Understanding Driving Stress in Urban Bangladesh: An Exploratory Study, Wearable Development and Experiment

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Driving stress significantly impacts driving behavior primarily from roadside factors, where driving is more challenging in developing countries (i.e., Bangladesh) for unique cultural and infrastructural setups. We conduct an exploratory study (Qualitative n=26, and Subjective Feedback n= 80) and a correlational analysis involving professional and private car drivers in urban Bangladesh. The study reveals drivers' demography and driving stress factors on the road. These findings motivate us to identify driving stress from physiological factors by developing a low-cost wearable, Stress Wear. This can detect stress from varying Heart Rates, validated by expensive commercial wearables. Between subject experiments on drivers (total n=14 in two phases) with wearables, we also found that road factors are responsible for driving stress. Therefore, the developed system is helpful for these drivers to self-sensing their stress.

CCS CONCEPTS • HCI→ Human Computer Interaction

Keywords: Drivers, Driving Stress, Poor Road Infrastructure, Heart Rate Variability (HRV), Low-Cost Wearable, Developing Country Context

1 INTRODUCTION

Driving is a complicated task where driving stress can be initiated anytime, and it can change driving behavior [66, 73, 75]. Driving is stressful because it interacts with the drivers, vehicles, and the environment [73, 74]. Given that driving stress was discussed widely from a road safety perspective [3, 7, 8, 9, 10, 11, 12, 18], factors such as mass workload, congestion, poor road condition, interference, etc., were less investigated. These factors drive stress [85, 87, 88, 89, 90], particularly in developing countries, and worsen the situation. Existing researchers studied the impact of drivers' stress levels [66, 73, 75] and offered wearables [51, 72, 75, 78, 83, 84, 85, 86, 90, 91] as useful in stress management in the developed country context. Nevertheless, driving stress still needs to be explored in developing countries [1, 2], where driving is challenging. We consider our study in Bangladesh, where driving is challenging due to several factors. Several incidents happened influenced by aggressive driving behavior [44, 45, 47, 48, 49], implying a genuine requirement to consider driving-

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induced stress. This work deals with driving stress factors, physiological driving stress measurement techniques, and possible support systems during driving in the Bangladesh context.

Driving in Bangladesh is challenging for road conditions. Several socio-cultural and socioeconomic contexts influence it. Historically, Bangladesh has second poor road infrastructure in Asia [55, 56]. The situation is worse in overpopulated Dhaka city (the capital of Bangladesh) [58], which creates heavy congestion in the transportation system, showing a loss of 3.2 million working hours [5, 59]. In 2021, Dhaka had a minimum of 1780597 registered vehicles where unlisted numbers of vehicles are unknown, negatively impacting traffic volume, which is around two times higher than its road capacity [114]. Accordingly, 60% of licensed drivers lack knowledge regarding traffic rules resulting in rule violations on the road, and this is caused due to weak policy management [54]. Thus, congestion, unruly traffic, overpopulation, lack of attention, and less driving awareness mentioned in the recent articles [34, 52, 55, 56, 58, 60, 61, 92, 93] are the factors that make the driving environment complex and responsible for unsatisfied driving experiences. These initiate stress resulting in aggressive driving outcomes and unwanted road accidents [20, 52, 53, 57, 58, 99].

The situation shows a requirement to briefly understand the reasons behind driving stress from user studies and physiological factors in developing countries. Existing research considered HRV (Heart Rate Variability) based wearable approaches to find driving stress [72, 75, 78, 83, 84, 85, 90, 91]. Also, wearable solutions such as Empatica E4 and Fitbit [50, 102] used in some studies conducted in developed countries are expensive. On the other hand, Bangladesh's *professional drivers* belong to the lower-income group and underrepresented community and have limited technology exposure. Considering the drivers, we develop a low-cost, easy-to-use sensing wearable device that can sense driving stress considering the road factors in Bangladesh.

Moreover, this research focuses on understanding how driving stress grows among drivers and, if driving stress exists, then how it can be measured. Following the HCI design technique, we aim to develop possible technology to support the drivers in becoming aware of their stress arousal, using available and affordable technology options. The research questions here are:

- **RQ1:** What factors are responsible for driving stress in Bangladesh?
- **RQ2**: Which physiological indicator is appropriate to measure stress? And how can it be measured effectively in Bangladesh?

We first conducted an exploratory study containing qualitative (n=26) and subjective feedback (n=80) to gather information regarding drivers' discomfort reasons, stress factors, and appropriate sensors to indicate stress. These study findings suggest ways to reduce stress by leveraging bodily stress indicators in real-time [13, 14, 15, 16, 17, 18, 19]. After getting strong evidence on the connection between increasing stress with heart rate (HR), considering the drivers' socioeconomic status, we develop a low-cost wearable prototype, Stress Wear, which can sense the driving stress by analyzing Heart Rate Variability (HRV). Then we conducted real-life between-subject experiments on drivers with the prototype with the efficacy validation process with a commercial wearable, Empatica E4. The experimental results indicate that several road factors are responsible for driving stress.

The contribution of this research is two-fold: first, we studied urban drivers of Bangladesh to understand factors of their driving stress; second, based on users' feedback on such cultural context, we developed a low-cost wearable device (Stress Wear) that can identify the driving stress in real-time by analyzing Heart Rate Variability (HRV) along with the road conditions. The proposed low-cost technology support system might help drivers in developing countries with an increased level of self-awareness by understanding personal stress in real time [65, 68, 69, 85], which may play a positive role in reducing stress.

2 BACKGROUND

2.1 Driving Experience, Behavior, and Stress

Driving experiences were investigated through year-long engagement [26, 27, 28] and drivers' accident data [27] from developed countries' perspectives. Stress brings negative consequences and changes this driving behavior experience and sometimes is responsible for accidents [32, 43], which is discussed through typical driving scenarios, minute simulation, and emission analysis in previous roadside safety research [3, 7, 8, 9, 10, 11, 12, 18]. Heavy work pressure, excessive work periods, traffic congestion, and family-related problems elevate stress levels. This phenomenon influences the release of the cortisol hormone in the human body, which is responsible for many chronic diseases [22, 66, 69, 72, 82]. Stress causes irregular behavioral changes [60, 78] that also harm the driving task [32, 43] and the state of interaction between vehicles, drivers, and the environment [73, 74]. Factors on the roads, such as traffic congestion, turns, poor road conditions, narrow lanes, sudden/hard breaks, overtaking, sudden stops, etc., increase driving stress [85, 87, 88, 89, 90]. On the other hand, anger and driving stress are sometimes responsible for road crashes [84]. That is why drivers' stress affects road safety and driving behavior.

The driving patterns can define driving behavior (e.g., turn, slow-down, speed, etc.). Researchers tried to classify new patterns as extrinsic (e.g., traffic data, road conditions, etc.) or intrinsic (e.g., the personality of the drivers, distraction, etc.) [70]. The driving decisions are related to many parameters, such as speed, traffic congestion, vehicle features, road network topology, driving plan, driver's demography, experience, patience, stress, etc. This makes driving behavior complex. Poor driving behavior distracts drivers and increases reaction time, and in the long run, brings stress towards negatively affecting the driver's overall health [6]. The driver's mood often positively affects driving behavior and experiences [4, 21, 22]. In contrast, bad attitudes sometimes initiate stress, which can change anytime (e.g., the mood improves while listening to music [23]. Researchers also showed that physiological changes potentially change the driver's mood and behavior [24, 25].

Based on past research, it is demonstrated that exploring driving behavior and experience will be a significant study in Bangladesh regarding road safety, specifically where the driving experience is different [108]. The probabilities of traffic rules violation in Dhaka city has been studied previously [4]. Our research work is different from others. We explore driving behaviors and develop stress indicators and factors related to the existing literature. Finally, we develop a low-cost wearable considering the drivers' community that can measure physiological stress and might help the drivers understand their stress in the long run.

2.2 Physiological Stress Indicators

The HRV (Heart Rate Variability) is a successful indicator of measuring stress [75, 76]. Stress is measured by irregular RR intervals (distance between the peaks in two R waves) in HRV [75, 77], whereas HRV is measured in millisecond units from HR (Heart Rate) BPM (Beats per Minute) data. It is considered that the user with lower values of HRV is more stressed [29]. HRV brings a fight or flight response in drivers, and then this HRV is considered a significant indicator of stress [32, 46]. According to the American Heart Association, stress releases the 'Adrenaline' hormone in the human body and boosts heart rate [62]. Poor value of HRV initiates cardiovascular diseases, and around 31% of people die worldwide [71, 72]. The correlation between HRV and user Divergent Thinking is analyzed, where HRV is the critical factor in monitoring physiological states. However, a very close relationship between HRV and neural activity changes emotions [80, 81]. HRV history can predict the user's next stressful period.

Skin conductivity is another parameter to measure stress. It changes due to the sympathetic nervous system's activity, representing an emotional state. So, when the sympathetic nervous system is activated, the plantar and palmar sweat glands fill, and a continuous wave of conductance occurs [94, 95, 96, 97]. Skin conductance is linked to blood pressure and HRV [98]. Blood volume is assessed at the skin surface and is directly related to HRV when it increases. Skin conductance also increases, which refers to stress [100, 101]. In our research work, we also consider HRV to analyze the driving stress by collecting heart rates through a low-cost affordable developed device.

