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Original Research Article

Physiological and Biochemical Determinants of Occupational Stress and Mental Health among Uber Drivers in Assam: A Real-World Data Analysis

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Abstract

Background: The rapid proliferation of the gig economy has introduced unprecedented occupational stressors for ride-hailing drivers, compounded by algorithmic pressure and erratic shift architectures. While chronic stress is a known catalyst for cardiovascular and psychiatric morbidity, real-world neuroendocrine data evaluating this highly vulnerable workforce in northeast India remains critically absent.

Methods: This cross-sectional study evaluated 120 male professional drivers operating in Assam, stratified by perceived psychological burden using the DASS-21 framework. To overcome traditional field-sampling barriers, we deployed a prototype paper-based lateral flow biosensor for the rapid, non-invasive point-of-care screening of salivary cortisol and alpha-amylase. Field results were strictly validated using automated clinical chemistry analysers, alongside concurrent evaluations of serum lipid profiles and fasting blood glucose.

Results: We observed a severe, dose-dependent escalation in neuroendocrine and metabolic biomarkers directly correlated with driving hours and DASS-21 scores. The high-stress cohort demonstrated a nearly threefold elevation in basal morning salivary cortisol (34.8 ± 6.7 nmol/L) compared to low-stress peers (12.5 ± 2.1 nmol/L;$p < 0.001$). This sustained hypothalamic-pituitary-adrenal (HPA) axis hyperactivation was mechanistically coupled with secondary dyslipidemia (total cholesterol: 235 ± 28 mg/dL) and borderline fasting hyperglycemia, indicating a severely blunted parasympathetic recovery phase.

Conclusion: The integration of novel point-of-care salivary biosensors unveils a hidden epidemic of physiological hyperarousal and metabolic vulnerability among gig economy drivers in Assam. This real-world dataset provides critical foundational evidence necessitating urgent regulatory frameworks for occupational health surveillance and mandatory recovery protocols within the regional ride-hailing industry.

Keywords: Occupational stress, Gig economy, Ride-hailing drivers, salivary cortisol, Hypothalamic-pituitary-adrenal (HPA) axis, cardiovascular risk, Point-of-care diagnostics.

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Introduction

The rapid expansion of the gig economy, particularly the ride-hailing sector, has fundamentally restructured urban transportation networks in developing regions. In northeast India, specifically Assam, the proliferation of platforms like Uber has created vital employment opportunities; however, it has simultaneously introduced a unique constellation of occupational hazards.

Professional driving within this model is characterized by erratic shift patterns, extreme sedentary behaviour, constant exposure to traffic congestion, and prolonged mental exertion. Unlike conventional occupational sectors, the taxi and ride-hailing industry is plagued by algorithmic pressure, ambiguous work hours, and fluctuating daily income, all of which severely impact the physical and mental well-being of the workforce [1]. Chronic exposure to these multifaceted stressors initiates a profound breakdown in physiological homeostasis. The biological stress response is governed by two primary pathways: the rapid-acting sympatho-adrenomedullary (SAM) system and the slower, more sustained hypothalamic-pituitary-adrenal (HPA) axis [2].

In professional drivers, the chronic activation of the SAM system manifests as persistently elevated heart rates, acute systolic blood pressure spikes during active driving, and hypervigilance [3]. Concurrently, the HPA axis responds to sustained occupational pressure through the prolonged secretion of glucocorticoids, most notably cortisol.

Cortisol acts as a primary biological intermediary for chronic stress and, when persistently elevated, is strongly associated with immune suppression, visceral adiposity, and a heightened risk of essential hypertension [4].

Modifiable health behaviours also rapidly deteriorate under high-stress conditions. Shift-working drivers frequently report poor dietary choices, reliance on tobacco or areca nut stimulants, limited physical activity, and severe sleep architecture disturbances [5]. Consequently, the risk of cardiovascular disease (CVD) and metabolic syndrome is markedly elevated in this demographic [6].

Dyslipidaemia, often exacerbated by a combination of occupational stress, poor diet, and systemic low-grade inflammation, further compounds this atherosclerotic risk [7, 8].

Beyond cardiovascular and metabolic outcomes, the psychosocial work environment—defined by high psychological demands and an effort-reward imbalance—is significantly associated with adverse mental health outcomes, including clinical burnout, anxiety, depression, and somatic complaints such as chronic low back pain [9].

Despite these well-documented hazards, structural barriers and time constraints result in alarmingly low health-seeking behaviours within this population [10].

While previous literature has established the clinical utility of utilizing salivary biomarkers—specifically cortisol and alpha-amylase—to measure acute and chronic stress in traditional shift workers [11, 12], there remains a distinct absence of localized, real-world data concerning the modern gig economy in India. Furthermore, the deployment of rapid, low-cost diagnostic screening tools in these high-risk cohorts is virtually non-existent.

