

Article

Identifying and Structuring Discretionary Lane-Changing Stimuli Using a Mixed-Methods Approach

Saeed Reza Ramezanpour Nargesi ^{1,*}, Somayeh Ramezanpour Nargesi ², Stephen Mattingly ³ , Vivian Miller ⁴ and Sina Shokoohyar ^{5,*} 

¹ Department of Civil and Environmental Engineering, Union College, 807 Union Street, Schenectady, NY 12308, USA

² School of Business, College of Professional Studies, Pacific Lutheran University, Tacoma, WA 98447, USA; nargesi@plu.edu

³ Department of Civil Engineering, The University of Texas at Arlington, Arlington, TX 76019, USA; mattingly@uta.edu

⁴ Department of Human Services, Bowling Green State University, Bowling Green, OH 43403, USA; millevj@bgsu.edu

⁵ Department of Computing and Decision Sciences, Stillman School of Business, Seton Hall University, South Orange, NJ 07079, USA

* Correspondence: ramezans@union.edu (S.R.R.N.); shokoosi@shu.edu (S.S.)

Abstract

This paper identifies and categorizes factors influencing discretionary lane-changing behavior. A mixed-methods approach combining qualitative and quantitative analysis is employed to structure lane-changing stimuli into clusters and determine their relative importance. Three focus groups of drivers with experience in the United States generated forty discretionary lane-changing reasons. These stimuli were subsequently evaluated through a stated-preference survey of 220 respondents. Exploratory Factor Analysis (EFA) revealed three latent categories: Hazard & Evasive, Situational & Environmental, and Operational & Efficiency factors. Quantitative assessment indicated that safety-critical stimuli, such as encountering a stopped emergency vehicle or road debris, were the highest-ranked individual factors triggering a lane change. Furthermore, preliminary cluster comparisons suggest that the “Hazard & Evasive” cluster is the most influential group of motives. This study offers a foundational step toward developing a “lane-changing propensity” scale. Rather than providing ready-to-integrate mathematical parameters, it contributes a foundational behavioral basis for future model development and validation, highlighting non-traditional driver motivations that future microscopic simulations may eventually explore.

Keywords: discretionary lane-changing; mixed-methods approach; driver behavior stimuli; Exploratory Factor Analysis (EFA); traffic psychology; microscopic traffic simulation



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1. Introduction

Studying lane-changing behavior remains central to traffic flow theory because lane changes frequently generate vehicle conflicts that may escalate into crashes or create traffic turbulence when poorly executed. A considerable body of research has relied on trajectory data to model lane-changing behavior, developing quantitative traffic flow models that inform optimization efforts for choice modeling, infrastructure design, and policy making.

Despite these advances, the literature falls short in identifying and understanding the underlying stimuli that motivate lane-changing behavior. A deeper understanding of these stimuli would enable highway designers, transportation planners, and policy makers

to incorporate implicit and non-numerical factors into their decision-making processes. Moreover, most microscopic traffic simulation models do not account for non-traditional elements such as weather conditions, pavement quality, or drivers' emotional states that may trigger a lane change. Identifying these factors would allow model developers to adjust error distributions or incorporate additional behavioral parameters into optimization procedures. Stated lane-changing stimuli are particularly relevant in semi-autonomous vehicle environments, where predicting lane change motives under varying conditions is critical.

Qualitative research methods are widely used to develop a robust understanding of behavioral motives [1–13]. Focus group questions are typically indirect and context-based, encouraging participants to recall concrete past experiences rather than provide abstract responses. The resulting data are therefore grounded in real-world decision-making situations. Unlike individual interviews, focus groups treat group attitudes as the unit of analysis. Consensus and disagreement within discussions offer deeper insights into the phenomenon, while group interaction stimulates memory recall and reflection.

Integrating qualitative insights with quantitative analysis enhances both reliability and generalizability. This mixed-method approach combines the depth and novelty of qualitative research with the robustness of quantitative techniques. Specifically, survey-based quantitative analysis enables clustering of identified lane-changing stimuli, facilitating the estimation of their relative importance—both at the cluster level and at the level of individual stimuli. Given the wide range of stated motives for lane-changing, identifying relative weights is essential for prioritizing interventions and informing optimization models.

