Accident Analysis and Prevention 40 (2008) 315–326

ACCIDENT ANALYSIS & PREVENTION

www.elsevier.com/locate/aap

Aggressiveness propensity index for driving behavior at signalized intersections

Samer H. Hamdar, Hani S. Mahmassani *, Roger B. Chen

Department of Civil and Environmental Engineering, University of Maryland, 3130 Jeong H. Kim Engineering Building, College Park, MD 20742-3021, United States

Received 27 March 2007; received in revised form 6 May 2007; accepted 25 June 2007

Abstract

The development of a quantitative intersection aggressiveness propensity index (API) is described in this paper. The index is intended to capture the overall propensity for aggressive driving to be experienced at a given signalized intersection. The index is a latent quantity that can be estimated from observed environmental, situational and driving behavior variables using structural equations modeling techniques. An empirical study of 10 major signalized intersections in the greater Washington DC metropolitan area was conducted to illustrate the approach. The API is shown to provide (a) an approach for capturing and quantifying aggressive driving behavior given certain measurements taken at a particular intersection, (b) understanding of the factors and intersection characteristics that may affect aggressiveness, and (c) an index for the cross comparison of different traffic areas with different features. This index has the potential to support safety policy analysis and decision-making.

Keywords: Aggressiveness propensity index (API); Structural equation modeling (SEM); Factor analysis; Signalized intersections

1. Introduction

Aggressive driving is considered a serious problem in a growing number of communities (National Highway Traffic Safety Administration, 1999). Past studies on aggressive driving behavior in transportation have focused primarily on identifying aggressive drivers (Dukes et al., 2001). However, aggressive drivers are not necessarily the only source of aggressive driving. Aggressive driving is defined as driving behavior instigated by a frustrating situation, behavior, or event (Hennessy and Wiesenthal, 1997). Depending on the environment and the personality of the driver, a particular situation may place the driver in an aggressive disposition. If the aggression cannot be manifested, aggressive driving is subdued, and becomes "displaced aggression". If the aggression can be manifested, aggressive driving may then be observed (Anderson and Bushman, 2002). Aggressive driving behavior can assume one of two forms: instrumental or hostile behavior (Lajunen and Parker, 2001). Instrumental aggressive behavior refers to driving behavior that enables the driver to move ahead and overcome frustrating obstacles. This is done if the "path" to the driver's goal is not blocked. Examples of instrumental aggression include weaving in and out of traffic to get ahead, and running red lights. However, if the "path" is blocked, hostile aggressive behavior is observed—this is behavior that makes individuals somehow "feel good" without resolving the problem, such as cursing other drivers or honking the horn at pedestrians (Shinar, 1998). The distinction between instrumental and hostile aggression is not clear-cut, nor is the distinction between aggressive drivers and aggressive driving.

Traffic engineers are primarily concerned with the instrumental aspect of observed aggressive driving, especially when it creates conflicts and becomes a safety hazard for both those engaging in such behavior as well as those who must share the right of the way with them (Miles and Johnson, 2003). As such, environmental and situational characteristics that contribute to aggressive driving become confounded with the personality traits of the drivers in determining observed aggressive behavior (Lajunen et al., 1999). Furthermore, to the extent that traffic engineers may reduce instances of aggressive driving by modifying those features that contribute to observe aggressive driving, it becomes important to identify what those features are and how they interact in determining actual aggressive driving (De Leur

* Corresponding author. Tel.: +1 301 405 0221; fax: +1 301 405 2585.
E-mail addresses: samerhamdar@gmail.com (S.H. Hamdar), masmah@northwestern.edu (H.S. Mahmassani), rbc@wam.umd.edu (R.B. Chen).

0001-4575/$ – see front matter
doi:10.1016/j.aap.2007.06.013

and Sayed, 2002). While the psychological and affective bases of aggressiveness are interesting in their own right, it is the manner in which they interact with environmental and situational factors that is the primary object of study here.

The objective of this paper is to describe aggressiveness as the outcome of a relationship between drivers and the environment they are driving in, through the development, specification and estimation of a quantitative "aggressiveness propensity index" (API). This index is intended as a measure of the propensity for aggressive driving to be experienced at a signalized intersection. In this study, aggressive driving is reflected in measures of four driving patterns: (i) start-up delay time, (ii) gap acceptance, (iii) accelerating or decelerating when facing an impending yellow (amber) signal indication, and (iv) changing lanes. As such, the API provides (a) an approach for capturing and quantifying aggressive driving behavior given certain measurements taken at a particular intersection, (b) understanding of the factors and intersection characteristics that may affect aggressiveness, and (c) an index and a scale for the cross comparison of different traffic areas with different features.

The conceptual framework for this relationship is presented in detail in Section 2. The index is realized through application of structural equation modeling (SEM), as described in Section 3. This technique transforms measurable variables into a descriptive aggressiveness propensity index. The SEM method is applied to a data set from a case study described in Section 4, followed by a discussion of the application results. Concluding comments are presented in Section 6.

2. Conceptual framework and background

Aggressive driving behavior is not a clear-cut phenomenon that can be directly measured and assessed. It generally involves several manifestations, at the microscopic level and in aggregate, such as high acceleration and abrupt deceleration, unannounced sudden lane changes, acceptance of very short, unsafe gaps that require oncoming traffic to decelerate, running red lights, and so on. As noted, such behavior at a signalized intersection may be reinforced by characteristics of the intersection, surrounding land use, the amount of traffic and associated congestion, and the behavior of "other" drivers, which heightens the perception of aggressiveness and the need to engage in it. Formulation of an empirically validated "aggressiveness propensity index" for driving at signalized intersections entails capturing the interrelation between several latent or endogenous quantities (capturing various underlying dimensions) on one hand, and measurements of several types of (observable) variables, characterizing the environment, features of the intersection, nature of the demand, socio-demographics of drivers, as well as instances of certain driving behaviors, on the other hand.

Fig. 1 presents a conceptual framework illustrating the main types of factors that enter in the formulation of the API, and its dependence on a set of complex relationships. The two main categories of factors are the characteristics of the network infrastructure, and the drivers using this network, with their given socio-demographic characteristics. In the first category, the specific intersection characteristics would play a primary role; however, one should also recognize at least the secondary effect of the surrounding infrastructure (especially that previously experienced by the driver). More generally, the driver's travel history, both in the near term (e.g. frustration in trip up to the intersection of interest), as well as over the longer run (e.g. previous experiences at that same intersection, or in the particular neighborhood where it is located). However, in trying to realize the framework empirically, the scope in this first step will focus on observable characteristics and behaviors, limited to the immediate vicinity of the specific intersections under consideration.

