ORIGINAL ARTICLE

COMPLETE BLOOD COUNT-BASED PREDICTIVE MODELLING FOR DIABETES MELLITUS AMONG MALAYSIAN WOMEN: IMPLICATIONS FOR PUBLIC HEALTH SCREENING

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ABSTRACT

Diabetes mellitus is a major global public health concern, with a rising prevalence among women. Early prediction using routine clinical data, such as complete blood count (CBC) parameters, provides a cost-effective strategy for identifying individuals at risk. This study compared the effectiveness of classical binary logistic regression and Bayesian binary logistic regression in predicting diabetes mellitus among females using CBC parameters. Data from 537 female patients were analysed, incorporating CBC variables and diabetes status. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC), Hosmer-Lemeshow goodness-of-fit test, posterior predictive checks, and sensitivity analyses. Bayesian diagnostics, including trace plots and credible intervals (CrIs), were used to ensure model reliability. The Bayesian model outperformed the classical approach, demonstrating higher AUC, improved calibration, and more informative uncertainty estimation. Significant predictors included age, mean corpuscular volume (MCV), mean corpuscular haemoglobin concentration (MCHC), white blood cell count (WBC), haematocrit (HCT), platelet count, and haemoglobin (Hb). The Bayesian model produced stable posterior estimates and robust convergence, supporting its suitability for small or correlated datasets. These findings highlight the potential of CBC parameters as early indicators of diabetes risk among women and underscore the value of Bayesian modelling in informing gender-sensitive screening strategies and interventions.

***Keywords**: Diabetes mellitus, Women's health, Complete blood count, Logistic regression, Bayesian regression, Public health screening, Predictive modelling*

INTRODUCTION

Diabetes mellitus (DM) is a chronic metabolic disorder characterised by persistent hyperglycaemia due to defects in insulin secretion, insulin action or both [1-2]. As a significant global public health challenge, diabetes has reached epidemic proportions, profoundly impacting individual health and societal resources worldwide. The global prevalence of diabetes is staggering, affecting approximately 463 million adults in 2019, which accounts for roughly 9.2% of the adult population aged between 20 to 79 years [3-4]. This number is projected to rise to about 578 million by 2030 and could reach 629 million by 2045 representing a concerning trend of increasing incidence over the years [3]. The burden of diabetes is not only a concern for patients; it poses economic challenges as the costs associated with diabetes management and its complications significantly affect healthcare systems [5-6]. In the Malaysian context, the situation mirrors global trends. The International Diabetes Federation has reported alarming statistics on diabetes prevalence in Malaysia, where approximately 3.9 million adults were living with diabetes in 2019, translating to a prevalence rate close to 18.3% among individuals aged 18 and above [1, 7]. The Malaysia National Health Survey indicates an ongoing increase, with projections suggesting that this number could escalate further in the coming years, potentially affecting an even larger segment of the population [7]. Furthermore, the prevalence of diabetes among Malaysian populations emphasizes the need for effective public health interventions and resources to combat this growing epidemic.

The complete blood count (CBC) is a fundamental laboratory test that provides comprehensive information about an individual's haematological status encompassing the measurement of red blood cells (RBCs), white blood cells (WBCs), haemoglobin (Hb), haematocrit (HCT) and

platelets counts [8, 9]. This widely performed test offers essential insights into various physiological and pathological states, making it invaluable for the early detection and monitoring of numerous diseases, including diabetes mellitus. In the context of diabetes mellitus (DM) management, the use of diagnostic tests is pivotal in identifying individuals at risk, enabling timely interventions. While Haemoglobin A1c (HbA1c) and fasting glucose are conventional markers for diabetes diagnosis and management, they also come with limitations. HbA1c values can be influenced by various factors such as anaemia, haemoglobinopathies and certain conditions like hyperthyroidism which can lead to misleading results in a subset of the population [10-11].

