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A quantile regression approach to identify risk factors for high blood glucose levels among Bangladeshi individuals

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Abstract

Background and Aims: Diabetes mellitus, characterized by high blood glucose, is an overwhelming public health concern globally, including in Bangladesh. The implication of this trend may pose a significant challenge to the health systems due to the lack of awareness and improper management of this chronic disease. To formulate strategies for public health planning, this study aims to explore the potential risk factors for elevated blood glucose levels among Bangladeshi individuals using advanced statistical methods and a nationally representative data set.

Methods: This study utilized data from the 2017–18 Bangladesh Demographic and Health Survey and included 11,863 individuals. A nonparametric Kruskal–Wallis test assessed the significant association between fasting plasma glucose levels and various risk factors. Additionally, a robust quantile regression model was applied to examine the net effects of each risk factor at different quantiles of the distribution.

Results: The prevalence of diabetes is 8.1% among individuals in the study population, with variations observed across different administrative divisions in the country. Respondents from the Dhaka division respondents had a higher likelihood (24.1%) of having elevated plasma glucose and the Rangpur division had a lower risk (10.3%) of developing diabetes disease. This study identified several potential risk factors associated with elevated blood glucose levels, including hypertensive disease, overweight and obese body mass index, higher economic status, reduced physical activities, and older age, significantly contributing to develop diabetes mellitus.

Conclusion: This study recommends promoting healthy lifestyles, increased physical activity, effective hypertension management, obesity reduction, and nationwide screening programs to control diabetes and noncommunicable diseases in Bangladesh. These preventive measures are crucial for reducing the existing prevalence of diabetes and working toward achieving the Sustainable Development Goals by 2030.

KEYWORDS

fasting plasma glucose, hypertension, Kruskal–Wallis test, quantile regression

1 | INTRODUCTION

Diabetes mellitus (DM) is a noncommunicable disease (NCD) characterized by persistent metabolic abnormalities leading to elevated blood glucose levels.[1] This condition can cause severe damage to vital organs, including the kidneys, blood vessels, nerves, eyes, and other organs.[2] DM poses a significant global public health challenge, with an estimated seven million deaths reported in 2021. The International Diabetes Federation projected that approximately 650 million will be affected by this disease by 2030, which is expected to reach 800 million by the end of 2045.[3] Recently, global policymakers have set a target to curb the rapid increase in the prevalence of DM and other NCDs.[4]

In Southeast Asia, one in every 11 adults is diagnosed with DM, but a significant number of adults remain undiagnosed and unaware of the implications of this chronic disease. It is estimated that around 110 million adults in this region will develop DM disease by 2030.[3] In Bangladesh, the current prevalence of hypertension and DM are 25% and 14%, respectively. A recent report indicates that about 60% of individuals with DM are still unaware of their elevated glucose level, and only 25% of those who have been diagnosed effectively control their glucose levels through medication.[5]

Bangladesh aims to transition from its status as one of the least developed countries in 2026 and has set the goal of becoming an upper-middle-income country by 2031. The government is actively working to achieve the the Sustainable Development Goals (SDGs), with a focus on improving maternal and child healthcare, reducing child mortality, increasing access to medical facilities, and ensuring treatments for people with NCDs, the current rise in DM presents a significant challenge and places a substantial burden to the health systems and economy in the country.[6]

Fasting plasma glucose (FPG) is often used as an indicator of DM and is measured on a continuous scale. Numerous studies have been conducted to analyze the risk factors of DM in Bangladesh[7–10] and similar endemic countries, with most of the research suggesting that individual characteristics such as residence, age group, educational level, household level, that is, socioeconomic condition, as well as community and biological factors including gender, physical exercise, body mass index (BMI), and hypertension status associated with individuals high blood glucose levels.[7,11–13] These research studies employed a variety of predictive models, including the binary logistic regression,[10,14] multinomial logistic regression,[8,9,15,16] ordinal logistic,[17,18] probit regression,[19,20] and various machine learning algorithms[21,22] to investigate the influence of risk factors on DM. Most of these studies consider individuals' FPG level as the outcome variable and categorize it into different subcategories, such as nondiabetic, prediabetic, and diabetic.[12,23,24] However, categorizing a continuous response variable to a nominal measurement scale may reduce statistical power.[25]

Due to the limitations associated with categorizing the response variable, this study aimed to utilize both the classical linear regression model (CLRM) and quantile regression (QR) model. The QR model is gaining popularity compared to other methods, primarily due to its ability to fit various distribution quantiles. Recent applications of the QR model include modeling women's BMI,[26] mothers' age at first birth,[27-30] children's stunting,[31] gene expression data,[32] and so forth. Another key advantage of the QR model over the CLRM model is that QR model estimates are more robust against outliers and violate linear model assumptions.[33] This suitability of the QR model serves as our motivation to utilize it in examining the impact of the potential risk factors on elevated glucose levels among individuals across different quantiles.

