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How Can IPMA Analysis Through PLS-SEM Identify Maternal Health Risk Factors?

Bagaimana Analisis IPMA Melalui Pendekatan SEM-PLS Dapat Mengidentifikasi Faktor Risiko Kesehatan Ibu?

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ABSTRACT

This quantitative study explores maternal health risk factors through Partial Least Squares Structural Equation Modeling (PLS-SEM), employing a cross-sectional design. The dataset, sourced from Kaggle, includes variables such as age, blood pressure, blood sugar, body temperature, and heart rate. Using SmartPLS version 4, the research integrates both exploratory and confirmatory approaches to identify significant predictors of maternal health risks. Importance-Performance Map Analysis (IPMA) highlights that blood sugar (path coefficient = 0.465) and systolic blood pressure (0.274) are the most critical factors. These findings suggest that managing blood sugar and blood pressure should be prioritised in maternal health interventions. Future studies should focus on predictive algorithms and refining sensor-based monitoring systems for real-time assessment.

Keywords: *Healthcare Analysis, Health Monitoring, Predictive Analysis, Risk Factor Identification, SmartPLS*

ABSTRAK

Penelitian kuantitatif ini menelaah faktor risiko kesehatan maternal melalui *Partial Least Squares Structural Equation Modeling* (PLS-SEM), dengan menggunakan desain cross-sectional. Dataset yang diambil dari Kaggle mencakup variabel seperti usia, tekanan darah, gula darah, suhu tubuh, dan denyut jantung. Dengan memanfaatkan SmartPLS versi 4, penelitian ini menggabungkan pendekatan eksploratif dan konfirmatori untuk mengidentifikasi prediktor signifikan risiko kesehatan maternal. Analisis Peta Penting-Performa (IPMA) menyoroti bahwa gula darah (koefisien jalur = 0,465) dan tekanan darah sistolik (0,274) adalah faktor paling kritis. Temuan ini menunjukkan pentingnya pengelolaan gula darah dan tekanan darah dalam intervensi kesehatan maternal. Penelitian lanjutan disarankan untuk fokus pada algoritma prediktif dan penyempurnaan sistem pemantauan berbasis sensor untuk penilaian risiko secara waktu nyata.

Kata Kunci: Analisis Kesehatan, Analisis Prediktif, Identifikasi Faktor Risiko, Pemantauan Kesehatan, SmartPLS

INTRODUCTION

Maternal health remains a critical public health issue globally, with complications during pregnancy and childbirth being leading causes of mortality and morbidity among women of reproductive age (Larasakti & Suyani, 2023; Wahyuhidaya & Apriliani, 2023). Despite advancements in medical technology and healthcare systems, disparities in maternal health outcomes persist, especially in low- and middle-income countries (Munawaroh et al., 2022; Paydar et al., 2017). Identifying and mitigating risk factors that contribute to poor maternal health outcomes is essential for improving maternal healthcare delivery (Andayani et al., 2021). In this context, effective analytical tools are needed to better understand the complex interplay of these risk factors and to develop targeted interventions (Awang et al., 2015). This research leverages the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, combined with Importance-Performance Map Analysis (IPMA), to identify and prioritise critical maternal health risk factors from a dataset.

The use of PLS-SEM in healthcare research has gained traction due to its ability to handle complex models with multiple latent variables, even with relatively small sample sizes (Cakir, 2019). This method is particularly advantageous in examining relationships between observed and unobserved variables, which is vital in understanding the multifaceted nature of maternal health risk factors (Tohari, 2018). By applying PLS-SEM to the Maternal Health Risk Dataset, this study aims to uncover latent variables that significantly influence maternal health outcomes. This approach not only helps in identifying key risk factors but also in understanding their relative importance, thus providing valuable insights for healthcare policymakers and practitioners.