Fig. 2 further elaborates on the main types of factors above and lists specific dimensions that comprise each, along with example variables or measures to capture that dimension. For instance, the intersection characteristics are divided into six dimensions: (1) traffic demand mix characteristics, (2) traffic performance (3) geometric characteristics, (4) signal timing, (5) law enforcement and (6) land use. The behavioral aspect of driving is comprised of four dimensions, each consisting of driving patterns that can be readily observed and measured: (i) start-up delay, (ii) acceleration at amber time, (iii) gap acceptance and (iv) lane changing. The selection of intersection characteristics, the dimensions in which they are grouped and the driving patterns was guided by the "safety guide report" published by the Federal Highway Administration (Rodegerdts et al., 2004).

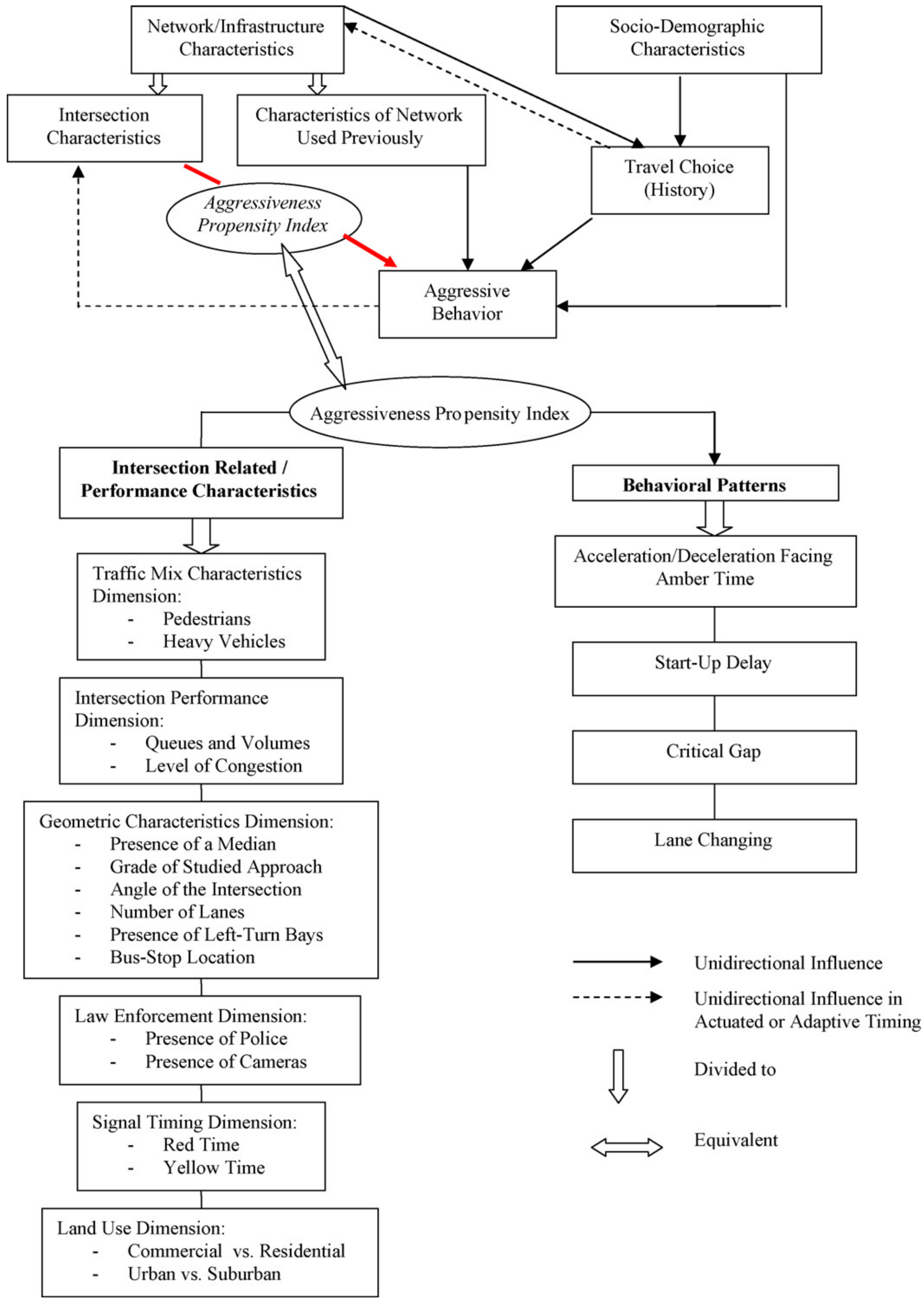
The above dimensions and driving patterns follow a complex set of interrelationships. The structural equations modeling (SEM) technique is used to formulate these relations in the form of a set of structural equations where each dimension will contribute in an unknown (unobservable) manner to an aggressiveness level expressed by the four behavioral patterns mentioned above.

Structural equations modeling is used widely as a tool for pattern identification and understanding relationships between different variables and parameters in a variety of disciplines, e.g. sociology, psychology, political science and travel behavior research (Golob, 2003). Applications of SEM methodology in travel behavior include:

- travel demand modeling using cross-sectional data (Golob and Meurs, 1987),
- dynamic travel demand modeling (Golob and Meurs, 1988),
- activity-based travel demand modeling (Golob and Pendyala, 1991),
- attitudes, perception and hypothesized choices (Loomboonruang and Sano, 2003),
- organizational behavior and values (Golob, 1987), and
- driver behavior (Golob et al., 1994)

The SEM approach can handle a large number of endogenous and exogenous variables simultaneously, as well as latent (unobserved) variables specified as linear combinations (weighted averages) of the observed variables. Because SEM is a "confirmatory rather than exploratory" tool, the analyst should be able to specify the model that best represents their system.

As noted, driver aggressiveness at intersections is not readily quantifiable and measurable, especially without detailed



Figs. 1and 2. (1) Aggressiveness propensity index framework. (2) Initial basic dimensions and patterns considered in the aggressiveness propensity index.

micro-level measurement and knowledge of individual socio-demographic and attitudinal information. By analyzing the outcome of this behavior through observable traffic measurements, the overall level of aggression, which is in turn unobservable, can be inferred and characterized. This aggressiveness is captured through a latent scale and index, and related to observable variables through the SEM formulation. This index enables comparative assessment of different locations, and assessment of the relative importance of different determinants. Specification of the SEM model system to obtain the aggressive propensity index at intersections is discussed in Section 3.

3. Model specification

In order to derive the aggressiveness propensity index, the general idea is to transform the relationships between the dimensions and patterns depicted in Fig. 2, and discussed in Section 2, to a set of structural equations, assumed to hold simultaneously. The aggressiveness indices (associated with each of the intersection locations) will be a vector of latent endogenous variables.