An improved understanding of lane-changing stimuli can ultimately support safer road design. Furthermore, by categorizing these non-traditional motivations, this study provides a foundational behavioral basis for future model development and validation, establishing the groundwork required before these implicit factors can be mathematically formulated into traffic flow models.

The remainder of the paper presents a comprehensive literature review of prior qualitative studies in transportation engineering, followed by a description of the data collection procedures, including focus group implementation and survey design. The paper then reports survey results and key findings, concluding with implications and recommendations for future research.

2. Literature Review

This study uses qualitative and quantitative research techniques such as focus groups and surveys to determine the most important factors that affect lane-changing behavior. Consequently, the authors provide a review of existing lane-changing models and applications of mixed methodological research approaches in the transportation engineering area.

Lane-changing behavior has represented a field of interest for transportation scholars for decades. Refs. [1–3,14–29] developed a lane-changing model for urban areas where traffic signals, heavy vehicles and other obstructions may affect driving behavior to capture the hierarchical processes of lane-changing maneuvers. Kesting et al. [21] developed a general model for merging and discretionary lane-changing behaviors with the goal of minimizing overall braking induced by lane change (MOBIL). Zhou et al. [30] studied the factors that affect discretionary lane-changing behavior in urban areas and found that the heterogeneity of drivers influences the speed of the subject vehicle, leading vehicles as well as the gap distance of the target lane. Hidas [19] also presented a model of cooperative lane-changing and merging behaviors under congested situations. Schakel et al. [7] developed an integrated lane-changing behavior model with a car-following model. However, these models have not investigated the parameters that cause lane-changing. Sun [11] de-

veloped a lane-changing probability model based on different lane-changing scenarios and drivers' characteristics. The structural equation modeling approach has been conducted by Shirke et al. [8] to investigate the effects of vehicle categories and traffic flow speed on lane utilization. The study by Kondyli and Elefteriadou [25,26] explored drivers' thinking process while they merge or pass through freeway-ramp merging sections. Lastly, Bham [31] modeled lane-changing behavior in freeway weaving sections using discretionary and mandatory logic of drivers for changing lanes.

Recent research on traffic behaviors includes lane-changing and merging scenarios modeled using game theoretical approaches in order to capture the interactions of drivers with each other, such as Kita [23], Liu et al. [28], Talebpour et al. [12], and Wang et al. [32]. Overall, most game theory models in lane-changing behavior consider the typical factors that influence lane changes, such as speed gain.

Some studies investigate the advantages and disadvantages of different lane-changing models. For instance, Moridpour et al. [2] explored the existing lane-changing models in the literature and investigated the strengths and weaknesses of each model. Rahman et al. [5] also reviewed and compared lane-changing models related to microscopic traffic simulation.

The issues related to qualitative research include theoretical frameworks, data collection, management, and analysis. To increase the number and quality of qualitative research in the transportation area, scholars and researchers should appreciate and understand the importance of qualitative research (Clifton and Handy [33,34]), such as focus groups, interviews or participant-observers in travel behavior research.

Surveys represent one of the most common qualitative research techniques to obtain people's points of view. This technique is also common in transportation studies, as evidenced by Rayle et al. [6], Golob and Regan [16], Agrawal et al. [35], Yim et al. [36], Björklund and Åberg [37], Bray [38] and Machado-León et al. [29]. Moreover, Knoop et al. [24] conducted an online survey to understand different drivers' lane-changing strategies and behaviors on freeways. However, they did not explore the external factors such as weather that may cause drivers to change lanes.

Generally, previous studies show that conducting a qualitative study such as focus groups may help researchers understand individuals' perceptions more effectively and identify factors that influence behavioral decision-making. Thus, mathematical models supported by qualitative studies appear more comprehensive than traditional models. Focus groups are a technique that helps scholars collect a specific target group's thinking processes and opinions. This qualitative method has been applied in transportation studies, such as Flamm and Agrawal [39], Glasgow and Blakely [15] and Huth et al. [20]. Most of the lane-changing models in transportation literature use vehicle trajectories to develop and validate these models without assessing drivers' characteristics. However, the focus groups in the Sun and Elefteriadou [10] study directed them to derive drivers' characteristics to consider in lane-changing models. In contrast to our paper, they did not investigate all factors that may cause drivers to change lanes. The Kondyli and Elefteriadou [25,26] study conducted three focus groups and in-field experiments to explore drivers' attitudes and thinking processes in different congested and uncongested freeway ramp merging scenarios. This paper also did not investigate all external and Situational & Environmental factors that force drivers to change lanes. Overall, focus groups represent a valuable technique to solicit feedback from target populations about a specific issue, concern, or research question, which can improve models by implicitly and explicitly considering people's opinions. Prior studies have explored hybrid clustering techniques in logistics; for instance, Anand et al. applied factor analysis to optimize the k-means algorithm on transportation datasets [40].