To enhance the practical relevance of the findings, the study integrates IPMA with PLS-SEM. IPMA is a powerful tool that enables the identification of areas where improvements can yield the most significant impact. By mapping the importance and performance of different risk factors, this analysis provides a more nuanced understanding of which factors should be prioritised for intervention (Teeluckdharry et al., 2022). This dual approach offers a comprehensive framework for evaluating maternal health risks, allowing for a more strategic allocation of resources and efforts in maternal health programmes.

Given the global urgency to reduce maternal mortality and improve maternal health outcomes, this research contributes to the growing body of literature by offering a robust analytical framework. The findings of this study are expected to inform evidence-based policy decisions and help in designing targeted interventions that address the most critical determinants of maternal health. Moreover, the use of advanced statistical techniques such as PLS-SEM and IPMA in this research underscores the potential of these tools in healthcare research, particularly in contexts where data complexity and resource constraints are significant challenges.

RESEARCH METHOD

Type of Research

This research is quantitative in nature, focusing on the analysis of maternal health risk factors through advanced statistical techniques. The study employs a cross-sectional design, collecting data at a single point in time to examine the relationships between variables using Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2012, 2019; Sarstedt et al., 2017). The following variables are used in this study including Age (Age), Systolic Blood Pressure (SystolicBP), Diastolic Blood Pressure (DiastolicBP), Body Temperature (BodyTemp(F)), Blood Sugar (BloodSugar), as well as Heart Rate (HeartRate). The Importance-Performance Map Analysis (IPMA) within the PLS-SEM framework is utilised to identify and prioritise critical factors that influence maternal health outcomes.

Research Design

The research design incorporates a combination of exploratory and confirmatory approaches. Initially, the study explores potential relationships between variables based on existing theories and literature. Following this, the PLS-SEM technique is applied to confirm these relationships and determine the significance of various risk factors. The design is structured to assess both the direct and indirect effects of latent variables on maternal health outcomes, allowing for a comprehensive understanding of the underlying risk factors (Hair et al., 2012, 2019; Sarstedt et al., 2017).

Population and Sample Size

The population of this study includes all pregnant women represented in the Maternal Health Risk Dataset from Kaggle. The dataset comprises 1,014 records, each containing detailed information on various health indicators and risk factors associated with maternal health. Given that the entire dataset is utilised for analysis, the sample size is equivalent to the total number of records, 1,014 cases. This sample size is deemed sufficient for conducting PLS-SEM analysis, as it exceeds the minimum sample size requirements for reliable results in structural equation modelling (Hair et al., 2012, 2019; Sarstedt et al., 2017).

Sampling Techniques

Since the study utilises an existing dataset, a non-probability sampling technique is employed, specifically a census sampling method. All available data from the Maternal Health Risk Dataset are included in the analysis, ensuring that no potential variations in risk factors are excluded. This approach allows for a comprehensive evaluation of maternal health risks across the dataset.

Characteristics of Respondents

The dataset includes various demographic and health-related variables such as age, systolic and diastolic blood pressure, blood sugar levels, body temperature, heart rate, and a risk level classification. The respondents, represented by the dataset, are pregnant women with ages ranging from 10 to 70 years. The dataset categorises the risk level of these women into three distinct groups: low, medium, and high risk, based on their health indicators. These characteristics are critical for understanding the health risks associated with maternal outcomes.

Time and Place of Research

This study is based on secondary data analysis. The Maternal Health Risk Dataset was collected and made publicly available on Kaggle (https://www.kaggle.com/datasets/csafrit2/maternal-health-risk-data/). The research and data analysis were conducted over a period of six months, from January 2024 to June 2024, at the Universitas Harapan Bangsa in Indonesia (https://maps.app.goo.gl/GncZ6wQkse64bhUx5), as well as using Google Collab (https://colab.research.google.com/) to facilitate research work where one of the authors is abroad (Ukraine).

Research Instruments

The primary instrument used for data analysis is the SmartPLS version 4 software, which facilitates the implementation of PLS-SEM and IPMA (Ringle et al., 2024). The software enables the modeling of relationships between latent variables and their respective manifest indicators, as well as the evaluation of the importance and performance of these variables (Hair et al., 2012, 2019; Sarstedt et al., 2017). No physical instruments or direct data collection tools were used, as the study relies on pre-existing data from the Maternal Health Risk Dataset.

