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Comparative assessment of driving behavior at signalized intersections using driving simulators

Mazen Danaf[a], Samer H. Hamdar[b], Maya Abou-Zeid[a], and Isam Kaysi[a]

[a]Department of Civil and Environmental Engineering, American University of Beirut, Beirut, Lebanon;
[b]Civil and Environmental Engineering, The George Washington University, Washington, DC, USA

ABSTRACT

The objective of this article is to investigate the differences in driving behavior and red-light violations between drivers in two countries: Lebanon and the United States of America. To realize the stated objective, two driving simulators were utilized. The first simulator is located at the American University of Beirut (AUB), Lebanon. The second simulator is located at the George Washington University (GWU), United States of America. An elaborate experimental scheme involving the occurrence of frustrating events at signalized intersections was designed, and 35 students from GWU and 81 students from AUB participated in the experiments. Detailed trajectory data was collected, and students were compared based on three surrogate measures: number of red-light violations, time-to-junction, average and maximum velocities. The results indicated that frustrating events occurring at intersections elicit red-light violations and speeding for both samples. In addition, speeding and red-light violations follow increasing trends as students drive through successive signalized intersections and experience frustrating events. In a postdriving survey, AUB students indicated that they engage in risky driving behavior more than GWU students. On the other hand, GWU students indicated that they are more likely to violate traffic rules and also committed more red-light violations in the simulator. The results of this study have implications on driving education and enforcement, as they indicate that driving violations might not be necessarily related to risky or aggressive driving, but to an individual's tendency to violate traffic rules in general.

KEYWORDS
driving behavior; driving simulator; red light violations; risky driving; traffic safety

1. Introduction

Road traffic accidents caused the death of 1.24 million persons in 2010 (World Health Organization, 2013). The roadway annual fatality rates (per habitant, per motor vehicle, per vehicle-km, etc.) differ tremendously across countries depending on the corresponding culture(s), the economic developments, and the

CONTACT Mazen Danaf msd14@aub.edu.lb Department of Civil and Environmental Engineering, American University of Beirut, 104 Bechtel, P.O. Box 11-0236, Riad El-Solh/Beirut 1107 2020, Lebanon.
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population sociodemographic characteristics. For example, the average traffic fatality rate per 100,000 persons is 18 worldwide. However, 92% of fatalities occur in low- to middle-income countries with the highest rates found in South-East Asia and Africa. It has been argued that human errors and aggressiveness are the main contributors to traffic accidents (Lewin, 1982). Accordingly, the driving behaviors leading to traffic accidents may vary, and different country-specific traffic safety mitigation measures may be needed to reduce the number of roadway fatalities. More in-depth studies on driving behavioral differences across countries are then needed to deal with such transportation safety problem.

In the United States of America , the Federal Highway Administration (FHWA) defined four primary areas of focus to improve roadway safety: intersections (contributing to 21% of the 2007 roadway fatalities), roadway departure (contributing to 58% of the 2007 roadway fatalities), pedestrians (contributing to 11% of the 2007 roadway fatalities), and speeding (contributing to 32% of the 2007 roadway fatalities) (Antonucci, Hardy, Slack, Prefer, & Neuman, 2004; National Highway Traffic Safety Administration [NHTSA], 2008). Focusing on intersections, one half of the intersections-related fatalities occurred in urban areas (where 82.4% of the U.S. population lives United Nations [UN], 2012) with the majority of these fatalities occurring at signalized intersections. For better illustration of the significance of collisions at signalized intersections, even though roughly 10% of intersections are signalized in the the United States of America, fatalities at signalized intersections constitute approximately one third of the total number of intersection-related fatalities. Looking at collision types, collisions at signalized intersections are typically classified as angle collisions (42% of fatal collisions), rear-end collisions (8% of fatal collisions), left-turn (21% of fatal collisions), sideswipe collisions (13% of fatal collisions), and pedestrian/bicycle involved collisions (25% of fatal collisions). This article adopts an experimental set-up that focuses on the safety of driver behavior without the involvement of pedestrians or bicycles.

In Lebanon, there were 4,583 roadway collisions in 2010 leading to 549 fatalities and 6,517 injuries (Interior Security Forces [ISF], 2011). The majority of these collisions involved passenger cars and sport utility vehicles (SUVs) (∼68% of collisions leading to 70% of fatalities) whereas collisions involving "motorcycles only" remain significant in number (∼26% leading to 19% of fatalities). If considering pedestrians' involvement, collisions involving pedestrians constitute 27% of the total number of collisions (leading to 33% of fatalities) while collisions involving only vehicles (intervehicular collisions) constitute 53% of the total number of collisions (leading to 37% of fatalities). Accordingly, collisions involving vehicles only is a dominant collision type that should be addressed when studying roadway traffic safety in Lebanon. On the other hand, the data encoding adopted by the Lebanese Ministry of Interior does not allow differentiating between collisions occurring at signalized intersections versus other collision types. One possible alternative to understand the significance of studying safety at signalized intersections is to look at the distribution of collisions by province and the urbanization rate in Lebanon. Of the Lebanese population 87.2% live in urban areas and the urbanization rate is 1.2% per year (UN, 2012). The urban centers in Lebanon are the site of many arterials with a high concentration of signalized intersections. Most of the corresponding signalization is pretimed and not coordinated, and many signals are installed inappropriately leading to limited sight distances. Moreover, until 2015, there was no traffic regulation enforcement at signalized intersections leading to significant number of red-light violations. Such violations are especially observed in the Greater Beirut Area where more than one half of the Lebanese population lives. This area consists of the Beirut Province (the capital) and some areas of the Mount Lebanon Province. These two provinces were the sites of approximately one half the collisions in Lebanon leading to almost half the collisions fatalities of 2010 (ISF, 2011).

Different efforts have been made to analyze collision data and to estimate the relationship between collision characteristics (i.e., collision rates, fatality and injury rates, collision type) and the surrounding environment (infrastructure characteristics, driver characteristics, vehicle characteristics, etc.) at signalized intersections (Abdel-Aty & Keller, 2005). Such research approaches require extensive data collection and mining and does not provide input from the individual drivers and thus insights into the corresponding perception–judgment–execution processes that may lead to collision formation. In other words, the widely used statistical approach linking collisions' characteristics to different exogenous factors does not focus on the frustrating events leading to the negative emotions that may lead to aggressiveness. Shinar (1998) utilized the psychological theory of aggression to define aggressiveness expressed by drivers. The author adopted the frustration-aggression model (the dominant theory of aggression in psychology) where frustration is considered to be a gateway emotion that leads to anger and ultimately to aggressive behavior (Galovsky & Blanchard, 2004). In other words, frustrating behaviors, situations, or events trigger all aggressive behaviors. The levels of aggressiveness expressed by drivers are dependent on three main factors (Shinar, 1998): (1) level of frustration experienced by drivers and the thresholds that might be tolerated by each driver (i.e., dependent on the driver's personality), (2) the perceived consequences of the frustrating event leading to a driver's aggressiveness, and (3) the "extent to which the frustration is seen as unfair or inappropriate." Based on the aforementioned three factors, drivers may express hostile aggressiveness and/or instrumental aggressiveness. Hostile aggressiveness is more emotional than rational and is intended to make the driver feel "good" without necessarily leading to improved consequences. Instrumental aggressiveness is a mean to an end that is to overcome the frustrating event or situation. It should be noted that aggressive drivers have higher tendency to show aggressive behaviors, but nonaggressive drivers may still behave aggressively depending on the three factors mentioned earlier.

In this article, the authors are focusing on "instrumental aggressiveness" (i.e., behaviors that can be observed) of two sets of drivers from two different countries facing "frustrating events" at signalized intersections. *Roadway frustrating events* have been defined in different manners in different studies. For example, Harris and Nass (2011) adopted the following scenarios as frustrating scenarios: "heavy traffic, merging cars, long stoplights, curvy roads, slippery surfaces, and low visibility." They used a driving simulator equipped by the STISIM software (same software adopted at the George Washington University Simulator). Because the focus of this article is on signalized intersections, we focus on a combination of traffic-related frustrating events and signal-related frustrating events (long stoplights, drivers blocking intersection boxes, and drivers disrespecting signal indications). Accordingly, the presented work attempts to compare how drivers located in two countries (Lebanon and the United States of America) respond differently to frustrating events encountered at signalized intersections. This article also investigates consistency between the observed and self-reported driving behavior. Although the study presents general trends in terms of surrogate safety measures and self-reported driving habits, there is also a focus on driving violations to study whether these violations are subset of, or correlated with, other driving characteristics such as risky or aggressive driving. To realize the stated objective, two driving simulators were utilized and participants were recruited to participate in a well-designed driving experiment. The first simulator used in the experiment is located at the American University of Beirut (AUB), Lebanon. The second simulator is located at the George Washington University (GWU), United States of America.

Given the framework, the objective and the approach stated earlier, studies on safety at signalized intersections and the difference in drivers' behaviors across countries are briefly reviewed in Section 2. Section 3 presents the specifications of the two driving simulators utilized in this article. The corresponding experimental set-up is detailed in Section 4. The numerical results are presented and analyzed in Section 5 before concluding with some future research needs.

