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Metabolic Risk Profile and Visual Function Among Ride-Hailing Drivers

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ABSTRACT

Fly ash- and pumice-based geopolymers have emerged as promising low-carbon construction materials with the potential to reduce the environmental impacts associated with Portland cement production. However, their performance is highly dependent on mixture proportions, particularly the liquid-to-solid (L/S) ratio. Therefore, this study aimed to identify the optimum L/S ratio and evaluate its influence on the characteristics of geopolymer mortar. A laboratory experimental program was conducted using five liquid-to-solid (L/S) ratios of 0.40, 0.45, 0.50, 0.55, and 0.60. The investigated properties included compressive strength, density, and water absorption. The statistical significance of the L/S ratio was evaluated using one-way analysis of variance (ANOVA). The L/S ratio significantly affected the compressive strength, density, and water absorption of geopolymer mortar. The optimum performance was achieved at an L/S ratio of 0.45, yielding the highest compressive strength (21.03 MPa), highest density (2.12 g/cm³), and lowest water absorption (6%). One-way ANOVA confirmed that variations in the L/S ratio had statistically significant effects on all investigated properties ($p < 0.001$), with coefficients of determination of 99.44% for compressive strength, 98.42% for density, and 75.04% for water absorption. The liquid-to-solid (L/S) ratio is a critical parameter governing matrix densification, porosity development, and the physical and mechanical properties of fly ash- and pumice-based geopolymer mortar. An L/S ratio of 0.45 is recommended as the optimum condition for achieving the best balance among compressive strength, density, and water absorption.

INTRODUCTION

Vision plays a fundamental role in occupational activities that require rapid environmental perception, accurate decision-making, and continuous interaction with dynamic surroundings. Driving is an occupation highly dependent on adequate visual capability because drivers must recognize road signs, detect potential hazards, estimate distances, and respond quickly to changing traffic conditions. However, visual impairment remains a significant global public health concern. The World Health Organization (WHO) reported that at least 2.2 billion people worldwide experience near or distance vision impairment, with approximately 1 billion cases considered preventable or unaddressed through appropriate interventions (World Health

Organization, 2019). This global burden highlights the importance of identifying populations with increased visual demands and occupational risks, including professional and platform-based transportation workers (Alrashidi et al., 2026; Apostolopoulos, 2026; Matilla-Santander et al., 2025; Useche et al., 2026; Yoo et al., 2024).

The expansion of digital transportation services has increased the number of ride-hailing motorcycle drivers worldwide, particularly in urban areas where these workers depend heavily on prolonged driving activities. Unlike conventional drivers, ride-hailing drivers frequently experience additional visual challenges due to extended exposure to sunlight, glare, dust, wind, and continuous smartphone-based navigation systems. These occupational conditions may contribute to visual fatigue and potentially increase the risk of impaired visual performance. Previous studies have emphasized that vision impairment among drivers is not only an ophthalmological concern but also an occupational safety issue because reduced visual capability may influence driving performance and road safety outcomes (Kumar et al., 2022; Nguyen et al., 2023).

Beyond environmental and occupational exposures, systemic health conditions may also influence visual function. Metabolic abnormalities, including hypertension, hyperglycemia, dyslipidemia, and hyperuricemia, have increasingly been recognized as factors associated with vascular dysfunction and ocular complications. Persistent hyperglycemia, for example, may contribute to retinal microvascular damage and the progression of diabetic retinopathy, while hypertension and lipid abnormalities may affect retinal vascular health through systemic inflammatory and vascular mechanisms (Haider et al., 2020; Trott et al., 2022; Silva et al., 2024; Zhang et al., 2024). Therefore, examining metabolic health profiles among workers with high visual demands is important because visual impairment may reflect not only ocular conditions but also broader systemic health risks.

Previous studies have investigated the relationship between metabolic disorders and visual impairment, particularly among patients with diabetes and populations at risk of diabetic retinopathy. Research has demonstrated that poor glycemic control, metabolic syndrome components, and cardiovascular risk factors may contribute to retinal abnormalities and declining visual function (Sun et al., 2021; Trott et al., 2022; Favas et al., 2025). However, most existing studies have focused on clinical populations with established metabolic diseases rather than occupational groups exposed to prolonged driving conditions. Consequently, limited evidence is available regarding whether common metabolic abnormalities among ride-hailing drivers are associated with reduced visual function (Huo et al., 2023; Jain, 2025; Jaydarifard et al., 2024; Zhao et al., 2025).

Research specifically involving ride-hailing motorcycle drivers has primarily focused on describing visual acuity characteristics rather than investigating metabolic-related factors. A previous study conducted among 70 online motorcycle taxi drivers in Keputih, Surabaya, examined visual acuity profiles, refractive errors, and non-refractive visual impairment using a descriptive cross-sectional design. Although the study provided important information regarding visual conditions among online motorcycle taxi drivers, it did not evaluate whether metabolic abnormalities contributed to visual impairment risk within this occupational population (Izdihar et al., 2026).

This limitation indicates a research gap concerning the interaction between occupational visual demands and systemic metabolic health among ride-hailing drivers. Existing evidence has not sufficiently explained whether metabolic indicators, such as blood pressure, blood glucose, uric acid, and cholesterol levels, are associated with visual impairment among workers who spend substantial time operating motorcycles. Furthermore, previous research has generally examined either occupational visual conditions or metabolic-related ocular diseases separately, leaving limited understanding of how these two dimensions interact in real-world occupational settings. Addressing this gap is important for developing a more comprehensive perspective on worker health protection (Pham et al., 2020; Sorensen et al., 2021).

The urgency of this research is strengthened by the increasing reliance on ride-hailing transportation services and the occupational vulnerability of drivers who depend on maintaining optimal physical and visual performance. Early identification of visual impairment and metabolic risk factors among drivers may support preventive health strategies, occupational screening programs, and improved workplace safety interventions. Since ride-hailing drivers represent a working population exposed to both environmental visual stressors and potential lifestyle-related metabolic risks, integrated assessment approaches may provide valuable evidence for occupational health management.