2.3 Experiment and Technology Interventions

Researchers conduct qualitative and subjective feedback studies to reveal the drivers' stress levels [84]. Many research works focus on identifying stress, personality, driving behavior, driving experience, etc. DAT (Driving Aptitude Test) is a test to understand driving behavior, intellectual skills, and the driver's assessment by considering traffic conditions, car following situations, etc. [74]. 'DriveContext' is a framework to characterize the correlation between driving behavior and traffic conditions [70]. Some researchers use driving simulators to analyze the driver's level of attention, fatigue state, and stress state. Biological signals such as Heart rate detect stress [51, 86]. Another similar research with over 68 participants was conducted inside a driving simulator in the same road conditions to understand how driving behavior varies among drivers. They observed Electrodermal Activity (EDA), HR, respiratory rates, and facial expressions to understand driving behaviors and stressors responsible for car crashes [42]. sVRI (Stress-Induced Vascular Response Index) measuring system is a PPG-based system (photoplethysmography) that uses HRV to identify mental stress and cognitive load [83]. HRV is widely used to monitor stress. An RFID-based (Radio Frequency Identification) HRV monitoring system is developed to extract stress [72]. Another experiment reveals the stress level variability in open and tunnel roads by measuring their HRV [84]. In recent years, wearables have become very popular, and sometimes they are designed to monitor HRV and get the stress level. A mobile-based system, 'StressWatch' extracts stress from HRV where they considered PPG (photoplethysmography) sensors to measure HRV, and through a history analyzer, they showed the correlation between stress and HRV [78]. The developed VVRRM real-time accelerometer-based automobile system monitors the HRV during driving [75]. The 'STRESS' is similar stress measuring unit through GPS data using mobile computing [85]. A wearable butterfly named 'MoodWings' was developed as an early stress warning system by analyzing the stress level from HRV metrics [90]. The MIT Media Lab researchers also use HRV to find driving stress [91].

The road infrastructures in South Asian countries are not driving-friendly [108], and traffic rules are often violated, as has been understood by the violation behavior model [110]. At this point, some extensive research shows the importance of understanding road behavior and improving road traffic environments through technological interventions designed with sensors and mobile phones instrument sophisticated vehicles [36, 37].

State-of-the-art simulators [35], etc., are used to collect data. However, those solutions are not deployed to the lower-income community. For example, for better traffic management and understanding of traffic patterns in India, researchers tried to monitor traffic density and speed through image processing tools [109].

Similarly, another low-cost technology approach was explored to estimate traffic density and speed through honks that collected wireless-enabled sensors [38], but installing roadside sensing infrastructure in a developing country is not feasible. On the other hand, mobile devices are used to understand road conditions [39] and record drivers' videos in real-time to understand their attention level [40, 41]. Smartphone camera-based AutoRate is a system that can identify facial expressions and the use of mobile phones during driving [111]. Through these works, some suggested technology interventions, such as making datasets through computer vision techniques, automated driving license techniques, autonomous driving, etc., that can bring road safety and a good environment in developing countries. Some other research [3, 4] and these research works focus more on understanding driving patterns and car monitoring in developing countries. Our research is different. We explore the driver's perception of understanding the driving experiences of Bangladeshi drivers as a complementary study to existing efforts. Then we identified driving stress from physiological factors that initiate from the current factors on the road through a low-cost wearable technology that might help drivers to change their driving behavior.

3 STUDY, DESIGN AND EXPERIMENT

This study aims to understand driving stress and driving behavior through a user study and real-life experiment in the wild setting in the context of Bangladesh, which was unexplored. For this study, we consider the drivers' community in Bangladesh, the low-income [112] group, and non-users of commercial healthcare wearables. We studied them in several phases by running two interview studies to identify the driving stress-causing factors and stress behaviors. For the experiment, we design and evaluate a minimalistic low-cost wearable system to identify the stress between subject settings from physiological factors in real time that might help drivers understand their stress. We have conducted this study in the following phases.:

- Phase I: Exploratory study
    - Qualitative Study
    - Subjective Feedback Study
- Phase II: Prototype Design
- Phase III: Experiment

3.1. Phase I: Exploratory Study

The exploratory study has two dimensions. The qualitative study brings discomfort, stress intensity, and stress indicators on the road during driving from *participants' voices, and self-reported entries* by subjective feedback study brings the intensity of the stress. This study then motivated us to know the stress from physiological indicators, where we designed a minimalistic prototype for low-income drivers. At the beginning of the exploratory analysis, we conducted a small-scale qualitative study among n = 26 drivers to know the overall discomfort factors during driving. Then, a subjective feedback study with n = 80 gives us an idea about the particular stress indicators, intensity, and traffic rule violations. These findings help to develop the prototype as we have understood the desired and required components to detect the stress factors initiated from the road, mentioned in Table 2. In the following subsections, we discuss them briefly.

3.1.1 Qualitative Study and Outcome

Study Method of Qualitative Study: The qualitative study aims to explore factors that impact the drivers' behaviors. We contacted 26 participants; two were female, and their ages ranged from 20 to 50 years (mean = 35, SD = 12.9). Among the participants, there were professional car drivers (n=8), private car drivers (n=8), and rickshaw pullers as participants (n=10). We chose professional and private car drivers because we could recruit them quickly rather than other drivers such as bus or truck drivers. On the other hand, we focused on talking with some of the rickshaw pullers as they are an integral part of the multimodal traffic in Bangladesh. Rickshaw is one of the most accessible and in-the-moment public vehicles in Bangladesh. We had individual discussions with 24 male participants and an FGD (Focus Group Discussion) with two female participants. Female participants were low in the study, as in Bangladesh, driving a car by women is culturally rare. We invited them to join FGD to ensure their utmost comfort zone, as women usually do not feel comfortable attending somewhere alone in Bangladesh. We recruit professional, private, and female car drivers through known close connections from relatives, friends, and colleagues. We shared our research objective with the close relationships, and they helped us to connect the drivers. For the rickshaw pullers, we randomly recruited them; self-interested pullers talked with us about knowing the research objective. We chose a semi-structured qualitative method as it helped to collect daily stories through interactive discussions regarding driving behavior and experiences. The discussion covered participants' age, name, lifestyles, daily driving hours and time management, factors of discomfort during driving, road conditions, and the relationship between drivers on the road. We have understood their daily driving pattern, discomfort factors, and road conditions.

Each discussion was around 20 minutes long in Bengali and audio-recorded, transcribed, and translated into English for analysis. A total of 9 hours of records have been transcribed. The Inductive content analysis method was followed to code the collected data that started with open coding [103]. The authors jointly coded each transcription and devised such codes as traffic jams, overtaking, passenger interferences, obstacles by pedestrians, power dynamics, etc., which were common in all discussions. We considered them as the discomfort factors on the road.

This research was IRB (Institutional Review Board) approved, and a social scientist familiar with the local context and language pursued the interview questions' validation. The researchers involved in the study are certified by NIH (National Institutes of Health) user study protocols. We took the consent of every participant at the beginning of the study by providing a consent form. Before starting the discussion, we summarized the research purposes to the participants. However, each participant had the independence to end the discussion without forfeiting the incentives. We keep our collected information in a locked drive; only researchers can access it. Finally, at the end of the discussion, we offered incentives to the participants. We provided a gift token worth BDT 100 to professional car drivers, private car drivers, and female drivers. For rickshaw pullers, we gave them a choice of cash BDT 100 or equivalent phone credit, which the participants willingly granted. The gifts were received with pleasantness, and they verbally thanked us. We gave gifts to friends and family members to support us in the recruitment process. We keep our collected information in a locked drive where only researchers have access to it.

Factors for Discomfort: From this qualitative study, we understood some fundamental factors, such as traffic congestion, passenger interference, and sudden obstacles, responsible for the participant drivers' discomfort, as discussed below.

Congestion: The majority of the participants mentioned their discomfort during traffic congestion. At this point, a private car driver shared his experience of discomfort situations that he said as stress, often initiated during school drop-off period as follows:

"I get stressed when there is traffic congestion out of nowhere, and it's getting late for school." - Age: 45, Male Driver, Banani, Dhaka.

Similar concerns resonated with other drivers as traffic congestion is heavy most of the day, which brings discomfort to them.

Sudden Obstacles and Passengers' Interference: Another reason came out as facing sudden obstacles drivers do not expect during driving. In Bangladesh, unruly traffic is typical. People usually do not follow and maintain the traffic signals and lanes. The pedestrians jump into the road to cross instead of using foot overpasses. On the other hand, other vehicles often overtake particular vehicles without maintaining lanes, which makes the situation more complicated for these drivers. Accordingly, a few professional drivers stated that passengers often interfere in driving decisions, which causes distraction and negative feelings. This finding is similar to the rickshaw pullers discussion as they have said that passengers always encourage them to go early and as fast as possible, which motivates them to break the law. It reflects power dynamics played between passengers, drivers, and pullers, and they mention that this is very common and accepted in the culture. A driver mentioned as:

"Passengers often shout at me, misbehave and comment on my driving. I feel irritated but cannot say anything since they can penalize me if there are complaints. Sometimes they (management personnel) do it to show their power over us (drivers)." - Age: 32. Male Driver. Bashundhara, Dhaka.