2. Literature review

In this section, two types of literature are presented. The first literature type is related to safety studies at signalized intersections. The second literature type is associated with studies analyzing driving behavioral differences across countries and the corresponding safety implications.

2.1. Signalized intersections safety studies

Safety at signalized intersections has been a subject of study since the 1980s (Hauer, Ng, & Lovell, 1988). Such studies require a significant amount of data either to estimate the corresponding statistical models or to calibrate/validate traffic models to deduce related safety surrogate measures. The statistical models utilize behavioral, traffic, and collision "macroscopic" data libraries in addition to information describing the driving environment. The traffic models rely on "microscopic" trajectory and behavioral data that may be collected through driving simulators reflecting or through sensors detecting the surrounding driving conditions. Even though many of the studies looked specifically at the safety of bicyclists

(Gårder, Leden, & Thedéen, 1994; Miranda-Moreno, Morency, & El-Geneidy, 2011; Wang & Nihan, 2004) and/or pedestrians (Leden, 2002; Tiwari, Bangdiwala, Saraswat, & Gaurav, 2007) at signalized intersections, this subsection presents more general studies involving intervehicular collisions among other collision types. Such scope is in line with the objective of the article presented in the Introduction.

As an example of statistical models, Hauer et al. (1988) used traffic and collisions data that were collected from 145 intersections in metropolitan Toronto to estimate multiple statistical safety models (a probability density function of the number of collisions given some traffic flow characteristics). Fifteen accident patterns were identified, and several suggestions were provided by the authors in order to avoid any illogical conclusions: (1) the frequency of collisions should be associated with traffic flow to take into consideration collision exposure at different intersections and not to over- or underestimate the contributions of some characteristics at a specific intersection to collision formation, (2) collisions should be categorized by the precollision movement rather than by the angle of impact, and (3) the functional relationship between collisions frequency and flow may not be predicted ahead of the estimation exercise.

More recently, Abdel-Aty and Keller (2005) used an ordered probit model and a tree-regression model to estimate the factors that contribute to injuries/injury severity at signalized intersections. The ordered probit model was chosen because the injury level is assumed to be an ordered variable (i.e., conditional on the collision occurrence). The tree-regression model was adopted to account for the multiple factors that might be involved in the occurrence and the severity of the injuries. The tree-based structure accounted for multicollinearity among variables, missing data, and the uncertainty related to the true form of the final model. Several data resources were combined, and the impacts of the quality and the completeness of the data on the models' significance were studied. The study found that having a (physical) median on minor roadway (i.e., divided) or a higher speed limit reduced the injury level. On the other hand, collisions involving pedestrians or bicyclists had the highest probability of leading to severe injuries. Finally, the study found that a more complete data set including all collisions (even those without any injuries) improved the significance of the suggested models. Using the same methodology, Abdel-Aty, Keller, and Brady (2005) looked at more specific factors affecting collision occurrences and the corresponding injuries. These factors included geometric characteristics, intersections configurations, and traffic volumes. The authors disaggregated the data by collision type and found that different factors affect the injury levels differently depending on the type of collisions the vehicles/bicyclists/pedestrians are involved in (especially when looking at head-on collisions vs. left-turn collisions).

Persaud and Nguyen (2015) adopted another advanced framework, a Bayesian framework to evaluate safety of three-legged and four-legged intersections in Ontario. Safety performance functions were used to link safety measures to intersection characteristics such as flows and speeds. The models adopted had different levels of aggregations and were differentiated depending on the time period, collision severity/type, and surrounding environment.

In addition to the statistical models that rely on relatively large data libraries, microscopic traffic models may be used to look into safety-related problems at signalized intersections. These studies rely on more limited data sets that have higher levels of accuracy. As an example, Cunto and Saccomanno (2008) presented a calibration and validation procedure to calibrate a collision-free microscopic traffic model (VISSIM) to be used for safety evaluation of rear-end collisions at signalized intersections. The authors used the Next Generation Simulation (NGSIM) detailed trajectory data (a Federal Highway Administration initiative) to calibrate the acceleration and the lane-changing/merging drivers' behaviors in four steps: "(1) heuristic selection of initial model inputs, (2) statistical screening using a Plackett–Burnman design, (3) fractional factorial analysis relating inputs to safety performance, and (4) genetic algorithm procedure for obtaining best estimate input values" (Cunto & Saccomanno, 2008). The safety surrogate measures adopted to evaluate safety were the Crash Potential Index (CPI), the number of vehicles in conflict, and the conflict duration per vehicle. In line of this study, Saccomanno, Cunto, Guido, and Vitale (2012) did use the same microscopic model to look into the effectiveness of roundabouts compared to conventional signalized intersections in reducing rear-end conflicts and thus improving safety. The authors used a slightly modified set of surrogate safety measures: "(a) time to collision (TTC), (b) deceleration rate to avoid the crash (DRAC), and (c) crash potential index (CPI)" (Cunto & Saccomanno, 2008). The authors suggest that roundabouts reduce exposures to real-end conflicts irrespectively of the volumes and the pavement types.

Another type of data that might be used when looking at individual drivers' behaviors is data collected through driving simulators. Yan, Abdel Aty, Radwan, Wang, and Chilakapati (2008) investigated the validity of using driving simulators to assess and evaluate safety at signalized intersections. Accordingly, a real-world signalized intersection was "implemented" in "a high-fidelity driving simulator." Multiple experiments corresponding to eight scenarios were conducted to study the speed patterns and the risk-taking patterns observed in the real world versus the patterns in the simulator virtual environment. The results showed that the "field" and the "simulator" speed distributions followed normal distributions with equal means for each intersection approach. As for the risk-taking patterns, the study showed that an increase in rear-end collisions formation at the right-turn lane was associated with "higher deceleration rate, higher non-stop right-turn rate, higher right-turn speed at stop line, shorter following distance and higher rear-end probability" (Yan et al., 2008). In other words, using a driving simulator to study traffic safety at signalized intersections was found to be relatively valid.

2.2. Driving behavioral safety studies across countries

Most of the studies analyzing driving behavioral differences across countries in general and the corresponding safety implications in particular have utilized surveys/questionnaires and existing publically available data/records (Özkan, Lajunen, Chliaoutakis, Parker, & Summala, 2006a).

Starting in 1989, Sivak, Soler, Tränkle, and Spagnhol (Sivak, Soler, Tränkle, & Spagnhol, 1989; Sivak, Soler, & Tränkle, 1989a, 1989b) performed a series of studies on the cross-cultural differences in driving behavior. Conducting the studies on American, Spanish, West German, and Brazilian participants, the variables considered were age, gender, employment status, and citizenship. The authors used questionnaires and simulation games to evaluate the impact of the stated variables on the risk ratings of some predetermined slides (risk perception), gap acceptance behavior (risk taking), and self-evaluation answers (driver's self-assessment). The impact of the driver's country was significant in all studies. American drivers considered themselves as safer drivers than West German and Spanish drivers. In addition, age had a high impact on the measured responses as younger drivers thought of themselves as less wise, showed lower safety margins accepting gaps, and underestimated the danger that may result from risky situations (i.e., slides). In 1995, another study used mailed questionnaires to look into the behavior and the perception related to drink-driving of company vehicle drivers distributed across eight countries (Guppy & Adams-Guppy, 1995). A multiple regression analysis was performed showing that, for all groups, driving after drinking is associated with fundamental psychological attachments (moral attachments) rather than situational conditions. Lajunen, Corry, Summala, and Hartley (1998) focused on Australians' and Finns' self-perceived skills when faced with unsafe driving situations. Through hierarchical regression and without considering the drivers' backgrounds, the study showed that drivers with strong "self-assessed" perceptual-motor skills (related to number of accidents, penalties, and driving speeds) tend to overestimate their capabilities whereas drivers with strong "self-assessed" safety skills (related to life-time mileage, gender, aggression/alertness, and sense of coherence) are more realistic in estimating their capabilities handling challenging driving conditions. Özkan, Lajunen, Chliaoutakis, Parker, and Summala (2006b) adopted the same skills classification scheme to study cross-cultural differences in driving for six different countries: Great Britain, The Netherlands, Finland, Greece, Iran, and Turkey. This classification is adopted by the Driver Skill Inventory (DSI) system and was used to establish the following hypothesis: high perceptual-motor skills ratings combined with low safety skills ratings lead to dangerous driving behavior and road accidents. It was found that western and northern European countries were "safe" compared to Eastern and Middle Eastern countries. Another study by Warner, Özkan, Lajunen, and Tzamalouka (2011) utilized a Driver Behavior Questionnaire (DBQ) to study aberrant driving maneuvering in four countries: Finland, Sweden, Greece, and Turkey. The maneuvers were classified as violations, errors, and lapses and were linked to aggressiveness and self-reported accident involvement. It was shown that different countries have different problems related to aberrant behavior, and thus different safety measures need to be taken to reduce the corresponding negative implications. Lately, Lim, Sheppard, and Crundall

(2013) focused on the differences of hazard perceptions in two countries: The United Kingdom and Malaysia. This cross-cultural study used “hazard clips” to investigate the changes in the hazard perception skills given the drivers’ backgrounds. One of the main findings was related to the “threshold of danger” as drivers from Malaysia needed a higher threshold before identifying a situation as hazardous. This finding may be explained by the more hazardous driving environments in developing countries.