Additionally, fasting glucose measurements often require patients to be in a fasted state for accurate results, which may not always be feasible, particularly in routine screenings. This requirement can lead to missed opportunities for early detection in cases where individuals may not adhere to fasting protocols [12]. In contrast, CBC parameters reflect the body's systemic response and can provide an early warning signal about underlying dysmetabolic states that may not be detected through standard glucose tests alone. Research indicates that parameters like WBCs and platelet counts significantly associate with diabetes mellitus risk, demonstrating predictive validity in various populations [13-14]. For instance, increased WBC counts have been linked to a higher incidence of diabetes and its associated complications, illustrating a potential predictive utility of CBC parameters in screening high-risk individuals even before conventional diabetes markers shift [12, 15, 16]. The integration of CBC testing into routine health assessments can help mitigate this issue, enabling healthcare providers to monitor populations more effectively and identify individuals at risk through a comprehensive approach.

Accurate prediction models are essential for identifying individuals at risk of developing diabetes mellitus. Binary logistic regression has been widely employed, providing a basic methodology for assessing the relationship between various health parameters and risk of diabetes mellitus [17-18]. However, the advent of Bayesian logistic regression, which incorporates prior information and quantifies uncertainty in parameter estimates, presents a compelling alternative. Bayesian methods can enhance model reliability, particularly in situations with limited data or numerous predictors, thus potentially improving diabetes mellitus prediction [19-20].

This study aimed to evaluate the predictive accuracy of binary logistic regression against Bayesian logistic regression in predicting diabetes mellitus utilizing CBC parameters. Prior studies have concentrated more on the risk factors and knowledge assessment of diabetes mellitus in various regions of Malaysia, including Sabah. Nonetheless, there was an obvious absence of research concentrating on determining the prevalence of diabetes mellitus through a Bayesian approach utilizing complete blood count data. The investigation discovered which CBC parameters possessed predictive importance in both methodological frameworks. The results were expected to highlight the preventive significance of each modelling technique in forecasting diabetes mellitus, emphasizing the potential benefits of employing routine CBC data for the early detection of at-risk populations.

METHODS

Data Collection and Variables

The secondary data were obtained from the Clinical Laboratory Faculty of Medicine & Health Sciences, Universiti Malaysia Sabah consisting of 537 women patients who underwent complete blood count tests between 2018 and 2022. The data obtained included diabetes status, age, ethnicity and eight complete blood count parameters including haemoglobin (Hb), mean corpuscular volume (MCV), mean corpuscular haemoglobin (MCH), mean corpuscular haemoglobin concentration (MCHC), platelet, red blood cell (RBC), white blood cell (WBC) and haematocrit (HCT). For the purpose of analysis, patients aged < 60 years were coded as "0" and those aged ≥ 60 years were coded "1". Non-Malay ethnicity was coded "0", while Malay ethnicity was coded "1". Normal CBC values were coded "0" and abnormal values were coded "1". The complete blood count parameters were classified as normal if the value fell within the normal reference interval and abnormal if the value was outside the normal reference interval [16]. For the outcome variable, patients with diabetes were coded "1" while those without diabetes were coded "0".

Model Development

This study employed a comprehensive methodology that integrated univariate analysis, binary logistic regression and Bayesian binary logistic regression to predict diabetes mellitus among women in Sabah, Malaysia using CBC parameters.

Binary logistic regression estimates the probability of an event through the logit link function and produces odds ratios to quantify how changes in predictors affect outcome likelihood. In general, the logistic regression model was:

$$logit(p_i) = ln\ ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$$

where p_i is the probability for each woman $i = 1,2,3,\ldots,n$ to have diabetes, and $X_{1i},\ldots,X_{ki}$ represent the predictors.

The odds ratio for the predictor X_k was $OR_k = exp(\beta_k)$.