The novelty of this study lies in integrating visual function assessment with metabolic risk profiling among ride-hailing motorcycle drivers. Unlike previous research that primarily described visual acuity patterns, this study evaluates visual impairment as an outcome and examines several metabolic abnormalities as potential associated factors. The study applies an analytical approach involving hypertension, hyperglycemia, hyperuricemia, and hypercholesterolemia variables to explore their associations with visual impairment among drivers. Therefore, this research expands the understanding of occupational visual health by incorporating systemic metabolic perspectives.

Accordingly, this study aimed to characterize the metabolic risk profile and visual function of ride-hailing motorcycle drivers in Petemon, Surabaya, and to explore the association between selected metabolic abnormalities and visual impairment. By analyzing clinical measurements and visual acuity outcomes, this research sought to provide preliminary evidence regarding whether metabolic conditions may represent relevant factors in occupational visual health among drivers.

This study contributes theoretically and practically to occupational health, public health, and vision science. Theoretically, it enriches existing literature by connecting metabolic health indicators with visual function in a specific occupational population that has received limited attention. Practically, the findings may support the development of integrated screening strategies combining visual assessment and metabolic evaluation for ride-hailing drivers. Although further studies with larger samples, repeated metabolic measurements, and comprehensive ophthalmic examinations are required, this research provides an initial foundation for understanding the relationship between metabolic risk and visual health in this workforce.

METHOD

This cross-sectional analytical study used a health-screening dataset from 73 ride-hailing motorcycle drivers in Petemon, Surabaya. The analytic dataset included complete measurements of visual acuity and metabolic variables relevant to the analysis.

The variables included age, sex, systolic and diastolic blood pressure, random blood glucose, uric acid, total cholesterol, presenting visual acuity of the right and left eyes, and pinhole findings when available. Data cleaning involved removing incomplete records, standardizing categorical responses, converting Snellen fractions to decimal acuity values, constructing the better-eye acuity variable, and deriving binary metabolic indicators from measured values.

Presenting visual acuity was converted into decimal values, and the better-eye acuity was determined based on the higher decimal value between the right and left eyes. Visual impairment was defined as better-eye presenting acuity <0.50 (worse than 6/12).

Hypertension was defined as systolic blood pressure >140 mmHg and/or diastolic blood pressure >90 mmHg. Hyperglycemia was defined as a random blood glucose level of ≥200 mg/dL. Hypercholesterolemia was defined as total cholesterol ≥200 mg/dL. Hyperuricemia was classified using sex-specific cutoffs applied during data preparation.

Continuous variables were summarized using mean ± standard deviation and median (interquartile range), while categorical variables were summarized using frequencies and percentages. Fisher's exact test was used for bivariate analysis because only nine visual impairment events were observed. Binary logistic regression was performed to estimate adjusted odds ratios (aORs) with 95% confidence intervals for the four metabolic predictors. Statistical significance was set at $p < 0.05$. Given the limited number of outcome events and predictors, the multivariable model was considered exploratory, and the estimates were interpreted cautiously.

RESULTS AND DISCUSSION

The analysis included 73 drivers. Mean age was 43.2±12.1 years (median 44 years). Mean systolic blood pressure was 128.2±19.2 mmHg, mean diastolic blood pressure 90.1±18.7 mmHg, mean random blood glucose 150.8±79.2 mg/dL, mean uric acid 6.41±1.77 mg/dL, and mean total cholesterol 192.9±43.8 mg/dL. Visual impairment was identified in 9 of 73 participants (12.3%).

Table 1. Clinical and metabolic characteristics of participants

Variable	Mean ± SD	Median (IQR)	Range
Age	43.18 ± 12.14	44.00 (34.00–52.00)	21.00–78.00
Systolic blood pressure	128.15 ± 19.25	125.00 (120.00–140.00)	85.00–210.00
Diastolic blood pressure	90.12 ± 18.72	85.00 (80.00–100.00)	55.00–135.00
Random blood glucose	150.81 ± 79.15	114.00 (95.00–198.00)	45.00–447.00
Uric acid	6.41 ± 1.77	6.30 (5.40–7.30)	3.30–15.10
Cholesterol	192.95 ± 43.78	190.00 (155.00–221.00)	122.00–307.00

Source: Primary data from health screening of ride-hailing motorcycle drivers in Petemon, Surabaya (2026).

Hypertension was the most prevalent metabolic abnormality (37/73, 50.7%), followed by hypercholesterolemia (34/73, 46.6%), hyperuricemia (28/73, 38.4%), and hyperglycemia (18/73, 24.7%). These findings (Table 2, Figures 1 and 2) indicate that metabolic risk factors were common in this occupational sample even though the present study was not designed to diagnose chronic metabolic disease.

Table 2. Prevalence of metabolic risk factors and visual impairment

Condition	n	%
Hypertension	37	50.7
Hyperglycemia	18	24.7
Hyperuricemia	28	38.4
Hypercholesterolemia	34	46.6
Visual impairment	9	12.3

Source: Primary data from health screening of ride-hailing motorcycle drivers in Petemon, Surabaya (2026).