Furthermore, it is worth noting that data on FPG levels among Bangladeshi individuals are not routinely collected, and much of the research relies on the data set from the 2011 Bangladesh Demographic and Health Survey (BDHS). The 2011 BDHS data set only includes only individuals aged 35 or older. As a result, the potential risk factors for DM have become relatively outdated and may not represent the general population. Therefore, this research aims to identify the contributing factors to elevated glucose levels using the latest 2017–18 BDHS data set and a more sophisticated QR model. The findings of this study hold significance for guiding health planners to reduce the current prevalence of DM and enhance awareness about the treatment. These results may contribute to achieving the health-related targets set in the SDGs by 2030.

2 | MATERIALS AND METHODS

2.1 | QR models

Let (x_i^T, y_i); $i = 1, 2, \ldots, n$ are independently drawn from a population, where y_i denotes the outcome variable and x_i the design matrix's vector $X_{n\times(k+1)}$. The $\tau^{th}(\tau \in [0, 1])$ linear quantile model can be expressed as follows

$$Q_{y_i}(\tau|X_i) = X_i^T\beta^{(\tau)};\ i = 1, 2, \ldots, n \tag{1}$$

where, $Q_{y_i}(.) \equiv F_{y_i}^{-1}(.)$ and $\beta^{(\tau)}$ denoted as $(k \times 1)$ vector of unknown parameters. Koenker and Bassett[34] derived the following minimization problem to solve $\beta^{(\tau)}$.

$$\hat{\beta}^{(\tau)} = \underset{\beta^{(\tau)}\in\Re^p}{\arg\min}\left\{\sum_{i\in(i:y_i\geq x_i^T\beta^{(\tau)})}\tau\left(y_i - x_i^T\beta^{(\tau)}\right) + \sum_{i\in(i:y_i<x_i^T\beta^{(\tau)})}(1-\tau)\left(y_i - x_i^T\beta^{(\tau)}\right)\right\} \tag{2}$$

$$= \underset{\beta^{(\tau)}\in\Re^p}{\arg\min}\sum_{i=1}^{n}\tau(y_i - x_i^T\beta^{(\tau)}) \tag{3}$$

The QR model coefficients were estimated using the "quantreg" package[35] in the R Programming environment (Version: 4.1.2).

2.2 | Data sources

The data used in this study was obtained from the 2017–18 BDHS. This is the second nationwide survey to collect biomarker measurements from individuals aged 18 or older. The collected biomarkers include FPG and blood pressure (BP) for DM and hypertension. This survey was conducted with the Ministry of Health and Welfare, Mitra and Associates, NIPORT, and USAID. Detailed information about the sampling designs can be found in the BDHS 2017–18 report.[5] The complete data set utilized in this study is accessible on the website "https://dhsprogram.com/."

2.3 | Study design and population

The BDHS 2017–18 employed a two-stage stratified sampling approach. In the first stage, 672 primary sampling units (423 clusters from rural and 249 from urban areas) were selected. Subsequently, 30 households from each PSU were chosen using a systematic sampling method. This resulted in 4864 homes being eligible for biomarker measurements out of the initially selected 20,160 families. The study population comprised 6691 men and 8013 women aged 18 or older. After removing missing cases from the relevant variables, the final study population included 11,863 respondents.