The questions that may be raised at this point are (1) is aggressive driving only related to self-assessed indicators without looking into the possible threat coming from other drivers? and (2) Is there a system/index other than the DSI or the DBQ that can be utilized to specify/quantify dangerous driving (without suggesting that the use of these indices is wrong)? To answer the first question, Özkan, Lajunen, Parker, Sümer, and Summala (2010) hypothesized that accidents are correlated with self-reported aggressive behaviors (“self-scale”) and the perception of being subject to other drivers’ aggressive acts (“other scale”). Using such framework, a survey was conducted with 3,673 driving participants from Finland, Great Britain, The Netherlands, and Turkey. It was found that other drivers’ aggressiveness contributed significantly to the risk of being involved in an accident. Such contribution is even higher than the contribution of the drivers’ self-assessed aggressiveness traits. Such finding may be expected as the driver’s direct “dynamic” surrounding may have a higher impact on manifested aggressiveness than the driver’s more “constant” trait characteristics (Warner & Ålberg, 2008). These trait characteristics may need further investigation especially in terms of their influence on the content of ideas considered by the driver at a specific instance and the resulting thinking styles (rumination, flashback, distraction, etc.) (Suhr & Nesbit, 2013). As for the second question, instead of using the DSI system, Willemsen, Dula, Declercq, and Verhaeghe (2008) used the Dula Dangerous Driving Index (DDDI) to compare data obtained from American drivers and Belgian drivers. An elaborate factor analysis was conducted and a four-factor structure with the following scales was established: drunk driving, risky driving, negative cognitive/emotional driving, and aggressive driving. All the DDDI subscales were inter-related (in all subgroups) suggesting that the index can be used as a surrogate measure for dangerous driving. This was confirmed given that the Belgian traffic offenders sample scored higher on all scales compared to the American university sample and the American community sample.

Young drivers are considered the most at-risk drivers when dealing with collision injuries and fatalities (Agran, Winn, Anderson, Trent, & Walton-Haynes, 2001). Steptoe et al. (2004) studied drinking attitudes and driving behavior collecting data on university students from 23 countries. The highest alcohol levels were found in men and women from the United States of America and in men from the Mediterranean and South American countries. These rates were positively correlated with the national road traffic accident death rates from one side and the legal blood alcohol threshold from the other side. Another study by Vassallo et al. (2007) focused on trait aggressiveness and the possible impact of the “circumstances in young drivers’ earlier lives” that may have led to the current risk-taking driving behavior. The study focused on

Australian participants that were age 19 to 20 years. It was found that young drivers can be differentiated from early childhood into a "high group" (with high levels of risky driving behavior) and a "low group" (with low levels of risky driving behavior). Such differentiation was possible through analyzing the following items: temperament style, behavior problems, social competence, school adjustment, and interpersonal relationships. Finally, Piyakul and Chomeya (2012) analyzed the aggressiveness of undergraduate students in three universities: Mahasarakham University, Thailand, Indonesia University of Education, Indonesia, and Monash University, Australia. Using an aggressiveness driving behavior measurement system, aggressiveness was linked to the country a driver is from, the academic achievement level, the gender, and the driver's experience. Through different statistical analyses (percentage, mean, standard deviation, *t* tests, and variance analysis), several conclusions have been drawn including (1) across cultures, male students were more aggressive than female students; (2) students with higher academic achievement had lower aggressiveness scores than students with lower academic achievement; and (3) experience may indicate higher aggressiveness scores (Thailand and Indonesia) or lower aggressiveness scores.

In summary, driving behavior across countries and cultures has been mainly studied using different survey methods and is mostly based on self-assessed indices/indicators. Researchers are interested in young and older driver populations given their vulnerability to traffic accidents (i.e., fatality and injury rates). A significant number of such accidents occur at signalized intersections predominantly located in urban areas. However, few studies focused on this specific type of accidents as the corresponding data needed is difficult to differentiate and to collect especially when dealing with underdeveloped countries with high urbanization rates and limited economic resources. Accordingly, this study utilizes a controlled driving environment where the surrounding (situational) driving conditions may be modified. Such an approach is useful for the purpose of designing traffic/roadway interventions that may reduce unsafe driving behavior, as indices based on self-reports are replaced by explicit traffic measures that are quantifiable, scalable, repeatable, and amenable to traffic-related interventions.

3. Driving simulators

Two midlevel driving simulators were utilized in this research. Even though the two simulators are different, they allow for designing a wide range of scenarios and support various environments. The STISIM Driving Simulator at the Virginia Campus of the George Washington University can exhibit high-fidelity virtual driving environment for use in vehicle safety research and driving behavior analysis. Specifically, the simulator is composed of a full-size, fixed-base Buick Regal car, including the original controls (throttle, brake, steering wheel, blinkers, etc.). The view is projected on a 135-degree concave screen in front of the vehicle and the rear view is displayed on the upper part of the display screen.

On the other hand, the driving simulator used at AUB is the DriveSafety DS-600c Research Simulator. It consists of a full-width, half-cab Ford Focus automobile with standard driver controls and instrumentation. The simulator is equipped with motion cues with two degrees of freedom. The view is projected onto a 180-degree display using three projectors and the rear view is displayed on three LCD screens connected to the vehicle cab and acting as side and middle mirrors.

Both simulators cover various kinds of driving scenarios, including highway, urban roads, mountainous roads, plain roads, signalized intersections, nonsignalized intersections, and so on. They also provide a high-fidelity driving environment with traffic signs, roadway markings, roadway surfaces, urban landscape, rural scenery, buildings, trees, skies, and weather. Both are also equipped with a system that replicates the sound of an engine. The sound varies when driving at different speeds; thus, drivers can feel the differences when they accelerate or decelerate to sustain the desired speed for the given kinematic conditions.

The authors are able to record several variables at user-defined regular intervals (e.g., 0.1 seconds) throughout the driving experiments. These variables are stored in accessible data files and include coordinates (lateral and longitudinal), speeds, lateral and longitudinal accelerations, headways, and collision state.

These two simulators are classified as midlevel simulators. Most validation studies done on midlevel simulators achieved relative validity (but not absolute validity) and thus concluded that these simulators can be used as valid research tools. Relative validity is achieved when the same trend of an effect is observed in real life and in the simulator. On the other hand, absolute validity is achieved when the numerical values between two systems are the same (Blaauw, 1982; Yan et al., 2008). It can be generally said that for a simulator to be a valid research tool, relative validity is a necessary and sufficient condition (Mullen, Carlton, Devlin, & Bédard, 2011).

Although these simulators are assumed to establish relative validity, the numerical values of the obtained surrogate safety measures (speed, acceleration, etc.) cannot be directly compared (unless absolute validity is verified for both simulators). In this study, differences in numerical values were observed in terms of speed, where AUB students drove consistently faster than GWU students throughout the experiment and reported that they did not perceive the speed in the simulator to be realistic (students were complaining that the speed perceived in the simulator is lower than the speed observed on the speedometer). Therefore, this article compares the trends observed in the two samples and the differences in numerical values observed within each sample, but not between the two samples.

4. Experimental set-up

Given that understanding the driving behaviors (in response to frustrating events) leading to intervehicular collisions at signalized intersections is needed in developed and developing/underdeveloped countries, the objective of this article is to investigate the differences in driving behavior at signalized intersections between drivers in Lebanon (underdeveloped county) and the United States of America (developed country). Attempting to observe, analyze, and explain the driving behavioral differences at signalized intersections is expected to provide some insights on possible divergences in behavior that are related to disparate driving experiences or contexts. An elaborate experimental scheme was designed taking into consideration the driving simulators' capabilities and specifications. Twenty-six participants from the George Washington University and 81 participants from the American University of Beirut students participated in the driving experiments. Detailed trajectory data was collected and processed to investigate any statistically significant differences in behaviors. Specific surrogate measures were used including number of red-light violations, time-to-junction, average and maximum velocities (Papaioannou, 2007). These measures were linked to signalized intersections' situational characteristics.

The experimental procedure was based on a driving simulator experiment and a postdriving survey. The simulator experiment included three scenarios intended to replicate the Lebanese driving environment (frustration, poor enforcement, disrespect for traffic laws, etc.). The survey was derived from the DDDI and designed to measure drivers' risk taking, aggression, tendency to violate, and negative emotions experienced while driving.

4.1. Experimental procedure

The experimental procedure included four main parts: (1) participant screening and briefing, (2) the simulator practice session, (3) the simulator experiment, and (4) the postdriving survey.

A screening interview was used to verify that participants were physically and mentally able to drive the simulator (participants were asked whether they suffered from certain diseases, dizziness, and other disorders), and legally eligible to drive in general (whether they had a driving license and whether they currently drive). Briefing was performed using a consent form that included information about the experiment, the setting, and the potential risks. Participants were also informed that the purpose of the experiment was studying driving behavior in general; however, they were not told that the purpose was studying the effects of frustrating events particularly. Afterwards, the participants were asked to drive the simulator vehicle for a minimum of 5 minutes for practice. After practicing, participants were verbally briefed about the actual experiment. They were asked to take the experiment seriously and drive as they do in real life (without colliding into other vehicles or objects and without driving off the road). They were also instructed to consider traffic regulations and conform to them to the same extent as they do in real life. Finally, participants were asked to fill out a postdriving survey.