Statistical Analysis Tests

The data analysis process involves several stages:

1. Data Preparation

   This includes cleaning the dataset, ensuring all variables are appropriately formatted, and handling any missing data or outliers. Descriptive statistics are generated to provide an overview of the dataset (Al Hakim, 2022; Al Hakim & Hidayah, 2022; Soelaiman et al., 2022; Soelaiman & Al-Hakim, 2022). Besides, data normalisation is done to make it easier to equalise the form of the data, which is very different, so we have used a data normalisation approach using Python in RStudio software (R Core Team, 2016). The form of data normalisation is done by decimal scaling.
2. Model Specification

   A conceptual model is developed based on the variables in the dataset. Latent variables, such as age, systolic and diastolic blood pressure, blood sugar levels, body temperature, heart rate, and a risk level classification, are identified and mapped to their respective manifest variables.
3. PLS-SEM Analysis

   The PLS-SEM technique is applied to evaluate the relationships between latent variables. This involves assessing the path coefficients, factor loadings, and model fit indices to ensure the model's validity and reliability (Hair et al., 2012, 2019; Sarstedt et al., 2017).
4. Importance-Performance Map Analysis (IPMA)

   IPMA is conducted to identify which factors are most critical in influencing maternal health outcomes. This analysis provides insights into the importance of each factor and how well it performs, helping to prioritise areas for intervention.

5. Evaluation of Results

   The final step involves interpreting the PLS-SEM and IPMA results, drawing conclusions about the significance of various maternal health risk factors, and providing recommendations based on these findings.

Ethical Considerations

Since the study uses publicly available secondary data, no direct ethical concerns involving human subjects are present. However, all analyses are conducted with a focus on maintaining the integrity of the data and ensuring that any findings are reported transparently and accurately.

This research method provides a comprehensive framework for evaluating maternal health risks, ensuring that the study's findings are robust, reliable, and relevant for improving maternal health outcomes.

RESULT AND DISCUSSION

Structural Model

Figure 2 shows the result of structural graphics in this model. The structural model analysis, using Importance-Performance Map Analysis (IPMA) in PLS-SEM, reveals several critical insights into the relationships between the latent variables and their influence on the risk level of maternal health. The performance values of the latent variables, as measured by the IPMA, demonstrate a wide range of impact. Specifically, Diastolic Blood Pressure (DiastolicBP) exhibits the highest performance value at 53.844, followed by Systolic Blood Pressure (SystolicBP) with a performance value of 47.998. These results suggest that both systolic and diastolic blood pressure are the most significant contributors to the overall performance in predicting risk levels, aligning with existing medical literature that highlights blood pressure as a critical factor in maternal health risks (Tohari, 2018). Interestingly, Body Temperature (BodyTemp(F)) shows a relatively low performance value of 13.302, indicating that while it is a contributing factor, it may not be as critical as blood pressure or blood sugar in this context.