In some studies, such as this paper, researchers organize both focus groups and surveys as a mixed methodological approach to reach their research goals. In some transportation area studies such as those by Ortúzar et al. [4], Stathopoulos et al. [9], and Fletcher et al. [41], a mixed methodological approach was used that enabled them to obtain and investigate multiple points of view from respondents. Lastly, Keyvan-Ekbatani et al. [22] explored the perspective of drivers regarding lane and speed choices while changing lanes using a two-stage test drive, but all possible lane-changing factors that cause drivers to change lanes were not investigated.

As noted, there is a noticeable number of attempts to model traffic behaviors mathematically using trajectory data. Investigations into the motives behind traffic actions are rather scarce. In the rare examples with a qualitative and direct opinion-seeking approach, processes of traffic maneuvers or drivers' choices of speed or lanes have been investigated. One example of qualitative inquiry for lane-changing stimuli lacks generalizability, which pure qualitative studies have always been criticized for.

To capture the complex decision-making processes of human drivers, recent modeling efforts in traffic flow theory have increasingly shifted toward addressing unobserved driver heterogeneity. Traditional deterministic or standard discrete choice models often treat driver behavior as homogeneous, which fails to capture the significant variations in preferences, risk tolerance, and driving styles across a population. To resolve this limitation, researchers have utilized mixed logit (random parameters logit) modeling frameworks.

For instance, Li et al. [27] investigated the dynamic trade-offs between safety and efficiency during discretionary lane-changing maneuvers using a random parameters logit approach. Their findings highlighted that human drivers exhibit significant unobserved heterogeneity, particularly in how they evaluate safety margins versus operational gains under varying traffic states. Similarly, in connected and automated vehicle (CAV) environments, mixed logit models have been utilized to demonstrate how different driver cohorts respond to situational awareness cues and communication interfaces, emphasizing that behavioral parameters and gap-acceptance thresholds are not uniform across the driving population.

More recently, the advent of connected and automated vehicles (CAVs) has fundamentally shifted the modeling landscape, necessitating a deeper understanding of human driver heterogeneity in mixed-traffic environments. Recent studies emphasize that human drivers exhibit significant unobserved heterogeneity—particularly in their dynamic trade-offs between safety and operational efficiency during lane changes Li et al. [27]. Furthermore, research into connected environments highlights that advanced communication can significantly alter discretionary lane-changing duration and gap acceptance by modifying a driver's situational awareness (Ali et al., [42]). As autonomous vehicle controllers increasingly rely on deep reinforcement learning and game-theoretic frameworks to navigate hybrid action spaces, accurately capturing the wide spectrum of human behavioral motives—ranging from aggressive overtaking to cautious, comfort-seeking maneuvers—has become paramount. However, despite these advanced computational methods, there remains a gap in directly translating qualitative, psychological stimuli into parameterized inputs for these models.

A systematic review of the literature reveals distinct methodological groupings based on data type, lane-changing context, considered stimuli, and modeling output. The vast majority of existing research relies on observational trajectory data to develop mathematical or probability models. For instance, models by Gipps [14], Kesting et al. [21], and Zhou et al. [30] successfully capture kinematic stimuli—such as speed differentials, braking thresholds, and gap acceptance—within urban and freeway contexts. However, these mathematical models often treat the driver as a purely rational agent, largely omitting unobserved heterogeneity driven by psychological states or specific environmental constraints.

Conversely, qualitative studies have begun to explore the human element of traffic maneuvers. Research by Kondyli & Elefteriadou [25,26] and Sun & Elefteriadou [10] utilized in-field observations and focus groups to investigate driver attitudes and thinking processes during freeway merging and urban arterial navigation, providing valuable conceptual frameworks. More recently, studies in Connected and Automated Vehicle (CAV) environments, such as Li et al. [27] and Ali et al. [42], have utilized simulator and trajectory data to model the trade-offs between safety and efficiency based on a driver's situational awareness and risk perception.

