INDIVIDUAL SELECTION OF DRIVING SPEEDS: ANALYSIS OF A STATED PREFERENCE SURVEY

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ABSTRACT

The diversity of drivers' speed selection in free flow conditions has been assumed to originate from various human factors, mainly differences in driver characteristics and preferences. This study uses a stated-preference web-based survey with a sample of 290 participants to investigate the diversity of speed selection in relations to driver characteristics. The survey included newly developed scales of estimating driving risks and estimating personal difficulty of performing vehicle-related technical tasks. Also included were items on performing spatial tasks, and drivers' own self-assessments. The analysis of the survey results revealed that newly developed latent driver characteristics, such as risk awareness and technical aversion, were found to strongly affect individual drivers' speed selection in a daily trip – Daily Speed Selection [DSS]. The perceived speed of the average driver, or Average Driver Perception [ADP], also had a significant effect on drivers' own speed selection. In addition, some latent characteristics were found to have stronger effects in certain demographic groups. Implications for further speed-selection researches and road safety policies are discussed.

Keywords: Driving Behavior, Human Factor, Factor Analysis, Survey Methods

1. INTRODUCTION

In recent years, there has been much interest in investigating the safety implications of driver speed selection and speed distributions (Hauer, 2009; Shinar, 1998). Recent studies have shown that higher crash rates are often related to large speed dispersions, where drivers travel at a wide range of speeds on a single road segment (Aarts & van Schagen, 2006). Lowering the speed of the fastest drivers has been suggested as a more beneficial safety measure than decreasing the average speed in a road segment (Taylor, Lynam, & Baruya, 2000). While unequivocal conclusions on the influence of overall higher operating speeds on crash probability have not yet been established, it is generally accepted that the severity of crashes increases as speed increases (Donnell, Hines, Mahoney, Porter, & McGee, 2009; Hauer, 2009; Shinar, 1998). Consequently, numerous attempts have been made to further understand drivers' speed selection which may offer insight into the nature of speed distributions as created by individual drivers, leading to improved speed management strategies for road safety.

Understanding drivers' selection of operating speeds in uncongested flows has been a challenge for many professionals, both in transportation engineering and human factors research. Studies that analyze and compare various speed prediction models have not been able to agree on a single method for predicting operating speeds in a given road segment (Fitzpatrick, Carlson, Brewer, Wooldridge, & Miaou, 2003). This seems to be a result of the many factors which intervene in drivers' selection of speed, such as the inferred design speed and visual cues, roadway and roadside elements, road classification, drivers' individual reaction times, speed enforcement, design consistency, drivers' attitudes and characteristics, and more (Fitzpatrick et al., 2003; Donnell et al., 2009). In addition, Hassan et al. (Hassan, Sarhan, Dimaiuta, & Porter, 2011) point out specific weaknesses of modern speed modeling studies, such as lack of speed distributions and lack of speed changes between road elements. In summary, speed choice and distributions are important elements of crash likelihood and severity, yet there is a need for additional research on the subject.

A few strategies of managing operating speeds focus on aspects of the road environment, through the concept of “self-explaining roads”, targeting drivers’ speed selection through their perception of the road’s classification using geometric features and visual cues (Theeuwes & Godthelp, 1995). These relationships between road geometry and speed have also been used in developing design consistency models and their related implications on safety (Mattar-Habib, Polus, & Farah, 2008). However, the use of geometric features in managing speeds is limited by lack of comprehensive information and costs of reconstruction (Donnell et al., 2009).

Other components of the road environment include traffic and posted speed limits. Traffic speed and density are eminently influential in unstable flow; however, some drivers were found to explain exceeding the speed limit (thus, in free-flow conditions) as an adaption to the speed of other surrounding vehicles (SWOV, 2012). Literature on speed selection and Theory of Planned Behavior generally supports the assertion that drivers are influenced by their perceived subjective social norms, i.e., what they believe is common or accepted behavior amongst their social circles, or in the general public (Leandro, 2012; Paris & Van den Broucke, 2008; Richard et al., 2012). Traffic control devices, and specifically posted speeds, are also often used in managing speeds, especially in the presence of enforcement (Haglund, 2001; Hauer, Ahlin, & Bowser, 1982). However, without enforcement, speed limits are often exceeded (Fitzpatrick et al., 2003; Donnell et al., 2009; Richard et al., 2012; Haglund, 2001).

The distributions of operating speeds and overall driving behaviors are often attributed to the various characteristics of the driver population, ranging from age and gender (Richard et al., 2012; Jorgensen & Polak, 1993; Wasielewski, 1984), temporary states of distraction and cognitive overload (Recarte & Nunes, 2002), to personality traits such as positive self-assessment and sensation seeking (McKenna, Stanier, & Lewis, 1991; Walton & Bathurst, 1998). Vehicle type and characteristics have also been studied for their influence on speed selection (Wasielewski, 1984).