2.4 | Variables

2.4.1 | Response variable

The respondent's FPG level is the response variable, measured continuously. Typically, an FPG level in the range of 6.00–7.00 mmol/L indicates a prediabetic condition, while a level exceeding 7.00 mmol/L suggests the presence of diabetic disease.[36]

2.4.2 | Predictor variables

Based on the literature reviews, a set of predictor variables was included to analyze the status of DM in Bangladesh. Their variables and categories are Divisions (Dhaka, Khulna, Chattogram, Rangpur, Sylhet, Barisal, Mymensingh, Rajshahi), residence type (rural, urban), wealth indices (richest, rich, middle, poor, poorest), education level (illiterate, primary, secondary, higher), age (15–24, 25–34, 35–44, 45–54, 55–64, 65+), gender (male, female), currently working status (no, yes), physical activity based occupation (no, yes), hypertension (hypertensive, non-hypertensive), and BMI (underweight, normal, overweight, obese). BMI categories were determined using the World Health Organization (WHO) cutoff scale: BMI < 18.5 as underweight, BMI range 18.5–24.9 as normal, BMI 24.9–29.9 as overweight, and BMI ≥ 30 as obese.[5] The respondents were classified as hypertensive if their systolic BP was >140 mmHg and diastolic BP was >90 mmHg. Physical exercise-based occupations include boatman, rickshaw puller, construction worker, fisherman, farmer, agriculture, and so forth. All other professions are considered nonphysical exercise occupations.

2.5 | Statistical methods

The response variable is continuous and the covariates variables are categorical. Initially, the distribution of the response variable was examined using a normality test and a box and whisker plot (Figure 1).

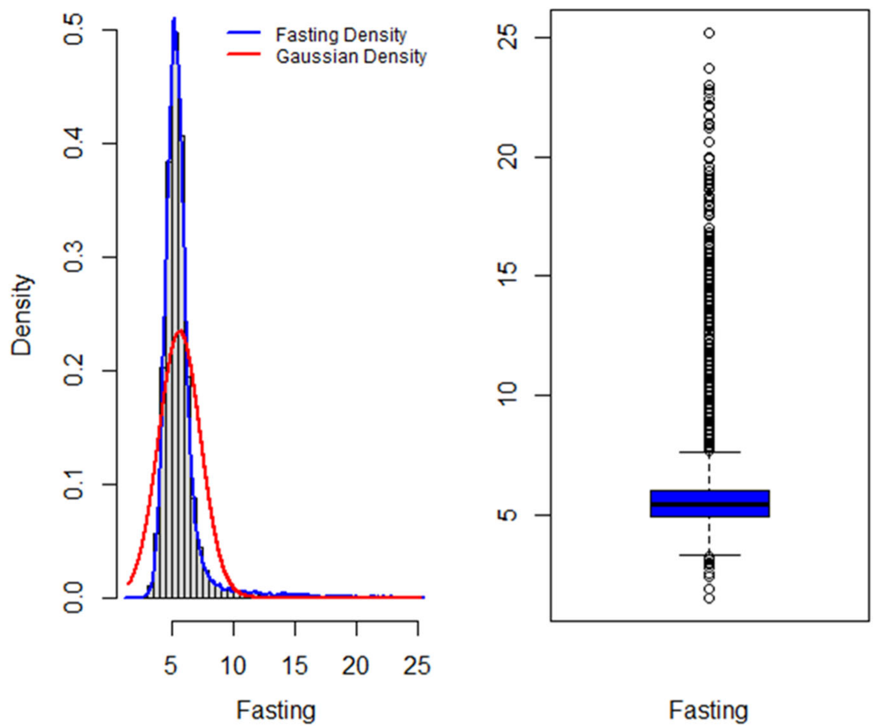

FIGURE 1 Density plot and box plot of FPG level among respondents in Bangladesh (n = 11,863). FPG, fasting plasma glucose.

The Shapiro–Wilks normality test indicates the non-normality of the FPG level distribution. Therefore, in bi-variate analysis, the non-parametric Kruskal–Wallis test was used to explore the significant association between FPG levels and covariates instead of the parametric analysis of variance (ANOVA) test. The ANOVA assumes that the data is independent, normally distributed, and satisfies the homogeneity of variance assumption.[37] The QR model was fitted at different quantiles further to investigate the net effects of each covariate (τ = 0.10, 0.25, 0.50, 0.75, 0.90). The significance of the tests is defined with a threshold of a *p*-value below 5% for all statistical tests.

3 | RESULTS

3.1 | Normality test: FPG values

The range (23.7) and quantile measures highlight the significant variability in FPG levels across different quantiles. Table 1 depicts the positive skewness coefficient (4.47) and a higher kurtosis measure (32.26), indicating that the response variable may not follow the Gaussian distribution assumption. Moreover, the box plot (Figure 1), Q–Q plot (Supporting Information S1: Figure 1), and Kolmogorov–Smirnov normality test (Supporting Information S1: Table 1) all affirm that the FPG levels distribution deviates from the normality assumption.

