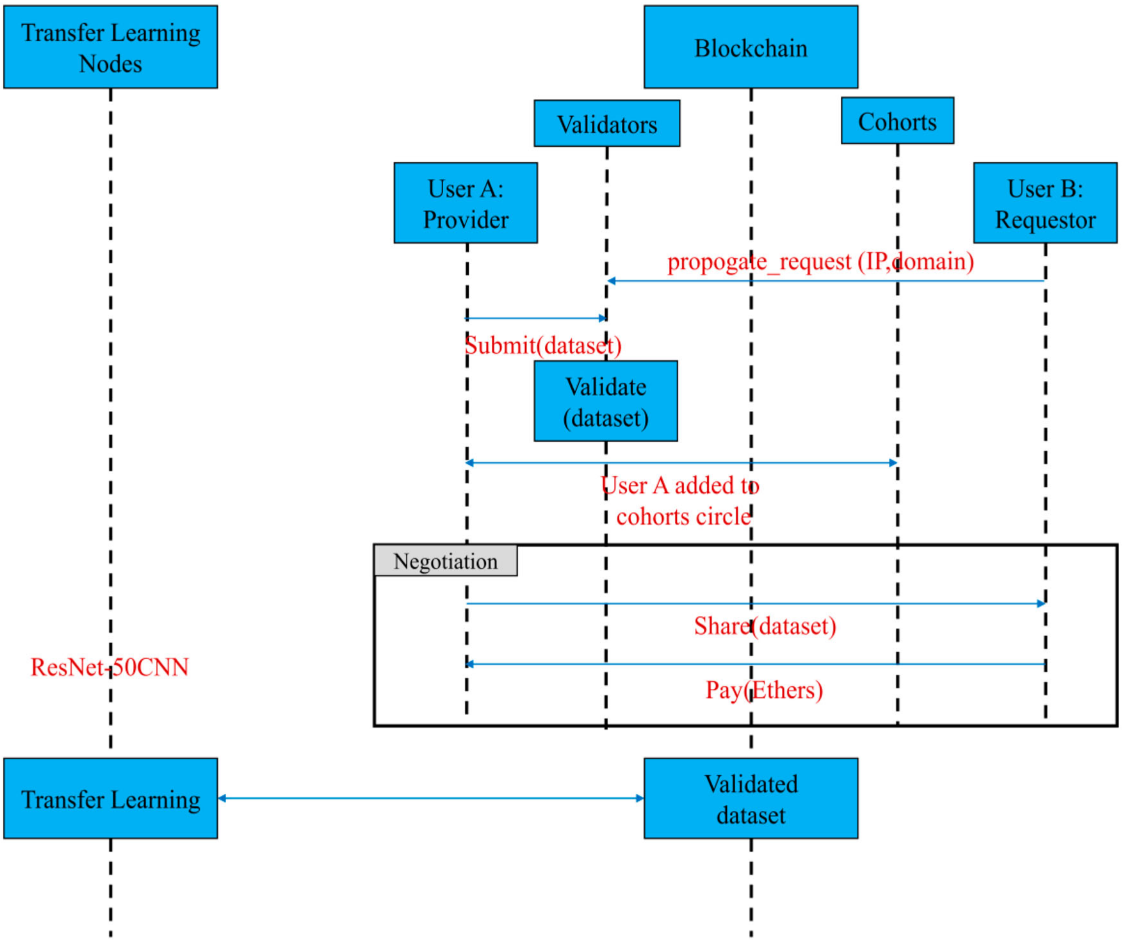

Figure 4. Focusing and validating on novel data-driven modelling with transfer learning.

etc.. These responses were used to analyze the correlations and relationships between the various parameters of interest. The baseline parameter considered for comparison was the current age of each subject. By comparing this parameter with others, such as symptoms and psychological changes experienced during the menstrual cycle, the study aimed to examine the associations between them. Figure 5 presents the percentage of subjects included in the data collection and analysis. It provides an overview of the sample size used in the study. Approximately 73% of the analyzed samples belong to the age group of 20–30 years, which is considered the prime age range for women characterized by increased physical activities and changes in work and living environments. The remaining 27% of the samples are divided into four categories: under 20 years, 30–40 years, 40–50 years, and above 50 years. It is worth noting that subjects under the less than 20 years category may face additional challenges due to their young age. Figure 6 provides insights into the marital status of the subjects. Among the analyzed samples, approximately 67% are unmarried women who are either studying or working.