Structural equations are divided into measurement and structural models. Measurement models are associated with the observed exogenous and endogenous variables, relating them to other observed as well as latent variables. The structural models relate the latent endogenous quantities to the observed variables. The data collected generally consist of a vector of exogenous variables (intersection characteristics) and endogenous variables (driving patterns), reflecting the same unidirectional structure presented in Section 2. Feedback loops are not specified explicitly, though model specification essentially implies the formulation of "recursive models" (Golob, 2003). The specification of both the measurement and structural models is discussed next.

3.1. Measurement models

Measurements models are normally specified in two sets of equations. The first set (the exogenous measurement model) is represented as follows:

$$\boldsymbol{X} = \boldsymbol{\Lambda}_X(\boldsymbol{\gamma}) + \boldsymbol{\omega} \quad (1)$$

$\boldsymbol{X}$ = vector of observed exogenous variables; $\boldsymbol{\Lambda}_X$ = matrix of structural coefficients for latent exogenous variables to their observed indicator variables; γ = vector of latent exogenous constructs; γ_1 = propensity for aggressive driving associated with "traffic demand mix dimension"; γ_2 = propensity for aggressive driving associated with "traffic performance dimension"; γ_3 = propensity for aggressive driving associated with "intersection's geometric characteristics"; γ_4 = propensity for aggressive driving associated with "signal timing dimension"; γ_5 = propensity for aggressive driving associated with "intersection law enforcement"; γ_6 = propensity for aggressive driving associated with "land-use dimension"; $\boldsymbol{\omega}$ = vector of measurement error terms for observed variables

The latent endogenous variables are a direct reflection of the dimensions initially considered in the framework of the study. The observed exogenous variables are described in Table 1A , including how they are measured and associated variable name by which they will be designated in Section 4.

The second (endogenous measurement model) is set of equations are summarized in Eq. (2):

$$\boldsymbol{Y} = \boldsymbol{\Lambda}_Y(\boldsymbol{\eta}) + \boldsymbol{\tau} \quad (2)$$

where $\boldsymbol{Y}$ = vector of observed endogenous variables; Y_1 = acceleration/deceleration behavior at Amber; Y_2 = startup delay time; Y_3 = critical gap; Y_4 = lane-changing; $\boldsymbol{\Lambda}_Y$ = matrix of structural coefficients for latent endogenous variables to their observed indicator variables; $\boldsymbol{\eta}$ = vector of latent endogenous variable;

Table 1A
Observed exogenous variables' description in the structural model

Exogenous variable	Description
X_1 (HV)	Number of heavy vehicles that has been seen per major through approach in each cycle. If there is not a left turn bay or right turn bay, all the vehicles are to be counted even if they do perform a left turn or right turn. Otherwise, only the through vehicles are considered in the study.
X_2 (Ped)	Number of crossing pedestrians per cycle. Only the pedestrians crossing the studied major approach are considered in the count. This value is interpolated to correspond for a 34 s duration.
X_3 (Vol)	Number of vehicles passing in the major through approach per cycle. As mentioned in X_1's description, if there is not a left turn bay or right turn bay, all the vehicles are to be counted even if they do perform a left turn or right turn. Otherwise, only the through vehicles are considered in the study. This value is interpolated so the number of vehicles passing is per 100 s duration.
X_4 (Queue)	Average queue length per major approach per cycle. As mentioned earlier, the major through approach is taken. The maximum queue formed between the considered lanes is to be noted.
X_5 (Grade)	Percent grade of the approach taken into consideration. It is rounded to be an integer number.
X_6 (Lane#)	Number of lanes per major approach.
X_7 (LeftLn#)	Number of left turn lanes.
X_8 (Angle)	Dummy variable corresponding to the angle between the crossing approaches. According to the angle between the approach of interest and the crossing approach to the left hand side: $= 90^\circ$, $X_8 = 0$ $\neq 90^\circ$, $X_8 = 1$
X_9 (BusStop)	Dummy variable indicating the presence of a bus stop at the entrance of the intersection from the given approach: $X_9 = 0$, no bus stop $X_9 = 1$, bus stop
X_{10} (Red)	Red time length for the major through approach.
X_{11} (Amber)	Amber time length corresponding to the major approach.
X_{12}(Camera)	As in X_9, dummy variable indicating the presence of a law enforcement camera at a given intersection.
X_{13} (LawOth)	As in X_9, dummy variable indicating the presence of other law enforcement factors at the intersection (police car, policeman . . . etc.)
X_{14} (LU1)	First dummy variable corresponding to the type of land use of the area in which the intersection is located. This is related more to the type of activity in the area of interest. $X_{14} = 0$, residential area $X_{14} = 1$, commercial area (taken from Maryland Department of Planning Data-MDP)
X_{15} (LU2)	Second dummy variable corresponding to the type of land use of the area in which the intersection is located. This variable is associated to the degree of urbanization and development of the area $X_{15} = 0$, suburban area $X_{15} = 1$, urban area (taken from Maryland Department of Planning Data-MDP)

Table 1B
Observed endogenous variables' description in the structural model

Observed endogenous variables	Description
Y_1 (StDelay)	Start up delay time observed in the given cycle. It is the time needed for a vehicle to move from rest at the beginning of a green phase. The shortest start-up delay in all the through lanes is noted.
Y_2 (%AcAmber)	Dummy variable indicating if there exists a vehicle that accelerated facing an amber time or passing through the red phase in a cycle. $Y_2=0$, no acceleration or running a red signal $Y_2=1$, acceleration is observed.
Y_3 (LnChange)	Number (#) of lane changes on the major through approach in a given cycle.
Y_4 (AccGap)	Average length of the accepted gap in seconds. This average is taken over all the drivers that accepted a left turn gap in the specified cycle.

η_1 = aggressiveness propensity index; $\boldsymbol{\tau}$ = vector of measurement error terms for observed endogenous variables

The observed endogenous variables represent the way aggressive driving is assumed to be manifested at a given intersection. They consist of the same driving patterns mentioned in Fig. 2. Table 1B summarizes the measurement techniques adopted and the variable names by which each is designated in the structural modeling.

Other factors, not considered in this study, may also contribute to the aggressiveness of drivers at signalized intersections. These factors are not included in the models presented in this paper because they turned out to be insignificant statistically (including presence of shared right and through traffic lanes, presence of a median, lane width, type of signalization and pedestrians' crossing conflicting with left-turning vehicles) or are not directly applicable to the locations under consideration.