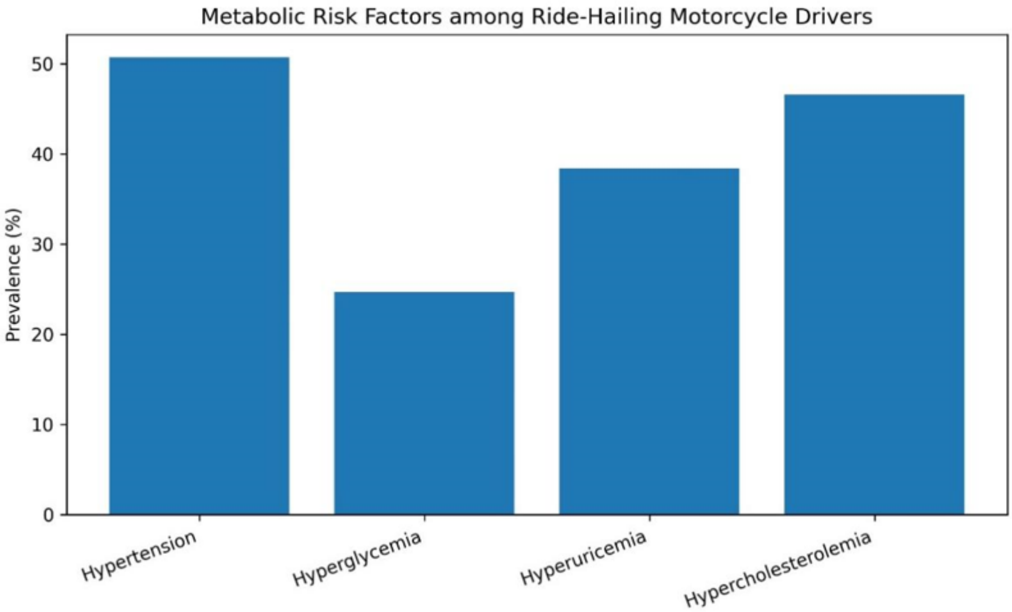

Figure 1. Prevalence of metabolic risk factors
Source: Primary data from health screening of ride-hailing motorcycle drivers in Petemon, Surabaya (2026).

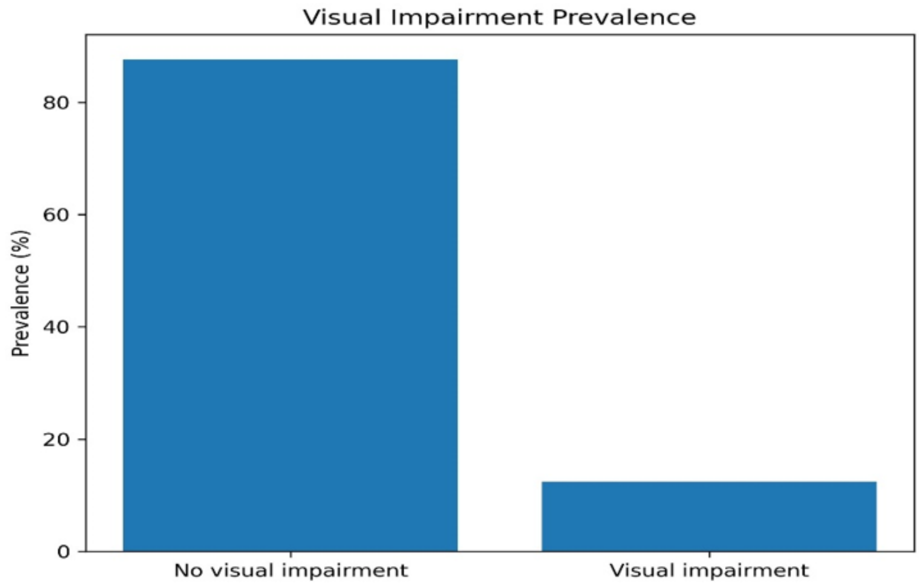

Figure 2. Prevalence of visual impairment
Source: Primary data from health screening of ride-hailing motorcycle drivers in Petemon, Surabaya (2026).

None of the four metabolic factors showed a statistically significant bivariate association with visual impairment (Table and Figure 3). Hyperuricemia had the largest crude odds ratio (OR 2.23; 95% CI 0.54–9.13; Fisher's exact p=0.291), whereas hypertension, hyperglycemia, and hypercholesterolemia had crude ORs below 1. The wide confidence intervals reflect the small number of visual-impairment events.

Table 3. Bivariate associations between metabolic factors and visual impairment

Predictor	Crude OR	95% CI	Fisher p
Hypertension	0.75	0.18–3.06	0.736
Hyperglycemia	0.86	0.16–4.55	1.000
Hyperuricemia	2.23	0.54–9.13	0.291
Hypercholesterolemia	0.53	0.12–2.32	0.489

Source: Primary data analysis using Fisher's exact test (2026).

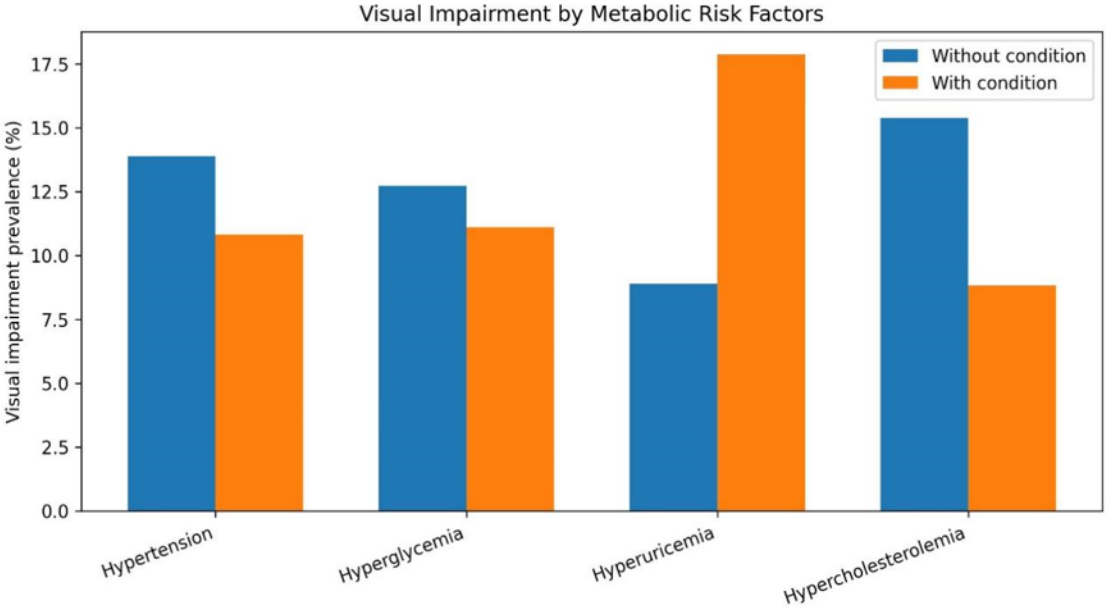

Figure 3. Visual impairment according to metabolic risk factors
Source: Primary data analysis from metabolic and visual assessment data (2026).