Despite these advancements, a critical research gap remains: there is a distinct lack of comprehensive, stated-preference research that explicitly categorizes and weights the full spectrum of psychological and environmental stimuli for discretionary lane changes. Modern microscopic simulations require a nuanced understanding of aggressive driving motives, subjective risk perception, and non-traditional triggers (e.g., driver mood, travel time constraints, distraction, weather conditions, pavement quality, and police presence) to navigate mixed-traffic environments effectively. Therefore, this study addresses this gap by utilizing a mixed-method approach to systematically extract, categorize, and prioritize these 40 distinct behavioral factors, providing a foundational behavioral basis for future model development and validation.

3. Methodology

This study seeks to determine the factors that influence lane change behavior, categorize these factors into different clusters, and identify their individual and cluster importance. To reach these goals, the authors conduct a mixed methodological approach that began with qualitative data collection (three focus groups) and continues with quantitative methodology using online surveys [10]. In this study, the focus groups determine all potential lane-changing reasons. We distinguish between mandatory and discretionary lane-changing behavior based strictly on route dependency. "Mandatory" lane changes are defined as those required to follow a specific navigational path (e.g., taking an exit or completing a mandatory merge). Consequently, we broadly define "discretionary" lane-changing as encompassing all non-route-dependent maneuvers. It is important to note that this broad definition captures a wide spectrum of urgency, ranging from purely free-choice actions (e.g., seeking comfort or gaining speed) to highly constrained, safety-critical, and evasive maneuvers (e.g., avoiding a stalled vehicle or making way for an emergency vehicle on the shoulder). While these latter scenarios are safety-driven, they require driver judgment and are not dictated by the route layout, thus falling under our operational definition of discretionary motives. The online survey asked participants for their opinions on the relative impact of each factor on their decision making during these non-mandatory lane changes. All the analysis are done in Addinsoft (version 2019) [43].

3.1. Focus Groups Design

The research team conducted three focus groups to identify a comprehensive set of potential lane-changing reasons expressed by drivers. Consequently, they intuitively clustered these reasons into four categories.

Table 1 shows questions developed for the focus groups based on the research team's brainstorming and literature review.

The participants of the study were not aware of the authors' intention for categorizing lane-changing reasons and only discussed the questions in Table 1. Table 2 shows the steps of focus group analysis.

Table 1. Focus group questions.

1- Warm-up questions: Introduce yourself. What is your job? How frequently do you drive? What is your experience in driving?
2- Getting to the topic: Today we are going to talk about lane-changing. Do you like lane-changing or not? Some drivers change lanes all the time. Some of them change lanes based on their situations, and some conservative ones try not to change lanes at all unless they have to.
3- Lane-changing moments: Would you please express your opinion about the following situations on freeway?
a- Trapped behind a slow vehicle.
b- Being behind a truck or bus. Does safety matter to you in this case?
c- Change a lane in order to exit or enter a freeway.
d- When congestion is seen downstream of your lane.
e- Change a lane in order to gain speed.
f- How is your driving style? Do you enjoy the added excitement of going zigzag?
g- What happens if the adjacent lane has better pavement conditions?
h- What do you do if someone is tailgating you?
i- What is your reaction if another vehicle is coming into your lane without considering the available gap?
j- Does your vehicle's condition affect your lane-changing behavior?
k- Which behaviors of adjacent vehicles affect your lane-changing behavior?
l- Can any distraction like listening to the radio or using your smart phone affect your lane-changing behavior?
m- Do signs affect your lane-changing behavior?
4- Imagine you are a target, lead or lag vehicle. What will be your possible actions in each case during the lane-changing process?
5- Do you have any comments or specific matters that you want to add to our conversation?

Table 2. Steps of focus groups analysis.

Step 1	Audio recordings of focus groups sessions
Step 2	Taking notes during focus groups sessions
Step 3	Listening to the recordings
Step 4	Taking comprehensive notes on participants' inputs
Step 5	Initial content analysis and placing factors in obtained categories found in the literature

3.2. Focus Groups Data Analysis

The researcher conducted three focus groups (five or six people in each) to obtain a broad spectrum of stated motives that cause drivers to change lanes. The focus groups used structured, open-ended questions to capture participants' views and opinions about lane-changing reasons. The focus group participants had driven for at least one year, had freeway driving experience and were older than 18 years. Participants were recruited by email, which was approved by the University of Texas at Arlington Institutional Review Board. The invitees were selected from the researcher's personal social network; however,

he attempted to maintain the heterogeneity of the focus group participants by inviting people from different age groups, genders, occupations and nationalities.