Sometimes this interference happened within the family where a young driver shared his irritation in this regard; his parents made comments on his driving behavior continuously.

"My parents continuously keep telling me how to do things that I do not like at all."- Age: 19, Male Driver (Student), Dhanmondi, Dhaka.

Through the discussions, we have found that the drivers mostly mentioned three factors: *congestion, obstacles, and interference*, which are the main reasons for their driving discomfort on the road during driving. These motivate us to understand the drivers on a large scale. We found their stress indicators, intensity, and reasons behind rule violation from all age groups of drivers in a more concrete setup through the conducted subjective feedback study that we discussed in the following subsection.

3.1.2 Subjective Feedback Study and Outcome

Study Method of Subjective Feedback Study: This subjective feedback study is the second phase of the user study after the qualitative study. We focused on understanding user-defined stress indicators along with participants' demographic information. We conducted a study process driven by a subjective feedback method for over a month. We recruited these participants randomly from five car parking locations around Dhaka city, such as Bashundhara, Tejgaon, the University of Dhaka, New Market, and Old Dhaka. These parking locations are always full of cars; drivers usually pass their idle time by talking to other drivers. We first introduced ourselves during the recruitment and clarified the research objectives. Self-interested drivers participated in the study. All the participants were male drivers, and their demographic status was similar to the qualitative study participants as they were all professional drivers. There were no repeated participants from the qualitative study. Their age range varied from 18 to 64 (n = 37, Age 18-30; n = 31, Age 31-40; and n = 20, Age >40). We did not find female drivers for the subjective feedback study, as female drivers were unfamiliar with Bangladesh.

The participants completed a questionnaire developed by Bangladeshi sociologists, psychologists, and HCI researchers, followed by DBQ (Driving Behavior Questionnaire) by Reason et al. [113]. The questionnaire contains 24 questions; Stress (10 questions) segments and Demography (14) (added in the appendix A.2). The participating drivers self-reported their information in the questionnaire, where sometimes participants added other factors that helped to identify the factors of stress (question sample added in Appendix). In the stress questionnaire segment, a few questions were a measurement of feeling stressed using a scale ranging from -2 to +2, indicating a feeling of very bad (-2), bad (-1), neutral (0), good (+1), and very good (+2) respectively. Here -2 denotes high intensity, and +2 indicates low intensity for stress. They were asked to mark indicator values. In addition, there were a few questions where participants wrote down the Reason behind stress and the breaking of traffic laws.

For each driver, it took around 15-20 minutes to fill up the questionnaire with the help of the researcher; however, participants were independent of the entries. When a driver faces a problem understanding any question, the researcher helps them understand it. Around 30 hours of fieldwork was done to conduct this study. Then the authors moderated all these findings of 80 drivers. Through the research of self-reported entries in the stress segment, the authors found the highest intensities for five parameters: congestion, presence of an obstacle, interference of passengers, Hunger, and Breaking of law that causes stress. We consider their self-reported entries to formalize the findings of this study.

Ethical considerations were followed, similar to the qualitative study discussed earlier in 3.1.1, and each driver was offered BDT 100 in cash, which was the same as the qualitative study, and they verbally thanked us. This study is also IRB-approved, and the same qualitative research researchers conducted this phase of research. Before performing this research, we explained the objective to them for transparency. We did not recruit any drivers who were not interested.

Stress Indicators: Findings from subjective feedback reveal the major stress indicators of driving. We focused on understanding elements that introduce stressful conditions for drivers. Drivers self-reported three reasons that caused stress, such as *congestion, the presence of unexpected emergencies, and long signals*, which are common indicators with the outcomes from qualitative findings.

Stress Intensity: Drivers self-reported their various parameters in the stress questionnaire. Usually, these drivers drive 12 hours daily (S.D. = 3.19). Figure 1 shows the heat map drawn from the data that most drivers marked about stress (indicated with pink or red) compared to lower levels of stress (shown in two different shades of blue). Figure 1 shows columns C, O, I, H, and B. They indicate Congestion, the presence of an Obstacle, Interference of passengers, Hunger, and Breaking of traffic law. It is observed that more than 60% of the drivers experienced negative intensity on particular five factors.

A significantly lower portion of 18% of the drivers reported a positive experience; others preferred to mention their experience as neutral. It is identified that these factors mostly initiate stress among drivers. We found that drivers reported breaking traffic rules under various circumstances (Figure 2).

Reasons behind Traffic Rule Violation: The participated drivers (n=80) individually reported various causes behind breaking the traffic rules under varying circumstances where the magnitude intensity is presented on the y-axis: 0 (minimum) - 5 (maximum), as shown in Figure 2. Here 0 denotes the slightest interest in breaking the traffic rules, and 5 represents the high interest in breaking the traffic rules. Congestion was the primary reason reported by the majority of the drivers for violating the traffic rule. Next, we found the employer's request, which means employers often influence them to break the law. Lastly, we have discovered hurrying to reach a place and trend following (following the behavior of what other drivers are doing), but a few participants mention these reasons. However, other reasons, such as emergencies, dropping kids off at school, etc., were unimportant. Drivers consider their reasons valid and use them to justify traffic rule disobedience. Asking about this was necessary as the reasons behind traffic rule violations initiate discomfort among the drivers, which further refers to stress.

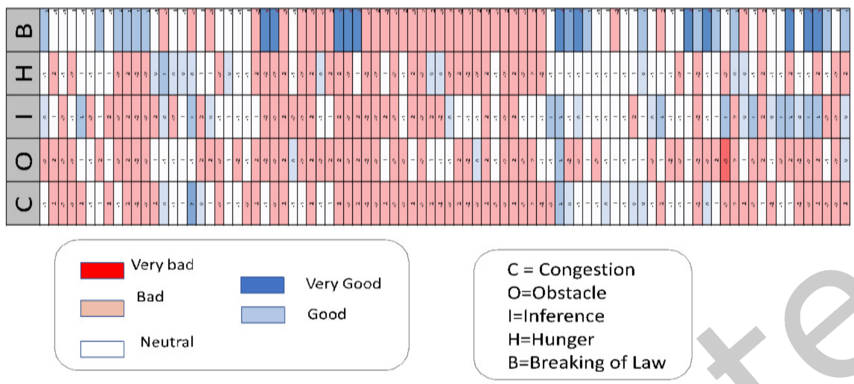

Figure 1: The Intensity of Stress in Heat Map from n=80 Drivers' Entries

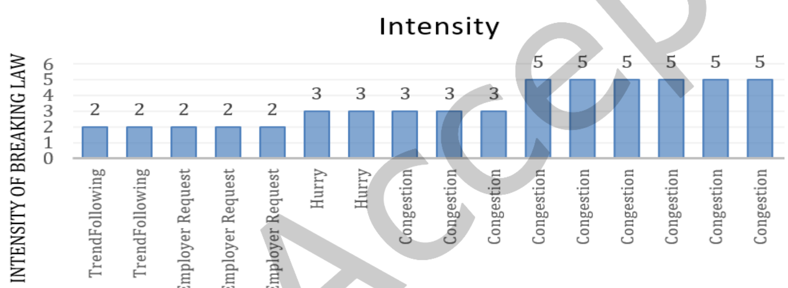

Figure 2: Self-reported Reasons for Breaking Traffic Rules by n=80 drivers (1 column = 5 drivers)

Correlational Analysis from Subjective Feedback: As the correlation coefficient can be biased, we preprocessed the data if the assumptions to use a coefficient calculation method are not satisfied. We checked whether there was any outlier in the data calculating the z-score. When the absolute z-score was above 3, we considered that as an outlier [115]. Besides, we explored the data distribution using the normaltest() of scipy [116], based on D'Agostino and Pearson's tests, where both the skewness and kurtosis test methods are used. As our data contained outliers or normally distributed data, we did not use the parametric method for finding the correlation coefficient. Instead, we used the nonparametric Spearman method, which is less sensitive to outliers [117].

There were some missing heart rate values in the case of a participant. Since we already had thousands of data points for each of the participants, we did not impute those missing values. Instead, we excluded the rows having missing data so that the calculated correlation coefficient becomes precise. Besides, there were 4 participants for whom the data regarding the living status with family were unavailable. Before doing the correlation analysis regarding the variable "Lives Without Family", we also removed those participants' data.

These drivers have mostly reported congestion; we consider it a correlational analysis with stress and drivers' demographic factors. In Table 1, we have presented some Spearman's correlations for 80 drivers between Stress (Variable 1) and Congestion (Variable 2) according to three demographic factors, and all have significant positive relations. It is noted that without any demographic condition, stress initiates during congestion. We found r_s = 0.336, p=0.0208 for older drivers (age >30), which shows that older drivers are stressed more. On the other hand, the drivers who lived alone also had much stress. However, we do not find significant relations between these variables and other demographic factors.