More specifically, it was found that drivers tend to rate themselves as better-skilled and safer drivers compared to their perceptions about the average driver (Horswill, Waylen, & Tofield, 2004; McKenna, Stanier, & Lewis, 1991; Walton & Bathurst, 1998). Positive self-perceptions correlated with faster selected speeds (Horswill, Waylen, & Tofield, 2004). Although drivers perceived they drove slower than the average driver, in combining their own selected speeds, the average selected speed resembled the average speed observed on similar roads (Walton & Bathurst, 1998).

Incentives can also play an important role in drivers' speed selection (Reagan, Bliss, Van Houten, & Hilton, 2013); a significant portion of studies analyzes speed-selection as an optimization point or a homeostasis balance between risks and benefits of driving speed as perceived by the individual driver (Rietveld & Shefer, 1998; Tarko, 2009). Whereas some factors in this optimization process may be individually assessed, such as value of time and crash risk, other incentives, such as avoiding detection by police cars, are more similar across drivers.

This paper uses a stated preference survey, a technique used frequently in transportation research (Kroes & Sheldon, 1988). The survey presents drivers with various driving scenarios, accompanied by a series of questions related to speed selection. The answers reveal how participants' speed preferences are related to different situations. This technique has been used by Walton and Bathurst (1998) to analyze speed selection preference. In the 1998 study, participants were asked to state their perceived daily speed on a continuous scale, in two speed limit conditions – 100 km per hour (kph) and 50 kph. Participants were also asked what they thought the speed of the average driver would be under the same circumstances. In our study, all participants were presented with additional pictures of the speed-limit areas (100kph and 50 kph), revealing wide pavement, unobstructed visibility, and light traffic, thus allowing free-flow conditions in clear daylight. Items of self-assessment, attitudes, and demographic characteristics were added for further examination of driver characteristics. The study was based on the hypothesis that drivers' speed selection will vary by both explicit (socio-demographic) and implicit (latent) driver characteristics, ranging from age and gender to characteristics that may be uncovered by analyzing participants' ratings of various items in the survey.

Our study uses data collected using a web-based survey. Web-based questionnaires are an efficient tool to collect preference information at a low cost (Cobanoglu, Warde, & Moreo, 2001). Data provided in internet surveys are at least as good in quality as those provided by traditional methods (Gosling, Vazire, Srivastava, & John, 2004). Web-based survey techniques have been similarly used in previous studies to assess driving behavior (Horswill, Waylen, & Tofield, 2004; Ivers, et al., 2009; Vingilis, et al., 2013).

The goal of this study is to outline the impact that driver characteristics have on driving speeds across the driver population, and explore some of the mechanisms involved in speed distributions. This study incorporates a wide range of driver characteristics, including different ages, gender and self-perceptions. The expected contribution of this study is characterizing the relationships between various driver characteristics and speed selections. A deeper understanding of the individual driver's selection of operating speeds could be beneficial in managing operating speeds and selecting effective countermeasures to improve road safety.

2. METHODOLOGY

2.1 Theoretical Framework

In this paper, the factors influencing the variability in drivers' speed selection are divided into two categories – explicit, socio-demographic characteristics, and implicit, latent characteristics, to be explored by the items in the survey. It is believed that drivers' speed selection in a driving situation depends on the prevailing road environment characteristics as well as their own individual characteristics and preferences. This basic speed selection is generally maintained unless other risk-related incentives are present. In our study, the speed selected for a daily trip is regarded as the basic speed at which the drivers will usually drive, unless other incentives are presented. This is defined as their Daily Speed Selection (DSS).

2.2 Survey Design

Before starting the survey, participants had to state if they held a driver's license, and how frequently they drove, in order to omit participation of non-drivers. The survey included speed selection questions, items of self-assessment and attitudes, and socio-demographic information. The speed selection questions were based on Walton and Bathurst's methodology (1998), with the additional pictures such as can be seen in figure 1:

<Figure 1>

Both pictures were taken in road segments in which the actual speed limit was the same as presented by the survey – 50 kph in the urban street (Figure 1a) and 100 kph on the freeway (Figure 1b). Thus, participants answered two scenarios accordingly. The question was phrased as follows (freeway condition): *"The picture above represents a freeway in which the speed limit is 100 kph."* Drivers were then asked to estimate their speed in a daily trip and the speed of the average driver, on a scale ranging from 0 to 150 kph. All participants answered both conditions in a randomized order.