When the period cycle duration is analyzed, we grouped the subjects into 5 age groups below 20 years, 20 - 30 years, 30 - 40 years, 40 - 50 years, and above 50

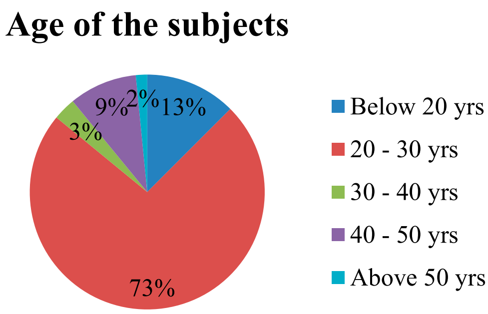

Figure 5. Age of the subjects under study.

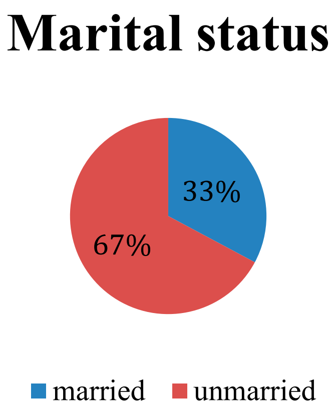

Figure 6. Marital status of the subjects under study.

Table 6. Questionnaire to inquire about the psychological state of the girls/women during the menstrual timings.

Q.no	Question	Option1	Option 2	Option 3	Option 4
GENERAL: Individual person's lifestyle questions					
1.	Your current age				
2.	Your Marital status	Married	UnMarried		
3.	What is your period cycle?	24 - 28 days	28 - 34 days	34 - 40 days	> 40 days
4.	How old were you when you started menstruating				
5.	What type of hygiene do you prefer during the menstrual timing?	Disposable sanitary pads	Reusable cloth pads	Menstrual cups	Others
6.	What are the abnormalities you face during your periods?	Unbearable cramps	Bearable cramps	Body pain	Smooth periods
Physiological, Metabolic and psychological parameters					
7.	Sleeping pattern during periods timing	Insomnia	Frequent awakening	Sleep has not been sufficiently refreshing	Normal
8.	Do you feel day time disturbances associated with menstruation?	Fatigue	Sleepiness	Decreased alertness	Anxiety
9.	Do you feel any slight rise in the body temperature in this period?	Yes		No	
10.	Do you feel excessive sweating before menstruation, especially at night?	Yes		No	
11.	Mention your comfortable sleeping position during menstrual cramps.	Sleeping in the fetal position	Sleeping on the back	Sleeping on the side	
12.	Can you involve in your routine physical activity during your periods?	Yes		No	
13.	What are the oral changes you would encounter during your periods?	Bleeding gums	Red swollen gums	Increased saliva secretion	Normal
14.	What are the negative emotions that affect your mood in periods?	Anger	Irritability	Mood swings	Normal
15.	What is your appetite during Menstrual times?	Hungry	Low appetite	Cravings	Normal
16.	Are you so stressed that your intake painkillers or muscle relaxant to get rid of menstrual cramps?	Yes		No	
17.	Do you feel notable rise in temperature in the pelvic region during the menstrual times?	Yes		No	
18.	Have irregular periods? If so, do you know the reason?	Stress	Obesity	Thyroid	Don't know the reason

years. In these groups above 50 age group has a minimum number of subjects as evidentially seen in Figure 5. Figure 7 shows the survey or count of the subjects with different menstrual cycles. The subjects under the age group of 20 - 30 years experience different cycle duration. Though the majority of the samples have a normal cycle, the minority of samples have irregular or abnormal menstrual cycles. But this minority of people in the 20 - 30 years group is the majority of the subjects with irregular menstrual cycles and experience or suffer from physical and psychological problems. On looking into the abnormalities faced by the subject, Figure 8 shows that the majority of the subjects experience body pain with normal menstrual length. Whereas the majority of subjects also experience unbearable cramps on those days which makes it difficult for them to undergo their daily routine tasks.