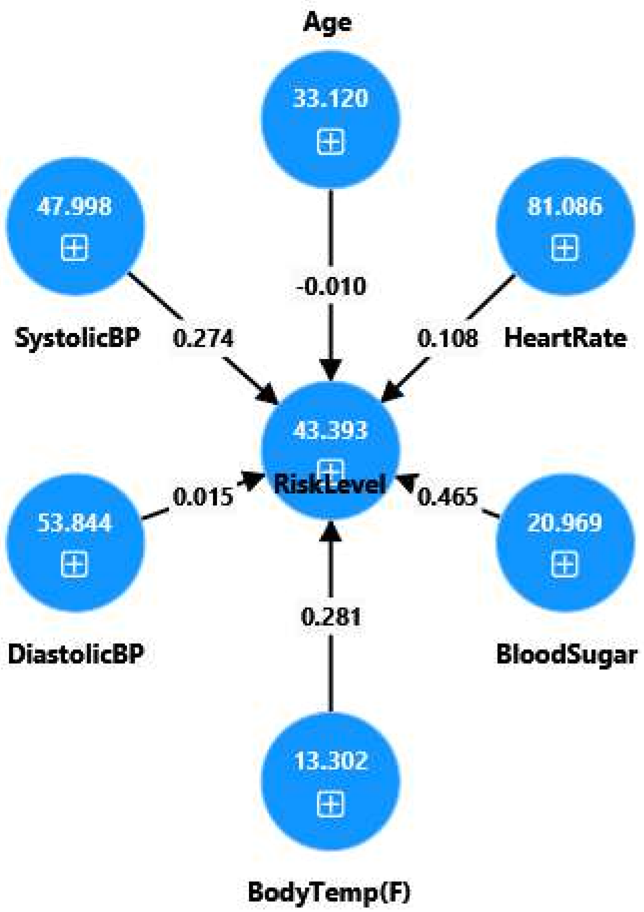

Figure 1. The structural model result with LV performance and total effects value of all latent variables, respectively.

In terms of path coefficients, the analysis highlights Blood Sugar (BloodSugar) as having the strongest total effect on Risk Level, with a path coefficient of 0.465. This indicates that blood sugar levels have a substantial and direct impact on determining maternal health risk, making it a key area for monitoring and intervention (Tohari, 2018). BodyTemp(F) also shows a significant positive influence on Risk Level, with a path coefficient of 0.281. This suggests that fluctuations in body temperature are also an essential predictor of maternal health risks, potentially indicating underlying issues that could exacerbate the risk level (Tohari, 2018). Conversely, the path from Age to Risk Level is minimal and slightly negative (-0.010), implying that within this model, age does not significantly affect the risk level when other factors are considered, which could be due to the relative uniformity of the age range in the dataset. Table 1 shows the complete indicator total effects result.

Table 1. Total effects - indicator total effects analysis result.

	Age	Blood Sugar	Body Temp (F)	Diastolic BP	Heart Rate	Risk Level	Systolic BP
Age	1.000					-0.010	
Blood Sugar		1.000				0.465	
Body Temp (F)			1.000			0.281	
Diastolic BP				1.000		0.015	
Heart Rate					1.000	0.108	
Risk Level						1.000	
Systolic BP						0.274	1.000

Moreover, the path coefficients from SystolicBP (0.274) and HeartRate (0.108) to Risk Level, though positive, are relatively moderate in comparison to Blood Sugar and BodyTemp. This further emphasizes the complexity of maternal health risks, where multiple factors interplay, but certain variables—such as blood sugar and blood pressure—are more dominant in influencing outcomes (Tohari, 2018). The low path coefficient from DiastolicBP to Risk Level (0.015) suggests that while diastolic pressure is critical in performance, its direct impact on the risk level might be overshadowed by other factors such as blood sugar and systolic pressure. These findings underline the importance of a holistic approach to monitoring maternal health, where multiple variables are considered in tandem rather than in isolation.

Overall, the results from the IPMA structural model provide crucial insights into the prioritization of health indicators for managing maternal risks. The significant path coefficients highlight the importance of blood sugar, systolic pressure, and body temperature as primary predictors, suggesting that targeted interventions in these areas could yield the most substantial benefits in reducing maternal health risks. These findings support the need for continued emphasis on comprehensive monitoring systems that integrate these critical indicators, potentially leading to more effective condition-based maintenance and timely interventions in healthcare settings.

Important Performance Map Analysis

Figure 3 shows the important performance map analysis result. The Importance-Performance Map Analysis (IPMA) provides a deeper understanding of the relationships between latent variables by combining their importance (total effects) and their performance (average values). This dual perspective helps identify which factors should be prioritized to improve the outcome—in this case, reducing maternal health risks. The results from the IPMA offer valuable insights into which variables require attention and optimization in healthcare management.