We also found that because of stress, these drivers break traffic laws intentionally. Breaking the traffic law is one of the activities aggravated by driving-induced reasons, personal reasons, or both**.** We tried to understand the relationship between Congestion (Variable 1) and the Breaking of traffic law (Variable 2) according to drivers' demographic factors in Table 1. Without any demographic condition, all the drivers tend to break the law during congestion (r_s = 0.258, p = 0.021). We also filtered the young drivers (age < 30) before the correlation had less tendency to break the law, whereas the drivers who were experienced in driving for more than ten years they break the law most (r_s = 0.344, p = 0.046). The drivers who lived without family also tended to break the law (r_s = 0.418, p = 0.0193). These findings show that the drivers are stressed as well.

Table 1: Correlation between Stress and Congestion and Congestion and Break Law

Variable 1	**Variable 2**	**Demographic Factor**	**N**	**Corr. Coef.**	**P**
Stress	Congestion	No Condition	80	$r_s = 0.227$	0.043
Stress	Congestion	Age < 30	47	$r_s = 0.336$	0.0208
Stress	Congestion	Lives Without Family	31	$r_s = 0.393$	0.0285
Variable 1	**Variable 2**	**Condition**	**N**	**Corr. Coef.**	**P**
Congestion	Break Law	No Condition	80	$r_s = 0.258$	0.021
Congestion	Break Law	Age > 30	33	$r_s = 0.305$	0.0839
Congestion	Break Law	Driving Experience <= 10	34	$r_s = 0.344$	0.0463
Congestion	Break Law	Lives without family	31	$r_s = 0.418$	0.0193

This exploratory study helps us understand the discomfort factors such as congestion, obstacles on the road, and passenger interference, which were consistently mentioned throughout the exploratory study. The correlational analysis shows how such factors as variables significantly correlated with drivers' demographic characteristics. However, all these factors are self-reported by the participating drivers, who face them regularly. These issues motivate us to understand their stress according to the mentioned road conditions from physiological indicators. We developed a low-cost wearable to identify the focus from physiological indicators after a specific evaluation process because existing wearables inspire us to specify the desired components for the prototype.

3.2 Phase II: Prototype Design

In phase II, we discuss wearables for ground truth consideration, the prototype design requirements we achieved from phase I, and the development process of minimalistic wearables considering the low-income driver's group, which they might use in the future. Before developing, we used Empatica E4 [102] wearable as ground truth to observe the driving stress in road conditions using multiple sensors in real-life settings. The usage of this wearable gives us a clear idea about the design implications for a minimalistic prototype. Finally, we developed a low-cost wearable, Stress Wear, considering the outcome of the exploratory study and the Empatica E4 wearable.

3.2.1 *Empatica E4 Wearable for Ground Truth*

We observed the driver's stress level using multiple parameters. We considered a commercial wearable Empatica E4 [102] (as shown in Figure 3) our *ground truth* for further exploration. We chose Empatica E4 for the validation rather than any medical device (e.g., EKG) as it is extensively used by researchers across the globe and has clinical quality observation in biometric data [23, 102]. This wearable device handles four different sensing modalities: a photoplethysmography (PPG) sensor in charge of measuring heart rate (HR), a 3-axis accelerometer sensor that measures orientation, a temperature sensor, and an electrodermal activity sensor that collects skin conductivity/Electrodermal activity (EDA). However, accelerometer values from Empatica E4 represent the value for hand movements where we are interested in understanding the vehicle's movement. That is why we also used accelerometer values provided by the smartphone.

A total of n=7 individuals (4 drivers and three passengers) used this wearable on the roads. This experiment was a real-life between-subject (one subject is a driver during the driving condition, and another is a passenger during the riding condition) in a runaway condition where time is the independent variable. We recruited passengers only to understand the difference between drivers' and passengers' physiological indicators changing according to the same road conditions (experiment on Dhaka city roads on a regular working day) simultaneously. This experiment helps us understand how driving with external factors initiates stress. The results are discussed in Section 4, and Figure 3 shows that a driver is wearing Empatica E4 while driving).

3.2.2 *Design Implication*

We consider congestion, sudden obstacles, and passenger interference factors from the exploratory study and try to analyze physiological indicators of such factors on the road to detect the presence of stress using sensing elements (as briefly presented in Table 2). The ground truth experiment found that heart rate (HR) significantly changes through road conditions, which we discuss in section 4. That is why we are motivated to collect heart rate (HR) as a physiological indicator (because HRV from HR is closely connected to stress). Accordingly, for understanding the congestion and sudden obstacles through GPS positioning, accelerometer, and magnetic field values. These understandings were vital because they helped to analyze stress during driving.

Figure 3: Empatica E4 Wearable in Use

Table 2: Required Design Components for Design Implication from Exploratory Study

The outcome of the Exploratory Study	Desired Components	Design Implication
Congestion	Understanding the traffic congestion of Roads	GPS positioning component
Obstacles on road	Detecting Real-time obstacles points on the road.	Accelerometer and Magnetic Field values as reading components
Physical Discomfort (initiate from roadside environments and other factors)	Driving Stress Indicator	Heart Rate and HRV and Heart Rate Variability
Any Supportive unit	Stress Monitoring	Real-time stress detection and feedback to reduce stress.

3.2.3 Design and Development of Stress Wear Wearable

We explored commercial devices [23, 50] for our studies to maintain standard practices of ubiquitous computing. Existing literature and experiences using the Empatica wearable gave us a clear direction toward using HR (heart rate) and sensing HRV as the external environmental indicators. Further, considering the low-income community, we developed a sensing system, Stress Wear, and validated it with available wearables.

Stress Wear Wearable: This research is inspired by prior work on low-income communities [33]. This prototype uses PCB (Printed Circuit Board) to significantly reduce the components' size. The compact packaging is shown in Figure 4. The early designed prototype could have been more user-friendly and had many flaws, and then through the HCI development process, we came up with a user-friendly prototype [21]. This new prototype consists of a Grove - Ear-Clip Heart Rate sensor [104], a well-accepted commercially available sensor that can perform with Arduino and Raspberry Pi platforms. This heart rate sensor is susceptible to low power consumption and is entirely RoHS compliant [105]. The wearable also contains a Bluetooth Module HC06, which helps connect this wearable to a developed smartphone application on an Android device to send the collected data. This device is powered by a rechargeable Lithium Polymer (LiPo) battery that can power up to 90 mins in a single fully charged cycle.

Figure 4 shows the wearable, implementation, and smartphone applications. In this wearable, we have used Arduino mini to operate the system. Heart rate (HR) sensors, Bluetooth module, rechargeable battery, and charger module connect in the Arduino that we have compiled in a small box. During the experiment, the heart rate (HR) sensor connects to the ear to collect heart rate (HR), as previous research collects physiological data in the same manner [79]. A smartphone application that performs with Stress Wear wearable is compatible only with Android platforms and can also be installed in the driver's phone. The wearable sends the sensed data to the application in real-time. There is a color dot in the application monitoring window as a stress indicator, and when the stress increases through analyzing the data, the color indicator goes red. We integrated this smartphone application with a timestamp, GPS, accelerometer, magnetic field values, and periodic physiological data collection. Here, the wearable sends the heart rate (HR) timestamped data to the smartphone, synced with GPS, accelerometer, and magnetic field values directly collected from the smartphone's built-in Gyro sensor and Hall effect sensor. The smartphone periodically sends data to a server that can be used for long-term data analytics. This wearable uses custom-designed middleware that handles the stream data processing method. The development is worth USD 20, significantly cheaper than other commercial wearables.

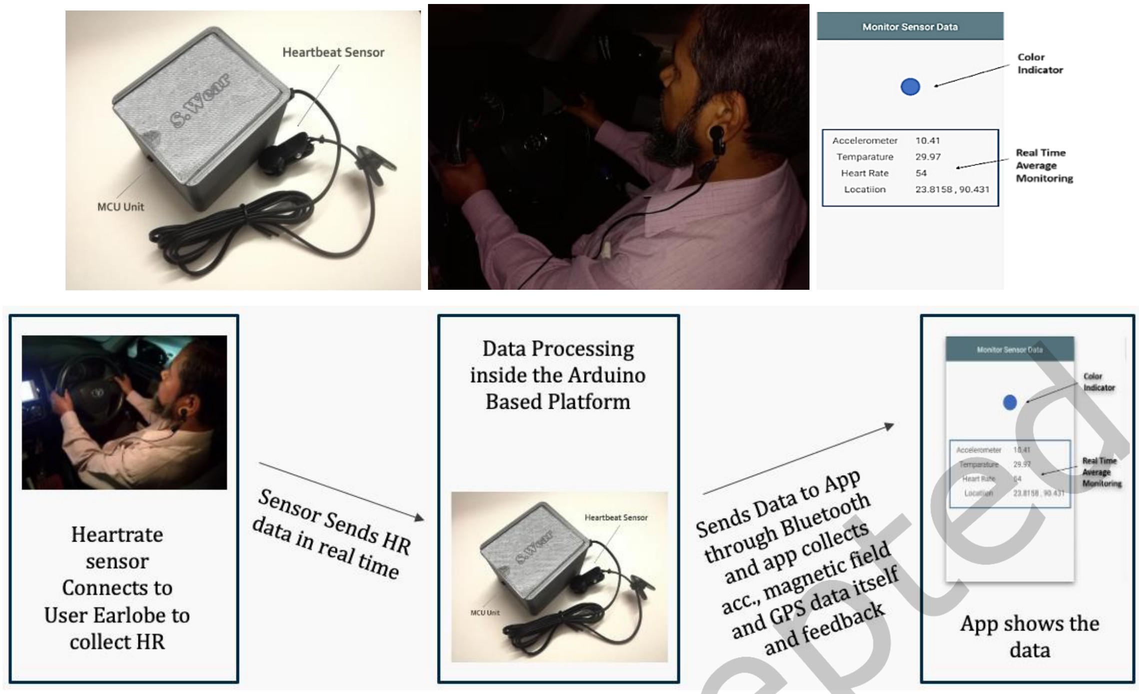

Figure 4: Stress Wear Wearable, Implementation, Smartphone Application and Activity Process