4.2. Driving scenarios

The experiment consists of a straight roadway section with two lanes in each direction separated by double yellow lines, and nine signalized intersections placed 800 meters apart. The roadway section is uniform throughout the experiment, and the intersections are geometrically similar. The surrounding setting is suburban, and the weather and visibility conditions are clear. No barriers or obstructions are placed on the road, and light ambient traffic is only observed in the opposite direction so as not to interfere with the participants' paths or affect their trajectories. Speed limit signs are regularly placed throughout the experiment. Signs indicating a speed limit of 30 miles/hour are displayed for the GWU sample, whereas those indicating 50 km/hour are displayed for the AUB sample (to be consistent with the driving environments familiar to both drivers). This speed limit was chosen because it was found to be consistent with the suburban setting and the roadway type.

The scenarios designed in both driving simulators are intended to be as similar as possible. Even though the two simulators support different authoring tools and simulation elements (makes and models of ambient vehicles, types of buildings, trees, roadway signs, etc.), the main elements that are expected to influence the driving behavior of participants are kept identical (including the roadway width and geometry, spacing between intersections, relative locations of signs compared to intersections, signal phasing cycles, and the number and location of ambient vehicles).

The first intersection is designed as an initial control intersection. As the participant approaches this intersection, the lights change from green to yellow, then red. Vehicles in the opposite direction will not violate the red light.

Each of the second, third, and fourth intersections is a treatment intersection whereby a single frustrating event occurs. The order of the corresponding three frustrating events (explained in detail below) was varied among participants to reduce the confounding effects of treatment order and analyze each scenario separately. This resulted in six different combinations of scenarios.

In the first frustrating event, the signal state changes from red to green as the participant approaches the intersection. However, the green interval ends just before the participant arrives at the intersection, and the lights display yellow, then red again. The short green interval typically ranges between 5 and 7 seconds depending on the participant's speed.

In the second frustrating event (also represented in Figures 1 and 2 below), the lights turn red as the participant arrives at the intersection. Vehicles start flowing in the perpendicular direction, but they soon stop and block the intersection totally. While the intersection is blocked, a full green interval in the participant's direction starts and ends, without leaving any space for the participant to move ahead. Afterwards, the lights turn red again as the intersection is cleared. Thus, drivers might violate the red light during the second cycle of this scenario.

In the third frustrating event, a participant approaches an intersection at which the lights also turn red; however, some vehicles will approach the driver from behind and violate the red light. In addition, some vehicles in the opposite direction will violate the red light. The violating vehicles will not interfere with the participant's path as the participant will take a right turn (on a minor road) soon after crossing the intersection. This event is presented in Figures 1 and 2.

The fifth and seventh intersections are designed as "dummy" intersections, at which the signals always display green lights. This ensures that the experiment seems realistic as much as possible because participants do not stop at every intersection they encounter.

The sixth and ninth intersections are similar to the initial control intersection where participants also arrive at a red light signal and no frustrating events take place. These are used to compare the behavior of participants between these intersections and the first, to analyze the changes in driving behavior resulting from the occurrence of the frustrating events at the previous intersections.

The eighth intersection is a treatment intersection involving two of the frustrating events described before. Participants can either experience a short green interval followed by red-light violations by other vehicles, a short green interval and vehicles in the perpendicular direction blocking the intersection, or vehicles in the perpendicular

Figure 1. Schematics showing the red-light violations scenario (to the left) and the blocked intersection scenario (to the right) from the American University of Beirut driving simulator user interface (Danaf, Abou-Zeid, & Kaysi, 2013).

Figure 2. Schematics showing the redlight violations scenario (to the left) and the blocked intersection scenario (to the right) from the George Washington University driving simulator (driver's perspective).

direction blocking the intersection followed by red-light violations by other vehicles in the participant's direction. Each of the two events experienced at this intersection is identical to the previously experienced similar event (at intersections 2 or 3), except for minor differences such as the types and colors of the violating vehicles.

At all seven treatment and control intersections, participants will have the choice whether to violate a red light.

4.3. The postdriving survey

The postdriving survey included four sections. The first two sections included 33 statements asking the participants about their driving characteristics, emotions experienced while driving, how often they perform specific actions/maneuvers while driving, and how they react to certain events occurring on the road. Most of the questions in these two sections were obtained from the DDDI (Dula, 2003; Dula & Ballard, 2003).

The original DDDI includes three subscales, namely, aggressive driving, negative emotional driving, and risky driving. Aggressive driving represents intentional physical, gestural, and verbal acts of aggression toward other road users (drivers, passengers, and/or pedestrians). Aggressive driving can be bodily (such as making rude gestures at another road user or verbally insulting him or her) or instrumental (such as flashing the headlights at another driver, tailgating him or her, or using one's vehicle to block his or her path). Negative emotional driving represents negative emotions felt while driving such as anger and rage, sadness, frustration, dejection, jealousy, and the like. Some examples of negative emotional driving include losing one's temper while driving, becoming irritated in a traffic jam, and being frustrated by the actions of other drivers/road users. Finally, risky driving represents dangerous risk-taking behaviors that are performed without the intent to harm the self or others. Such behaviors include speeding, running red lights, weaving in and out of slower traffic, and drunk or intoxicated driving (Dula, 2003, Dula & Ballard, 2003).

A few questions that were found adequate to the objectives of the experiment (studying driving violations in particular) were added from the DSI (Matthews, Desmond, Joyner, Carcary, & Gilliland, 1997) and the DBQ (Reason, Manstead, Stradling, Baxter, & Campbell, 1990). Some questions were modified or explained further to avoid confusion, and some questions were removed from the DDDI because they were not applicable to the Lebanese driving environment. These changes are explained below:

1. A question related to driving behavior at a railroad crossing was eliminated because there are no such crossings or rail in Lebanon.
2. A question related to crossing double yellow lines was eliminated because most of the Lebanese roads do not have any markings, and even when markings are available they are not respected by drivers.

3. Questions related to drunk and intoxicated driving were eliminated to avoid confusion. Although these questions loaded on the risky driving factor in the findings of Dula (2003), they loaded on a separate factor labeled as Drunk Driving in the findings of Willemsen et al. (2008). In addition, some Lebanese drivers might avoid drinking for cultural or religious reasons, and this does not necessarily mean they are not risky.
4. Questions were added from the DBQ and DSI to measure or assess other factors such as driving confidence and the propensity to commit driving violations, as these factors were not captured directly by the DDDI. The authors were also interested in differentiating between risky driving and propensity toward violations or to simply disrespecting traffic laws.
5. Some questions were rephrased after testing the survey on a few participants to clarify certain terms and avoid confusion.

In the third section, participants were asked how often they drive, what type of vehicle they drive, and whether they own that vehicle. They were also asked about their previous crash and ticket history. In the final section, participants were asked whether they felt the simulator was realistic, and whether they were affected by dizziness or other factors that influenced their driving behavior. The surveys were given in English because both samples were expected to be highly proficient in English (which is the primary language in both universities and the language in which most of the courses are taught). The survey is presented in the appendix.

4.4. Recruitment and sample description

Recruitment for both experiments was mainly based on flyers distributed all over the GWU Science and Technology Campus and the AUB campus. In addition, some participants were recruited by personal approach. A total of 100 AUB students and 53 GWU students and staff members participated. Data collection took place during the spring 2012 semester at AUB, and during the summer 2012 semester at GWU. Additional data from GWU were collected during February 2013 and February 2015.

Seventeen AUB students and 11 GWU students were excluded from the analysis due to one of the following reasons:

1. The participant driver felt extremely dizzy during the experiment.
2. The participant driver drove recklessly and did not take the experiment seriously.
3. The participant driver was overspeeding and missed the occurrence of a scenario.
4. 4.The participant driver did not follow the posted road directions.
5. Or the participant driver had an accident during the experiment. Participants who had accidents were excluded because they became more alarmed after the occurrence of the accident, and therefore their whole driving patterns changed.

It should be noted that staff members from GWU were excluded from the analysis to allow more uniformity in the drivers' sociodemographic characteristics. The remaining samples consisted of 35 GWU students, 21 of whom were males and 14 were females, and 81 AUB students, 62 of whom were males and 19 were females. In the GWU sample, ages ranged between 19 and 28 with an average age of 21.6 and a standard deviation equal to 2.59. In the AUB sample, ages ranged between 18 and 29, with an average age of 19.8 and a standard deviation equal to 2.00. The distribution of the sociodemographic characteristics of the two samples is shown in Figure 3. GWU students reported that they drive on average 1.2 h per day and drive on average 2.46 days in a typical week. Of GWU students 14% indicated that they received at least one moving violation ticket, and 43% reported that they were involved in at least one accident in the past 3 years. On the other hand, AUB students reported that they drive on average 2.1 h a day and 5.6 days in a typical week. Of AUB students 20% indicated that they received at least one moving violation ticket, and 16% said that they were involved in at least one accident in the past 3 years. The overall duration of the experiment ranged between 30 and 45 min. The time to complete the simulator drive ranged between 10 and 15 min.