3.2. Structural model

A structural model relating the endogenous latent variable η_1 to the exogenous latent variables γ_1, γ_2, and γ_3 can be expressed as:

$$\boldsymbol{\eta} = \boldsymbol{\Delta}\boldsymbol{\gamma} + \boldsymbol{\xi} \tag{3}$$

where $\boldsymbol{\eta}$ = vector of latent endogenous variable; η_1 = aggressiveness propensity index; $\boldsymbol{\Delta}$ = matrix of structural coefficients for exogenous latent variables to endogenous latent variables; $\boldsymbol{\gamma}$ = vector of latent exogenous constructs; $\gamma_{1,\ldots,}\ \gamma_6$ are as previously defined; $\boldsymbol{\xi}$ = vector of measurement error terms for latent endogenous variables

The hypothesized structure among the nine latent variables (η_1, γ_1, γ_2, γ_3, γ_4, γ_5, γ_6) can be represented in the following equation:

$$[\eta_1] = \begin{bmatrix} \delta_{11} & \delta_{12} & \delta_{13} & \delta_{14} & \delta_{15} & \delta_{16} \end{bmatrix} \times \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \\ \gamma_6 \end{bmatrix} + [\xi_1] \tag{4}$$

Similarly the measurement equations can be expressed as follows:

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \\ X_7 \\ X_8 \\ X_9 \\ X_{10} \\ X_{11} \\ X_{12} \\ X_{13} \\ X_{14} \\ X_{15} \end{bmatrix} = \begin{bmatrix} \Omega_{11} & 0 & 0 & 0 & 0 & 0 \\ \Omega_{21} & 0 & 0 & 0 & 0 & 0 \\ 0 & \Omega_{32} & 0 & 0 & 0 & 0 \\ 0 & \Omega_{42} & 0 & 0 & 0 & 0 \\ 0 & 0 & \Omega_{53} & 0 & 0 & 0 \\ 0 & 0 & \Omega_{63} & 0 & 0 & 0 \\ 0 & 0 & \Omega_{73} & 0 & 0 & 0 \\ 0 & 0 & \Omega_{83} & 0 & 0 & 0 \\ 0 & 0 & \Omega_{93} & 0 & 0 & 0 \\ 0 & 0 & 0 & \Omega_{10,4} & 0 & 0 \\ 0 & 0 & 0 & \Omega_{11,4} & 0 & 0 \\ 0 & 0 & 0 & 0 & \Omega_{12,5} & 0 \\ 0 & 0 & 0 & 0 & \Omega_{13,5} & 0 \\ 0 & 0 & 0 & 0 & 0 & \Omega_{14,6} \\ 0 & 0 & 0 & 0 & 0 & \Omega_{15,6} \end{bmatrix} \times \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \\ \gamma_6 \end{bmatrix} + \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \omega_4 \\ \omega_5 \\ \omega_6 \\ \omega_7 \\ \omega_8 \\ \omega_9 \\ \omega_{10} \\ \omega_{11} \\ \omega_{12} \\ \omega_{13} \\ \omega_{14} \\ \omega_{15} \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} \lambda_{11} \\ \lambda_{12} \\ \lambda_{13} \\ \lambda_{14} \end{bmatrix} \times [\eta_1] + \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \\ \tau_4 \end{bmatrix} \tag{6}$$

Table 2
Signalized intersections included in the study and their corresponding APIs

Serial number	Intersection	Main approach	API (ranking)
1	Route 1– Knox Road	Route 1: Northbound/through	6.60 (6)
2	Route 1 – Cherry Hill Road	Route 1: Northbound/through	9.80 (1)
3	Connecticut Avenue (NW)–Nebraska Avenue (NW)	Connecticut: Northbound/through	6.28 (7)
4	Fessenmen Street–Reno Street	Fressenmen: Northbound/through	5.18 (10)
5	Fenton Street–Colesville Street	Fenton: Northbound/Through	8.77 (3)
6	Spring Street–Cameron Street	Spring: Northbound/through	7.18 (4)
7	Wisconsin Avenue–Cheltenham Road	Wisconsin: Southbound/through	5.73 (8)
8	Arlington Street–Edge Moore Street	Arlington: Southbound/through	5.66 (9)
9	16th Street–L Street	16th: Southbound/through	9.71 (2)
10	M Street–31st Street	M: Westbound/through	7.06 (5)

In addition to the three structural matrices Λ_X, Λ_Y, and Δ, the following four variance/covariance matrices need to be specified to determine a general structural equation model:

(1) a VC-matrix of latent exogenous variables (Φ)
(2) a VC-matrix of error terms associated with model implied structural equations (Ψ)
(3) a VC-matrix of measurement errors or observed exogenous variables (Θ_ω)
(4) a VC-matrix of measurement error terms associated with the observed endogenous variables (Θ_τ)

The VC-matrices of the exogenous and the endogenous variables are specified with zero covariance terms as an initial step. The variances of the latent variables are initially specified as equal to 1. It should be noted that this is an initial hypothesized model that will be modified in light of the collected data and analysis. This hypothesized model is illustrated in Fig. 3.

4. Application to intersections in the Washington, DC area

To illustrate the validity of the formulation scheme presented in Section 3, a real-world application with existing intersections is conducted. The intersections considered are all located in the state of Maryland and in Washington DC, USA. The data are collected during the evening peak period between 4:00 and 8:00 pm. The main through approach is the approach of interest. Table 2 presents the intersections included in the study. The selection of the intersections precluded spatially induced interdependence between intersections, consistently with the assumptions of the adopted SEM approach.

Most of the approaches considered in this study carry traffic outbound from Washington, DC, during the busy evening peak. As such, some of these approaches experience very heavy traffic at certain times, and may become oversaturated at certain times. All the intersections were video recorded during the data collection time. The corresponding data were then extracted by two persons and cross-validated for consistency with collected data.

It should be noted that each stratum of data (X_1–X_{15} and Y_1–Y_4 of Tables 1A and 1B) is recorded during the same signal cycle. If a given cycle does not offer the possibility of measuring all the observable exogenous and endogenous variables, the cycle is ignored, and the corresponding data is omitted. Accordingly, the final sample includes 157 out of 195 data points or signal cycles.

In the SEM specification for the aggressiveness propensity index, the exogenous variables are grouped into patterns or factors that are related to one another in the SEM context (Anderson and Gerbing, 1988). These factors are constructed from the measured variables using a technique called factor analysis, presented in Subsection 4.1.

4.1. Factor analysis

In factor analysis, relationships are established through a mathematical function $f(W, Z)$ connecting one variable, X, with the set of variables W and Z. The measurable values of Y are known. Though the values of the right hand side variables are measurable, neither the type of function $f(.)$ that should be used nor the variables to be included in this function are usually known. Facing this problem, we assume that a set of Y variables are related to a number of functions that operate linearly:

$$X_n = \boldsymbol{\alpha}_{n1} F_1 + \boldsymbol{\alpha}_{n2} F_2 + \ldots + \boldsymbol{\alpha}_{nm} F_m \tag{7}$$

where X = a variable with known data; $\boldsymbol{\alpha}$ = a constant that is the loading; F_j = a function, f_j () of some unknown variables, $j = 1, \ldots, m$; this is also called a factor

A pattern is defined as the number of variables X's similarly related to the same F functions.