It should be noted that drivers were not explicitly asked to refer to the location presented in their replies. However, both pictures display a wide road with long sight distances and high visibility conditions, avoiding any signs which may enable participants to recognize the location and compromise results. Our assumption was that drivers will be influenced by these pictures, although the speed limit in each area was clearly mentioned, a phenomenon known as *priming* in psychological theories, by which behavior is unconsciously affected by a certain stimuli (Bargh, Chen, & Burrows, 1996). Our intention was to recall driving conditions in which drivers are prone to exceed the speed limit, and since the survey was anonymous, participants could answer honestly – as they were kindly asked – without fear of being recognized or singled-out.

Drivers were then asked how many years have they owned a driver's license and how many years have they had a vehicle in which they were the primary users. Then, drivers were asked to rate items on a Likert scale (1-7 ratings) in a number of sections – *self-assessment* of driving habits, *driving risks* assessment (newly developed), and difficulty of performing either vehicle-related *technical tasks* (newly developed) or everyday *spatial tasks* (selected questions from Prato, Bekhor, & Pronello, 2005).

The *self-assessment* questions were designed as follows, based on Walton and Bathurst (1998): "*Rate your driving safety compared with the average driver (1 – much riskier, 7 – much safer)*". Similarly, drivers were asked to rate their driving skills (1 – much worse, 7 – much better). In the *driving risks* section, drivers were asked: *"Rate the risk of an accident during the following driving scenarios (1 – very low, 7 – very high)"*. In *vehicle-related technical tasks*, drivers were asked: *"Rate the following vehicle operation tasks by your would-be difficulty to* *perform them independently (1 – very easy, 7 – very difficult)"*. The last scale appeared also rating the feasibility of performing *spatial tasks*, such as planning a route to an unfamiliar destination. Last, drivers were asked for their demographic information such as age, gender, education, employment, and whether they had taken a driver improvement course in the past. The web-based survey was distributed via social networks and mailing lists, in Hebrew, and translated from/to English on need basis.

2.3 Survey Structure

To avoid any priming of demographic and personal characteristics, which may cause participants to distort their answers due to stereotype priming (Bargh, Chen, & Burrows, 1996), the only questions that preceded the speed selection questions were the sample selection questions. The order of the speed selection questions was randomized between the freeway and the urban street conditions. The appearance of the sections of driving risks, vehicle-related technical tasks, and spatial skills was also randomized, as well as the items within each section. Only after all the stated preferences questions were completely, were the participants asked to fill out their demographic information. The web-based survey allows for logical tests, such as time to complete the survey and unreliable answering patterns.

2.4 Sample Characteristics

After omitting incomplete responses, the valid sample was composed of 297 participants, out of which 290 had a driver's license. The main sample characteristics are as follows: 44% were females; 87% had a bachelor degree or higher education; 61% were between 25 and 34 years old; 91% had a driver's license more than 5 years, and 72% have been the primary user of their vehicle for more than 3 years. These characteristics reflect the methods by which the survey was distributed since many contacts were made through university mailing lists.

3. RESULTS

3.1 Daily Speed Selection

First, the distribution of drivers' Daily Speed Selection [DSS] was compared to their estimations of average driver speed, hence Average Drive Perception [ADP]. Figure 2 displays the distributions of the DSS and the ADP [(a) for freeway and (b) for urban street]:

<Figure 2>

It can be seen from figure 2 that the distributions of the drivers' self-selected speeds are somewhat similar to their perception of the speed of the average driver [ADP]. However, there are higher speeds for the average driver, meaning some drivers estimate that other drivers drive faster than themselves. These findings will be further analyzed in the prediction models for drivers' speed selection.

The Daily Speed Selection (DSS) was also analyzed for its deviation from the speed limit of the road (SL). Thus, the average DSS in each condition was found to be significantly different from its respective speed limit (SL) in both conditions: $\overline{DSS_{100kph}} - 100kph = 8.28\ kph, SD = 10.60$; $\overline{DSS_{50kph}} - 50kph = 10.63\ kph,\ SD = 9.86$. A two-way ANOVA analysis also revealed significant main effects of *age over 50* [F(1,264)=4.60, p=0.03] and *gender* [F(1,264)=22.48, p<0.001] on the selected deviation from the 100 kph speed limit, where drivers over 50 years of age chose lower speeds, and also females chose lower speeds than males. An interaction effect emerged in the freeway condition [F(1,264)=11.98, p=0.001], by which the difference between females and males is much more pronounce in the age group over 50. Similar main effects emerged in the urban street. Other socio-demographic characteristics were also found to have significantly additional value in drivers' selected deviation from the speed limit in a daily trip. This will be detailed in the prediction models section.