In the multivariable model (Table and Figure 4), hyperuricemia retained the largest point estimate (aOR 2.34; 95% CI 0.55–10.03; p=0.251), but the confidence interval included 1. Hypertension (aOR 0.71; 95% CI 0.16–3.10; p=0.649), hyperglycemia (aOR 1.30; 95% CI 0.19–8.89; p=0.791), and hypercholesterolemia (aOR 0.53; 95% CI 0.10–2.91; p=0.465) were also not statistically significant. Therefore, the data do not support a conclusion that any of the four metabolic abnormalities independently predicts visual impairment in this sample.

Table 4. Multivariable logistic regression of metabolic factors associated with visual impairment

Predictor	Adjusted OR	95% CI	p
Hypertension	0.71	0.16–3.10	0.649
Hyperglycemia	1.30	0.19–8.89	0.791
Hyperuricemia	2.34	0.55–10.03	0.251
Hypercholesterolemia	0.53	0.10–2.91	0.465

Source: Primary data analysis using binary logistic regression (2026).

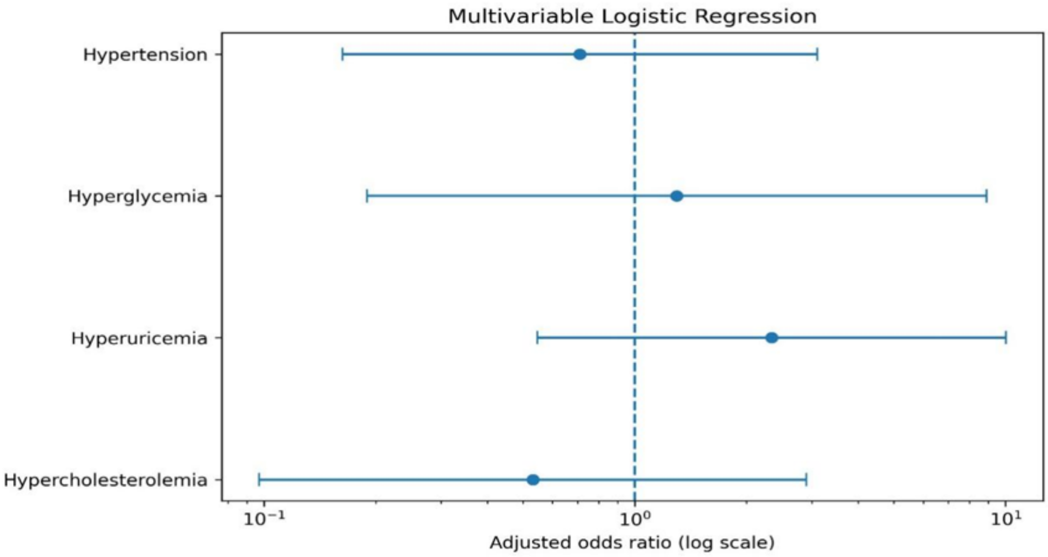

Figure 4. Adjusted odds ratios from the multivariable model
Source: Primary data analysis using binary logistic regression model (2026).

The hyperuricemia point estimate is nevertheless hypothesis-generating rather than confirmatory. A larger sample could determine whether the observed direction persists after adjustment for age, sex, refractive status, and other clinically relevant covariates. The present model should not be interpreted as evidence of a protective effect for variables with ORs below 1, because the confidence intervals are wide and cross the null.

The metabolic findings should also be interpreted in relation to the outcome definition. The outcome was a presentation of visual acuity rather than a definitive retinal diagnosis. Hyperglycemia may contribute to visual loss through chronic microvascular mechanisms, but a single random glucose measurement cannot capture duration or long-term glycemic exposure. Similarly, the study did not include fundus photography, optical coherence tomography, or a standardized ophthalmic diagnosis of diabetic retinopathy, cataract, glaucoma, or other causes of visual impairment. Consequently, the observed association structure should not be extrapolated directly to specific ocular diseases.

The previous Keputih publication reported 70 drivers and primarily described visual acuity categories, refractive errors, and non-refractive visual impairments (Izdihar et al., 2026). The present analysis differs in its research question, exposure variables, and statistical framework: it treats visual impairment as the outcome and metabolic abnormalities as candidate correlates.

Additional exploratory analyses broadened the assessment of visual function. The Spearman correlation matrix (Figure 5) showed the strongest correlation between systolic and diastolic blood pressure (rho=0.825), followed by age with systolic blood pressure (rho=0.414) and random glucose (rho=0.404). Better eye visual acuity had a weak negative correlation with age (rho=nan, p=nan), while correlations with the measured metabolic biomarkers were weak.

Figure 6 showed visual impairment prevalence of 13.3% (2/15) with no metabolic abnormality, 11.1% (2/18) with one, 12.5% (3/24) with two, and 15.4% (2/13) with three abnormalities; none of the three drivers with all four abnormalities had impairment. Thus, there was no monotonic dose-response pattern, and the four-abnormality subgroup was too small for stable inference.

ROC analysis (Figure 7) showed poor discrimination: AUC 0.588 for age, 0.522 for uric acid, 0.417 for random glucose, 0.496 for cholesterol, and 0.577 for systolic BP. Values close to 0.50 indicate limited discriminatory performance. The random-glucose AUC below 0.50 should not be interpreted as a protective effect.

Figure 8 showed a weak inverse relationship between age and better-eye visual acuity (Spearman's rho = nan, p = nan). The small effect size supports cautious, exploratory interpretation.

Figures 9–12 showed substantial overlap between visual-impairment groups. Mean uric acid was 6.40 versus 6.48 mg/dL (p=0.840); random glucose 152.59 versus 138.11 mg/dL (p=0.425); cholesterol 192.81 versus 193.89 mg/dL (p=0.973); and systolic BP 127.50 versus 132.78 mmHg (p=0.454). These differences do not indicate useful separation by any individual biomarker.