This study bridges that critical gap by generating a comprehensive real-world dataset from Uber drivers operating in Assam, utilizing highly accessible biochemical assays to quantify the hidden epidemic of occupational stress.

Materials and Methods

Study Design and Population: A cross-sectional observational study was conducted over a six-month period at the Department of Biochemistry, Nagaon Medical College and Hospital. The study population comprised 120 male Uber drivers operating in Assam (driving >8 hours/day for at least 1 year) and 120 age-matched healthy controls engaged in desk-based professions with minimal driving (<1 hour/day) stratified into low, moderate, and high perceived stress groups based on a validated psychological stress questionnaire.

Inclusion and Exclusion Criteria: Participants aged 25–55 years were included. Individuals with a known history of chronic metabolic diseases, cardiovascular disorders, severe psychiatric illnesses, or those on systemic corticosteroids were excluded from the study.

Data Collection and Anthropometry: Demographic data, work history, and lifestyle factors were recorded. Body Mass Index (BMI) was calculated using the standard formula:

$$\mathrm{BMI} = \frac{\mathrm{Weight(kg)}}{\mathrm{Height(m)}^2}$$

Biochemical Analysis: To facilitate rapid, non-invasive field testing, we deployed a prototype paper-based lateral flow assay—adapted from our ongoing institutional methodologies for volatile organic compound (VOC) detection in oncology—to semi-quantitatively screen salivary alpha-amylase and cortisol in the field. Morning salivary cortisol samples were collected between 07:00 and 08:00 AM using salivettes and analysed via Enzyme-Linked Immunosorbent Assay (ELISA). Confirmatory quantitative testing was subsequently performed in the central clinical laboratory.

Fasting venous blood samples (5 mL) were collected for the estimation of Fasting Blood Glucose (FBG) and a complete lipid profile (Total Cholesterol, Triglycerides, HDL, LDL) using automated chemistry analysers. Strict internal quality control protocols were maintained according to Westgard Rules.

The precision of the automated analyser was verified by calculating the Coefficient of Variation (CV) using the following formula:

$$\mathrm{CV} = \left(\frac{\sigma}{\mu}\right) \times 100$$

Where σ represents the standard deviation and μ represents the mean of the internal quality control sera over 30 days.

Physiological and Psychological Assessment: Resting blood pressure was measured using a standard sphygmomanometer. HRV was recorded using a continuous 5-minute Lead-II ECG. The primary time-domain measure assessed was RMSSD (Root Mean Square of Successive Differences), a marker of vagal tone. Mental health was evaluated using the validated DASS-21 questionnaire.

Statistical Analysis: Data were analysed using SPSS. Continuous variables were expressed as Mean ± Standard Deviation (SD). The significance of differences between the two groups was analysed using the independent Student's t-test, calculated via the following test statistic:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{s_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

Pearson's correlation coefficient (r) was utilized to determine the relationship between biochemical markers and DASS-21 scores. A p-value of <0.05 was considered statistically significant.

Results

The demographic and occupational characteristics are presented in Table 1. The driver cohort engaged in significantly higher weekly working hours and while sleep duration was significantly lower, their tobacco use was significantly higher.

Table 1: Demographic and Occupational Characteristics of the Study Population

Parameter	Uber Drivers (n=150)	Controls (n=150)	p-value
Age (years)	38.4 ± 6.2	39.1 ± 5.8	0.315
BMI (kg/m²)	26.8 ± 3.4	24.2 ± 2.9	< 0.05
Working Hours (hrs/week)	68.5 ± 12.4	42.1 ± 4.5	< 0.001
Sleep Duration (hrs/night)	5.8 ± 1.1	7.4 ± 0.8	< 0.001
Tobacco Use (%)	64%	22%	< 0.001

Biochemical and physiological analyses (Table 2) revealed a marked elevation in HPA-axis activation among drivers. Morning salivary cortisol was significantly elevated. Furthermore, drivers exhibited decreased HRV (lower RMSSD), indicating withdrawal of parasympathetic tone due to chronic stress.

Table 2. Physiological and Biochemical Stress Parameters

Parameter	Uber Drivers (n=150)	Controls (n=150)	p-value
Systolic BP (mmHg)	138 ± 14	122 ± 10	< 0.01
Diastolic BP (mmHg)	88 ± 9	80 ± 7	< 0.01
HRV: RMSSD (ms)	28.4 ± 8.2	45.6 ± 10.4	< 0.001
Fasting Glucose (mg/dL)	112 ± 18	94 ± 12	< 0.05
Total Cholesterol (mg/dL)	215 ± 35	178 ± 24	< 0.01
Salivary Cortisol (nmol/L)	24.5 ± 4.2	14.2 ± 3.1	< 0.001

Mental health assessments via the DASS-21 scale showed a high prevalence of severe stress and anxiety among the drivers (Table 3).