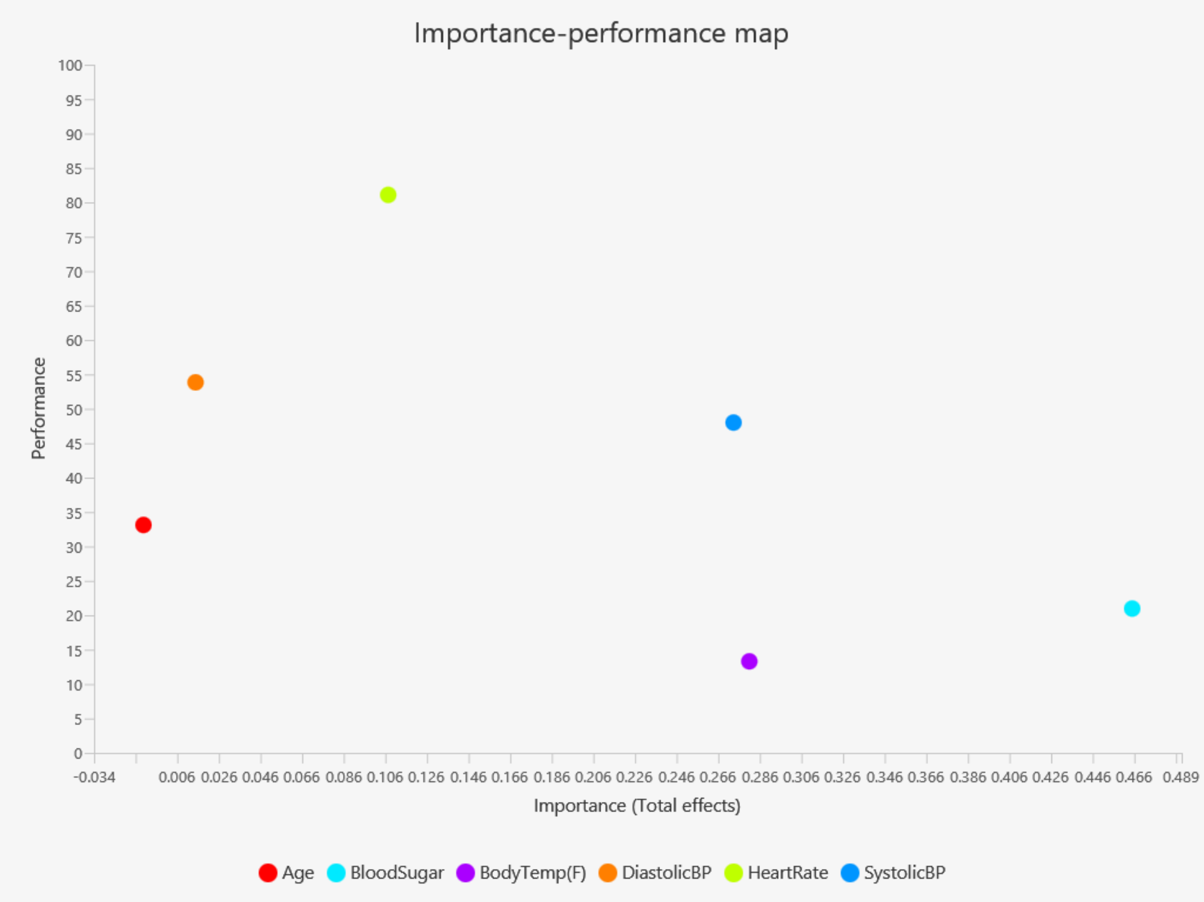

Figure 2. IPMA construct level result.

Blood Sugar (BS) emerges as the most critical variable with the highest path coefficient (0.465) and a moderate performance value of 20.969. This indicates that while blood sugar significantly impacts maternal health risk, there is substantial room for improvement in managing this factor. The moderate performance suggests that current practices may not adequately address blood sugar levels, underscoring the need for more focused interventions. Enhancing the management of blood sugar, such as through improved screening and monitoring protocols, could have a considerable impact on lowering maternal health risks. The importance of blood sugar in predicting maternal health outcomes aligns with existing medical research, which consistently links high blood sugar levels with complications during pregnancy (Tohari, 2018).