3.2 Latent Driver Characteristics

The items of self-assessment, driving risks, vehicle-related technical tasks, and spatial skills, were analyzed for latent driver characteristics. In the factor analysis, oblique rotations were used since the scales were newly developed and independence between factors was not established. Principal Axis Factoring was used for factor extraction since normal distributions have not been fully verified in our sample.

3.2.1 Self Assessment Drivers' self-assessment of their individual driving safety and skills were analyzed by sorting selected speeds in each speed limit scenario, and comparing the self-ratings of drivers with the 25% highest speeds with the self-ratings of drivers with the 25% lowest speeds. The results are presented in Table 1:

<Table 1>

The differences between drivers in their self assessment of skills and safety displayed interesting trends, in which personal driving safety was rated lower and skills were rated higher for high-speed drivers, compared with low-speed drivers. Thus, a new variable was devised: Skills-Safety Gap [SSG] – the gap between a driver's self-assessment of skills and safety. If drivers believe they are well-skilled, and they do not claim to drive very safely, the gap grows positively, and vice versa, ranging from 3 to (-3). This new variable was found to have significant contributions to speed selection in our sample, in both SL conditions.

3.2.2 Driving Risks An exploratory factor analysis of driving risks revealed two main factors which may affect drivers' speed selection, detailed in Table 2:

<Table 2>

The dominant risks in each factor are highlighted in bold. As can be seen from Table 2, the *risk awareness* [RA] factor is governed by driving risks which are not commonly considered as highly risky, in comparison to the rest. We conclude that drivers who rated these items higher are overall more aware to driving risks. In contrast, *law awareness* [LA] highest items are highly regarded as risky, in the public media and by law, and thus govern the second factor.

3.2.3 Technical and Spatial Tasks An exploratory factor analysis on vehicle-related technical tasks revealed a single factor, as can be seen in Table 3:

<Table 3>

The single factor found in the vehicle-related technical tasks analysis was then titled as *technical aversion* – aversion from performing technical tasks on the vehicle [TA]. The prominent tasks in this factor may be considered difficult to persons who do not view themselves as technically adept. This factor was found to have a strong contribution to drivers' speed selection in our sample. A similar analysis was conducted on *spatial tasks* items, and two factors were found – spatial skills in unfamiliar tasks, and spatial skills in spatial tasks. However, since these factors did not contribute to speed selection as significantly as the previous factors, they are not detailed any further.

3.2.4 Average Driver Perception In search for additional information on driver speed selection we turned into estimations of the average driver, under the assumption that the perception of how the average driver, or most drivers act, influences personal speed selection. Figure 3 displays the distributions of the difference between each driver's DSS and ADP in both speed limit conditions:

<Figure 3>

Figure 3 above shows that in both conditions, more than 40% of drivers chose the same speed for themselves as the speed they think chosen by the average driver. This shows a possible effect of social norms on the speed selection, since drivers assume they act according to the prevalent norms on the road.

3.3 Prediction Models for Driver's Daily Speed Selection (DSS)

For the prediction models of drivers' speed selection in a daily trip (DSS – Daily Speed Selection), multiple linear regression models were considered, assuming that speed can be considered as a scale variable, and its distribution in the population is normal as generally described by speed studies (Donnell, Hines, Mahoney, Porter, & McGee, 2009). Three types of variables were used in the analysis: *Socio-demographic characteristics* are all defined as dummy variables, and they refer to explicit characteristics as stated by the participants. *Latent characteristics* are all measured as either scale or ordinal variables, and they were either explicitly stated or extracted by the factor analysis, as detailed above. *The interaction variables* are products of the socio-demographic characteristics with the latent characteristics. Equation 1 shows the general structure of the prediction model:

$$DSS - SL = \alpha + [\beta_{sd}] * [X_{sd}] + [\beta_l] * [X_l] + [\beta_{in}] * [X_{sd}] * [X_l] + e_i \qquad (1)$$

where:

DSS – The driver's Daily Speed Selection

SL – Speed Limit in the driving scenario

α – A constant

$[\beta_{sd}]$ – A coefficient vector for Socio-Demographic Characteristics

$[X_{sd}]$ – A variable vector of Socio-Demographic Characteristics

$[\beta_l]$ – A coefficient vector for Latent Characteristics

$[X_l]$ – A variable vector of Latent Characteristics

$[\beta_{in}]$ – A coefficient vector for the interaction variables.

e_i – An error term for the prediction model

Three versions of the prediction model were evaluated: *Model 1* considered only the socio-demographic characteristics, *Model 2* considered both socio-demographic and latent characteristics, and *Model 3* considered all driver characteristics, including possible interactions between the socio-demographic and latent characteristics, extracted from a MANOVA analysis between the socio-demographic and the latent characteristics. Each interaction variable used in our analysis was constructed as a result of a significant main effect of the socio-demographic characteristics on the latent characteristic in question. Table 4 presents the results of the multiple regressions for the deviation between the Daily Speed Selection [DSS] and its relevant speed limit [SL] with the set of variables included in each model (1 through 3). Each model is estimated in respect to the infrastructure picture presented, with a speed limit of 100kph in the freeway condition and 50kph in the urban street.