The main useful output derived from factor analysis in this study:

1. Un-rotated factor matrix: deals solely with uncorrelated patterns. Each pattern may involve all or almost all the variables (X's), and the variables may therefore have moderate or high loadings for several factor patterns.
2. Rotated factor matrix: this type of matrix can be either orthogonal or oblique. The orthogonal matrix seeks to identify only uncorrelated patterns. The oblique matrix covers correlated patterns in addition to the uncorrelated ones. The researcher can hypothesize particular patterns and rotate the factor analysis accordingly. The resulting patterns are easier to uncover and will not include most of the variables.

In what follows, the variables are referred to using the abbreviated names or symbols presented in Tables 1A and 1B.

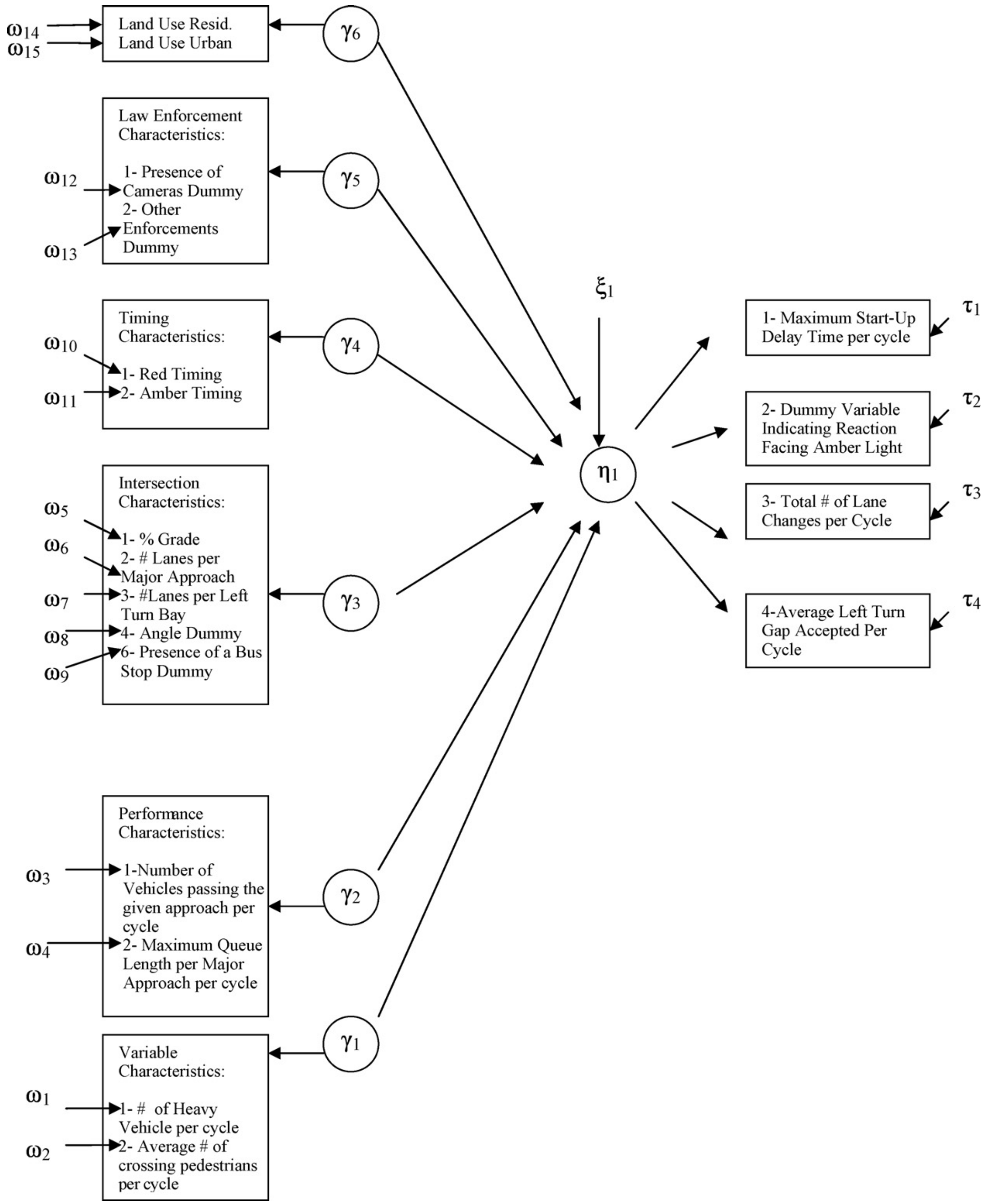


Fig. 3. Initial theoretical model structure; η_1 is the aggressiveness propensity index.

The SEM software used in this study is LISREL 8.7 for Windows.

Factor analysis is performed on 13 of the 15 exogenous variables described earlier (the volume and the pedestrian variables, normalized over standard durations, could not be included). The results of the factor analysis with un-rotated, orthogonally rotated and oblique rotated factor matrices are shown in Table 3. The factor analysis identified five patterns (factors) instead of the six suggested in the initial hypothesized model. The un-rotated factor scores help identify the variables that are significant enough to be included in the final model. Those with scores higher than 0.1 are: HV, Queue, Grade, Red, Camera, LU1, Lane#, LeftLn# and Amber. To group these variables into separate identifiable patterns, the orthogonal rotation factor analysis

Table 3A
Un-rotated factor analysis results

UFA	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
HV	0.584	0	0	0	0
Queue	0.916	0.401	0	0	0
Grade	0.799	−0.365	0.478	0	0
Lane#	0.144	0.479	0.11	−0.021	0
LeftLn#	0.246	−0.681	−0.482	−0.297	−0.394
Angle	0.024	−0.922	−0.136	−0.302	−0.2
BusStop	−0.066	0.336	0.587	0.197	−0.707
Red	0.485	0.27	0.611	0.118	0.551
Amber	−0.251	−0.269	−0.186	−0.066	−0.272
Camera	0.777	−0.227	−0.344	−0.431	−0.199
LawOth	0.071	0.122	−0.139	0.88	0.431
LU1	0.908	0.244	0.308	0.095	−0.11
LU2	−0.024	0.922	0.136	0.302	0.199

Table 3B
Rotated factor analysis results: orthogonal rotation

ORFA	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
HV	0.569	0.017	0.119	0.036	0.035
Queue	0.919	−0.367	0.14	0.022	0.017
Grade	0.7	0.367	0.58	−0.007	−0.199
Lane#	0.16	−0.469	0.058	−0.071	−0.094
LeftLn#	0.331	0.775	−0.467	−0.214	0.16
Angle	0.025	0.961	−0.102	−0.23	0.111
BusStop	0.008	−0.238	−0.008	−0.115	−0.964
Red	0.319	−0.371	0.861	0.137	0.018
Amber	−0.19	0.312	−0.321	−0.085	−0.062
Camera	0.833	0.313	−0.191	−0.327	0.254
LawOth	−0.014	−0.233	0.127	0.956	0.125
LU1	0.882	−0.209	0.332	0.044	−0.259
LU2	−0.025	−0.961	0.102	0.23	−0.112

results are used (Table 3B). Each factor takes the high score variable (higher than 0.1) and is assumed to correspond to its initial dimension described in Section 2