Bayesian binary logistic regression incorporates prior information into model estimation producing posterior parameter distributions that better quantify uncertainty. This approach is particularly advantageous in biomedical research where small samples, complex variable interactions or correlated predictors are common. Diagnostics, such as trace plots and the R-hat statistic allow for assessment of model convergence and reliability. The likelihood was $Y_i \sim Bernoulli(p_i)$ and the prior was $\beta_k \sim N(0, \sigma^2)$. In general, the model was given by:

$$logit(p_i) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$$

where p_i is the probability for each woman $i = 1,2,3,\ldots,n$ to have diabetes, and $X_{1i}, \ldots, X_{ki}$ represent the predictors.

The first step in the analysis involved performing descriptive statistics to summarize the demographic and clinical characteristics of the study population. Following this, the data were split into training and test datasets with a ratio of 80:20, with 80% used for training and 20% for model validation [16]. Next, univariate analysis was conducted employing the Chi-square test to assess relationships between categorical variables and diabetes status. Variables with p-values < 0.05 were considered statistically significant and included for further analysis in the binary logistic regression model [21-22].

To assess multicollinearity among the variables, Variance Inflation Factor (VIF) analysis was implemented. A threshold of VIF values exceeding 5 indicated potential multicollinearity concerns, prompting a review of variable selection to maintain the integrity of the regression models. The modelling process began with binary logistic regression to determine the odds ratio (OR) of diabetes based on significant predictors identified in the univariate analysis. The Hosmer-Lemeshow test was applied to evaluate the goodness-of-fit of the model with a non-significant p-value indicating an adequate model fit [23]. The performance of the binary logistic regression model was assessed through the area under the receiver operating characteristic (ROC) curve (AUC) and other relevant metrics such as specificity, sensitivity and accuracy [13, 22].

Following the binary logistic regression, Bayesian binary logistic regression was conducted using the Bayesian Regression Models using Stan (brms) package in R. In this step, a normal prior distribution was specified for the regression coefficients based on previous studies [24]. The Bayesian model fitting was executed using the brm() function from the brms package, which enabled the implementation of Markov Chain Monte Carlo (MCMC) methodologies to estimate posterior distributions of the model parameters. The simulation involved of four independent chains with 100,000 iterations and 50,000 warm-up iterations. After fitting the model, diagnostics were conducted using trace plots to assess convergence, while effective sample sizes and potential scale reduction factors (R-hat) were evaluated to confirm that the chains have adequately mixed [25-26].

Finally, model performance was compared through posterior predictive checks and evaluation against the binary logistic regression model. Sensitivity analysis was performed to examine the robustness of the results against variation in prior settings and model specifications.

RESULTS

Descriptive Statistics

The dataset comprised a total of 537 participants. Table 1 presents the descriptive statistics of the study variables. The majority of the women were without diabetes (75.2%). Of the 537 women, 283 (52.7%) were aged ≥ 60 years, and 329 (61.3%) were Malay. With regard to CBC parameters, 355 (66.1%) had normal MCV values, 306 (57%) had abnormal MCHC values, 360 (67%) had normal MCH values, 348 (60.2%) had abnormal RBC levels, 280 (52.1%) had normal WBC levels, 312 (58.15) had abnormal HCT levels, 392 (73%) had abnormal platelet levels and 348 (64.8%) had normal haemoglobin levels.

Although the results of univariate analysis are not shown, out of 10 independent variables, only ethnicity was not statistically significant (p-value>0.05). Hence, it was excluded from the multivariate analysis. Before proceeding to multivariate analysis, multicollinearity among the independent variables was assessed. All VIF values were below the recommended threshold of 5, indicating no evidence of serious multicollinearity.

Binary Logistic Regression

In the preliminary binary logistic regression analysis, MCH and RBC were not statistically significant (p-value > 0.05). Consequently, the multivariate analysis was run one more time by excluding MCH and RBC. In the final model presented in Table 2, age ($\beta_1 = 1.02$, 95% CI: 0.40 – 1.94, OR = 3.16), MCV ($\beta_2 = 3.47$, 95% CI: 2.63 – 4.42, OR = 31.99), MCHC ($\beta_3 = 1.01$, 95% CI: 0.24 – 1.81, OR = 2.73), WBC ($\beta_4 = 1.54$, 95% CI: 0.79 – 2.35, OR = 4.66), HCT ($\beta_5 = 1.07$, 95% CI: 0.31 – 1.86, OR = 2.91), platelet ($\beta_6 = 2.06$, 95% CI: 1.12 – 3.10, OR = 7.85) and Hb ($\beta_7 = 2.98$, 95% CI: 2.20 – 3.86, OR = 19.67) were statistically significant.