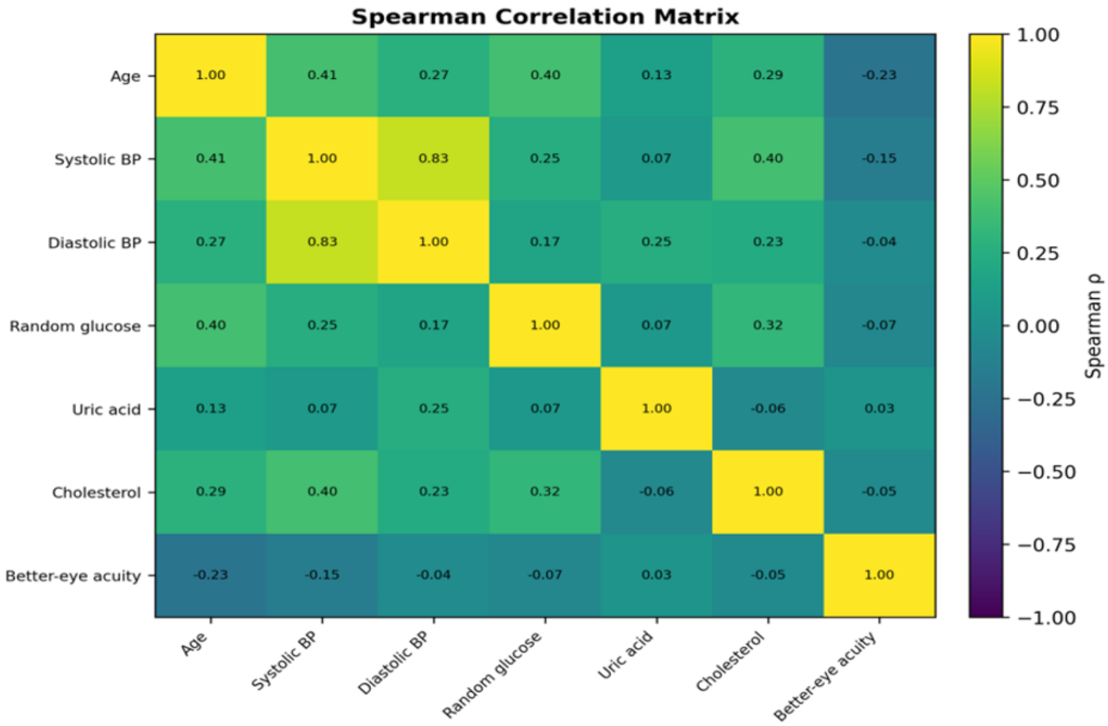

Figure 5. Spearman correlation matrix of age, blood pressure, metabolic biomarkers, and better-eye presenting visual acuity.

Source: Primary data analysis using Spearman correlation test (2026).

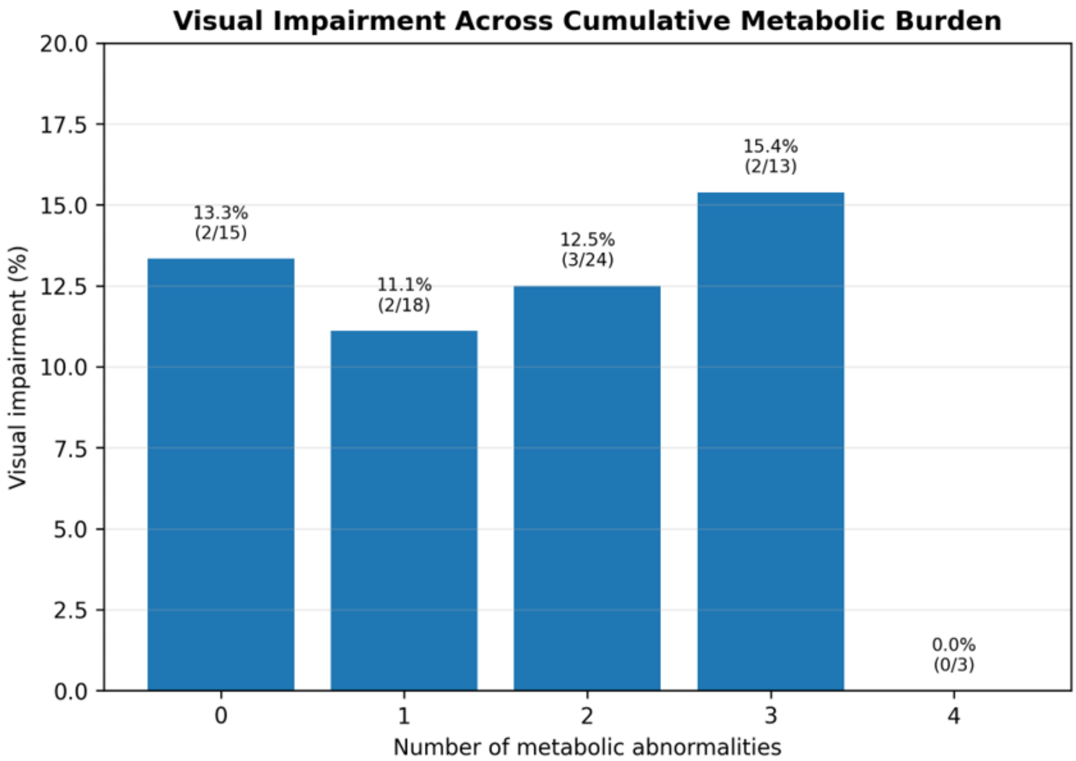

Figure 6. Visual impairment prevalence according to cumulative metabolic burden.
Source: Primary data analysis from cumulative metabolic risk assessment (2026).