<Table 4>

In Table 4, the interaction variables starting with the letter “I” signify the inverse of the original dummy variable, for example, “IGF” refers to males only, “IHF” refers to drivers with low trip-frequency, etc. This was done following some differences found between socio-demographic groups in their variance of the estimated latent variables. The model fit statistics display an improvement of the model from the first version to the last version, showing that both latent variables and interaction variables are significant in drivers’ DSS.

Model 1 The results of model 1 show that female drivers and drivers over the age of 50 tend to select lower speed than their counterparts. In addition, high-frequency drivers tend to select higher speeds, which is reasonable since they probably gain more confidence in their driving abilities by being on the road often. These three variables may also prove useful in the further analysis of interaction variables.

Model 2 The results of model 2 show why searching for latent variables can be valuable. Three latent variables show consistent significance in the two speed limit conditions – skill-safety gap, technical aversion, and risk awareness. They outdo the demographic characteristics by providing scale variables which can better account for the variability in the speed selection distribution. These variables also play a part in the interaction variables developed in model 3.

Model 3 The results of model 3 show that not only do socio-demographic and latent characteristics influence speed selection, but some latent characteristics have stronger effects on specific groups in their speed selection. For example, while being a female [GF] and technical aversion [TA] have significant effects when examined independently for the full sample (but not concurrently), the interaction variable [GF]x[TA] – technical aversion for females – takes both into account and provides a more accurate picture, in which high TA for females lowers their daily speed selection. Technical aversion [TA] is also significant for infrequent drivers [IHF], showing that infrequent drivers with high technical aversion tend to select faster speeds, perhaps as a result of not understanding the resultant risks. Males [IFG], however, are more influenced by their risk awareness [RA]; being aware to prevalent driving risks lowers their speed selection. However, it seems that variables of social norms [ADP] and self-assessment [SSG] have a similar effect across all drivers. Interestingly, ADP also has an additional interaction effect in the urban street condition [ADPUR], showing that older people [AG] are less affected by social norms.

Comparing all three model types for the different scenarios presented (freeway and urban street) shows additional differences in the significance of interaction variables. For example, the coefficient of the variable [DC]x[LA] indicates that individuals with high law awareness which took a driving course, will select lower speeds in freeways. In contrast, the coefficient of the variable [IHF]x[LA] indicates that non-frequent drivers with high law awareness will select lower speeds in urban streets. Such results could point to differences in the perception of drivers between freeways and urban streets in general, or rather specific differences in the infrastructure portrayed. These differences might arise from interactions between infrastructure characteristics and driver characteristics. These interaction effects demand further and deeper investigation.

4. DISCUSSION

The findings of this research demonstrate the importance of understanding the differences between drivers and how these differences influence driving speed selection. Comparing the distributions of drivers' Daily Speed Selection [DSS] and their perception of the average driver speed [ADP] suggests that although the distributions are similar, drivers believe the average driver drives a little faster than themselves. However, the differences among the DSS and ADP distributions and the results of the multiple regression results suggest many drivers select speeds similar or identical to their expectations of the "average driver". Therefore, drivers' perception of other drivers' speeds significantly influences personal speed selection.

Unique scales were developed in this study for obtaining deeper insights into drivers' perceptions, namely, *self-assessment*, *driving risks* assessment, and performance of *vehicle-related technical tasks.* The scales revealed three latent driver characteristics which were consistently significant in drivers' speed selection. First, the *skills-safety gap* [SSG] relates to how people who considered themselves skilled drivers are prone to select higher speeds, especially if they claim not to drive safely. Second, increased *risk awareness* [RA], on the other hand, may lead drivers to decrease their selected speeds. Third, *technical aversion* [TA] goes into effect when a drivers' low confidence in his or her abilities to perform technical tasks – leads to selecting a lower speed. The inverse effect of TA is a combination of positive self-assessment in performing technical tasks, as well as a feeling of "knowing" the vehicle and its abilities. The above findings are consistent with the results of previous studies (Horswill, Waylen, & Tofield, 2004; McKenna, Stanier, & Lewis, 1991; Walton & Bathurst, 1998), by which most drivers believe they are better than the average driver in both skills and safety. The higher a driver regards is or her driving, technical and maintenance abilities, the more they tend to select higher driving speeds. However, even these drivers, who appraise their own skills, often believe that others drive even faster than themselves.