Table 1: Descriptive statistics (N = 537)

Variable	Category	n (%)
Diabetes status	With diabetes	133 (24.77%)
	Without diabetes	404 (75.23%)
1. Age	< 60 years old	254 (47.30%)
	≥ 60 years old	283 (52.70%)
2. Ethnicity	Malay	329 (61.27%)
	Non-Malay	208 (38.73%)
3. MCV	Normal	355 (66.11%)
	Abnormal	182 (33.89%)
4. MCHC	Normal	231 (43.02%)
	Abnormal	306 (56.98%)
5. MCH	Normal	360 (67.04%)
	Abnormal	177 (32.96%)
6. RBC	Normal	187 (34.82%)
	Abnormal	348 (60.21%)
7. WBC	Normal	280 (52.14%)
	Abnormal	257 (47.86%)
9. HCT	Normal	225 (41.90%)
	Abnormal	312 (58.10%)
10. Platelet	Normal	145 (27.00%)
	Abnormal	392 (73.00%)
11. Haemoglobin	Normal	348 (64.80%)
	Abnormal	189 (35.20%)

Table 2: Final model for binary logistic regression (N = 537)

Variable	Estimate (95% CI)	Standard Error	p-value	Odd ratio (95% CI)
Constant	-8.7445 (-10.8965, -6.9240)	1.0084	<0.0001*	-
1. Age	1.1501 (0.4032, 1.9432)	0.3909	0.0032*	3.1587 (1.4966, 6.9814)
2. MCV	3.4654 (2.6276, 4.4229)	0.4550	<0.0001*	31.9892 (13.8403, 83.3400)
3. MCHC	1.0055 (0.2365, 1.8138)	0.4003	0.0120*	2.7333 (1.2629, 6.1336)
4. WBC	1.5397 (0.7850, 2.3478)	0.3965	0.0001*	4.6631 (2.1923, 10.4621)
5. HCT	1.0689 (0.3142, 1.8620)	0.3929	0.0065*	2.9122 (1.3693, 6.4367)
6. Platelet	2.0609 (1.1221, 3.1010)	0.5024	<0.0001*	7.8530 (3.0714, 22.2205)
7. Haemoglobin	2.9789 (2.1964, 3.8610)	0.4216	<0.0001*	19.6668 (8.9928, 47.5133)

The final fitted binary logistic regression model for predicting diabetes mellitus among women was:

$$logit(p) = -8.7445 + 1.1501(Age) + 3.4654(MCV) + 1.0055(MCHC) + 1.5397(WBC) + 1.0689(HCT) + 2.0609(Platelet) + 2.9789(Hb)$$

where p represents the probability of having diabetes mellitus. All predictors included in the final model were statistically significant ($p < 0.05$).

Bayesian Binary Logistic Regression

In the pre-model for Bayesian binary logistic regression results, MCH and RBC were not statistically significant, as the 95% credible interval included zero. Consequently, the Bayesian multivariate analysis was run one more time by excluding MCH and RBC. In the final model results showed in Table 3, age ($\beta_1 = 1.13$, 95% CrI: 0.40 - 1.90, OR = 3.10), MCV ($\beta_2 = 3.43$, 95% CrI: 2.63 - 4.33, OR = 30.94), MCHC ($\beta_3 = 1.00$, 95% CrI: 0.24

- 1.83, OR = 2.73), WBC ($\beta_4 = 1.53$, 95% CrI: 0.78 - 2.35, OR = 4.64), HCT ($\beta_5 = 1.07$, 95% CrI: 0.33 - 1.82, OR = 2.92), platelet ($\beta_6 = 2.00$, 95% CrI: 1.08 - 2.99, OR = 7.37) and Hb ($\beta_7 = 2.96$, 95% CrI: 2.20 - 3.80, OR = 19.35). All R-hat values were approximately 1.00, indicating convergence.