3.2 | Bivariate analysis: Kruskal–Wallis test results

Due to the violation of normality assumptions, the nonparametric Kruskal–Wallis test is suitable for the equality of median FPG level among predictors in bivariate analysis.[38]

The Kruskal–Wallis test examined statistically significant differences in median FPG levels among various predictor categories. The *p*-value of the Kruskal–Wallis test indicates that the median FPG level significantly varies across different administrative divisions, residence types, wealth indices, respondents' age groups, employment statuses, physical activity levels, hypertension statuses, and BMI categories (Table 2). However, respondents' education status and sex were not statistically significant in the bivariate analysis. Notably, the respondent's mean FPG level was highest in the Dhaka division (6.05) while lowest among respondents from the Rangpur division (5.39). Urban residents showed higher mean FPG values (5.95) than their rural counterparts (5.59). Additionally, mean elevated glucose levels were more prevalent among those in the wealthiest age group, aged 45–54. The mean FPG level was highest among hypertensive individuals, respondents with an obese BMI, and those predominantly engaged in desk-related occupations (Table 2).

3.3 | QR model results

In regression analysis, the ordinary least square model is efficient under ideal conditions (without outlying observations and satisfies the linear model assumptions). However, as evident from the Box plot (Figure 1), quantile–quantile plot (Supporting Information S1: Figure 1), and Kolmogorov–Smirnov test result, it is apparent that the FPG scores contain influential outliers and deviate from the normality assumption. Given these considerations, a robust QR approach becomes preferable to any parametric method since the QR model is less sensitive to influential outliers and model assumptions.

The significant variables (from bivariate analysis) were included in the QR model to examine the relative impact of each predictor on the respondents' FPG scores at different quantiles (τ = 0.10, 0.25, 0.50, 0.75, 0.90). The statistical significance of the difference between the two QR model estimates was also presented (Supporting Information S1: Table 2). In this test, the null hypothesis assumed that estimates are equal at different quantiles. The *p*-value of *F* statistic in statistics at the parameter estimates of QR models significantly varies across different quantiles (p-value < 0.05).

Table 3 reports QR model results at various percentiles. The intercept coefficients were positive and statistically significant in each quantile. Regarding the administrative division variable, negative coefficients were observed at different quantiles, suggesting a larger DM prevalence in respondents from other than Dhaka. Specifically, individuals from Chattogram, Barisal, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet show significantly lower FPG coefficients at all quantile levels than those from the Dhaka division. The rural coefficients gradually increase from the 25th to 90th quantiles, although the result did not show significance at any quantile. The wealthiest respondents exhibited a higher risk (0.32, 0.31, 0.31, 0.39, 0.73) at each quantile than their less affluent counterparts. Age-related coefficients were also notable, with individuals aged 35 or older showing significantly higher FPG levels than younger adults aged 15–25 across various quantiles. In addition, the likelihood of DM was higher in individuals aged 45 to 64 years at different quantile levels (Supporting Information S1: Table 3). In contrast, the respondent's current employment was not found to have a statistically significant effect except at the 25th quantile level.

TABLE 1 Descriptive statistics of FPG level among respondents in Bangladesh (n = 11,863).

						Percentiles				
Mean	SD	Minimum	Maximum	Skewness	Kurtosis	10%	25%	50%	75%	90%
5.67	1.70	1.50	25.2	4.47	32.26	4.40	4.90	5.40	6.00	6.80

Abbreviations: FPG, fasting plasma glucose; SD, standard deviation.

TABLE 2 Mean FPG level and Kruskal–Wallis test results by predictor variables (n = 11,863).