These discomforts or abnormalities also lead to disturbances in the sleeping pattern. Some sleep in the normal position (Sleeping on their back), but the rest sleeps in a position like on their side or in a fetal position the full night. This further leads to disturbances in sleeping duration which affects their daily routine life. In the survey undertaken, the majority of the subjects

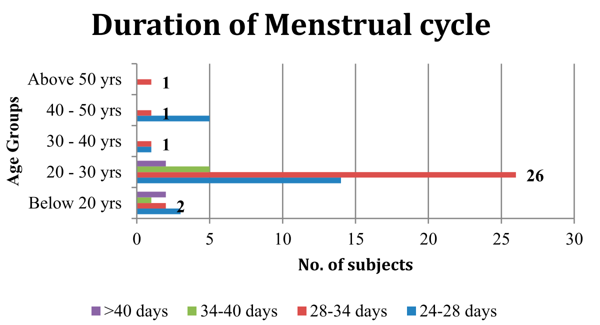

Figure 7. Menstrual cycle duration for the subjects under study.

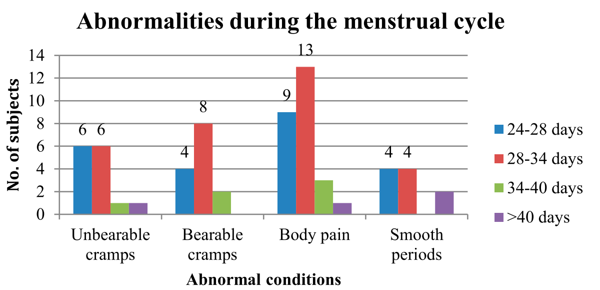

Figure 8. Physical abnormalities faced by the subjects during the week of menstruation.

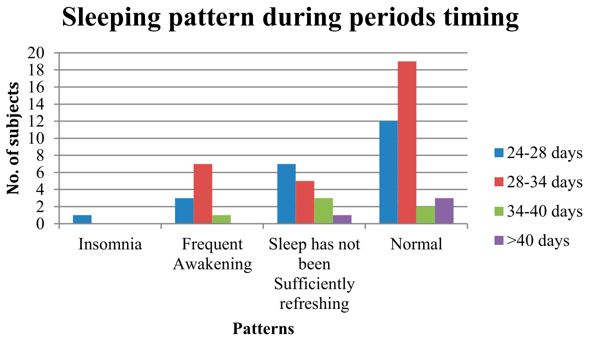

Figure 9. Sleeping pattern or the difficulties in sleeping for the subjects during the week of menstruation.

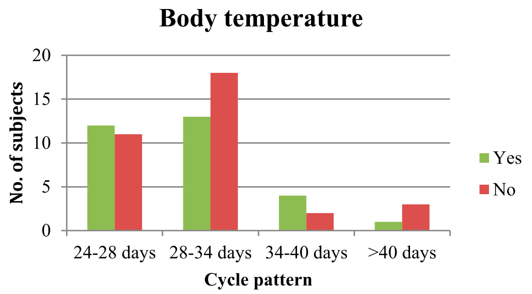

Figure 10. Body temperature status of the subjects during the menstruation week.

had normal sleeping patterns, whereas the rest has difficulty even sleeping. Either they have disturbed sleep due to Insomnia or frequent awakening due to cramps or insufficient sleep i.e. sleep is not enough to stay refreshing the next day. Figure 9 shows the disturbance in the sleep of the samples.

Among the subjects included in the study, the majority exhibited normal body temperature without any significant changes. However, a fraction of the samples reported a noticeable increase in body temperature. Similarly, regarding the pelvic region temperature, some women noted an elevation in temperature in the lower part of the body during their menstrual period. These findings are depicted in Figures 10 and 11, which provide specific details about body temperature and the pelvic region. The menstrual cycle also had an impact on the eating patterns of the subjects. Most participants experienced a decreased appetite during their menstrual period, while others maintained normal eating habits. Some individuals reported cravings for specific foods, while a few felt hungry throughout the menstrual cycle. These changes in eating habits also had implications for the subjects' daily physical activity, particularly for those with irregular menstrual cycles. Figures 12 and 13 present further information on the subjects' eating habits and their levels of daily physical activity.