- Factor 1: traffic performance dimension (Queue, HV, Camera, LU1 and Grade)
- Factor 2: intersection geometry dimension (Angle, LeftLn# and LU2)

Table 3C
Rotated factor analysis results: oblique rotation

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
HV	0.555	0.048	0.032	0.07	0.08
Queue	0.957	−0.36	0.034	0.019	0.035
Grade	0.539	0.541	−0.158	0.605	0.036
Lane#	0.206	−0.494	−0.053	0.011	−0.149
LeftLn#	0.351	0.711	0.032	−0.452	0.025
Angle	−0.077	0.977	0.048	0.031	−0.069
BusStop	0.066	−0.125	−0.999	−0.154	−0.07
Red	0.163	−0.233	0.182	0.921	−0.064
Amber	−0.155	0.279	−0.134	−0.32	0.015
Camera	0.847	0.232	0.209	−0.184	−0.195
LawOth	0.018	−0.11	0.082	−0.076	0.981
LU1	0.862	−0.108	−0.237	0.217	0.07
LU2	0.077	−0.977	−0.049	−0.031	0.069

- Factor 3: signal timing dimension (Red and Grade)
- Factor 4: law enforcement dimension (LawOth)
- Factor 5: a new transit dimension (BusStop)

The same classification is found using oblique rotation factor analysis (Table 3C). Accordingly, three major patterns are retained (traffic performance, intersection geometry and signal timing) and two secondary ones (law enforcement and transit)

Several structures were then tested to construct an exogenous measurement model, reclassifying the significant exogenous variables into the three major patterns. The orthogonal rotation is used to reduce the correlation between patterns. The key is to add "Amber" to the signal timing dimension, remove the two secondary dimensions, add "Ped" and Volume" and only keep the variables that fits intuitively into each dimension (for example, LU1 does not fit in the geometry dimension). This allowed constructing an exogenous measurement model that converges to a unique value. The model is presented in Fig. 4; $L1$ corresponds to the latent variable reflecting the performance dimension, $L2$ the geometric dimension and $L3$ the signal-timing dimension. The analysis of this model is not relevant since it is not tested for statistical significance, and only serves as a base to construct the final structural equation model.

4.2. Structural equation model (SEM) development and results

The main objective of the study is to obtain a statistically acceptable structural equation model and thus specify the aggressiveness propensity index. Adopting the exogenous measurement model presented in Fig. 4 did not accomplish this goal. Building on the insight derived from the analysis performed in Subsection 4.1, the intended model was obtained when the "Red" and "LawOth" variables were combined into a single dimension, interpreted as an "impedance" dimension. Moreover, the "Grade" variable is replaced by the "Angle" variable in the intersection geometry dimension. The traffic performance dimension remained unchanged.

Since LISREL offers the capability of guiding the analyst to construct specific correlation relationships between different variables, the covariance matrices are enriched so that the chi-square value is reduced to an acceptable level. Moreover, a path is suggested between the "Leftln#" variable and the impedance dimension ($L3$). The final model is shown in Fig. 5. $L1$ is the latent variable associated with the traffic performance dimension, $L2$ with the intersection geometric characteristics dimension and $L3$ with the impedance dimension.

The results summarizing the model are presented below:

1. Endogenous measurement model:
   - StDelay = 0.26*API, Errorvar. = 0.63
   - %AcAmber = −0.036*API, Errorvar. = 0.24
   - LnChange = 1.50*API, Errorvar. = 2.46
   - AccGap = −1.00*API, Errorvar. = 3.80
2. Exogenous measurement model:
   - HV = 0.24*$L1$, Errorvar. = 0.43

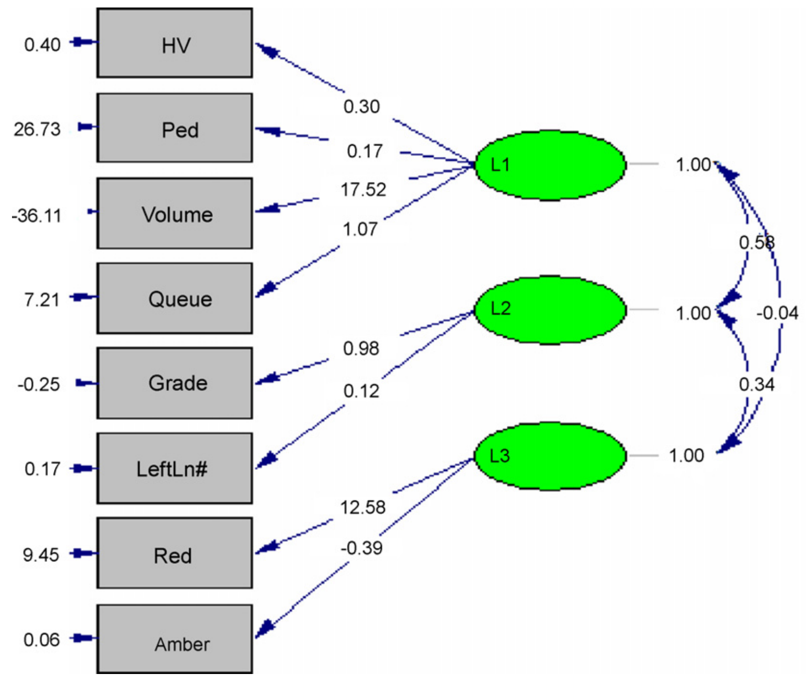


Fig. 4. An initial exogenous measurement model.

- Ped = 1.32*$L1$, Errorvar. = 25.00
- Volume = 10.19*$L1$, Errorvar. = 177.14
- Queue = 2.05*$L1$, Errorvar. = 4.00
- Lane# = 0.43*$L2$, Errorvar. = 0.19
- LeftLn# = −0.39*$L2$ − 0.077*$L3$, Errorvar. = 0.020
- Angle = −0.34*$L2$, Errorvar. = 0.033
- Red = 9.51*$L3$, Errorvar. = 70.49
- LawOth = 0.35*$L3$, Errorvar. = 0.10

3. Structural model:
   - API = 0.32*$L1$ + 0.12*$L2$ + 0.14*$L3$, Errorvar. = −0.24
4. Covariance terms:
   - Error covariance for HV and StDelay = 0.12
   - Error covariance for Volume and LnChange = 2.17
   - Error covariance for Volume and HV = 1.77
   - Error covariance for Lane# and LnChange = 0.33
   - Error covariance for Lane# and HV = 0.11
   - Error covariance for Lane# and Volume = 2.20
   - Error covariance for Lane# and Queue = 0.37
   - Error covariance for LeftLn# and AccGap = -0.11
   - Error covariance for LeftLn# and Volume = 3.34
   - Error covariance for LeftLn# and Queue = 0.26
   - Error covariance for Angle and Volume = 3.19
   - Error covariance for Red and StDelay = 2.06
   - Error covariance for Red and Ped = 12.33