Variables	Frequency	Mean	Mean rank	χ^2 (*df*)	*p*-value
Division					
Dhaka	2863	6.05	7173.36	573.48 (7)	0.00
Chattogram	776	5.67	5947.45		
Barishal	2053	5.74	5842.75		
Khulna	1444	5.61	5571.72		
Mymensingh	1043	5.52	5492.28		
Rajshahi	1512	5.49	5226.98		
Rangpur	1222	5.39	4975.53		
Sylhet	950	5.62	5753.99		
Residence					
Urban	2983	5.95	6879.16	305.22 (1)	0.00
Rural	8880	5.59	5613.83		
Wealth status					
Poorest	2294	5.37	5216.55	715.38 (4)	0.00
Poor	2370	5.43	5206.86		
Middle	2425	5.52	5466.70		
Rich	2390	5.83	6368.47		
Richest	2384	6.25	7377.06		
Age group					
15–24	2425	5.32	5319.17	140.92 (5)	0.00
25–34	2949	5.53	5771.05		
35–44	2401	5.82	6229.60		
45–54	1623	5.98	6362.59		
55–64	1346	5.95	6251.80		
65+	1119	5.81	6036.49		
Education status					
Illiterate	2993	5.68	5882.32	1.63 (3)	0.65
Primary	3632	5.67	5911.17		
Secondary	3544	5.71	5981.78		
Higher	1694	5.66	5960.29		
Gender					
Male	5074	5.66	5864.84	3.41 (1)	0.06
Female	6789	5.70	5982.19		
Job					
Yes	4640	5.79	6187.43	42.45 (1)	0.00
No	7223	5.61	5767.92		
Physical activity-based occupation					
Yes	5793	5.52	5587.20	114.91 (1)	0.00
No	6070	5.84	6261.06		

(Continues)

TABLE 2 (Continued)

Variables	Frequency	Mean	Mean rank	χ^2 (*df*)	*p*-value
Hypertension					
Hypertensive	2816	6.01	6338.43	52.07 (1)	0.00
Non-hypertensive	9047	5.58	5805.49		
Body mass index					
Underweight	2077	5.43	5372.94	235.72 (3)	0.00
Normal	6965	5.61	5778.08		
Overweight	2351	5.99	6611.04		
Obese	470	6.28	7286.87		

Abbreviation: FPG, fasting plasma glucose.

It is observed from Supporting Information S1: Table 3 that the effect of exercise-based occupation on FPG levels is significantly positive at the 50th and 75th quantile levels. This indicates a higher likelihood of developing DM for mostly desk-related individuals than those engaged in physical activity-based professions. Furthermore, respondents who are non-hypertensive are less likely to develop DM than those who have hypertension disease. The results are particularly significant in higher quantiles. The effect of BMI indicates that as the BMI level increases, the coefficient at different quantiles also increases, reflecting a greater likelihood of developing DM than an underweight BMI. Each coefficient for overweight and obese individuals at different quantile levels is positive, initially decreasing at the 25th quantile and then increasing up to the 90th quantile level (Figure 2). The results were significant across all quantiles, demonstrating that the higher a respondent's BMI, the greater the likelihood of developing DM.

4 | DISCUSSION

This analysis is based on younger, adult, and older individuals in Bangladesh. It is important to note that the prevalence of DM is typically lower among younger adults, which could lead to deflated results. This study focuses on several demographics, socio-economic, and health-related variables as potential risk factors for developing DM, including region, type of residence, wealth index, current age, education status, gender, current employment, physical activity-based occupation, hypertension status, and BMI. The QR model allows us to explore the impact of these covariates in each percentile of the FPG measurements. Among these factors, age, hypertension, physical activity-based occupation, and BMI emerged as the primary risk factors for developing DM in Bangladesh. The findings align with other studies conducted in Bangladesh[7,10,12,39-41] and various other countries (India,[42] China,[24] Tiwan[43]). All these researches highlight the significant variation in DM across different regions.

Adult and older people showed a higher risk for developing DM across all quantiles compared to younger adults in Bangladesh, which aligns with findings from previous studies.[12,40,41,44] This increased risk is often attributed to insulin secretion deficiencies that rise with age.[45] This study uncovered considerable regional variations in developing DM among the Bangladeshi population. Individuals from the Dhaka division showed higher blood glucose levels in each quantile. This could be attributed to unhealthy dietary habits and reduced physical activity among the population in the Dhaka division. However, our findings indicate that the type of living places did not exhibit a significant association with the development of DM. This result differs from the findings made by Akter et al.[12] They noted that diabetes was more common among urban residents, possibly due to their sedentary lifestyles or higher likelihood of being overweight or obese.[12]