Table 3: Final model for Bayesian binary logistic regression (N = 537)

Variable	Posterior mean (95% CrI)	Estimated Error	R-hat	Odd ratio (95% CI)
Constant	-8.6728 (-10.6820, -6.9626)	0.9561	1.0013	-
1. Age	1.1328 (0.4016, 1.8956)	0.3845	1.0004	3.1043 (1.4943, 6.6567)
2. MCV	3.4320 (2.6254, 4.3259)	0.4418	1.0001	30.9373 (13.8101, 75.6337)
3. MCHC	1.0040 (0.2413, 1.8308)	0.3987	1.0002	2.7291 (1.2729, 6.2387)
4. WBC	1.5347 (0.7824, 2.3484)	0.3966	1.0007	4.6401 (2.1866, 10.4687)
5. HCT	1.0704 (0.3318, 1.8247)	0.3829	1.0010	2.9165 (1.3934, 6.2012)
6. Platelet	1.9977 (1.0750, 2.9904)	0.4823	1.0000	7.3718 (2.9301, 19.8941)
7. Haemoglobin	2.9626 (2.1952, 3.8009)	0.4093	0.9998	19.3477 (8.9819, 44.7407)

The final fitted Bayesian posterior mean model was:

$$logit(p) = -8.6728 + 1.1328(Age) + 3.4320(MCV) + 1.0040(MCHC) + 1.5347(WBC) + 1.0704(HCT) + 1.9977(Platelet) + 2.9626(Hb)$$

where p represents the probability of having diabetes mellitus. All 95% credible intervals (CrI) excluded zero, indicating significant effects for all predictors.

Trace plots in Figure 1 showed good mixing of the chains without divergences, supporting the reliability of the posterior estimates. The Hosmer-Lemeshow goodness of fit test conducted using test data yielded a p-value of 0.707, indicating a strong fit and demonstrating that the model predictions aligned with the observed outcomes. Figure 2 illustrates that the ROC curve for the binary logistic regression yielded an AUC of 0.9548, demonstrating effective discrimination between positive and negative cases, whereas the Bayesian binary logistic regression achieved an AUC of 0.9615, also suggesting proficient discriminating between positive and negative cases.