Significant interactions were found between drivers' demographic characteristics and their self-perceptions, assessed by the factors developed in this study. The analysis of the interaction variables suggests that technical aversion is more influential for female drivers, and risk awareness has a greater influence on male drivers. In contrast, self-assessment of driving skills vs. driving safety [SSG] was not connected to socio-demographic characteristics, meaning self-perception in comparison to the average driver has a uniform effect on all drivers. Perception of the average driver [ADP], which was considered as a latent variable of social norms, had an almost uniform effect except for older drivers, who were found to be less influenced by these social norms for their speed selection.

In different scenarios (freeway or urban), different relationships between law awareness [LA] and driver characteristics were observed. These differences may demonstrate the influence of infrastructure on driver populations. Since infrastructure was kept constant in our study by the pictures and road descriptions in the two scenarios (freeway vs urban street), further research is needed to investigate how infrastructure characteristics interact with driver characteristics.

Implementing risk awareness education is a measure that can help offset the dangers of speed selection for both male and female drivers (such as in Fisher, et al., 2002). With each new generation, people are increasingly exposed to technology, and given more technical education. Current discussions focus on the Net Generation, or “Digital Natives”, who grew up around computers and the internet, and are much more technologically adapt than their older counterparts (Bennett, Maton, & Kervin, 2008; Oblinger & Oblinger, 2005). Support for the effect of age on gender differences in technological affinity has also been presented (Morris, Venkatesh, & Ackerman, 2005). The results of this study indicate that higher confidence in technical tasks could bring about riskier driving behaviors. Infrequent drivers also increase their speeds with higher TA. To offset this disadvantage, technical knowledge should be supplemented with education on about the technical limitations of vehicles. It is vital to educate drivers about the dangers of exceeding critical thresholds such as perception reaction times and braking distances. Such an education will help create a more informed generation, aware of the risks and physical limitations of driving, and lead to drivers’ selection of safer speeds and better-informed driving behaviors.

The latent driver characteristics scales developed by this study are useful not only for speed selection studies, but also for other studies about driving behaviors. These scales could enable researchers to find interactions between demographic characteristics and latent factors that promote other risky driving behaviors (such as in Ivers, et al., 2009; Vingilis, et al., 2013). It should be noted that while other questionnaires ask drivers to confess their own driving misdemeanors, which may put them in an uncomfortable position, the terminology of the questionnaire used in this study (specifically regarding risky driving behaviors) is more indirect yet nonetheless revealing, thereby avoids creating a spotlight that alienates the participants.

Although our sample of 290 participants has a variety of socio-demographic characteristics, it is still not large enough to represent the overall population of drivers. A large proportion of participants had academic educations, and so a wider sample should be examined to validate our findings. Existing correlations between some driver characteristics in our present sample may have limited the ability to evaluate the effect of each driver characteristic individually. Therefore, further investigation is required using a larger sample, or alternatively, several homogenous groups.

This study employed a web-based survey which does not necessarily reflect the real-life driving behaviors of the participants. However, it was assumed that experienced drivers, which constitute most of the sample (by license and vehicle ownership), are relatively familiar and aware of their everyday speeding habits, and thus their statements can be considered reliable. Since the purpose of this study was to explore the variability of speeds in relations to driver characteristics, drivers' statements about speeding intentions may be valuable for understanding speed variability in real-life settings. Nevertheless, these findings should be further validated by comparing drivers' intentions for speed selection with their real-life behavior, and operating speed variability with individual driver characteristics.

ACKNOWLEDGEMENTS

We thank the two anonymous reviewers for their valuable comments. We would also like to thank David Suchinsky for his thorough revision of the paper.