Most of the participants in the AUB sample were Lebanese, living in Lebanon, and familiar with the Lebanese driving context. In the absence of strict enforcement and proper driver education, driving in Lebanon is characterized by frequent violations (often undetected), risky maneuvers, aggressive competition among drivers, and excessive honking. On the other hand, participants in the GWU sample came from different nationalities and cultural backgrounds. All of these students lived in Washington, D.C., or northern Virginia, where driving regulations are strictly enforced and violations are often detected and fined.

5. Results

Participants in both groups were compared based on their self-reported driving behavior (using the survey) and revealed driving behavior (red-light violations, time-to-

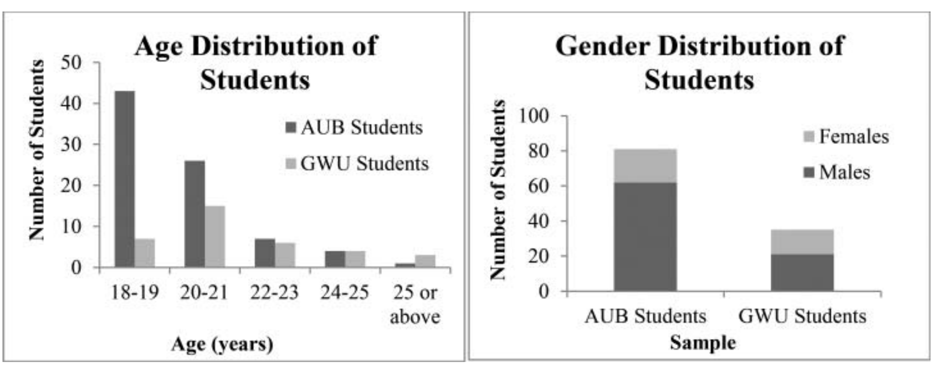

Figure 3. Sociodemographic characteristics of the two samples. GWU = George Washington University; AUB = American University of Beirut.

junction, and speed patterns following the intersections—data collected through the simulator).

5.1. Self-reported measures

Because the standard DDDI survey was not used entirely and questions were added from other instruments, the modified survey was tested for validity and internal reliability. Exploratory factor analysis was carried out and the varimax rotation method was used. Cronbach's alpha was then used to assess the internal reliability of the obtained factors.

When only DDDI questions were considered (additional questions were excluded), the results were consistent with the findings of Dula (2003), whereby the three subscales (risky driving, aggressive driving, and negative emotional driving) were established. All questions of the DDDI had high factor loadings on their expected subscales. In addition, all of the obtained factors had acceptable internal reliability and the values of Cronbach's alpha were 0.84, 0.84, and 0.74 for negative emotional, aggressive, and risky driving, respectively.

When additional survey questions were considered, an additional factor was extracted representing "tendency towards violations," and was associated with high factor loadings on the following statements:

- I feel that most traffic "laws" could be considered as suggestions.
- I tend to disregard traffic laws when I see others disregarding them.
- I exceed the speed limit without realizing it.
- I intentionally disregard the speed limit.
- I intentionally cross a red light.
- I will illegally pass a car/truck that is going too slowly.

All factors had acceptable internal reliability, and the Cronbach's alpha values were 0.83, 0.80, 0.78, and 0.72 for negative emotional driving, aggressive driving, risky driving, and tendency toward violations, respectively.

The first two statements in the survey were used to test whether the two samples differ in terms of driving confidence and self-rated experience according to the non-parametric Mann-Whitney U Test:

- I am a confident driver.
- I believe I have enough experience and training to deal with risky situations on the road safely.

The differences were not significant at the 95% level of confidence (p values were 0.48 and 0.56 for Questions 1 and 2, respectively), indicating that there are no significant differences in driving confidence and self-rated driving experience between the two samples.

Bartlett's method was used to extract factor scores. The results indicated that AUB students had significantly higher values for negative emotional driving (p value $< .01$), whereas GWU students scored higher on the factor representing tendency toward violations (p value $= .02$). No significant differences were observed

Table 1. Average extracted factor scores for the two samples.

	Negative Emotional Driving	Risky Driving	Aggressive Driving	Tendency to Violate
GWU students	−0.91	−0.20	0.20	0.37
AUB students	0.39	0.09	−0.09	−0.17
p Value	< 0.01	0.19	0.22	0.02

GWU = George Washington University; AUB = American University of Beirut.

between the two samples in terms of risky driving and aggressive driving. The average extracted factor scores of the two samples are presented in Table 1 below. Gender and age did not have a significant effect on the survey responses in any of the two samples except for aggressive driving, where males scored on average significantly higher than females in both samples (p value $<$ .01 in the AUB sample and .08 in the GWU sample), and risky driving in the GWU sample where males scored on average higher than females too (p value = .04).

5.2. Red-light violations

A red-light violation was recorded when a participant crossed the intersection to the other side (and not only the marked stop line, as it is common for Lebanese drivers to stop after the stop lines) while the signal indication was red. Only violations that were on purpose were recorded. Unintentional violations were committed by drivers who were speeding excessively and could not stop; however, these cases were eliminated from the analyses.

Red-light violations were compared by scenario type and by intersection number, keeping in mind that the order of the three scenarios mentioned before was varied among participants at the second, third, and fourth intersections. In addition, these were compared to the factors extracted from the survey.

5.2.1. Comparison by scenario type

A total of 32 violations were committed by 23 GWU students at all intersections, compared to 28 violations committed by 19 AUB students. Considering the sizes of the two samples, GWU students had a significantly higher proportion of

Table 2. Differences in red-light violations by scenario type.

	Number/Percentage[a] of Violations		
Scenario type	GWU Students	AUB Students	z Statistic for Proportions
Scenario 1 - Short green scenario	7 (20.00%)	4 (4.94%)	2.54
Scenario 2 - Blocked intersection scenario	13 (37.14%)	4 (4.94%)	4.50
Scenario 3 - Violations by other vehicles	2 (5.71%)	6 (7.41%)	−0.33
Control intersections	5 (4.76%)	9 (3.70%)	0.46
Combination of two scenarios	5 (14.29%)	5 (6.17%)	1.43
Total	32 (13.06%)	28 (4.94%)	4.06

GWU = George Washington University; AUB = American University of Beirut.
[a]Percentages represent the fraction of violations relative to all instances where the scenario occurred (percentage of violations relative to all potential violations).

violators (z-statistic = 4.35), and a significantly higher frequency of violations (13.06% of potential violations for GWU students compared to 4.94% of potential violations for AUB students, z-statistic = 4.06).

The violations by scenario type are presented in Table 2.

Compared to the total potential violations, GWU students had a higher proportion of violations for all scenario types except for Scenario 3 (violations by other vehicles). However, the differences were only statistically significant for Scenario 1 (short green) and Scenario 2 (blocked intersection) at the 95% level of confidence (z-statistics = 2.54 and 4.50, respectively). Significant differences were observed between treatment and control intersections for the GWU sample (z-statistic = 3.34).

5.2.2. Comparison by intersection number

Although GWU students had a higher frequency of red-light violations, similar trends in violations are observed in the two samples. None of the students in either sample violated a red light at the first control intersection, before experiencing any frustrating event. As participants arrived at the second, third, and fourth intersections and experienced more frustrating events, the number of violations increased in both samples as indicated in Table 3 below. The number of violations at the fourth intersection was significantly greater than that at the initial control intersection for both samples (z-statistics were 4.37 for the GWU sample and 2.90 for the AUB sample), and greater than all previous three intersections for the GWU sample (z-statistics were 3.28 and 2.96 compared to Intersections 2 and 3, respectively). However, this number dropped again at the sixth intersection, at which no frustrating events took place (second control intersection), and the decrease was significant (z-statistics were 3.62 for the GWU sample and 2.40 for the AUB sample). Nevertheless, several violations were observed at the eighth intersection, at which two combined frustrating events took place. At the last intersection, GWU students committed two violations, compared to eight violations committed by AUB students despite the fact that no frustrating events were encountered at this intersection.

5.2.3. Comparison with self-reported factors

In the AUB sample, red-light violations were correlated positively with negative emotional driving ($r = .29$, t statistic = 2.72) and tendency to violate ($r = .50$, t statistic = 5.18). The correlation with risky driving was positive but not significant ($r = .138$, t statistic = 1.24). In addition, no significant relationships were observed between red-light

Table 3. Differences in red-light violations by intersection number.

Intersection Number	1	2	3	4	6	8	9	Total
GWU Sample	0	3	4	15	2	5	3	32
AUB Sample	0	2	4	8	1	5	8	28

GWU = George Washington University; AUB = American University of Beirut.

Table 4. Differences in average extracted factor scores between violators and nonviolators.

	Negative Emotional Driving	Risky Driving	Aggressive Driving	Tendency Towards Violations
GWU students				
Nonviolators	−0.85	−0.33	−0.11	0.24
Violators	−0.95	−0.11	0.41	0.46
p Value	0.75	0.59	0.17	0.56
AUB students				
Nonviolators	0.28	0.00	−0.07	−0.44
Violators	0.72	0.39	−0.16	0.71
p Value	0.05	0.15	0.76	< 0.01

GWU = George Washington University; AUB = American University of Beirut.

violations and aggressive driving. In the GWU sample, red-light violations were not significantly correlated with any of the survey factors. Table 4 below presents a comparison between the average extracted factor scores of violators (those who committed at least one red-light violation) and nonviolators for both samples.