Systolic Blood Pressure (SystolicBP) also shows a strong influence on Risk Level with a path coefficient of 0.274 and a high-performance value of 47.998. This suggests that while systolic pressure is already a focus in maternal health monitoring, its influence on risk levels remains significant. The high-performance score indicates that interventions related to systolic blood pressure are being implemented effectively, but further improvements could still enhance outcomes (Tohari, 2018). Given that high systolic pressure is often a precursor to conditions like preeclampsia, maintaining stringent monitoring and control measures is essential. The IPMA results reinforce the importance of sustained attention to blood pressure management in reducing maternal risks.

In contrast, Diastolic Blood Pressure (DiastolicBP) presents an interesting case. Despite having the highest performance value (53.844), its path coefficient (0.015) is relatively low. This discrepancy suggests that while diastolic pressure is well-managed within the current healthcare framework, its direct impact on maternal health risk may be less significant compared to other factors like blood sugar and systolic pressure. However, this does not diminish the importance of diastolic pressure; rather, it highlights that effective management of diastolic pressure is already in place, and its contribution to risk levels may be more nuanced or indirect. Healthcare providers should continue to monitor diastolic pressure closely, but additional efforts may be better allocated to other areas, such as blood sugar management (Tohari, 2018).

Body Temperature (BodyTemp), with a path coefficient of 0.281 and a low-performance value of 13.302, presents a clear opportunity for improvement. Although it has a strong impact on Risk Level, its low performance suggests that body temperature is not being monitored or managed as effectively as it could be. This could be due to a lack of focus on temperature fluctuations as a significant risk factor in maternal health. To address this, healthcare providers could integrate more rigorous temperature monitoring into routine care, especially in environments where infections or other temperature-related complications are common. By improving the management of body temperature, it may be possible to mitigate certain risks associated with maternal health, thereby improving overall outcomes (Tohari, 2018).

Lastly, Age and Heart Rate (HeartRate) exhibit unique patterns in the IPMA. Age has a minimal path coefficient (-0.010), indicating that it does not significantly influence Risk Level in this model. However, it is essential to consider that age-related risks may be more apparent when isolated from other variables or when dealing with extreme age ranges. Heart Rate, with a path coefficient of 0.108 and moderate performance, suggests that while it does contribute to risk levels, its role is secondary compared to blood pressure and blood sugar. Nevertheless, maintaining optimal heart rate levels is still crucial, particularly in high-risk pregnancies where heart complications can arise (Tohari, 2018). The IPMA results suggest that interventions aimed at stabilizing heart rate should complement efforts to manage blood pressure and blood sugar. In comparison to our study, which focuses on identifying key maternal health risk factors using Partial Least Squares Structural Equation Modeling (PLS-SEM), the related research conducted in India used Structural Equation Modeling (SEM) to explore maternal complications through two latent variables: pregnancy complications (PREGCOMP) and delivery complications (DELCOMP). Both studies highlight the impact of socioeconomic factors on maternal health risks. However, while the Indian study emphasises socioeconomic characteristics and antenatal care (ANC) timing, our study prioritises physiological factors like blood sugar and blood pressure as the most critical predictors. This divergence in focus underlines the importance of integrating both socioeconomic and physiological aspects to improve maternal health outcomes comprehensively (Kumar & Dhillon, 2021).

Furthermore, both studies agree that early interventions and comprehensive healthcare services are critical in reducing maternal health risks, though our findings suggest that managing blood sugar and systolic blood pressure should be a priority for mitigating risks. This comparison underscores the broader applicability of health risk models across diverse populations, with varying emphasis depending on regional and demographic conditions.

Another study in comparison to our study, which uses PLS-SEM to prioritise physiological factors like blood sugar and blood pressure in assessing maternal health risks, the Kenyan study investigates the continuum of care (before, during, and after delivery) using SEM. Both studies highlight the significance of healthcare services, but the Kenyan research focuses on the relationships between antenatal, delivery, and postnatal care. Notably, it finds that socioeconomic factors and personal barriers influence the use of care throughout the maternal health continuum, underscoring the need for comprehensive, integrated care systems across different phases of maternal health (Owili et al., 2017).