4.4. Technological stack

The experimental configuration involved establishing connections between the various components within a

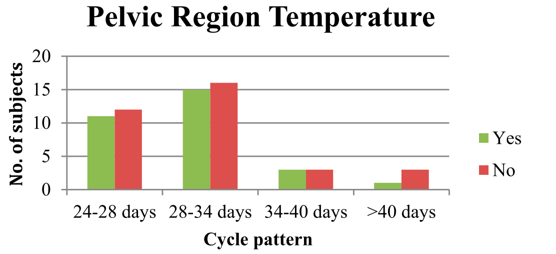

Figure 11. Pelvic region or lower abdomen temperature during the menstruation week.

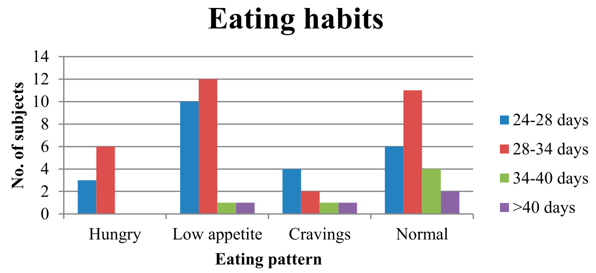

Figure 12. Eating habits or the pattern of eating by the subjects during the menstruation week.

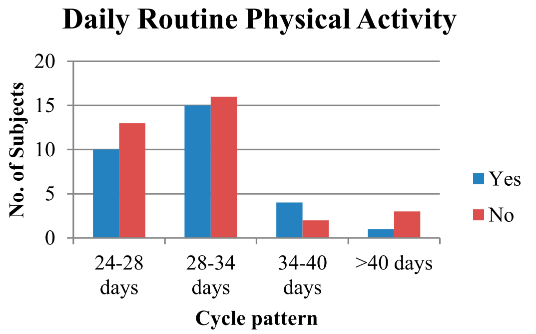

Figure 13. Status of daily routine physical activities of the subjects during the week of the menstruation.

local area network (LAN). To replicate the clients, we set up the Multichain network on a Windows server machine and created virtual instances [27]. Performance tests were conducted using Apache JMeter, a widely utilized testing tool, running on a separate Windows machine. This setup facilitated the measurement and recording of test results. Several experiments were carried out to assess the system's performance, with particular emphasis on two essential metrics: average response time and throughput. Average response time refers to the duration taken by the server to respond to each request, which holds significant importance in real-world applications as delays can have a considerable impact on user experience and may even result in request timeouts. Throughput measures the maximum rate at which the system can handle incoming requests, providing insights into its scalability and overall effectiveness. Additionally, we extended our analysis to include the blockchain environment with backend cloud storage. It should be noted that Amazon Cloud ensures internal communication between servers remains within the internal network, facilitating data synchronization within the blockchain cluster. The experiments conducted in this study involved the university network and the Amazon EC2 network to support comprehensive analysis and evaluation [28].

5. Results and discussions

The experimental test bed was deployed, and comprehensive experiments were conducted considering various conditions and variables. The first variable focused on the number of clients accessing the decentralized blockchain network, ranging from 1 to 480 clients. This extensive range enabled a thorough analysis of the system's performance under varying user loads. The second variable involved configuring the system with either 1 server or 3 servers, aiming to evaluate the impact of horizontal scaling on overall performance. This investigation provided insights into how the system responds and scales with increasing server resources. The third variable introduced delays between requests, with two delay configurations: 0 and 250 ms. This aspect accounted for real-world scenarios where temporal gaps exist between consecutive requests, shedding light on the system's behaviour and response patterns in different delay conditions. Furthermore, the experiments encompassed both the LAN environment and a decentralized application, representing distinct network settings. The LAN configuration provided a benchmark for evaluating system performance in an ideal environment, whereas the examination of the blockchain infrastructure aimed to replicate a realistic real-world scenario. This dual approach allowed for a comprehensive understanding of the system's behaviour in different network environments. In total, a meticulous examination and analysis were performed for 56 different scenarios, considering the combination of 2 server configurations, 7 client configurations, 2 delay configurations, and 2 network settings. The subsequent sections provide a detailed presentation and discussion of the results obtained from these experiments.