3.3 Phase III: Experiment

We conducted the between-subject real-time experiment with Empatica E4 and Stress Wear wearable to understand the drivers' stress levels in multiple routes during the test drives. Here the routes were randomly chosen where unruly traffic, congestion, and presence of pedestrians were different. We conducted test drives in natural conditions where there was no control situation. We did a between-subject experiment as the main objective is to understand driving behavior according to road conditions. Also, there was a challenge in real-life experiments with wearables in the context of developing countries with a specific population having limited technology exposure and being unknown of wearables. Using multiple wearables on a subject at a time might initiate tension or any unnatural feeling, which may increase discomfort, as in prior research in Bangladesh. Before using the wearable, researchers had to take concerned authorities' permission and discuss wearable functions several times with the participants [106]. We faced a similar problem here as such experiments are not commonly practiced in this region. We focused on between-subject experiments to keep participants in their comfort zone. Also, through this phase, we validate the Stress Wear wearable with Empatica E4 to identify the effect of Stress Wear on the BPM (Beats Per Minute) unit's heart rate (HR) value. We found the maximum standard deviation of error was 2.61 for the Stress Wear wearable on heart rate (HR) value.

3.3.1 Participants Demography for Experiments

During the experiment with Empatica E4, seven participants (six male and one female) traveled through various Dhaka city routes. Three passengers traveled simultaneously with four professional male car drivers in uncontrolled conditions. The age range of participants varied from 20-40 years [mean = 36, SD = 5.5]. Measuring user behavior through driving and non-driving activities took over two weeks. We recruited these participants through close connections with friends and colleagues.

We experimented with Stress Wear with seven male private car drivers, where one car driver was common in the Empatica E4 experiment. However, the drivers from the previous experiment (except one driver) did not show interest in participating in the second experiment but helped recruit the new drivers. Their age range varied from 30-50 years (mean = 41, SD = 6.4). They participated in 9 different test drives wearing the Stress Wear wearable.

3.3.2 Apparatus

For an experiment with Empatica E4, a passenger in the car and a driver simultaneously carried two Empatica E4 wearables on their wrists. For the Stress Wear experiment, only drivers wear the wearable. Before starting the driving task, drivers wear the wearable for a few minutes to get their regular heart rate (HR) at resting position because it is considered an HR baseline for a particular user that differs according to person. Additionally, we always used a smartphone with Empatica E4 and our developed application for Stress Wear to collect variables such as accelerometer and magnetic field values. We found significant changes in magnetic field values (μT) rather than accelerometer values (m/s2). Due to the sudden movement of different vehicles, the AMR-type magnetic sensor can detect the changes in uniform earth's magnetic field [63, 64]. Through Hall Effect sensors in the smartphone, it can detect the magnetic field by producing voltage, which is later converted into the digital signal represented by 3 axes as magnetic field intensity [65]. These set of data are also considered in correlational analysis in Table 3 and 4.

3.3.3 Dependent and Independent Variable

In our experiments, time is an independent variable. Apart from this, the dependent variables are collected Heart Rate, analyzed HRV, accelerometer values (for both experiments), and magnetic field values (for the Stress Wear experiment).

We calculated HRV from the HR values of the experiments, which were collected according to the time. There are several ways to calculate HRV from HR, such as the Time Domain method (statistical measures and geometric measures), Frequency Domain Method (Descriptive steps and Entire 24h analysis), Rhythmic Pattern analysis, and Nonlinear Method [30]. We followed Statistical steps named RMSSD (Square Root of the mean of the sum of the squares of differences between adjacent RR intervals) in the Time-Domain Method to get the HRV in millisecond units. We used the following theorem for getting the RMSSD variable for HRV [30, 31]. It is noted that the lower values of HRV indicate stress.

$$RMSSD\ (ms) = \sqrt{\begin{array}{c}((RR\ Int\ 1 - RR\ Int\ 2)^2 + \ (RR\ Int\ 2 - RR\ Int\ 3)^2 + \cdots \\ + (RR\ Int\ (n-1) - RR\ Int\ n)^2)/\ No.of\ RR\ Int\end{array}} \tag{1}$$

Here,

- RMSSD = Square Root of the mean of the sum of the squares of differences between adjacent RR intervals
- RR Int or RR Interval = inter-beat interval or the interval between successive heartbeats per minute (R denotes a peak of a beat)
- RR Int 1 = 1st RR Interval; RR Int 2 = 2nd RR Interval.
- No. of RR Int = Total number of RR intervals.

- ms = Millisecond.

3.3.4 Procedure

We conducted the experiments through approval. The institutional ethics committee approved the experiments, and we followed the legal procedure of taking permission. Then we communicated with participants separately for both experiments and discussed our research objectives. We then recruited those participants who showed their interest in joining the experiments. Informed consent was taken from all the participants. On average, two researchers joined in every test drive. They cooperated with the experimenters to install the wearables and manually log the driving conditions (e.g., congestion, roadblock, fast driving, reverse driving, resting, accident, moderate driving, etc.). Each test drive was around 40 minutes long. The driving routes covered congestion, unruly traffic, and the sudden presence of pedestrians in our study. We extracted the data for analysis that is presented in Section 4. All the drivers received a monetary incentive of BDT 300 for each test drive except the three passengers because they joined voluntarily.

4 RESULTS OF THE EXPERIMENT

This section will discuss the Empatica E4 and Stress Wear wearable results. As we understand through existing literature, HRV is closely connected with stress and its lower value, so we present our HRV analysis results. In the following subsections, we will discuss the outcomes of both experiments.

4.1 Results from Empatica E4

We collected multiple physiological parameters and analyzed data for congestion, obstacles, overtaking, resting, and hard braking conditions with Empatica E4 during the driving. We presented a visual representation of how a driver and a passenger are impacted by various driving-related factors using MATLAB in Figure 5. This graphic provides a snapshot of sensors (e.g., Heart rate, Skin conductivity, and Temperature) of Empatica E4 that react to various external traffic parameters. We extracted raw data for the same time interval and analyzed it manually. The real-time interface shows interpolated data through a live streaming interface and software graph interface, as in Figure 5.

In Figure 5, we have four subgraphs: accelerometer (m/sÂ²), heart rate (HR in BPM), skin conductivity (EDA in µS), and body temperature (°C). Y-axis is the magnitude for all subgraphs, X-axis for the HR subgraph denotes time in the second unit. The X-axis represents the total data number for the rest of the subgraphs. Here, accelerometer values are collected through a smartphone sensor in 3.3.2. We have 5750 HR values in total 5750 seconds (1:1), where at the same time, we have 11700 values for the accelerometer (2:1) and 23000 data for both EDA and body temperature (4:1). We keep the default setup for collecting data.

The regular heart rate (HR) level (resting condition as baseline) for the driver was 70 BPM, and for the passenger was 90 BPM. We identified closely that during congestion, both drivers' and passengers' HR values are highly responsive (around 120 BPM), rather than body temperature, which refers to lower HRV. At the same time, EDA (Skin conductivity) was responsive, but the responses were not equally responsive in different conditions. The road condition was bumpy, and sudden breaks increased HR (BPM). It was found that drivers' HR increased significantly, starting from 70 BPM and ending at 110+ BPM, whereas the passengers' HR started from 90 BPM and ended at 100+ BPM having the highest peak of 120 BPM once. We did a similar experiment for four sessions; the findings were identical all-time, with significant HR changes for drivers. It is also reported that congestion on the road is one of the considerable elements of stress. The overall scenario during driving and riding on the road is similar and stressful for drivers and passengers.