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FIGURES AND TABLES

(a) Urban street, 50 kph speed limit

(b) Freeway, 100 kph speed limit

Figure 1: Road pictures presented in the speed selection survey

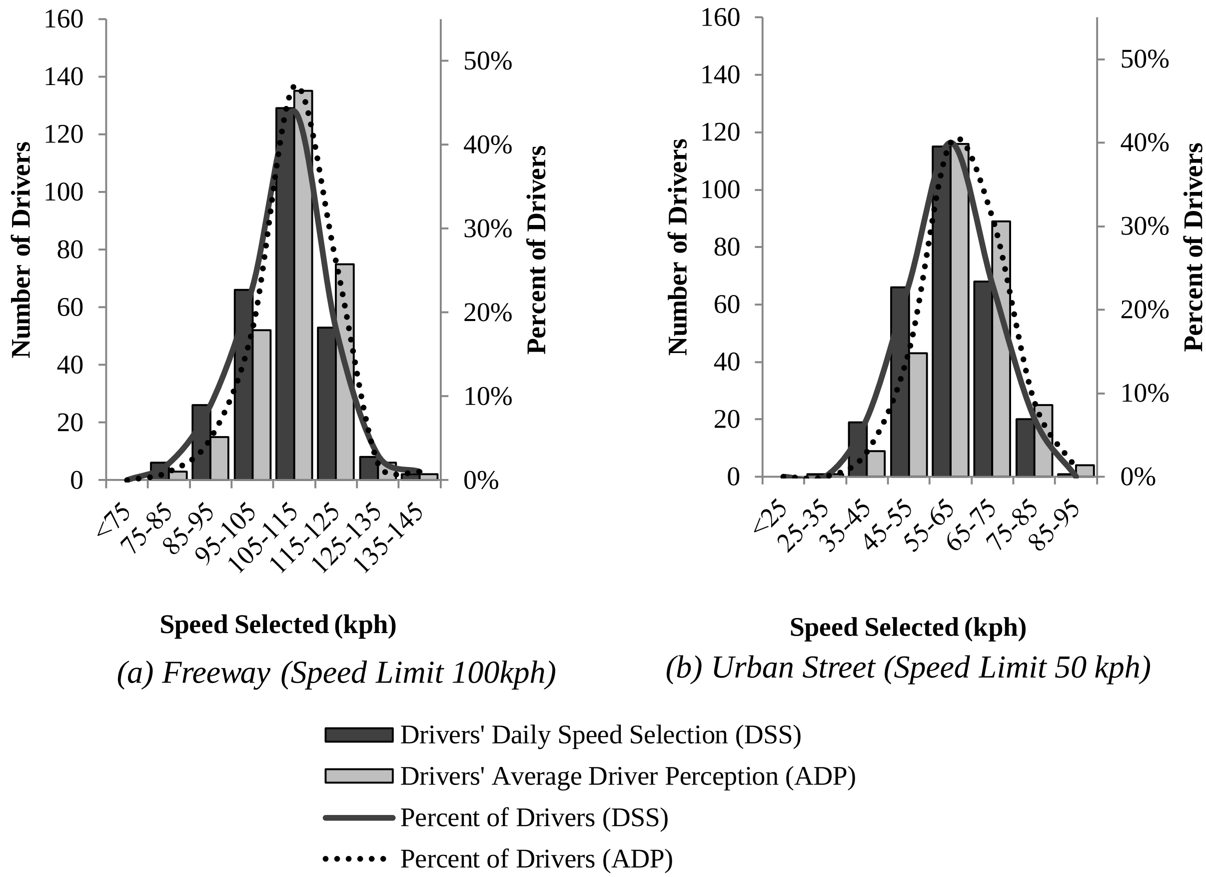

Figure 2: Daily Speed Selections (DSS) and Average Driver Perception (ADP)

Table 1: Differences in Self-Assessment of Driving Safety and Skills between High-Speed and Low-Speed Drivers

Speed Limit	SL100kph			SL50kph		
Drivers	High-Speed	Low-Speed	T-test	High-Speed	Low-Speed	T-test
Safety (Mean)	5.26	5.54	1.61	5.42	5.53	0.71
Skills (Mean)	5.20	4.96	-1.30	5.45	5.10	-1.98

Table 2: Driving Risks Factors

Driving Risk Items	**Factor Loadings**	
	Risk Awareness	**Law Awareness**
Speaking on a mobile phone without a speaker [a]		.670
Speaking on a mobile phone with a speaker [a]	.501	.295
Writing text messages		.827
Driving after drinking alcohol mildly	.282	.566
Driving after driving alcohol heavily	-.305	.904
Driving under mild fatigue	.563	.252
Driving under heavy fatigue		.689
Driving a little over the speed limit	.810	
Driving much over the speed limit	.293	.525
Listening to music in a high volume	.438	.413
Listening to music in a low volume	.870	-.305

[a] While using a mobile phone without a speaker during driving is prohibited in Israel, using a mobile phone with a speaker is allowed, even if not recommended.