The results from the QR model highlight the significant contribution of individuals' socioeconomic status to the development of DM in Bangladesh. Lower-income quintile individuals are typically engaged in physical activities and consume fresh food, which may contribute to a reduced risk of DM compared to those with higher economic status. Therefore, individuals with greater wealth are more susceptible to developing DM than their counterparts. These findings align with results from previous studies.[7,41,46] Furthermore, it has been observed that physical activity-based occupations may reduce the risk of DM among individuals. Labor-intensive work is believed to burn more calories to keep the body fit and healthier. Similar agreements were found in other studies.[47,48]

In this study, hypertension status was found to be a significant contributor to high FPG levels among the Bangladeshi population. The negative coefficients in the upper quantile indicate that non-hypertensive individuals are less likely to have high FPG than hypertensive counterparts. These results are consistent with previous studies conducted in Bangladesh and other countries.[23,43,49,50] A higher BMI emerged as a leading cause of elevated FPG levels in Bangladeshi individuals. Overweight and obese individuals exhibited an increasing trend in the QR model estimates and a notably significant coefficient in upper quantiles. This factor should also be a priority to reduce the current prevalence of DM in Bangladesh. Similar studies were conducted in Bangladesh,[40,51] China,[23,47] and Nigeria[39,52] and reported similar findings.

TABLE 3 Quantile regression model showing only significant (p-value < 0.05) variables of FPG level among Bangladeshi individuals (n = 11,863).

Variables	Quantile regression estimates [confidence interval] $\hat{Q}_{10}$	$\hat{Q}_{25}$	$\hat{Q}_{50}$	$\hat{Q}_{75}$	$\hat{Q}_{90}$
Division Dhaka (Ref)					
Chattogram	−0.37*** [−0.45 to −0.3]	−0.35*** [−0.42 to −0.28]	−0.33*** [−0.40 to −0.26]	−0.29*** [−0.38 to −0.19]	−0.30*** [−0.44 to −0.16]
Barisal	−0.27*** [−0.36 to −0.18]	−0.24*** [−0.31 to −0.17]	−0.25*** [−0.33 to −0.18]	−0.21*** [−0.32 to −0.11]	−0.23** [−0.41 to −0.06]
Khulna	−0.34*** [−0.42 to −0.26]	−0.33*** [−0.40 to −0.26]	−0.38*** [−0.44 to −0.32]	−0.43*** [−0.52 to −0.35]	−0.60*** [−0.76 to −0.44]
Mymensingh	−0.30*** [−0.38 to −0.21]	−0.36*** [−0.43 to −0.28]	−0.34*** [−0.41 to −0.26]	−0.34*** [−0.44 to −0.24]	−0.50*** [−0.64 to −0.35]
Rajshahi	−0.37*** [−0.44 to −0.29]	−0.44*** [−0.51 to −0.36]	−0.46*** [−0.53 to −0.39]	−0.46*** [−0.56 to −0.36]	−0.50*** [−0.66 to −0.34]
Rangpur	−0.40*** [−0.48 to −0.31]	−0.45*** [−0.52 to −0.37]	−0.47*** [−0.54 to −0.40]	−0.51*** [−0.60 to −0.42]	−0.70*** [−0.83 to −0.57]
Sylhet	−0.36*** [−0.43 to −0.29]	−0.35*** [−0.42 to −0.27]	−0.35*** [−0.42 to −0.28]	−0.34*** [−0.43 to −0.26]	−0.47*** [−0.65 to −0.27]
Wealth index poor (Ref)					
Poorer	ns	ns	ns	ns	ns
Middle	ns	ns	ns	ns	0.10* [−0.02 to 0.21]
Rich	0.12*** [0.05–0.19]	0.13*** [0.06–0.18]	0.15*** [0.10–0.21]	0.15*** [0.08–0.22]	0.28*** [0.13–0.40]
Richest	0.32*** [0.24–0.39]	0.31*** [0.25–0.38]	0.31*** [0.25–0.36]	0.39*** [0.31–0.48]	0.73*** [0.52–0.94]
Age group 15–24 (Ref)					
25–34	0.12*** [0.06, 0.18]	0.13*** [0.07–0.18]	0.09*** [0.04–0.14]	0.15*** [0.09–0.20]	0.17*** [0.08–0.25]
35–44	0.25*** [0.19–0.31]	0.22*** [0.16–0.27]	0.18*** [0.13–0.23]	0.33*** [0.26–0.40]	0.50*** [0.38–0.61]
45–54	0.25*** [0.18–0.32]	0.23*** [0.17–0.28]	0.25*** [0.19–0.30]	0.368*** [0.29–0.44]	0.80*** [0.58–1.02]
55–64	0.17*** [0.09–0.24]	0.18*** [0.10–0.25]	0.28*** [0.20–0.35]	0.43*** [0.33–0.52]	0.83*** [0.57–1.09]
65+	3.46*** [3.45–3.46]	0.19*** [0.10–0.28]	0.23*** [0.16–0.29]	0.34*** [0.25–0.43]	0.50*** [0.21–0.89]
Job no (Ref)					
Yes	−0.11** [−0.19 to −0.003]	ns	ns	ns	ns
Physical activity based occupation yes (Ref)					
No	ns	ns	0.06** [0.01–0.12]	0.10** [0.01–0.19]	ns
Hypertension hypertensive (Ref)					
Non-hypertensive	ns	ns	ns	−0.08** [−0.15 to −0.01]	−0.53*** [−0.73 to −0.33]