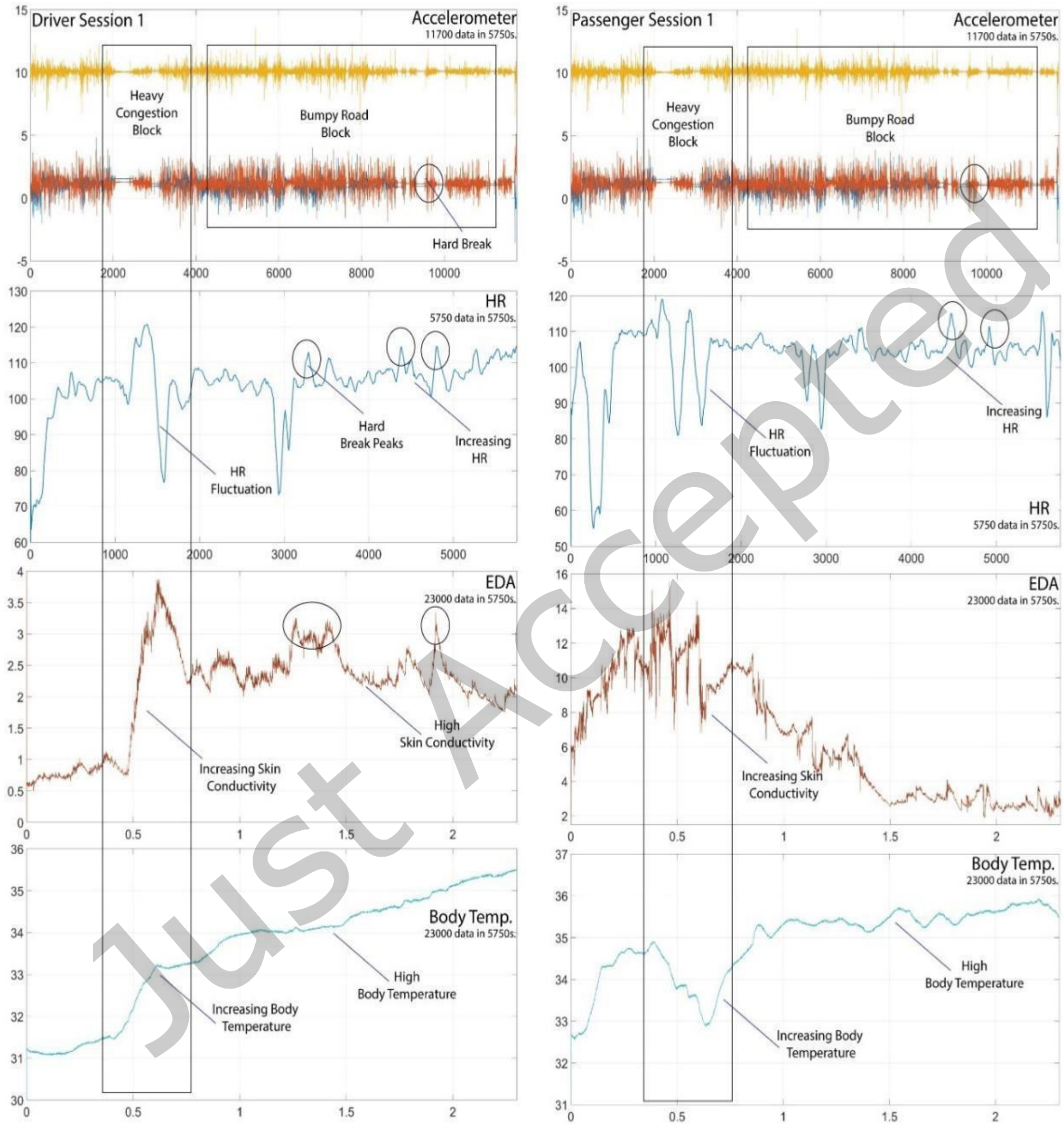

Figure 5: Empatica Wearable Data for Driver Session 1 and Passenger Session 1

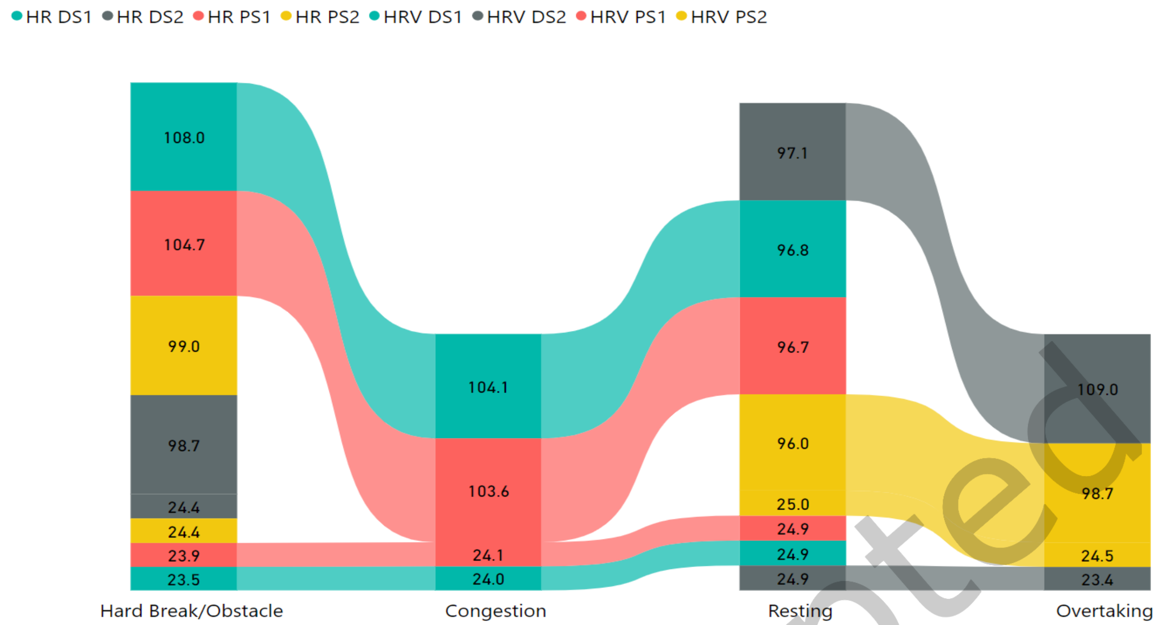

Figure 6: HR Mean (BPM) and HRV in RMSSD (ms) for Drivers Sessions 1 & 2 (DS1, DS2) and Passengers Sessions 1 & 2 (PS1, PS2) in Several Driving Conditions.

In Figure 6, we presented only HR and HRV data from two separate driving sessions for two drivers and passengers (Color codes for HR and HRV are the same for each persona). It is identified (in Mean values) that participants' normal (baseline) HR Mean level at the resting period (before driving) was initially below 100 BPM for all, but during several driving conditions (mentioned in the X-axis), the HR Mean increased to different levels up to 109 BPM for a driver. Accordingly, the analyzed HRV values decreased according to conditions that refer to stress. The changes were significant for the two drivers. The value 0 denotes that we did not get HR mean values on overtaking condition for HR PS1, which refers to HRV PS1 also 0.

4.2 Results from Stress Wear Wearable

From the understanding of Empatica E4, we continued the experiment with the Stress Wear wearable and collected HR for seven drivers. We considered only HR data a minimalist sensing method because HRV from heart rate data gives us an immediate indication of stress. Figure 7 provides an understanding of HR data during the several conditions in the test drives for the drivers. The following figure shows the HR Mean of 10 driving conditions for nine separate driving sessions. Here drivers 6 and 7 joined for two driving sessions. The resting bar is the average (baseline) HR mean level for all the drivers collected before driving. It shows that, except resting, all drivers' HR values increase at different levels according to several driving conditions. For example, the mean HR at the resting period for driver 1 was 69 BPM, gradually rising to 75 BPM at congestion, and later on, it was around 114 BPM during the accident. The scenarios were similar for the rest of the drivers, whose HR value increased from baseline heart rates.

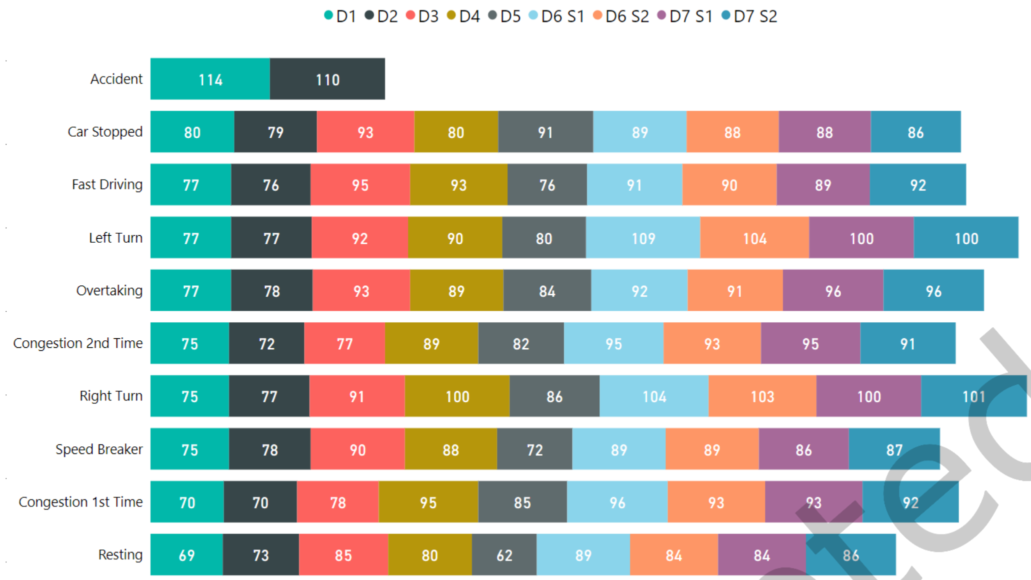

Figure 7: HR Mean (BPM), Data from Stress Wear on Several Driving Factors for 7 Different Drivers in 9 Driving Sessions [DS = Driving Session, D= Driver]