The mean response time of the system when functioning ona LAN network, experiencing no latency was recorded as 46 ms when tested with a single client using both 1 and 3 server configurations. However, when the system was subjected to a load of 480 clients, the average response time increased significantly to 4826.5 ms for a single server configuration and 3496.3 ms for amulti-server configuration. This unequivocally showcases the influence of horizontal scaling, achieved by adding more servers, on vital performance metrics like average response time. When the system operated over a LAN connection with a 250 ms delay and subjected to a single client load, the average response time for both the one-server and three-server configurations was recorded as 76.9ms. Notably, when utilizing a client and a server, the average response time had already exceeded the inter-requests latency, indicating efficient processing and responsiveness of the system., indicating that the addition of more servers would not result in a speed improvement. Following the induction of the 250 ms delay, the mean response time rose to 4278 and 3603 ms for the single-server and three-server configurations, respectively. When comparing these outcomes to the experiments conducted without any delay between requests, it becomes evident that the 250 ms delay had only a minimal impact on the performance improvement (Figures 14 and 15).

The experimental setup utilized a t2.medium instance type located in the us-east-1b availability zone. The operating system used was Ubuntu 16.04 LTS. The instance was equipped with an Intel(R) Xeon(R) CPU E5-2676 v3 processor running at a frequency of 2.40 GHz [29]. Additionally, the instance had 4 GB of RAM available for processing and storage. These specifications provided the necessary computational resources for conducting the experiments and analyzing the data. In contrast to LAN networking, the performance on the cloud exhibited higher mean response times. Under optimal conditions with no delays, the mean response time varied between 117.4 milliseconds for a single client in both one and three-server setups, and reached as high as 13,102 milliseconds for the single-server configuration. However, the three-server configuration demonstrated significantly improved performance, with an average response time of 3764 milliseconds, only around 200 milliseconds slower than the LAN connection in similar conditions. This indicates that the application's performance can be effectively enhanced through horizontal scaling by adding more servers when operating on cloud infrastructure. When a delay of 250 milliseconds was introduced, the system's average response time became comparable to the conditions without any delay. It ranged from 109 milliseconds for a single client to 11,130 and 3369 milliseconds for the single and three-server configurations, respectively, with 480 clients. Although the difference was minimal, the average response time slightly improved for both server configurations with the 250 ms delay compared to the 0 ms delay (Figure 16).

When executing the system on a compute instance without any latency, the overall throughput was lower compared to running it locally. The peak throughput, observed with a single client, reached 7.9 requests per second for both the one-server and multi-server configurations. However, as the system faced the load of 480 clients, the throughput experienced a substantial decline, dropping to 0.12 and 0.28 requests per second for the single and multi-server configurations respectively. Interestingly, when introducing a 250 ms delay,

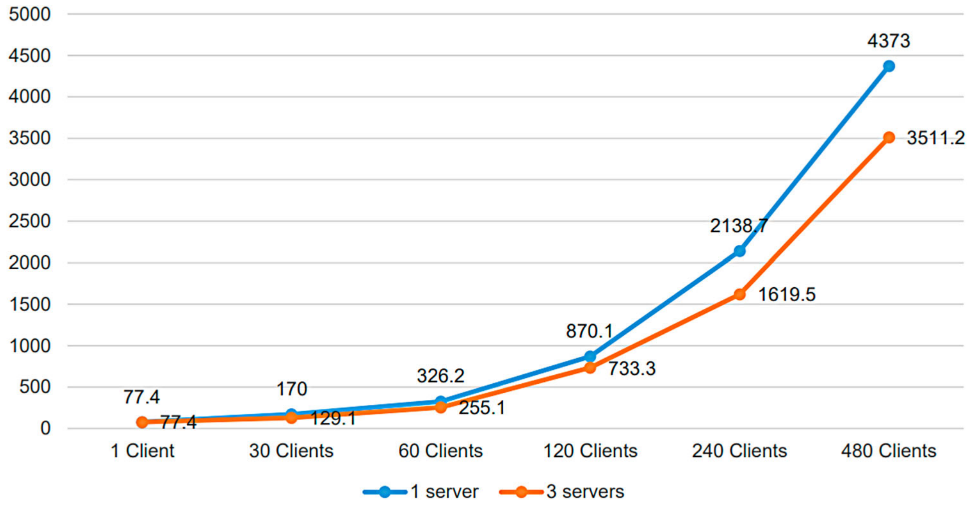

Figure 14. Mean response time of components with LAN (induced delay of 250 ms).

Figure 15. System throughput with LAN (induced delay of 250 ms).