5.3. Time-to-junction

Time-to-junction was calculated as the expected time to reach the intersection at the moment the signal turns red for the first time (while the participant is approaching) based on the participant's speed at that moment (the same as time-to-collision, but with respect to the intersection ahead rather than a leading vehicle).

The Freidman test was used to test the null hypothesis that there are no differences between the average values of time-to-junction across successive intersections within

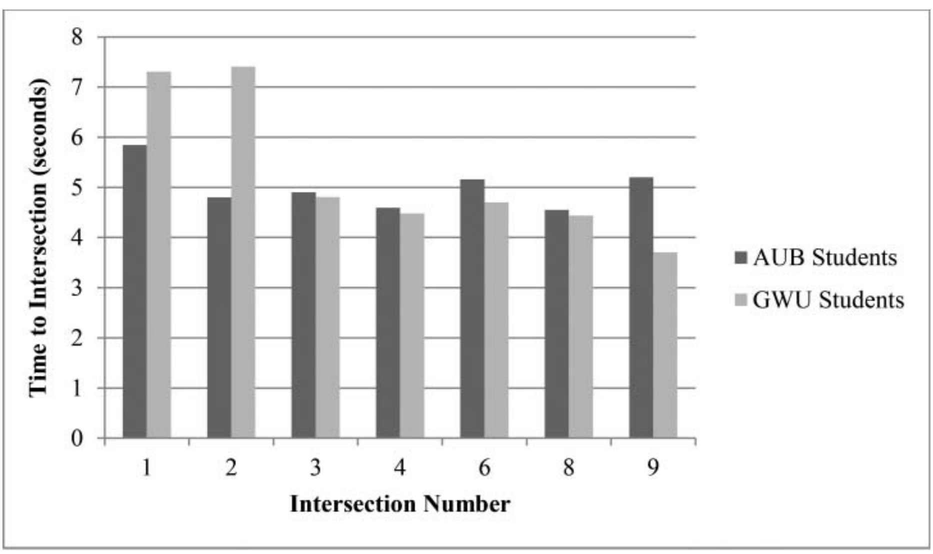

Figure 4. Differences in time-to-junction before each intersection. GWU = George Washington University; AUB =American University of Beirut.

each sample as a nonparametric alternative to the repeated measures ANOVA (because the values were not normally distributed according to the Anderson-Darling test). The results indicated that the null hypotheses can be rejected in both samples, as the test statistics were 113.37 for AUB students, and 49.82 for GWU students, both higher than the critical value at the 5% level of significance (12.59).

As indicated in Figure 4 below, GWU students had higher (safer) time-to-junction values while approaching the first and second intersections (before experiencing any frustrating event) compared to the following intersections. However, these students were significantly influenced by the occurrence of the first frustrating event at the second intersection, and thus the time-to-junction values dropped significantly. The lowest average value was observed before the ninth intersection (after experiencing two frustrating events at the eighth intersection).

AUB students also demonstrated a decreasing trend in the time-to-junction values throughout the seven intersections, but the values were not correlated with the occurrence of frustrating events at the previous intersection.

For AUB students, time-to-junction values were significantly correlated with the tendency toward violations factor at all seven intersections. Positive correlations were also observed with risky driving and negative emotional driving, but they were

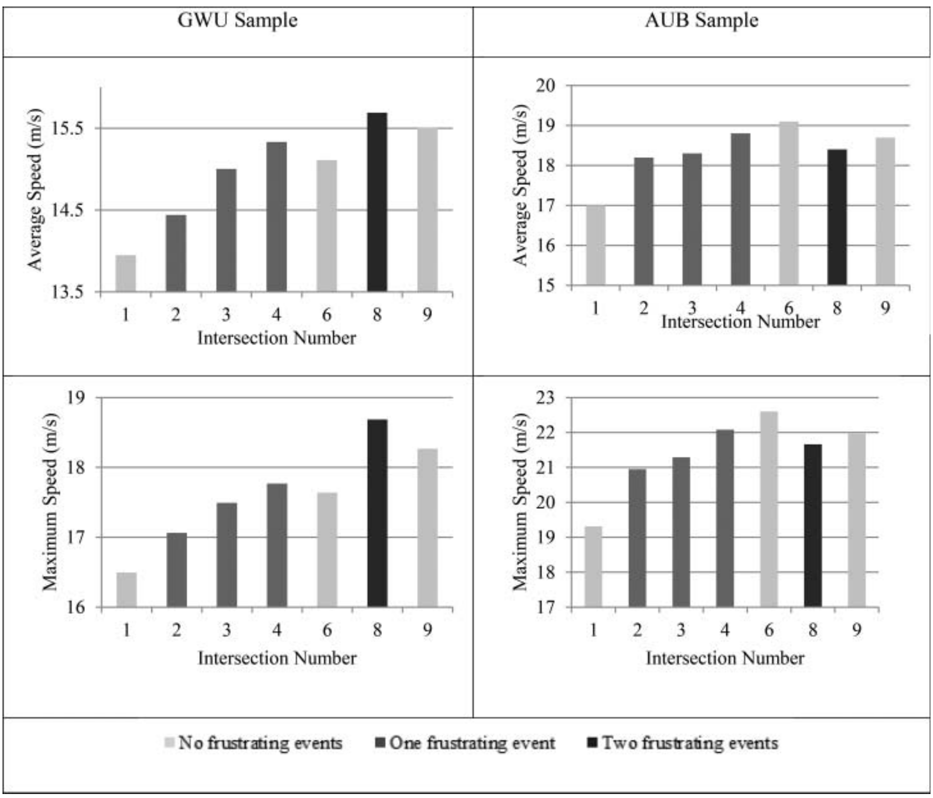

Figure 5. Average and maximum speed profiles for the two samples. GWU = George Washington University; AUB = American University of Beirut.

significant at a few intersections only. No significant correlations were observed between time-to-junction and any of the survey factors for GWU students.

5.4. Speed dynamics

Speed was recorded for each individual in the 400-meter stretches after each intersection, and the average and maximum values were then extracted. As indicated in Figure 5, participants from both samples drove faster at all intersections compared to the initial control intersection.

The Freidman test was used to test the null hypotheses that there are no differences between the average values of average and maximum speed within each sample among all seven intersections. The test statistics for both samples indicated that the null hypotheses can be rejected at the 5% level of significance, for average and maximum speed as indicated in Table 5.

In addition, both samples demonstrated increasing trends in the values of average and maximum speed throughout the experiment. To test this trend, the values of average and maximum speed for every individual at every intersection were regressed on intersection number t where $t = 1,2,\ldots,7$ (excluding dummy intersections). The panel effect was accounted for using the entity-demeaned ordinary least squares (OLS) regression (and therefore the constants were eliminated from the regression models). In addition, a dummy variable was used to represent control intersections. The results are shown in Table 6.

All of the estimated coefficients for intersection number were positive and significant, indicating general increasing trends in terms of average and maxi-

Table 5. Freidman test results for average and maximum speed.

Measure	Freidman Test Statistic	Critical Value at 5% Level of Significance
Average speed (AUB sample)	45.03	12.6
Average speed (GWU sample)	24.87	
Maximum speed (AUB sample)	66.97	
Maximum speed (GWU sample)	26.94	

GWU = George Washington University; AUB = American University of Beirut.

Table 6. Regression results for average and maximum speed.

Variable	Parameter	Slope	t-Statistic
Average speed (AUB sample)	Intersection number	0.24	6.24
	Control dummy	−0.30	−1.88
Average speed (GWU sample)	Intersection number	0.27	5.10
	Control dummy	−0.42	−1.93
Maximum speed (AUB sample)	Intersection number	0.40	7.32
	Control dummy	−0.43	−1.97
Maximum speed (GWU sample)	Intersection number	0.33	5.72
	Control dummy	−0.48	−2.06

GWU = George Washington University; AUB = American University of Beirut.

mum speed for both samples. Thus, the average and maximum speed profiles were in accordance with previous findings on red-light violations, as the values were increasing as participants moved from one intersection to another. In addition, all of the coefficients for control intersection dummies were negative and significant (at the 10% level of significance), indicating that participants drove at a slower speed at control intersections compared to treatment intersections.

Average and maximum speed were also significantly correlated with the tendency to violate factor for AUB students at all seven intersections, but not for GWU students. Average and maximum speed were not significantly correlated with any of the other survey factors except for occasional correlations at a few intersections.

6. Discussion

The frustrating events faced in the simulator were intended to replicate the driving environment in which AUB students drive, characterized by frequent violations, poor enforcement, and frustrating delays. AUB and GWU students were tested under these conditions. After analyzing the results, we were able to identify similarities and differences in the self-reported and simulated driving behavior of the two samples. In addition, we identified the effects of frustrating events on this behavior and its correlation with self-reported factors.

6.1. Self-reported factors

The survey used in this experiment was modified relative to the DDDI to differentiate between driving violations and other elements of the DDDI, particularly risky driving. Using the DDDI modified survey and the additional questions, the authors were able to establish factors similar to the standard DDDI subscales (negative emotional driving, risky driving, and aggressive driving) in addition to an additional factor representing propensity toward violations.