Table 3: Vehicle-Related Technical Tasks Factors

Vehicle-related technical tasks	**Factor Loading**
Changing Tires	.776
Filling Windshield Fluid	.795
Charging a Mobile Phone	.509
Charging the Battery	.835
Changing Windshield Wipers	.743
Setting the Radio Stations	.570
Filling Coolant Fluid	.779
Changing Light Bulbs in the Headlights	.785

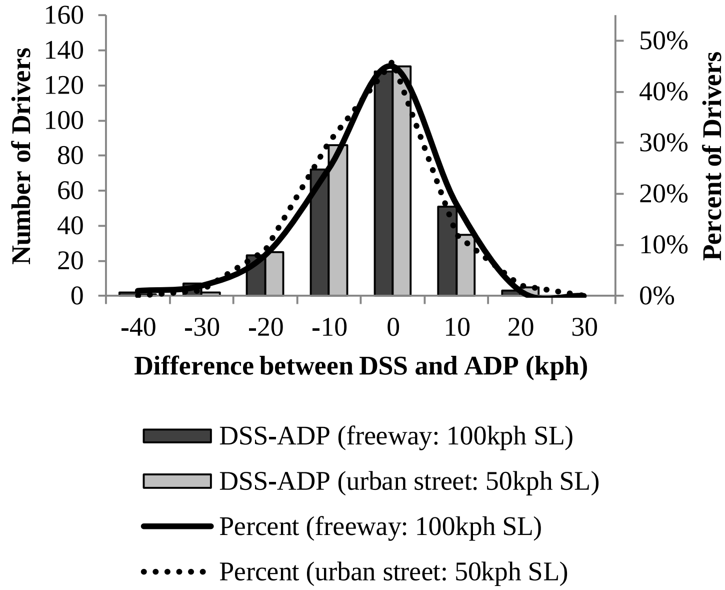

Figure 3: Distributions of the Differences between Each Driver's Daily Speed Selection (DSS) and Average Driver Perception (ADP)

Table 4: Modeling Results for the Prediction of Drivers' Daily Speed Selection (kph)

		(1)		(2)		(3)	
		Freeway	**Urban Street**	**Freeway**	**Urban Street**	**Freeway**	**Urban Street**
Speed Limit		100	50	100	50	100	50
Constant (α)		7.20*	9.49*	3.99**	3.71**	3.05	2.13
Socio-Demographic Characteristics (β_{sd})	Gender: Female [GF]	-3.72*	-4.36*	-0.52	-0.94	0.01	-1.89
	Age Over 50 [AG]	-7.66*	-6.79*	-2.94	-2.28	-3.26	2.06
	High Frequency (trips) [HF]	3.61**	4.49*	-0.81	-0.42	0.99	0.92
	High Frequency (long trips) [HL]	1.54	.-1.21	0.86	-1.01	0.49	-1.11
	Driving Improvement Course [DC]	1.60	2.66**	0.19	0.33	1.97	0.46
Latent Characteristics (β_l)	Skills-Safety Gap [SSG]			1.83*	1.73*	1.60**	1.82*
	Risk Awareness [RA]			-1.61**	-1.15**		
	Law Awareness [LA]			-0.83	-0.05		
	Technical Aversion [TA]			-2.14**	-1.78**		
	Spatial Familiar Tasks [SF]			-0.78	2.16**	1.11	1.89
	Spatial Unfamiliar Tasks [SU]			-0.06	-0.26		
	Average Driver Perception, freeway [ADPFW]			0.51*		0.44*	
	Average Driver Perception, urban street [ADPUR]				0.58*		0.76*
First-Order Interactions (β_{in})	[DC]x[LA]					-2.78**	0.69
	[GF]x[LA]					0.06	1.13
	[GF] x [RA]					-1.07	-0.17
	[GF] x [TA]					-4.13*	-3.53*
	[GF] x [SU]					0.66	0.70
	[IHF] x [LA]					-1.49	-2.42**
	[IDC] x [LA]					-0.09	
	[IGF] x [LA]						-0.57
	[IGF] x [RA]					-1.84**	-2.21*
	[IGF] x [TA]					-2.20	0.33
	[IGF] x [SU]					-1.23	-1.57
	[IHF] x [TA]					4.22**	3.12**
	[AG] x [ADPFW]					0.18	
	[IGF] x [ADPFW]					-0.03	
	[IHF] x [ADPFW]					0.07	
	[AG] x [ADPUR]						-0.36**
	[IGF] x [ADPUR]						-0.05
Model Fit	**R**	**0.372**	**0.397**	**0.668**	**0.724**	**0.696**	**0.769**
	R^2	**0.138**	**0.158**	**0.446**	**0.523**	**0.485**	**0.592**
	Adjusted R^2	**0.122**	**0.141**	**0.406**	**0.489**	**0.413**	**0.538**

*P_{value}<0.01
**P_{value}<0.05