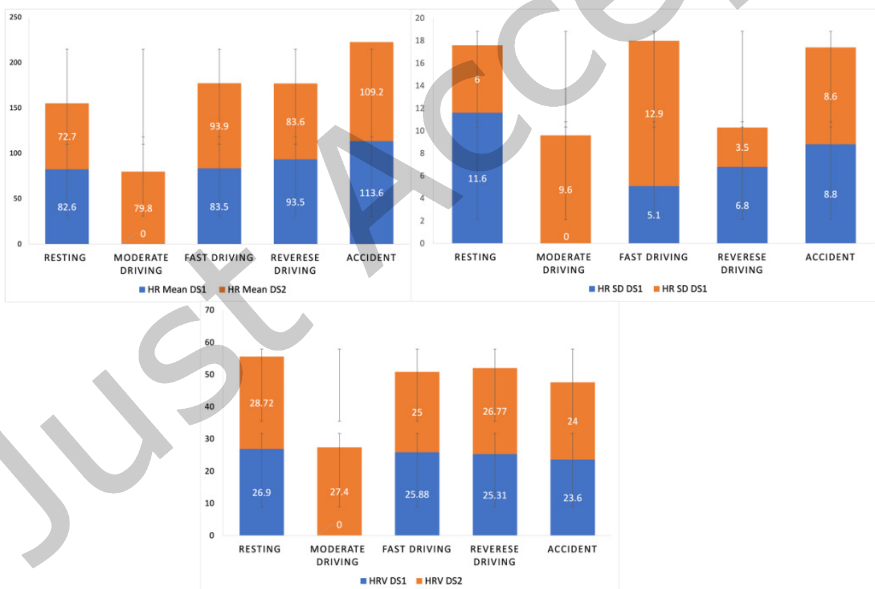

Figure 8: HR Mean (BPM) HR Standard Deviation (SD) and HRV in RMSSD (ms) for Driver 1 (DS1) and 2 (DS2) using Stress Wear

In Figure 8, we again present HR data's mean and standard deviation and analyze HRV for two drivers who experienced driving accidents. The road conditions are mentioned in the X-axis. During resting, the normal (baseline) average HR mean was around 83 BPM and 73 BPM, respectively. We saw a sharp rise in the HR mean values in other driving factors. During accidents, the HR means were higher for these drivers, 113 BPM, and 109 BPM, respectively, clearly showing HR increased significantly. We analyzed HRV from these values, where we found HRV around 27 and 29, respectively, during resting but gradually decreased below 24 according to driving factors that refer to stress. The value 0 denotes that we did not have HR mean values on moderate driving conditions for driving session 1 (DS1), which refers to other values also 0.

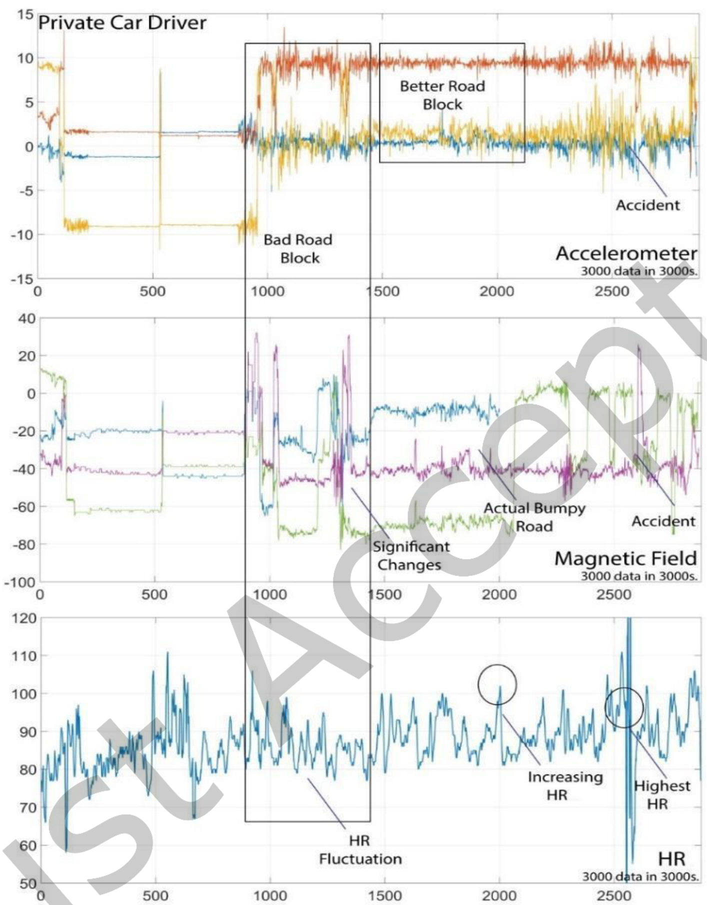

Figure 9: Stress Wear data for a Private Car Driver 1 in Road Conditions.

We also visually present the Driver 1 driving session result visually in Figure 9 with Stress Wear data and the parameters collected from smartphones through our software system. We extracted accelerometer values (m/s2) and also considered the Magnetic field values (X, Y, and Z parameters presented in 3 different colors in each graph) in (μT) extracted from the Hall Effect sensor from the mobile device to define the road condition perfectly. Here we have 3000 data in 3000 seconds for all parameters (1:1). The Y-axis is the magnitude for all subgraphs, and the X-axis for the HR subgraph denotes time. The X-axis in other subgraphs represents the total number of data. In the figure, the magnetic field changes for road conditions are significant rather than accelerometer values, as seen in bad roadblocks. Also, we have substantial differences in HR data throughout the driving session as the road conditions are visible in magnetic field data, specifically the accident data in all subgraphs.

In Table 3, we have presented Spearman's correlation between the accelerometer X-axis (as a road condition) and Heart Rate (as a physiological indicator) that had a positive correlation which indicates that heart rate (HR) changes due to road conditions that clearly shows stress might happen for such situations. We analyzed around 40,000 data where significant relationships were found for almost every session. We did not find any correlation between the Y and Z axes of accelerometer values.

Table 3: Correlation between Accelerometer (X-axis) and Heart Rate

DS	Variables		No. of Data	Correlational Analysis	
	Variable 1	*Variable 2*		*Coefficient*	*p value*
DS1	Acc. X	Heart Rate	2852	$r_s = 0.162$	2.65E-18
DS2			2613	$r_s = 0.067$	0.0006
DS3			2694	$r_s = -0.091$	2.06E-06
DS4			6188	$r_s = 0.057$	5.91E-06
DS5			6018	$r_s = 0.131$	1.57E-24
DS6			5781	$r_s = -0.004$	0.7306
DS7			3968	$r_s = -0.152$	6.06E-22
DS8			5723	$r_s = 0.095$	3.56E-13
DS9			4090	$r_s = 0.255$	7.03E-62

From Table 3, we understand heart rate changes through abrupt changes in road conditions. We also analyzed magnetic field values to justify the road conditions from another point of view that might be responsible for stress. Spearman's correlation in Table 4, we have presented magnetic field data (as road condition). We found a significant relationship between Heart Rate and magnetic field. Table 4 shows that for driving sessions 1, 3, 6, and 7, there was a significant positive correlation between magnetic field data and heart rate. However, driving sessions 2, 4, and 5 had a significant negative correlation. There might be a fluctuation of Inter Beat Interval (IBI) [107] where the negative correlation was also considered. On the other hand, for driving sessions 8 and 9, we did not find any significant correlation between the magnetic field and heart rate. Moreover, the experiment results show that road factors impact drivers that, cause stress.

Table 4: Correlation between Magnetic Field and Heart Rate

DS	Variables		No. of Data	Correlational Analysis	
	Variable 1	*Variable 2*		*Coefficient*	*p value*
DS1	Magnetic Field	Heart Rate	1995	$r_s = 0.164$	1.51E-13
DS2			2613	$r_s = -0.174$	2.12E-19
DS3			2694	$r_s = 0.045$	0.0193
DS4			6188	$r_s = -0.053$	2.42E-05
DS5			6018	$r_s = -0.280$	3.76E-109
DS6			5781	$r_s = 0.118$	1.56E-19
DS7			3968	$r_s = 0.262$	1.37E-63
DS8			5723	$r_s = 0.000$	0.9428
DS9			4090	$r_s = 0.026$	0.0894

5 DISCUSSION

This study explains driving stress behaviors in Bangladesh in (1) road and traffic conditions and (2) unexpected behaviors of pedestrians and other vehicle drivers. The exploratory research unfolds the exact reasons for their discomforts as congestion along with some other road factors such as sudden obstacles, interference of passengers, stress indicators, and intensity during driving which are contextually unique. This study shows the requirement to understand the stress generators with sensing mechanisms sensitive to measuring sudden variability of traffic conditions, which influenced us towards choosing the minimalistic option of sensing modalities. Therefore, we developed a low-cost technology-based support system that can identify stress from HRV by sensing the Heart Rate in real-time.