Meanwhile, related study in comparison to our study, which focuses on physiological factors like blood sugar and blood pressure, the related research conducted in Lampung, Indonesia examines the impact of environmental factors (water quality, sanitation), health behaviour (ANC adherence, labour operator), and health services (access, maternal complication care) on maternal health. Using SmartPLS for analysis, this study highlights that these determinants significantly influence maternal health, suggesting that addressing these external factors can complement the management of physiological risks. Both studies underscore the need for multifaceted interventions to improve maternal outcomes (Sari et al., 2020).

In conclusion, the IPMA highlights Blood Sugar, Systolic Blood Pressure, and Body Temperature as the most critical areas for improvement to reduce maternal health risks. While Diastolic Blood Pressure and Heart Rate are also important, their management appears more effective within the current system. Age, though less impactful in this analysis, should not be overlooked, especially in different demographic contexts. The insights gained from the IPMA can guide healthcare providers in prioritizing interventions that will have the most significant impact on improving maternal health outcomes, ultimately contributing to more effective and targeted healthcare strategies.

CONCLUSION AND RECOMMENDATION

Conclusion

This study has highlighted the critical factors influencing maternal health risks using the Importance-Performance Map Analysis (IPMA) within the PLS-SEM framework. Among the various factors analysed, Blood Sugar (BS), Systolic Blood Pressure (SystolicBP), and Body Temperature (BodyTemp(F)) emerged as the most significant predictors of maternal health risks. These variables exhibited strong path coefficients, indicating their substantial impact on maternal outcomes. Despite the effective management of Diastolic Blood Pressure (DiastolicBP) and Heart Rate (HeartRate), these factors showed a less direct influence on maternal health risks in comparison to Blood Sugar and Systolic Blood Pressure. The insights gained from this analysis underscore the importance of targeted interventions in these key areas to optimize maternal health outcomes.

The findings also revealed that while certain variables like Diastolic Blood Pressure and Heart Rate are being managed effectively, others, such as Body Temperature and Blood Sugar, present opportunities for improvement. The study's integration of IPMA with PLS-SEM offers a nuanced understanding of how each factor contributes to maternal health risks, allowing for more precise and informed decision-making in healthcare settings. Ultimately, this research demonstrates that optimizing the management of critical health indicators can significantly reduce maternal risks, thereby enhancing the overall quality of care for pregnant women.

Recommendation

For further details of the maternal health risk data, especially in the context of pregnancy affects, the following recommendations are useful to considering in the future:

1. Enhance Blood Sugar Monitoring and Management: Given its significant impact on maternal health risks, healthcare providers should prioritize the implementation of more rigorous blood sugar management protocols. This could involve frequent monitoring, early detection of abnormalities, and tailored interventions to maintain optimal blood sugar levels throughout pregnancy.
2. Strengthen Systolic Blood Pressure Control: While systolic blood pressure is already effectively managed, continued efforts to monitor and control it are essential. Regular screenings and interventions aimed at preventing conditions like preeclampsia should remain a high priority in maternal health programs.
3. Improve Body Temperature Monitoring: The low performance of body temperature management suggests a gap in current practices. Healthcare facilities should integrate more comprehensive temperature monitoring protocols, especially in environments where infections or other temperature-related complications are prevalent.
4. Conduct Further Research on Diastolic Blood Pressure and Heart Rate: Although these factors show less direct influence on maternal risks, further research is needed to explore their roles in different contexts or populations. Understanding the nuanced effects of these variables could lead to more refined strategies for reducing maternal health risks.

5. Develop Predictive Algorithms: Building on the insights from this study, future research should focus on developing predictive algorithms that use real-time data from these key indicators. Such algorithms could help optimize the timing of interventions, improving maternal outcomes by preventing complications before they arise

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