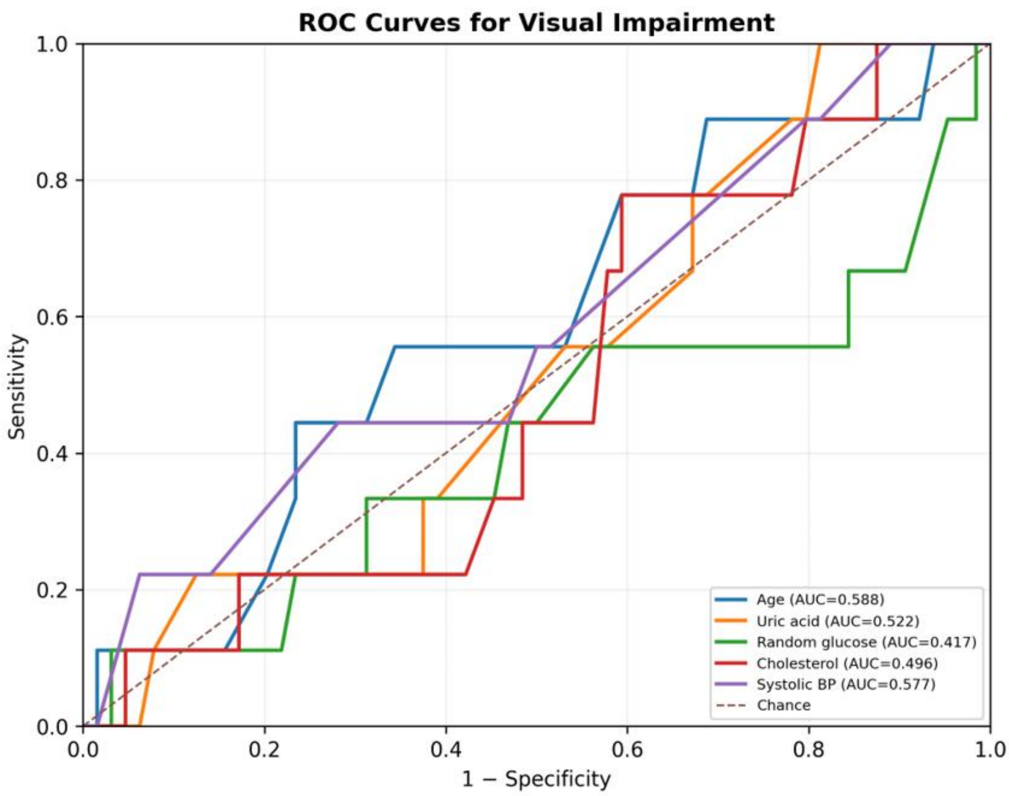

Figure 7. ROC curves for age and metabolic biomarkers in discriminating visual impairment.
Source: Primary data analysis using Receiver Operating Characteristic (ROC) analysis (2026).

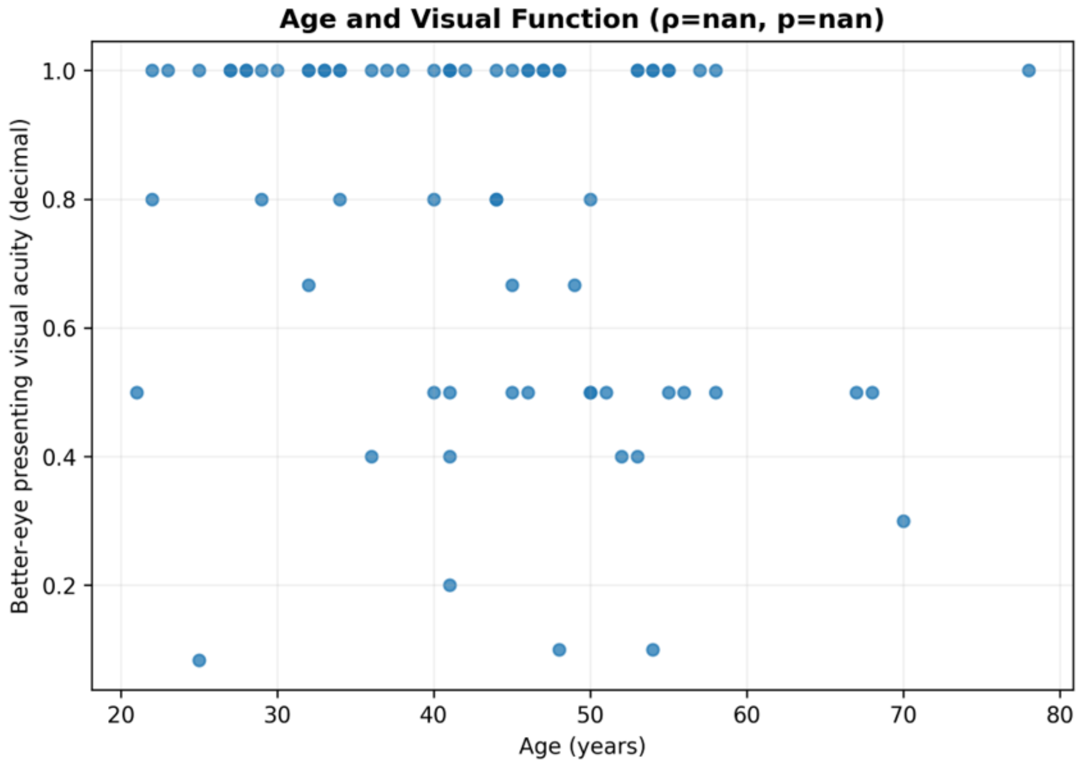

Figure 8. Relationship between age and better-eye presenting visual acuity.
Source: Primary data analysis from visual acuity assessment (2026).