5.1 Self-Sensing for Enhancing Self-Awareness

The drivers in this study provided perceptions that are responsible for their stress. As per drivers' thinking, pedestrians only use the foot-over bridges and crossroads sections while crossing the roads and highways. Many passengers have the mentality to advise the drivers to go faster, stop the car anywhere, break the signals, etc., to violate the traffic rules. For these reasons, user behaviors negatively impact most drivers, contributing to stress building. Additionally, the road infrastructure in Bangladesh needs to be better, similar to other developing countries [108]. The country faces challenges with poor road conditions, congestion, and unruly traffic [34, 60, 61, 92, 93] that impact the drivers and causes stress.

The drivers in developing countries are involved in aggressive behavior without being aware of their stress state. Many civilians are impacted only in road accidents [53] where road conditions, traffic management, and breaking of the traffic laws are closely related—sometimes driving-related incidents caused by aggressive driving behavior [44, 45, 47, 48, 49] because of driving stress. At this point, we propose a low-cost technology approach that might help to reduce driving stress by understanding road condition scenarios, traffic management, and pedestrian behaviors. Sensing driving stress will help drivers understand the mental health status that can make them cautious. This supports previous work results on awakening self-awareness, which can potentially reduce driving stress [85]. We consider heart rate variability to understand stress, where HRV-based biofeedback techniques can help self-sensing to generate awareness of stress responses [67, 68, 69]. This system can ignite self-awareness in them. Once the drivers understand that their stress involves them in aggressive behavior, this self-awareness can prevent them from such aggressive strategies for improving their driving experiences.

5.2 Low Cost Wearable to Support Low-Income Groups

Researchers and developers must consider some challenges working with low-income communities in developing countries. This study focuses on the driver community in Bangladesh from the lower spectrum of the income group. This group needs more technology exposure, requiring effective technology design for them. Considering the drivers' socioeconomic state, we develop low-cost wearable technology to understand the driving-induced stress from their cardiovascular parameters. The existing wearables are expensive for low-income people; drivers cannot buy and use these costly wearables. For example, we have used Empatica E4 to validate our device, which costs around USD 1700 [102], whereas our developed system, Stress Wear, costs below USD 20, which is reasonable. Also, exploratory study outcomes motivated us to design this low-cost wearable as Stress Wear has basic features compared to expensive wearables to identify stress.

The proposed wearable technology might help reduce driving stress, which researchers have extensively studied using intrusive and non-intrusive measures [38, 39, 40, 70, 74, 84]. It is to be noted that the most prolific research methods were applied to the Western world's citizens and that methods are often challenging in developing countries. For example, experiments with the same road condition are done using simulators in developed countries with a complete set of sensors and wearables [42]. Such experiments are currently not possible in Bangladesh for lacking these research facilities, but they can be possible in the future as research on transportation has already started. That is why real-time experiments in the wild setting have been chosen for this research method. However, real-time experimentation and long-term within-subject testing with multiple setups of expensive wearables are not commonly practiced here, which might initiate discomfort among low-technology users found in previous research in Bangladesh [106]. Researchers developed several wearable technologies that can be used to understand stress [72, 75, 78, 83, 84, 85, 90, 91], but those were not applied and were not usable to drivers. Moreover, considering these research issues, we as researchers come up with such minimalistic low-cost wearable for the driver's community in Bangladesh which is a mobile-based ubiquitous technology approach, usable and affordable to the drivers.

6 STRESS WEAR FEEDBACK TECHNIQUE AND IMPROVEMENT

During the experiment with Stress Wear, the drivers provided informal perceptions of using the devices. An easy-to-use device might help them adapt and understand their health situation. During the experiment, the feedback technique of this device was not in operation, but according to drivers' perceptions and suggestions, initially, we added feedback visually. When the stress level increases, the color indicator in the application turns red, which might help drivers understand the stress situation. Additional suggestions to send feedback in textual messages popped on the application screen. As HRV will not change instantly, a daily report with visual representation at the end of the day might help them to look into stress in-depth. These feedback techniques can be improved. They are looking at the application screen while driving might distract the driver. Considering the safety issues, there are possibilities to implement verbal feedback systems in the native language instead of visual feedback, which is an ongoing process. The drivers do not need to look at the application screen while driving. This technique can suggest feedback such as turning on the Air Conditioner, rest adequately, listening to music, etc. It is proven that music changes the drivers' mood anytime [23]. These techniques will be a practical approach to improving the device's usability among low-technology users.

The proposed system provides two features that are susceptible to dealing with extensive data in the future and will be effective in this context for social good: The history analyzer feature can capture long-term stress scenarios and corresponding behaviors of the drivers. Accordingly, we can leverage various machine learning algorithms to predict possible stress levels more accurately based on sizeable long-term driving stress data.

Our experiment collects road condition data through accelerometers and Hall Effect (magnetic field data) sensors. At this point, cloud computing technology could help identify a specific road's critical issues from such a large dataset. The data will also help Bangladesh's stakeholders and transportation authorities identify and repair the road infrastructure quickly. The development and improvement of such low-cost technology impact the personalized level of the drivers in any similar road environment setup and can help improve the road infrastructure in developing countries.

7 LIMITATION AND FUTURE WORK

We only explored the urban drivers in Bangladesh and did not include passengers in the riding state on the Stress Wear experiment as we did for the Empatica E4 experiment. Due to contextual and infrastructural limitations, the study covered a limited number of participants in different settings in experiments. Also, we could not explore implementing the feedback technique of Stress Wear through application because the experimental process was stopped due to the COVID-19 pandemic. There might be data loss during data transfer through the Bluetooth system, which we consider a system limitation. However, there are limitations in the study, but the results are valid. We wanted to introduce a cost-effective contextual wearable that can monitor driving stress. Although we have a small sample size in experiments, we are trying to make our results generalizable to only some.

There are many scopes to improve the prototype. The feedback technique will be implemented and presented in future articles. We are exploring other measures, such as minimizing the size, maximizing the run time, standalone device, etc., in future work.

8 CONCLUSION

Driving stress impacts driving behavior, often from road factors prevalent in developing nations. This study focuses on Bangladesh and the driver's stress considering the cultural and infrastructural setups different from any developed nation. We qualitatively studied n=26 urban drivers and continued subjective feedback studies over n=80 urban drivers in Bangladesh. We understood the factors, indicators, and intensity of driving stress during driving through these approaches, where congestions, obstacles, passengers interferences, etc., are the prime stress indicators. Also, the roadside environment and cultural behavior trigger stress in these drivers. These studies motivated us to identify the driving stress technologically, which might help to reduce stress through technology integration. We developed a low-cost wearable, 'Stress Wear,' that can sense driving stress in real-time by analyzing the HRV considering cultural context, users' feedback, and existing research works. We performed between-subject experiments on n=14 drivers in two phases with Empatica E4 and developed a wearable that shows road factors initiate driving stress. This development of this low-cost wearable was significant considering the low-income user in this context and will impact their stress monitoring at work. Moreover, the proposed system is helpful for drivers self-sensing their stress, which might increase self-awareness and reduce driving stress.

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A APPENDICES

A.1 Abbreviations:

- HR: Heart Rate
- HRV: Heart Rate Variability
- EDA: Electrodermal Activity.
- SD: Standard Deviation
- FGD: Focus Group Discussion
- PPG: Photoplethysmography
- EKG: Electrocardiogram (in German form)
- PCB: Printed Circuit Board
- LiPo: Lithium Polymer
- RMSSD: Square Root of the mean of the sum of the squares of differences between adjacent RR intervals
- RR Int or RR Interval: inter-beat interval or the interval between successive heartbeats per minute (R denotes a peak of a beat)
- RR Int 1: 1st RR Interval; RR Int 2: 2nd RR Interval.
- No. of RR Int: Total number of RR intervals.
- ms: Millisecond.
- r_{s}: Spearman's Correlation

A.2 DBQ questionnaire set:

Demography: Self-reported entry

What is your name? What about your age? Your Gender? What is your Education Level? Marital Status? What kind of car you drive? How many years you drive the car? How many hours you drive daily? How often do you stop the car during/after driving? What is your regular duty hour? How much time you can take rest? Do you live with your family? How many kids you have? How many people live with you in family/mess?

Stress: Likert scale with self-reported entry

What it feels spending time in Traffic Jam during driving? What it feels when sudden obstacles (e.g., car/human) come in front of the car during driving? What it feels when someone advise you inside the car during driving? What it feels to drive with hunger? What makes the body feel bad while driving (e.g., no AC / long road / jam etc.)? What makes you feel bad (mood) while driving? At what time are you forced to break traffic rules? What do you think on this (There is no problem if you do not follow any traffic rules)? Suppose you are giving an opinion but the family does not agree - then what do you do? What to do if your mind is good?