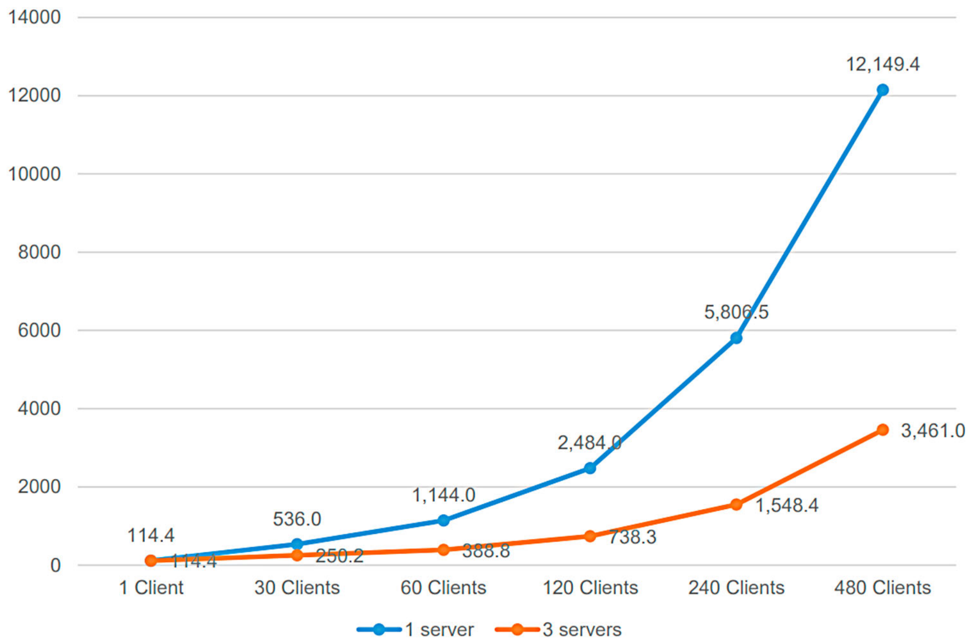

Figure 16. Mean response time of blockchain with cloud storage (induced delay of 250 ms).

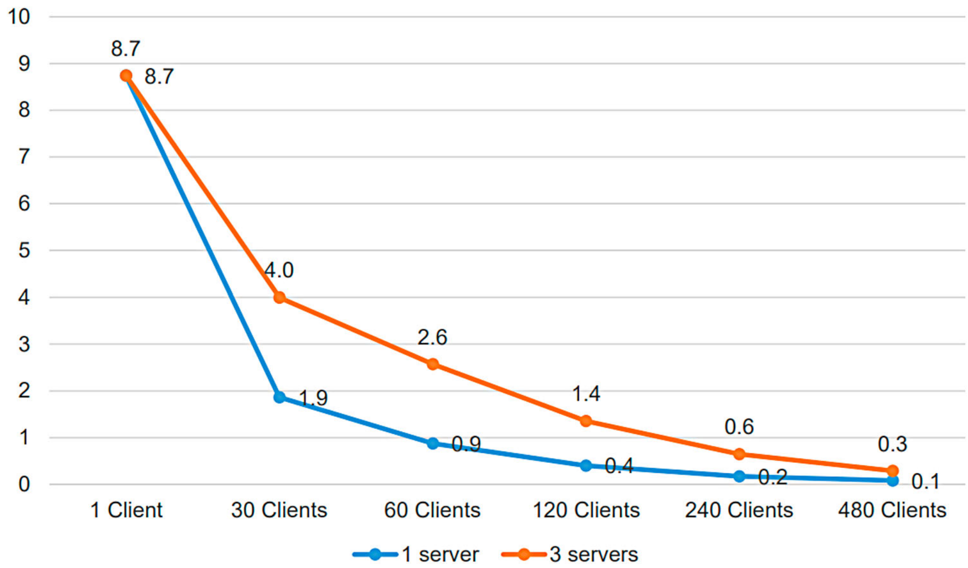

Figure 17. Throughput with blockchain running on AWS cloud (induced delay of 250 ms).