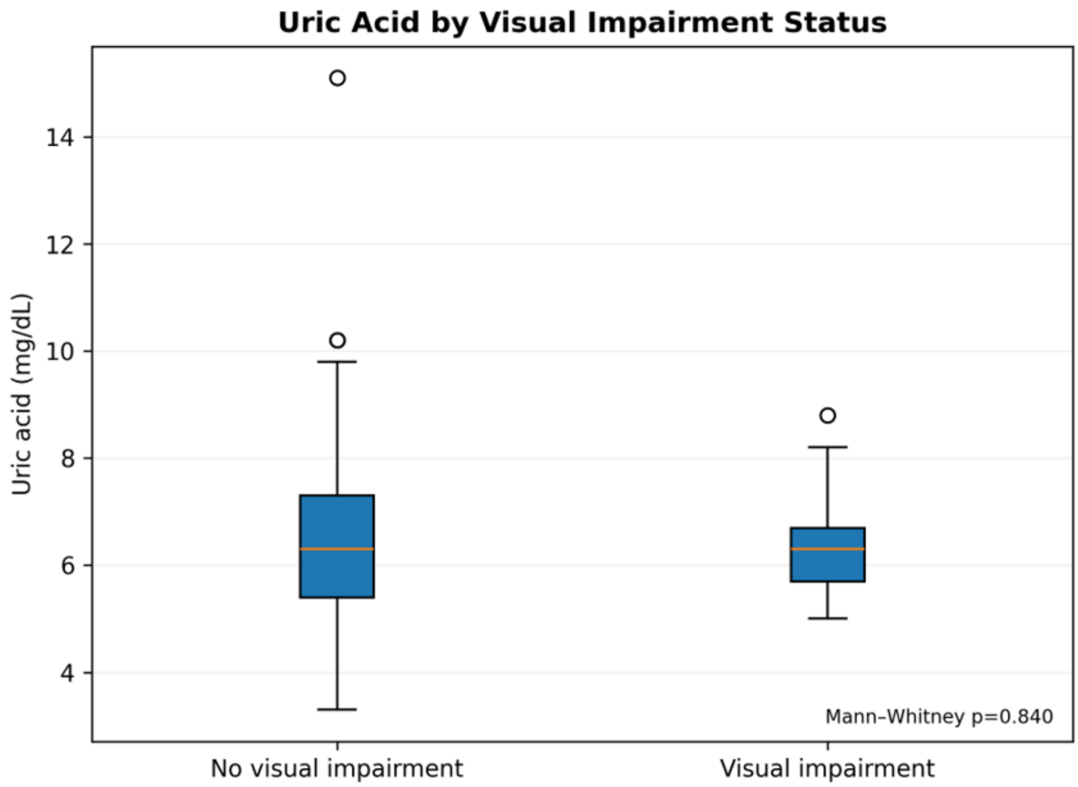

Figure 9. Uric acid distribution according to visual impairment status.
Source: Primary data analysis from metabolic measurements (2026).

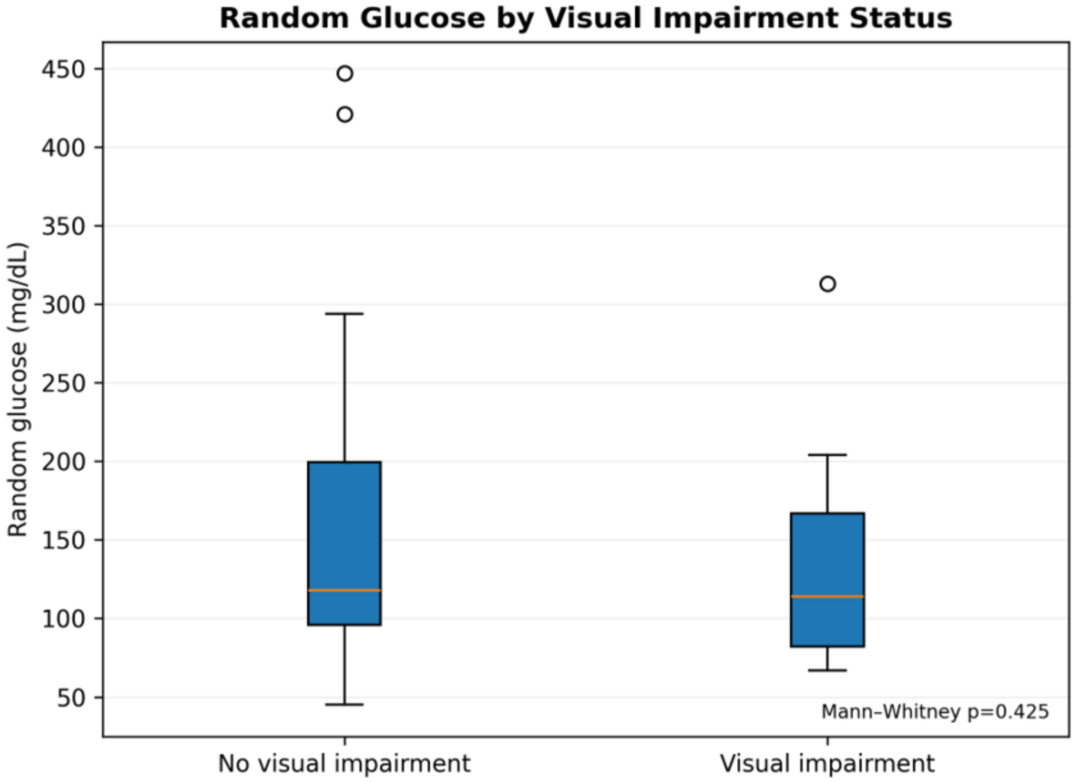

Figure 10. Random glucose distribution according to visual impairment status.
Source: Primary data analysis from metabolic measurements (2026).