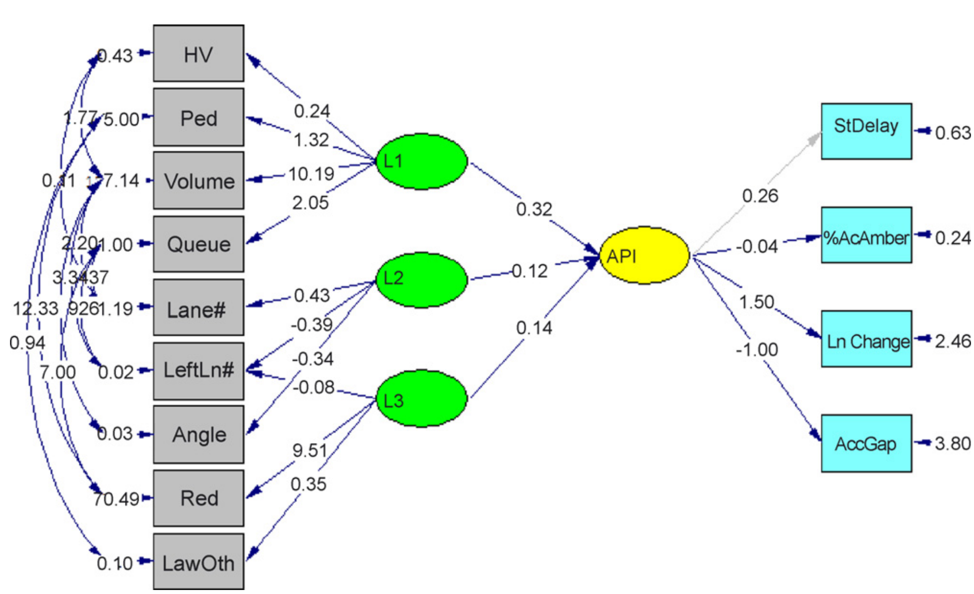


Fig. 5. Final aggressiveness propensity structural model; API, aggressiveness propensity index.

- Error covariance for Red and Queue = 7.00
- Error covariance for LawOth and Ped = 0.94

The estimated model possesses 43 d.f., with a chi-square value of 78.49. Accordingly, the sample size 157 is greater than the critical number of observation N corresponding to a $p = 0.05$: this suggests that the fit of the model is acceptable. Moreover, the root mean square error of approximation (RMSEA) is equal to 0.064 which is in the range of 0.05.

The endogenous measurement model represents the strength of the relation between the different driving patterns (StDelay, %AcAmber, LnChange and AccGap) and the value of the aggressiveness propensity index. If the parameter preceding API is higher in absolute value, the corresponding driving pattern is considered to be more representative of aggressiveness. The sign of the parameter indicates the correlation between "aggressiveness" and the driving pattern measure.

The exogenous measurement model shows how the intersection's characteristics are grouped into several dimensions ($L1$–$L3$). The higher the absolute value of the parameter linking each characteristic to dimension L is, the more important the contribution of this characteristic to aggressiveness will be.

The structural model illustrates the importance of each dimension in increasing (positive parameter) or decreasing (negative parameter) the "aggressive driving patterns" through API.

5. Interpretation and discussion of results

In the Washington DC Metropolitan area, the intersection characteristics contribute positively to drivers' aggressiveness through three main dimensions: the performance measures ($L1$) reflecting the surrounding moving traffic and pedestrians, the intersection geometry ($L2$), reflecting the intersection design features, and the impedance ($L3$) that includes the red timing and the presence of law enforcement figures. The major contributor to the defined instrumental aggressiveness is the performance measures dimension (structural coefficient relating the exogenous latent variable $L1$ to the endogenous one API = 0.32 > 0.14 > 0.12). This result is expected since the frustration of drivers is mostly linked to the traffic situation at a given location. Being stuck in long queues, surrounded by a greater number of heavy vehicles and with increasing numbers of pedestrians and vehicles, cause the drivers to lose their patience.

The second dimension $L2$ is a more controllable aspect of the problem. It is seen that increasing the number of lanes at a given intersection is not a means to avoid aggressive driving patterns, as suggested by a positive value of 0.43 of the structural coefficient of "Lane#" in the latent variable $L2$ equation. However, providing a left-turn bay contributes to decreasing this aggression (coefficient value of −0.39). The third dimension, red time duration, is one of the major contributors of driver aggressiveness. It dominates the presence of law enforcement variable that surprisingly, appears to be associated with greater driver aggressiveness. However, the latter may well be a reflection of the fact that law enforcement elements are generally assigned to locations that exhibit aggressive or otherwise potentially unsafe behavior.

Examining the driving pattern variables, it is seen that accelerating or decelerating when approaching an amber signal indication is likely not a result of the intersection's properties as much as it may be a reflection of the driver's personality. This is suggested by the low structural coefficient value linking "%AcAmber" to the API (−0.04). As for the other variables, the corresponding coefficient signs suggest that aggressiveness is mostly manifested in conjunction with more lane changing maneuvers (1.5), smaller acceptable gaps (−1) and longer start-up delay time (0.34) i.e. drivers become more aggressive when the start up delay time is longer than necessary.

Finally, the error-covariance matrices show expected strong relationships between the different observable variables. As an example, there is a strong positive correlation between the red time and the queue length (7.0) and red time and the number of pedestrians crossing (12.93). Somewhat less initially predictable is that the presence of left turn bays encourages drivers to accept shorter gaps (−0.11), possibly because the traversal distance to complete the left turn maneuver is shorter from the left turn bay, thereby requiring a shorter gap. Another somewhat unexpected result is that longer red phase duration is associated with a slightly greater start-up delay time (2.06); this may be attributed to driver loss of attention or focus during long idle periods. It should be noted that the above results are not intended to offer definitive conclusions, especially when the corresponding coefficient or covariance term are small in relative magnitude. However, they illustrate how the technique proposed in this paper can be an effective tool for intersection performance assessment in support of safety policy analysis.