Similar to the original DDDI factors, the negative emotional driving factor measured negative emotions experienced while driving such as anger, irritation, frustration, discontent, and the like (Dula, 2003). Aggressive driving represented offensive behaviors and gestures toward other road users. On the other hand, risky driving represented risky behaviors such as speeding, sudden lane changing, tailgating, and others but did not include driving violations.

The survey results indicated that AUB students on average scored significantly higher on the negative emotional and risky driving subscales compared to GWU students. This is in accordance with the finding of Özkan et al. (2006a), stating that “Western” drivers consider themselves to be safer drivers than Middle Eastern drivers. On the other hand, GWU students scored significantly higher on the additional factor representing their tendency to commit driving violations. However, these findings are dependent on the assumption of the scalar invariance of the survey factors. Although the original DDDI factors were validated across cultures for scalar invariance (Willemsen et al., 2008), the factors derived from this survey (particularly tendency to violate) might be affected by scalar differences. Due to sample size issues (particularly in the GWU sample), scalar invariance could not be tested. However, this is not a limitation when comparing the survey responses of each group to the observed driving behavior of that group.

6.2. Observed driving behavior and the effects of the driving setting

After analyzing the general driving behavior of the two samples and their observed trends, several similarities and differences were identified.

Increasing trends over intersections were generally observed in both samples in terms of red-light violations and speeding. In addition, both samples had a higher proportion of red-light violations occurring at treatment intersections (those with frustrating events) compared to control intersections. Similarly, the dummy variable representing control intersections in the entity demeaned regression analyses presented in Section 5.4 had negative and statistically significant coefficients in both samples for average and maximum speed. Therefore, the occurrence of frustrating events had a significant effect on the driving behavior of both samples.

GWU students committed more red-light violations (relative to the sample size) in the driving simulator experiment. Even though those students reported fewer negative emotions while driving compared to AUB students on average, they committed most of their violations at the scenarios representing frustrating delays (blocked intersection and short green scenarios). This was consistent with the self-reported "tendency to violate" factor, whereby GWU students indicated that they are more likely to commit violations compared to AUB students.

The large number of violations observed in both samples may be attributed to several factors. First, participants might have been encouraged to commit red-light violations by the frustrating events they faced (because ambient vehicles were also violating red lights). Other potential explanations might be how seriously the participants took the experiment (in the absence of an incentive or a condition that creates motivation) and the extent to which they found the simulator realistic. However, we could not test for these explanations under the given experimental setup and data collected.

In addition, previous research has shown that the relative validity of driving simulators does apply not only to dynamics (such as speed, acceleration, etc.), but also to driving behaviors (Mullen et al., 2011). Therefore, and assuming relative validity, the number of red-light violations observed in the simulator might be exaggerated but representative of the trends that would have been observed in real-life driving.

6.3. Correlation between self-reported factors and driving behavior

In this experiment, the number of red-light violations was not correlated with self-reported risky driving in any of the two samples. This is consistent with the findings of Skaar and Williams (2005); however, the latter found that none of the DDDI scales was correlated with traffic violations among students from a small midwestern university and two high schools in Minnesota and Iowa, whereas in this study, the number of committed red-light violations by AUB students in the simulator was correlated with the negative emotional driving factor. This suggests that the more drivers become irritated behind the wheel (e.g., waiting at a red light for a long duration), the more likely they are to violate. This is in accordance with the findings of Shinar (1998) stating that red-light violations are positively correlated with the actual and perceived waiting time at the intersection. Also in the AUB sample, violations were also strongly correlated with the additional scale representing participants' tendency to violate traffic laws. This scale was intended to be distinguished from risky driving or "sensation seeking" and merely reflects drivers' disregard for traffic laws.

In terms of speeding, the behavior of AUB students was correlated with their self-reported tendency to violate traffic laws, and to a lesser degree with their self-reported risky and negative emotional driving. However, the speeding behavior of GWU students did not reflect any of their self-reported characteristics. Unlike GWU students, the driving behavior of AUB students in the simulator experiment was similar to their everyday driving behavior; those who reported that they usually commit violations did so in the driving simulator experiment.

The positive correlation between negative emotional driving and the observed driving performance (red-light violations and speeding) in the AUB sample may also be related to the increasing patterns in speeding and red light violations over intersections; as participants experienced more frustrating events, they became more irritated and therefore more likely to violate.

6.4. Effect of demographics on driving behavior and self-reported measures

In both samples, the effects of demographics (age and gender) were neither significant on any of these measures nor on the survey responses (except for aggressive driving, where males scored higher than females in both samples on average, and risky driving where males in the GWU sample scored higher than females on average). The effects of these characteristics on different driving behaviors (violations, risky driving, aggressive driving, etc.) have been extensively studied by researchers. Some of these studies found significant relationships between age and gender and these behaviors, whereas others did not. For example, Porter (1999) found that younger drivers and males are more likely to run red lights. In a simulator study carried out by Lee (2010), age was considered as the most significant factor affecting safe driving and awareness. On the other hand, a simulator study by Richer and Bergeron, (2011) found that age was neither related to risky driving nor to aggressive driving. Another simulator experiment by Deffenbacher, Deffenbacher, Lynch, and Richards (2003) found that gender could not be related to anger, but to speed (males engaged in more speeding compared to females). Similarly, Suhr and Nesbit (2013) found no gender effects on trait anger and driving anger in a survey experiment. In this experiment, the absence of the age effect might be attributed to the homogeneity among participants, since all of them were young university students.

6.5. Study implications

The findings of this study suggest that driving violations should be considered as separate driving behaviors that are independent of risky driving. Although Dula (2003) attributed red-light violations to risk taking, driving violations have been studied before independently of risky driving. For example, Rimmö and Åberg (1999) considered disinhibition to be a better predictor of driving violations and accidents than thrill seeking. Brown and Cotton (2003) stated that drivers who engaged in speeding believed that they could do so but still drive safely. Forward (2008) stated several factors that can influence driving violations such as descriptive norms (perceived consensus), risk perception (considering that a violation is carried out when it is regarded as “safe” to do so), disinhibition, and poor enforcement.

The outcomes of this study support the findings of Shinar (1998), stating that aggression on the roads is related to characteristics of the drivers, the situations they face, and their interpretation of these situations (Shinar, 1998, considered red-light violations as “instrumental aggression”). However, when put in driving conditions that are uncommon in Washington, D.C. and north Virginia (characterized in the simulator by frequent disregard for traffic laws and poor enforcement), the driving behavior of GWU students was not correlated with their self-reported driving behavior, and thus the effects of the drivers’ characteristics were not confirmed. A possible explanation for this inconsistency could be that the drivers’ familiarity with driving situations plays a major role in their interpretation and therefore affects the resulting driving behavior.

In the AUB sample, speeding and red-light violations were correlated with two factors, namely, negative emotional driving and tendency to violate. The first correlation suggests that driving violations in Lebanon might be reduced by eliminating unnecessary frustrating delays such as those resulting from short green intervals, blocked intersections, and the like. The second correlation highlights the importance of enforcement and education in order to prohibit violations.

On the other hand, we should further investigate why GWU students committed more red-light violations in the driving simulator and reported a higher tendency to violate even though they drive in an environment with better traffic law enforcement.

The main results and implications of this study are summarized in Table 7.

6.6. Study limitations

We have attempted to explain differences in driving behavior between the two samples by analyzing the participants’ reactions to the driving scenarios and comparing them to their survey responses. However, the differences may also be partly attributed to differences between the driving simulators and differences between

Table 7. Main results and their respective implications.

Category	Result	Implication
Self-reported driving behavior	A driving construct labeled as "tendency towards violations" was identified.	Driving violations cannot be fully explained by risky, aggressive, or negative emotional driving.
Observed driving violations and surrogate safety measures	GWU students, who reported higher tendency to violate, committed more red-light violations relative to the sample size.	With the lack of enforcement, and in a similar driving environment, drivers with higher tendency to violate are more likely to commit violations.
	Similar (increasing) trends in driving violations were observed in the two samples.	The more drivers are exposed to frustrating events, the more likely they are to commit violations and drive at a higher speed.
	GWU students were mostly sensitive to the blocked intersection scenario while AUB students were more sensitive to violations by other vehicles.	Drivers in different cultures react differently to different frustrating events.

GWU = George Washington University; AUB = American University of Beirut.

the motivations/task attentiveness of the two participant samples. The samples were tested using two different driving simulators; the vehicle types were different, the projection screens were different, the finer details in the two simulations were also different (types and colors of ambient vehicles, building facades, etc.), and a car honk was available in the AUB driving simulator (and used by most participants), but not in the GWU simulator. Determining the extent to which the two samples of participants differed in terms of how motivated they were and how seriously they took the experiment is difficult, despite the same set of instructions given to both. In future extensions of this study, the use of incentives may be considered to enhance the realism of the experiment and improve participants' motivation.

This research also studied a limited range of frustrating events (occurring at signalized intersections only). Even though these events were chosen based on existing literature (Harris & Nass, 2011) and because of their frequent occurrence in Beirut, the results should be validated for other scenarios that can possibly cause frustration.