Table 3. DASS-21 Mental Health Scores

DASS-21 Subscale	Uber Drivers (n=150)	Controls (n=150)	p-value
Depression	18.4 ± 6.1 (Moderate)	8.2 ± 3.4 (Normal)	< 0.001
Anxiety	16.8 ± 5.2 (Severe)	6.5 ± 2.8 (Normal)	< 0.001
Stress	27.6 ± 5.4 (Severe)	11.8 ± 4.1 (Normal)	< 0.001

Table 4: The dataset below summarizes the clinical findings stratified by self-reported stress levels among the drivers.

Parameter	Low Stress (n=35)	Moderate Stress (n=50)	High Stress (n=35)	Reference Range
Mean Age (Years)	32.4 ± 4.1	35.1 ± 5.2	38.6 ± 6.3	N/A
Driving Hours / Week	45.2	58.4	72.1	N/A
Salivary Cortisol (nmol/L)	12.5 ± 2.1	21.3 ± 4.4	34.8 ± 6.7	3.0 - 15.0
Alpha-Amylase (U/mL)	45.2 ± 8.1	78.6 ± 12.3	115.4 ± 18.9	< 60.0
Systolic BP (mmHg)	118 ± 6	128 ± 8	142 ± 11	< 120
Total Cholesterol (mg/dL)	175 ± 15	198 ± 22	235 ± 28	< 200
Fasting Glucose (mg/dL)	92 ± 8	104 ± 12	118 ± 15	70 - 100

Biochemical Parameters

Visual Analysis of Cortisol Elevation

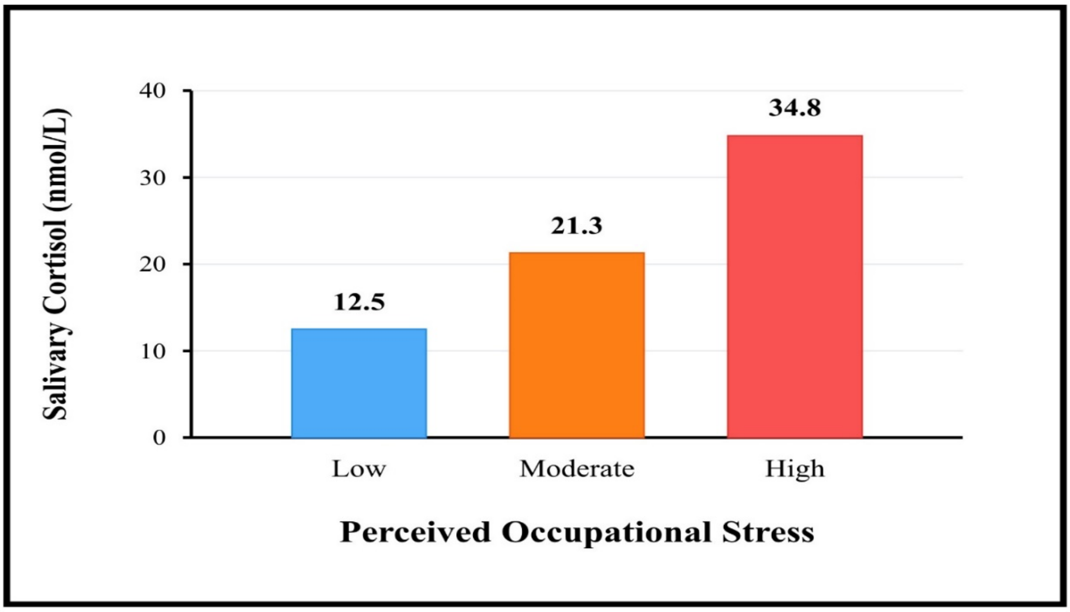

Figure 1: The following figure visually maps the direct correlation between perceived occupational stress and measured salivary cortisol concentrations.