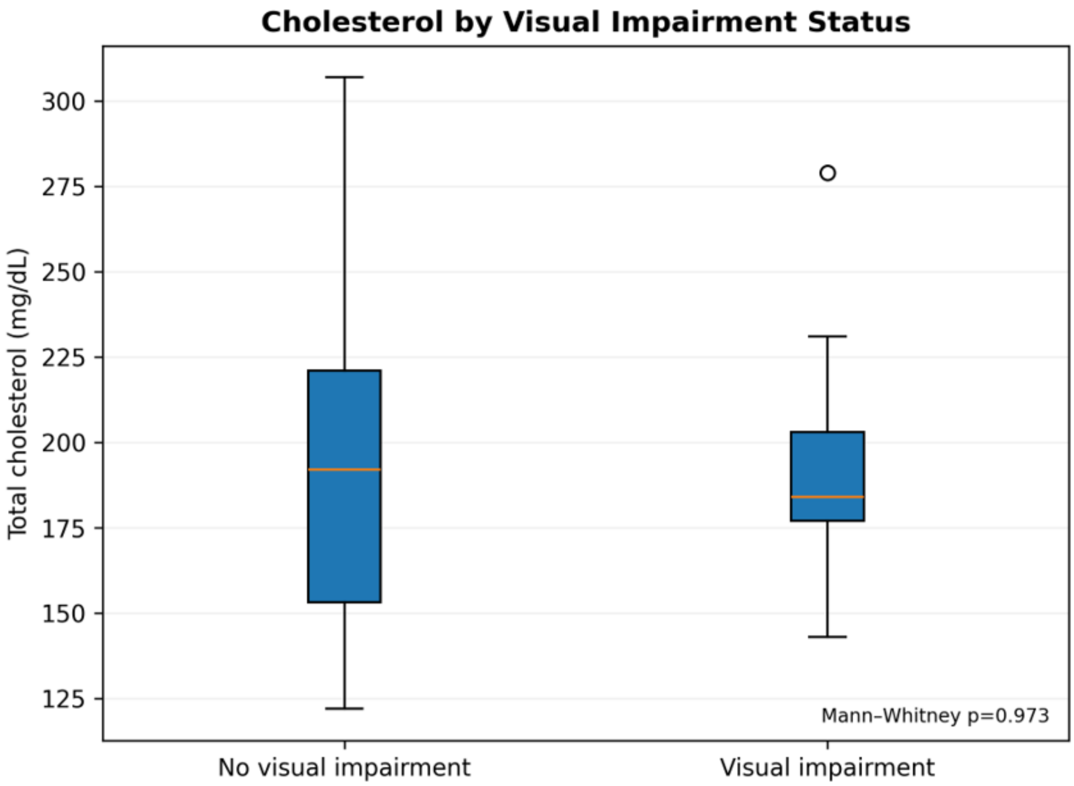

Figure 11. Total cholesterol distribution according to visual impairment status.
Source: Primary data analysis from metabolic measurements (2026).

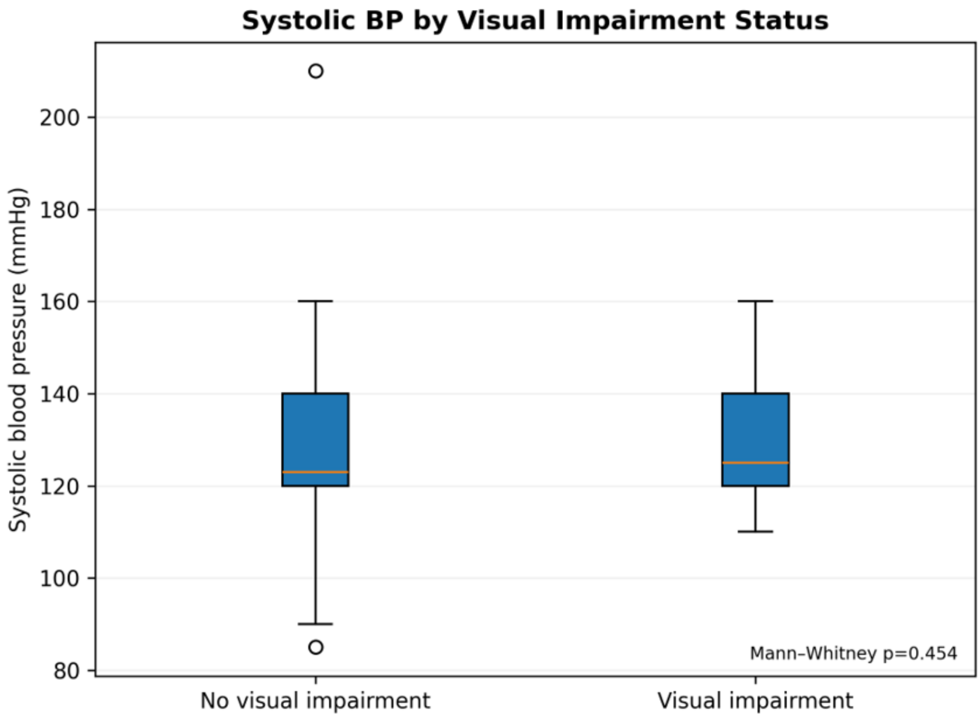

Figure 12. Systolic blood pressure distribution according to visual impairment status.
Source: Primary data analysis from metabolic measurements (2026).

Several limitations affect interpretation. The cross-sectional design prevents causal inference. Only nine visual-impairment events were available, resulting in imprecise estimates and limited power for a four-predictor logistic model. Metabolic classifications were based on single measurements rather than repeated measurements or long-term biomarkers such as HbA1c. The dataset also lacked comprehensive ophthalmic diagnoses and several potential confounders. Finally, the sample was drawn from one occupational setting and may not represent all ride-hailing drivers.

Despite these limitations, the study provides a useful preliminary analytical signal. The 12.3% prevalence of visual impairment supports the practical value of occupational vision screening, while the high prevalence of metabolic abnormalities suggests that integrated health screening may be relevant for this population. Future studies should use larger samples, prospectively defined ocular outcomes, repeated metabolic measurements, and multivariable models with sufficient outcome events.

CONCLUSION

Visual impairment was identified in 9 of 73 ride-hailing motorcycle drivers (12.3%), while metabolic abnormalities were common, particularly hypertension (50.7%) and hypercholesterolemia (46.6%). Exploratory correlation, cumulative burden, ROC, and groupwise analyses did not demonstrate a consistent or strong association between the measured metabolic markers and visual impairment. Age showed a weak inverse correlation with better-eye visual acuity, whereas individual metabolic biomarkers demonstrated poor discriminatory performance. Hyperuricemia had the largest adjusted odds ratio (aOR = 2.34); however, its confidence interval was wide and included the null value. Therefore, the findings indicate a clinically relevant burden of visual and metabolic health issues in this occupational group but do not establish independent metabolic predictors of visual impairment. Larger studies with sufficient numbers of visual impairment events, repeated metabolic measurements, and comprehensive ophthalmic assessments are warranted.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest related to the conduct of the research, preparation, or publication of this article.

AUTHOR CONTRIBUTIONS

All authors contributed to the preparation of this article. William Sayogo, Victor Setiawan Tandean, Minarni Wartiningsih, Christina Destri Wiwis Wijayanti, Eveline Yulia Darmadi, was responsible for the conceptualization of the study, data collection and analysis, interpretation of the results, and manuscript preparation. The other authors contributed to the review, editing, and final approval of the manuscript.

GENERATIVE AI STATEMENT

The authors declare that no generative artificial intelligence was used in the preparation of this article.

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