(Continues)

TABLE 3 (Continued)

Variables	Quantile regression estimates [confidence interval] $\hat{Q}_{10}$	$\hat{Q}_{25}$	$\hat{Q}_{50}$	$\hat{Q}_{75}$	$\hat{Q}_{90}$
BMI Underweight (Ref)					
Normal	0.08** [0.07–0.09]	0.04* [−0.01 to 0.09]	0.05** [0.01–0.09]	0.05* [0.00–0.10]	0.10** [0.02–0.17]
Overweight	0.17*** [0.10–0.24]	0.14*** [0.07–0.19]	0.17*** [0.11–0.23]	0.19*** [0.10–0.28]	0.53*** [0.30–0.76]
Obese	0.29*** [0.15–0.41]	0.22*** [0.13–0.31]	0.28*** [0.18–0.38]	0.35*** [0.20–0.51]	0.90** [0.34–1.45]
Intercept	4.52*** [4.37–4.65]	4.96*** [4.84–5.08]	5.37*** [5.27–5.47]	5.82*** [5.67–5.98]	6.63*** [6.22–7.04]

Note: Detailed results are provided in Supporting Information files.

Abbreviations: BMI, body mass index; FPG, fasting plasma glucose; ns, not significant; Ref, reference category.

***p-value < 0.001; **0.001 ≤ p-value < 0.05; *p-value < 0.10.

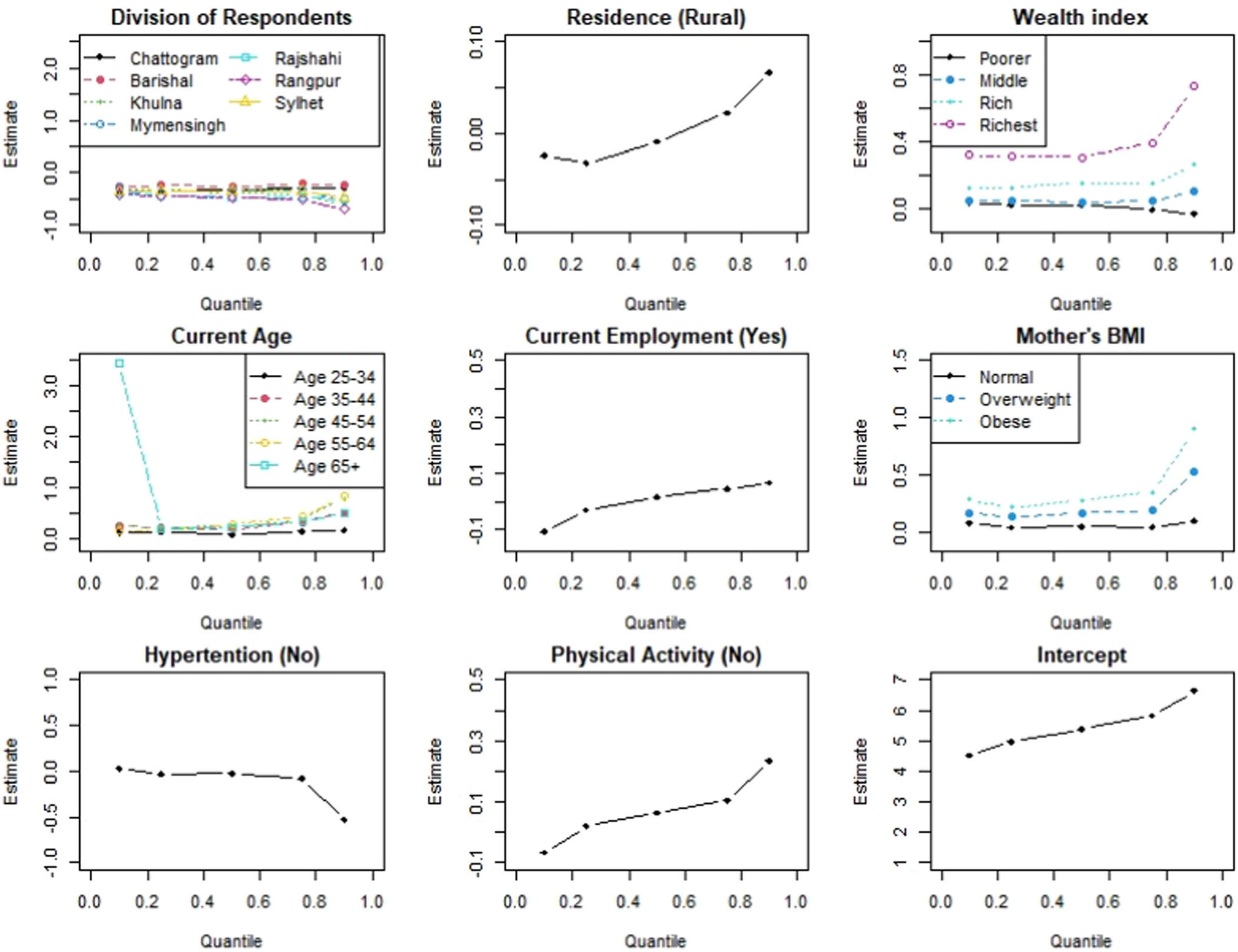

FIGURE 2 Parameter estimates of risk factors of diabetes at different quantiles levels.

5 | STRENGTHS AND LIMITATIONS

This study has several strengths. It leverages the latest BDHS data set and employs advanced statistical methods to identify potential risk factors associated with elevated blood glucose levels in Bangladesh. Unlike previous research work that primarily relied on categorizing the outcome variable and investigating the impact of covariates on DM, this study provides a comprehensive view of FPG levels at various quantiles using the QR model. To our knowledge, no previous research has utilized the QR model to examine the influence of risk factors on FPG levels across different quantiles. The limitation of this research is that it deals with the data from a cross-sectional study, which may impact the ability to establish causal relationships between variables. In addition, the analysis is constrained by the absence of genetic and behavioral factors, such as family history of DM, dietary habits, lifestyle, sleep duration, smoking status, alcohol consumption, and stress, among others. However, these factors are not covered in BDHS 2017–18 data.

6 | CONCLUSION