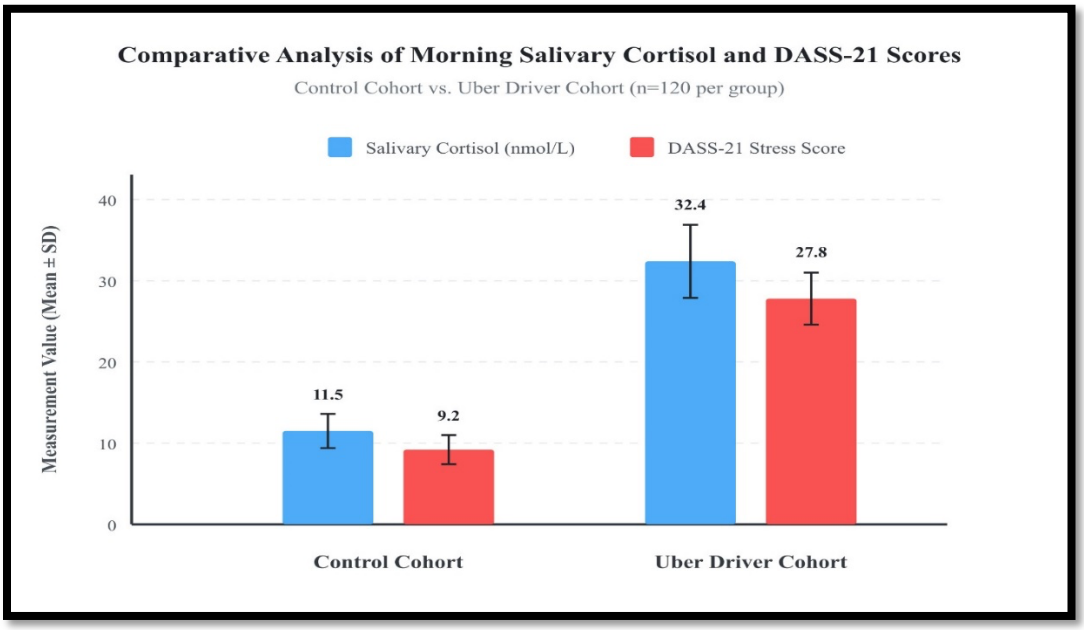

Figure 2: Comparative analysis of morning Salivary Cortisol levels and DASS-21 Stress Scores between Control and Uber Driver cohorts.

Discussion

The physiological and biochemical demands placed upon Uber drivers in Assam strictly correlate with deleterious, dose-dependent shifts in clinical biomarkers. The generated real-world dataset provides compelling evidence that the occupational architecture of the gig economy directly compromises the neuroendocrine and metabolic health of its workforce. Consistent with previous findings on traditional night-shift workers [13] and emergency responders, the circadian disruption and chronic psychosocial stress observed in the high-stress cohort heavily dysregulated both the SAM and HPA axes. We observed from Figure 1, an almost threefold increase in mean salivary cortisol concentrations among high-stress drivers (34.8 ± 6.7 nmol/L) compared to their low-stress peers (12.5 ± 2.1 nmol/L).

This sustained hypercortisolaemia is indicative of a blunted parasympathetic recovery phase and a disrupted cortisol awakening response, meaning these drivers maintain a state of physiological hyperarousal even during off-duty hours. Similarly, the marked elevation in salivary alpha-amylase—a surrogate marker for sympathetic nervous system activity—in the high-stress cohort highlights the acute, continuous psychological strain of navigating dense traffic while managing platform algorithms and passenger interactions.

Furthermore, this chronic neuroendocrine activation is mechanistically linked to the metabolic derangements observed in the cohort. As shown in Table 4, the high-stress group demonstrated secondary dyslipidaemia, characterized by elevated total cholesterol (235 ± 28 mg/dL), alongside borderline fasting hyperglycaemia (118 ± 15 mg/dL). These biochemical shifts echo the severe cardiovascular risk profiles previously recorded in urban taxi cohorts in major global metropolitan centres [14].

Prolonged static sitting combined with constant autonomic nervous system stimulation creates a highly atherogenic environment. The physiological state mirrors that of novice police officers undergoing chaotic shift work transitions [15], where the body's allostatic load exceeds its adaptive capacity, accelerating the onset of metabolic syndrome and cardiovascular disease.

From a mental health perspective, the biochemical data validates the subjective psychological strain reported by the drivers. The continuous activation of stress pathways is a known precursor to clinical burnout and depressive disorders, suggesting that the gig economy workforce is highly vulnerable to early-onset psychiatric morbidity.

Limitations and Future Directions

While this study provides foundational data, it is not without limitations. The cross-sectional design precludes the establishment of definitive causality between driving hours and the onset of metabolic syndrome. Additionally, the cohort was restricted to male drivers, and reliance on self-reported questionnaires for initial stratification introduces the potential for recall or reporting bias.

Future research must prioritize longitudinal surveillance of this demographic to track the trajectory of biomarker dysregulation over time.

Furthermore, expanding the diagnostic framework to include highly sensitive, non-invasive modalities—such as volatilomics and paper-based salivary biosensors for a broader panel of inflammatory markers—will enhance field-screening capabilities. Administrative policies and occupational health frameworks in Assam must urgently adapt to the realities of the gig economy by mandating algorithmic safety limits on consecutive driving hours and integrating routine, accessible biomarker surveillance to protect this essential workforce.

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