On the other hand, there is a lack of safety/collision data associated with signalized intersections in Lebanon. Mainly, data associated with the impact of regulation enforcement on driver behavior including red-light violations is not currently available. Even though traffic regulations at signalized intersections are the same in Lebanon and in the United States of America, the discrepancy in the observed behaviors of the AUB and the GWU samples may be attributed to the discrepancy in the enforcement measures adopted in both countries during the time of the study. Another discrepancy may be associated with the differences between the signal layouts in the United States of America and in Lebanon. In Lebanon, the signal posts are often at the stop line, as it is the case in many cities in Europe. In the United States of America, the signal posts are usually installed after the intersection post. To have comparable driving conditions, the authors adopt the U.S. traffic signal layout with both samples (AUB and GWU samples).

Finally, the results were based on small sample sizes (especially in the GWU sample). Even though small sample sizes are common in most driving simulator experiments (most of which range between 20 and 30 participants) (Papantoniou, Papadimitriou, & Yannis, 2013), they can have adverse effects on the representativeness of the samples. In addition, the discrepancy between the two sample sizes was a major limitation. Nevertheless, the simulator experiment was designed to account for small sample sizes by collecting multiple records from each individual (at seven successive intersections). Since participation was voluntary, the two sample sizes might not have been representative of drivers in both countries; for example, the AUB sample included a high proportion of males (mainly due to the snowballing effect). The snowballing effect might have also affected the representativeness of the GWU sample especially that no financial incentive was given for participating in this experiment.

7. Conclusion

As a step toward dealing with the corresponding traffic safety problem and understanding cultural differences in driving behavior, the objective of this article is to investigate the differences in driving behavior and particularly speeding and red-light violations at signalized intersections between drivers located in two countries: a Middle Eastern country—Lebanon (students from the American University of Beirut [AUB]) and a Western country—the United States of America (students from the George Washington University [GWU]). To realize the stated objective, several research contributions were made: (1) The authors were able to design a controlled driving environment to analyze surrogate measures that are measurable, scalable, repeatable, and amenable to traffic-related interventions. (2) The corresponding experiments were implemented using two different driving simulators with different specifications and that were located in two different countries. (3) In addition to self-reported measures related to risky driving, aggressive driving, negative emotional driving, and tendency to violate traffic rules, the authors utilized the simulators to analyze observable driver behaviors. (4) The authors, through a basic exploratory analysis, were able to find similarities and differences between driving behavior at signalized intersections in a developed country and in a third world country. The results indicate that (1) the frustrating events faced in the simulator caused red-light violations and postintersection speeding for the AUB sample and the GWU sample; (2) speeding and red light violations followed increasing trends as students experienced more frustrating events; (3) AUB students considered themselves as more risky than GWU students and indicated that they experience negative emotions more often, while GWU students reported that they are more likely to commit driving violations compared to AUB students; (4) the driving behavior of AUB students was correlated with their self-reported characteristics, particularly negative emotional driving and tendency to violate; (5) on the other hand, GWU students made more red light violations and their driving behavior was not correlated with their self-reported characteristics.

The findings of this research have implications on enforcement and driver education. These results indicate that driving violations might not be necessarily related to risky or aggressive driving, but to an individual's tendency to violate traffic rules in general.

Even though the adopted approach is promising in terms of studying traffic safety across cultures, several improvements may be made to the work performed in this article. Larger sample sizes and more representative samples should be used in future studies. More elaborate experiments may be designed adding more traffic and thus dealing with different congested and uncongested regimes. With information of the surrounding vehicles, car-following and lane-changing behaviors may be studied after recording trajectory data at extremely small time steps (i.e., 0.1 second). This may allow studying inter- and intradriver heterogeneity distributions/patterns and their impact on roadway safety.

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Appendix

Postdriving survey

Driving behavior survey

This survey is intended to study the driving behavior of AUB students. All your answers will remain confidential.

Subject ID [Filled out by Research Assistant]: ……….…………………………

Survey Date and Time [Filled out by Research Assistant]: ………………………

Please answer each of the following items as honestly as possible. Please read each item carefully and then circle or check the box corresponding to the answer you choose on the form. If none of the choices seem to be your ideal answer, then select the answer that comes closest. THERE ARE NO RIGHT OR WRONG ANSWERS. Select your answers quickly and do not spend too much time analyzing your answers. If you change an answer, erase the first one well. The expected completion time of this survey is 10 minutes.

I. Please indicate your level of agreement with the following statements:

Section 1:		Strongly Disagree Disagree Neither Agree Agree Strongly Agree Nor Disagree
1.	I am a confident driver.	☐ ☐ ☐ ☐ ☐
2.	I believe I have enough experience and training to deal with risky situations on the road safely.	☐ ☐ ☐ ☐ ☐
3.	I get a real thrill out of driving fast.	☐ ☐ ☐ ☐ ☐
4.	I enjoy the sensation of accelerating rapidly.	☐ ☐ ☐ ☐ ☐
5.	I consider myself to be a risk-taker.	☐ ☐ ☐ ☐ ☐
6.	I like to raise my adrenaline levels while driving.	☐ ☐ ☐ ☐ ☐
7.	I feel that most traffic "laws" could be considered as suggestions.	☐ ☐ ☐ ☐ ☐
8.	Driving brings out the worst in people.	☐ ☐ ☐ ☐ ☐
9.	I feel it is my right to get where I need to go as quickly as possible.	☐ ☐ ☐ ☐ ☐
10.	I consider the actions of other drivers to be inappropriate or "stupid."	☐ ☐ ☐ ☐ ☐
11.	I feel it is my right to strike back in some way, if I feel another driver has been aggressive toward me.	☐ ☐ ☐ ☐ ☐
12.	I feel that passive drivers (who are slow to react) should learn how to drive or stay home.	☐ ☐ ☐ ☐ ☐
13.	I tend to disregard traffic laws when I see others disregarding them.	☐ ☐ ☐ ☐ ☐

II. Please indicate how often you engage in the following driving behaviors or experience the following situations:

Section 2:		Never	Rarely	Sometimes	Often	Always
1.	I exceed the speed limit without realizing it.	☐	☐	☐	☐	☐
2.	I intentionally disregard the speed limit.	☐	☐	☐	☐	☐
3.	I intentionally cross a red light.	☐	☐	☐	☐	☐
4.	I drive even when I am angry or upset.	☐	☐	☐	☐	☐
5.	I lose my temper while driving.	☐	☐	☐	☐	☐
6.	I flash my headlights when I am annoyed by another driver.	☐	☐	☐	☐	☐
7.	I honk the horn when I am annoyed by another driver.	☐	☐	☐	☐	☐
8.	I make rude or inappropriate gestures towards drivers who annoy me.	☐	☐	☐	☐	☐
9.	I verbally insult drivers who annoy me.	☐	☐	☐	☐	☐
10.	I deliberately use my car to block drivers who tailgate me (follow me closely).	☐	☐	☐	☐	☐
11.	I would tailgate a driver who annoys me.	☐	☐	☐	☐	☐
12.	I race other drivers at traffic lights to get ahead once lights turn green.	☐	☐	☐	☐	☐
13.	I will illegally pass a car/truck that is going too slowly.	☐	☐	☐	☐	☐
14.	When I get stuck in a traffic jam I get very irritated.	☐	☐	☐	☐	☐
15.	I will weave (move from lane to lane) to avoid slower traffic.	☐	☐	☐	☐	☐
16.	When someone cuts me off (changes lane in front of me abruptly), I feel I should punish him/her.	☐	☐	☐	☐	☐
17.	I get impatient and/or upset when I fall behind schedule when I am driving.	☐	☐	☐	☐	☐
18.	Passengers in my car/truck tell me to calm down.	☐	☐	☐	☐	☐
19.	I get irritated when a car/truck in front of me slows down for no reason.	☐	☐	☐	☐	☐
20.	I will drive in the shoulder lane or median (extreme right or left) to get around a traffic jam.	☐	☐	☐	☐	☐

III. Demographics:

(The following questions are to ensure that we have a representative sample of AUB students)

1. How many hours do you study/work (academic or nonacademic, for pay) per week?_____________
2. How many hours did you drive today?_____________
3. How many of these were in heavy traffic? _____________
4. How many hours do you drive on an average weekday? _____________
5. How many days a week do you drive on average? _____________
6. Do you own the vehicle you drive? _____________
7. Please indicate the make, model, and the year of manufacture of this vehicle: Make (e.g. Honda, Mercedes, etc.): _________ Model (e.g., Accord, 3-Series, etc.): ___________ Year of manufacture: _________
8. How many major accidents in the past 3 years have you been involved in as a driver?_____________
9. How many moving violation tickets (speeding tickets, tickets for crossing red lights, etc., but not including tickets obtained for not wearing the seatbelt) have you been given in the past 3 years as a driver? _____________

IV. Finally, we'd like to ask you a few questions below about the driving experiments you just did using the simulator.

1. Overall, to what extent did driving in the simulator feel like real world driving?

Not at all close	Somewhat close	Very close
☐	☐	☐

2. How realistic did the driving speed in the simulator feel to you?

Very unrealistic	Somewhat realistic	Very realistic
☐	☐	☐

3. To what extent did you feel dizzy while driving the simulator?

Not at all	A little	Very much
☐	☐	☐

4. Do you believe that dizziness or other factors affected your driving behavior in the simulator to differ from your actual driving behavior on the roads?

Not at all	A little	Very much
☐	☐	☐

V. If you have any comments about this survey or the drive in the driving simulator, please write them below:

____

____

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