NCDs are a major global health burden and economic concern today. The increasing prevalence of high blood glucose levels has emerged as a significant public health concern among the adult population in Bangladesh. The QR model employed in this study provides more comprehensive results and explores the likelihood that individuals with hypertension, higher BMI, good economic status, less physical activity, and older age are at an increased risk of developing high blood glucose levels across quantiles. The findings also highlight regional variation, indicating that a relatively smaller portion of the individuals know the consequences and treatments of DM in Bangladesh. To address this issue, specific efforts should focus on healthy lifestyles, increasing physical activities, encouraging regular follow-up, managing hypertension, reducing obesity, and implementing nationwide screening programs among the population in Bangladesh. Furthermore, targeted interventions for adults are essential to reduce health complications in older age. The findings can be helpful for government authorities in the development of interventions aimed at controlling DM and NCDs.

AUTHOR CONTRIBUTIONS

Mst. Farjana Aktar: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Mashfiqul Huq Chowdhury**: Data curation; formal analysis; funding acquisition; investigation; methodology; project administration; software; supervision; validation; visualization; writing—original draft; writing—review and editing. **Md. Siddikur Rahman**: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing—original draft; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data are available at https://dhsprogram.com/.

ETHICS STATEMENT

The study does not require ethical approval as the BDHS 2017–18 survey was approved by the local Ethics Committee of Bangladesh and the ICF Macro at Calverton, New York, USA. Permission to use and analyze the data set was obtained by registering the study on the DHS website. Patients and the public were not involved in the design, conduct, reporting, or dissemination plans of this research.

TRANSPARENCY STATEMENT

The lead author Md. Siddikur Rahman affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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