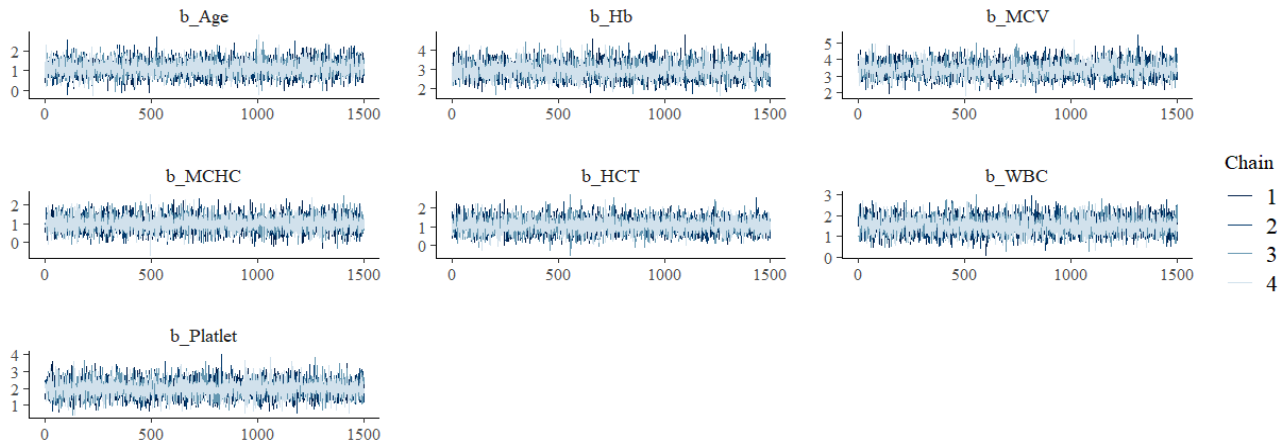

Figure 1: Trace plots

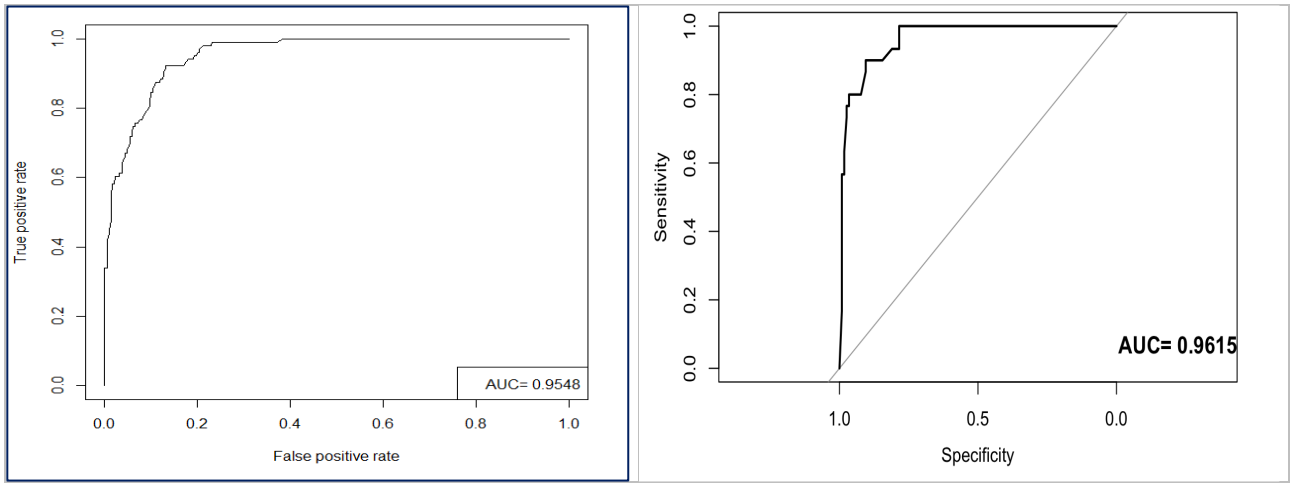

Figure 2: ROC curve and AUC value for the binary regression models

Both models revealed age, MCV, MCHC, WBC, HCT, platelet count, and Hb as significant predictors of the probability of acquiring diabetes mellitus in females. The Bayesian method exhibited enhanced efficacy, as indicated by a greater area under the ROC curve (AUC), superior model calibration, and refined posterior predictive assessments. The Bayesian model demonstrated more stable estimates and smoother convergence, as shown by trace plots and R-hat values. These findings correspond with the current literature, indicating that the Bayesian strategy may proficiently address model uncertainty by integrating previous knowledge and mitigating biases using adaptable models[27-29].

DISCUSSION

Both men and women were at risk of developing diabetes, however, this study focused on gender-specific approaches that consider the complications in diabetes risk and management were crucial for tailoring effective interventions. The risk was influenced by various physiological, hormonal and societal factors that create unique challenges for women in managing their health [30-32]. Previous studies by Mustafa et al. (2023) and Cherchi et al. (2020) indicated that women frequently present with diabetes at an older age and generally exhibit a higher body mass index (BMI) at diagnosis than men. This aligned with our findings, which revealed that women aged 60 years and older have a 3.1-fold increased risk of developing diabetes mellitus compared to those under 60 years old. This implies older women are more than three times likely to have diabetes mellitus, demonstrating the strong influence of age-related metabolic changes. Importantly, these findings highlight the need for gender-responsive screening programs in Malaysia, where older women remain an underserved group in diabetes prevention efforts. Public health strategies that emphasize early risk detection through widely available clinical tools such as CBC tests could bridge this gap and reduce the long-term burden of diabetes complications.