Another important aspect of the contribution of this study is the ability to obtain numerical values of each intersection's API. The results are summarized in Table 2 for the intersections included in this study. The intersection that exhibits the greatest propensity for aggressive driving is the Cherry Hill Road – Route 1 intersection in College Park, MD. This result was expected because this intersection receives a high level of traffic due to its location at the exit/entrance of the Washington DC Beltway (I-495). Moreover, it has an unconventional design with uneven approaches. The least aggressiveness-inducing intersection is Intersection 4 (Fessenden and Reno), which is located in a suburban residential area in the Chevy Chase area. To relate the aggressiveness propensity index to the collected data, Table 4 summarizes the intersection characteristics by averaging each type of variable over the number of corresponding observations; the high volume for Intersection 3 (63) with a relatively long red time phase are key reasons for the Cherry Hill Road Intersection with Baltimore Avenue appearing as the most "aggressive". Interestingly, for a much lower volume (29), Intersection 9 exhibits a very close API value to Intersection 3 (9.8–9.71). This is due in part to the very high number of pedestrians (22). With a further decrease in volume at Intersection 5, the high API can be explained by a very long red phase duration, thus, increasing the impatience level of drivers.

Table 4
Observed intersection data averaged over the corresponding number of observations

Intersection	1	2	3	4	5	6	7	8	9	10
HV	1	3	0	0	1	0	1	0	1	2
Ped	3	0	2	0	1	2	4	0	22	3
Volume	30	63	39	13	18	6	39	19	26	23
Queue	8	9	7	0	6	3	4	3	4	5
Grade	0	3	1	0	1	0	0	0	0	0
Lane#	2	2	3	1	2	2	3	2	2	3
LeftLn#	1	1	0	1	0	0	0	0	0	0
Angle	0	1	0	1	0	0	0	0	0	0
BusStop	0	0	1	0	0	0	1	0	0	0
Red	25	39	31	23	70	31	32	31	46	30
Amber	4	4	4	5	3	4	4	4	4	4
Camera	1	1	0	0	0	0	0	0	0	0
LawOth	0	0	0	0	1	0	0	1	1	1
LU1	1	1	1	0	1	0	1	0	1	1
LU2	1	0	1	0	1	1	1	1	1	1
StDelay	1.72	2.34	1.63	1.48	1.69	1.36	1.34	1.16	2.32	1.50
%AcAmber	0.5	0.5	0	0	1	0.5	0	0	1	0.5
LnChange	1	3	3	0	1	1	1	1	2	4
AccGap	3.93	6.28	5.69	5.87	4.65	4.96	2.79	6.31	3.10	7.03

6. Concluding comments

A quantitative intersection aggressiveness propensity index was developed in this paper, based on the comparative aggressiveness performance of signalized intersections. This index helps to characterize the strength of the relationship between intersection-related characteristics and aggressiveness' behavioral dimensions. The strength of this relationship is captured by an aggressiveness propensity index. This is accomplished through the use of multiple structural equations (SEM).

After defining all the possible variables that may be related to aggressiveness at signalized intersections, an initial structural model is proposed and the resulting equations are developed. Based on these equations, an exploratory analysis is conducted and applied to 10 different intersections in the Washington DC Metropolitan Area. Using the LISREL Software, factor analysis is performed to improve the initial model. A brief description of the relationships found is presented, resulting in an API value for each intersection. The Cherry Hill Road and Baltimore Avenue (Route 1) Intersection was found to exhibit the highest API among the 10 intersections included in the study sample. This result can be explained by the high traffic volumes and the complicated geometric and signal design of that intersection.

The analysis could be further enhanced by considering traffic conflict data, citations and incident reports at the various intersections as a source against which to validate the API values. This kind of information may help refine the boundary between relatively safe API values, and unsafe API levels causing accidents at a given intersection.

A natural question that arises is the applicability of this model (Fig. 5) to other intersections in other areas. Would the patterns grouping the exogenous observable variables remain the same? Would the coefficients relating these patterns remain in their respective range of values? The extent of applicability in other locations is an empirical matter that can only be answered through additional observational research. However, it is expected that the approach developed and illustrated in this paper can form the basis for a systematic and common conceptual and quantitative framework for understanding driving patterns through intersections, and eventually through entire networks.

References

Anderson, C.A., Bushman, B.J., 2002. Human aggression. Annu. Rev. Psychol., 2002.

Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: a review and recommended two-step approach. Psychol. Bull. 103 (3), 411–423.

De Leur, P., Sayed, T., 2002. Development of a Road Safety Risk Index. Transport. Res. Record 1784, 32–42.

Dukes, R.L., et al., 2001. Effects of aggressive driving and driver characteristics on road rage. Social Sci. J. 38 (2), 323–331.

Golob, T.F., 1987. Effects of income and car ownership on trip generation: a structural equations model and its temporal stability. Institute of Transportation Studies, University of California, Irvine, accessed 31 January 2007, http://www.its.uci.edu/its/puplications/papers/CASA/UCI-ITS-AS-WP-87-2.pdf.

Golob, T.F., 2003. Structural equation for travel behavior research. Transport. Res. Part B 37, 1–25.

Golob, T.F., Kim, S., Ren, W., 1994. A structural model of vehicle use in two-vehicle households, CASA Working Paper Series, Institute of Transportation Studies, University of California, Irvine, accessed on 31st January 2007, http://www.uctc.net/papers/224.pdf.

Golob, T.F., Meurs, T., 1987. A structural model of temporal change in multimodal travel demand. Transport. Res. Part A 21, 391–400.

Golob, T.F., Meurs, T., 1988. Development of structural equations models of the dynamics of passenger travel demand. Environ. Planning 20(A), 1197–1218.

Golob, T.F., Pendyala, R.M., 1991. Structural models and the effects of the commute trip on travel and activity participation. In: North American Meeting of the Regional Science Association, New Orleans, November, pp. 7–10.

Hennessy, D.A., Wiesenthal, D.L., 1997. The relationship between traffic congestion, driver stress and direct versus indirect coping behaviours. Ergonomics 40 (3), 348–361.

Lajunen, T., Parker, D., 2001. Are aggressive people aggressive drivers? A study of the relationship between self-reported general aggressiveness, driver anger and aggressive driving. Accid. Anal. Prevent. 33 (2), 242–255.

Lajunen, T., Parker, D., Summala, H., 1999. Does traffic congestion increase driver aggression? Transport. Res. Part F 2 (4), 225–236.

Loomboonruang, S., Sano, K., 2003. Analysis of access modes in suburban communities using SEM approach. J. Eastern Asia Soc. Transport. Stud. 5, 111–126.

Miles, E.D., Johnson, L.G., 2003. Aggressive driving behaviors: are there psychological and attitudinal predictors? Transport. Res. 6, 147–161.

National Highway Traffic Safety Administration, 1999. Traffic Safety Facts 1998: A Compilation of Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates System. Prepared by the National Center for Statistics and Analysis, U.S. Department of Transportation, Washington D.C, p. 226.

Rodegerdts, et al., 2004. Signalized Intersections: Informational Guide. Report Prepared by the Federal Highway Administration, Publication No. FHWA-HRT-04-091, accessed 1 June 2006, http://www.tfhrc.gov/safety/pubs/04091/#toc.

Shinar, D., 1998. Aggressive driving: the contribution of the drivers and the situation. Transport. Res. Part F 1, 137–160.