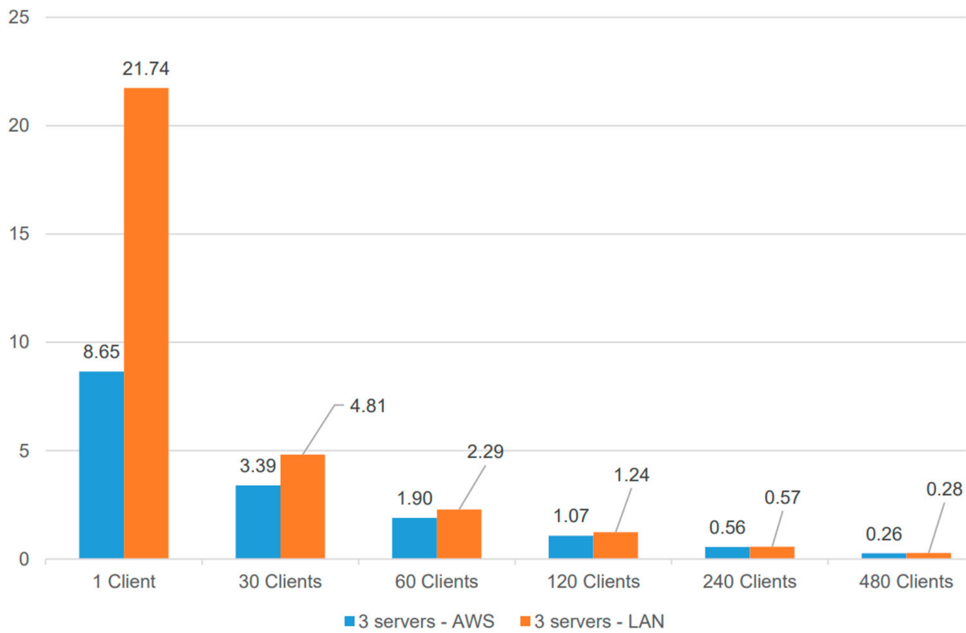

Figure 18. Throughput comparisons between blockchain and LAN in a multiserver environment.

the throughput remained almost identical to the conditions without any delay. The highest throughput was still observed with a single client, maintaining a rate of 8.7 requests per second for both server configurations. Similarly, under the load of 480 clients, The throughput for the one-server and three-server configurations remained consistent at 0.1 and 0.3 requests per second respectively. These results indicate that the system's performance is hardly impacted by introducing a delay between client requests when operating in the cloud (Figure 17).

When evaluating the data transfer rates of different scenarios on blockchain cloud storage and LAN, notable trends can be observed for both test setupson a single server and those involving three servers. During periods of reduced client activity, the LAN surpasses AWS in terms of performance, demonstrating a roughly twofold advantage. This performance gap becomes more prominent when a single server is solely responsible for request handling. When the number of clients surpasses 100 in a configuration with a single server, the LAN connection achieves up to three times greater workload compared to the back-end cloud connection. However, the introduction of three servers significantly diminishes this discrepancy. When three servers are utilized, at client loads greater than 100, the performance disparity between the LAN and cloud connections becomes negligible. This highlights the potential enhancements in performance that can be achieved by horizontally scaling the application across multiple cloud servers. These experiments serve as a testament to the Multichain blockchain's capability to handle requests in a decentralized environment. Although the LAN environment exhibits superior performance,

Figure 18 illustrates that further horizontal scaling leads to even more favourable performance outcomes.

6. Conclusion

The data collection process in this study specifically targeted working and studying women in college. The collected data was categorized into groups based on the duration of their menstrual cycles, enabling a more focused and comprehensive analysis. The results revealed that women with irregular menstrual cycles tend to experience more intense physical and psychological changes in their daily lives compared to those with regular cycles. These findings highlight the significant impact of the menstrual cycle on both the physical and psychological well-being of women. To further advance research in this area, future studies can adopt a real-time data collection approach using the mentioned device, allowing for the continuous monitoring of subjects' menstrual patterns and associated parameters in their daily lives. By leveraging the identified parameters, such as body temperature and eating habits, predictive models can be developed to anticipate and manage potential challenges and discomforts associated with the menstrual cycle. Ultimately, this could contribute to enhancing the quality of life for women and addressing specific needs during different phases of the menstrual cycle. As the idea focuses on acquiring real time data from the users and processing it using transfer learning and block chain based mechanisms for analyzing, the proposed work is a novel way to establish a relationship between the physical and psychological health of the subjects.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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