Our findings suggest that abnormalities in CBC parameters may act as early indicators of diabetes risk in females. The research by Mansoori et al., 2023, demonstrated that age, MCHC, and WBC were more substantial predictors of diabetes mellitus, supporting our findings. They found that RBC showed a correlation with diabetes mellitus and mentioned that MCV, MCHC, and platelet counts may not reliably function as early biomarkers for diabetes risk, which contradicts our findings. Most of the previous studies highlighted the importance of platelet parameters as potential risk markers for diabetes on platelet indices could serve as effective and cost-efficient tools for monitoring glycaemic control and the progression of diabetes [16, 34, 35]. Thrombosis and inflammatory responses mediated by platelets could impact cardiovascular health in diabetic patients, which is crucial for understanding the broader implications of diabetes management [36]. From a a public health policy perspective, platelet indices could be integrated into primary healthcare check-ups to provide low-cost monitoring, particularly in rural or resource-limited settings where advanced diagnostic tools are unavailable.

WBC counts have been progressively acknowledged as a potential biomarker for diabetes risk, with numerous studies indicating a substantial correlation between elevated WBC counts and the onset of diabetes mellitus. Our findings demonstrated that females with abnormal WBC counts had a 4.6-fold increased likelihood of developing diabetes compared to those with normal WBC counts. Consistent with Liu et al. (2024) shown that individuals with obesity and elevated WBC counts experienced a significantly greater likelihood of developing diabetes, supporting the concept that chronic inflammation played a role in metabolic dysregulation. These findings were consistent with Shin et al. (2020), which indicated that higher WBC counts may function as prognostic markers of hyperglycaemia worsening. This reinforces the public health message that routine CBC tests, already part of standard medical check-ups, can be repurposed as

an affordable community-level screening tool to identify at-risk women before clinical symptoms of diabetes emerge.

Hb played a multifaceted role in the context of diabetes. Our results highlighted that females with abnormal Hb had 19.3-fold higher risk of developing diabetes compared to normal Hb counts. Similarly, Alaidy et al. (2024) highlighted that elevated blood glucose leads to structural modifications in the haemoglobin that can impact RBC functions and increase the risk of diabetes related complications such as diabetic nephropathy. Additionally, Arkew et al. (2021) discovered diabetic individuals exhibited lower haemoglobin counts than their non-diabetic counterparts, potentially contributing to the onset of problems due to diminished oxygen supply to tissues. These findings imply that incorporating Hb abnormalities into community screening guidelines could improve early referral systems in Malaysia, ultimately supporting national strategies for reducing diabetes-related complications such as nephropathy and cardiovascular disease.

CONCLUSION

This study demonstrated that Bayesian binary logistic regression outperformed conventional binary logistic regression in predicting diabetes mellitus using complete blood count (CBC) parameters among females. The Bayesian framework yielded more robust parameter estimates and richer uncertainty characterization through posterior distributions, strengthening the reliability of the findings. Our findings support the need for further investigation into how these CBC parameters influence gender-specific health outcomes, particularly in women. Understanding these patterns could enhance early detection strategies and support the development of tailored interventions aimed at reducing diabetes risk in female populations. From a public health perspective, integrating CBC-based risk indicators into routine screenings at primary care level could provide a cost-effective approach to early diabetes detection among women in Malaysia. Such integration would align with national diabetes prevention strategies, helping to reduce the burden of complications while improving health equity, particularly for older women and those in underserved rural communities. Policymakers and healthcare practitioners are therefore encouraged to consider incorporating simple laboratory tests such as CBC into community health programs to strengthen early warning systems and guide resource allocation more effectively.

ACKNOWLEGDEMENT

This research was supported by Universiti Malaysia Sabah through UMSGreat Scheme (Project Code: GUG0642-2/2023).

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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