Each focus group lasted between 40 and 60 min. First, the researcher introduced himself; then, he asked the participants to introduce themselves and reveal their driving experience, especially on freeways. Afterwards, a warm-up question was asked (Table 1) regarding the general sense and feelings of the participants about lane-changing behavior by asking, “What comes to your mind when I ask you about changing lanes?” Finally, the participants answered multiple structured open-ended questions to capture the potential reasons that cause them to change lanes. Once saturation occurred in the discussion, the researcher continued the session with a new question. Lastly, the researcher asked the participants if they had any more input that they had previously not shared. The audio of all focus groups was recorded for collecting data afterwards. The focus groups were discontinued after achieving saturation in responses. In this study, saturation was operationally defined as the point during the discussions when consecutive probes and questions yielded no newly distinct motives or themes from the participants, indicating that the breadth of discretionary lane-changing stimuli for this cohort had been adequately captured.

To transition from the raw focus group discussions to the definitive list of 40 factors, the investigators employed the “hearing voices” method [17], utilizing audio recordings directly to determine themes and analyze responses. This type of focus group data analysis has the advantage of being cost-effective and trustworthy compared to the traditional transcription analysis approach [17]. The authors reviewed the audio recordings carefully and collected the lane-changing factors identified by the participants, as shown in Table 3. The researcher took comprehensive notes on participant input and tried to place the lane-changing stimuli into categories (Emotional, Environmental, Safety, Operational & Efficiency) identified in previous studies.

Table 3. Lane-changing factors and clusters.

	Factor ID	Lane-Changing Factor
Emotional	27	Driver distraction (e.g., radio, phone, passengers)
	37	Vehicle maneuverability preferences (e.g., newer/smaller car)
	40	Positive emotional state (e.g., excitement)
Environmental	17	Navigating sharp curves
	21	Navigating a weaving, merging, or diverging area
	22	Familiarity with the road
	29	Presence of a police vehicle
	30	Adverse weather conditions (rain, snow, wind)
	31	Water accumulation in the current lane
	34	Poor pavement condition (e.g., bumpy road)
	43	Aggressive driving environments (e.g., specific cities)
	46	Leading vehicle producing excessive exhaust/smoke
	51	Erratic behavior from occupants of another vehicle
	53	Passenger request
	55	Lane blockage (e.g., stalled vehicle)

Table 3. Cont.

	Factor ID	Lane-Changing Factor
Safety	16	Crossing a train track for safety /comfort
	18	Increasing spatial buffer on curves
	23	Poor vehicle condition (e.g., steering/braking issues)
	25	Driver fatigue or sleepiness
	26	Vehicle parked or stopped on the shoulder
	28	Leading vehicle braking unnecessarily or frequently
	32	Moving to the middle lane to avoid merging traffic
	36	Emergency vehicle stopped on the shoulder
	38	Debris or object in the lane
	41	Passing a heavy vehicle regardless of its speed
	42	Heavy vehicle traveling in the adjacent lane
	44	Roadside hazard (e.g., fire)
	45	Tailgating by a trailing vehicle
	47	Yielding the left lane to faster traffic
	48	Stopped vehicle on the shoulder with occupants outside
	49	Trailing vehicle flashing headlights
	50	Leading vehicle carrying an insecure cargo load
	52	Sudden evasive action due to a vehicle malfunction
Operational & Efficiency	54	Adjacent driver using a phone
	12	Anticipation of speed gain
	15	Travel time constraints (e.g., being in a rush)
	24	Nighttime driving conditions
	33	Downstream traffic congestion
	35	Heavy general traffic
	39	Entering a lane with truck prohibitions

3.3. Survey Design

The authors designed a survey to determine the lane change factor load in order to determine the importance of each factor within its category as well as the importance of each category on lane-changing execution. In the designed survey, the respondents ranked lane-changing reasons using a Likert-type scale from 1 to 7, with 1 being “strongly disagree” to 7 being “strongly agree,” to identify the most important factors in the lane-changing process. The survey used random ordering of questions to eliminate order bias [44].

Sample Characteristics

Participants were recruited using a non-probability convenience sampling framework via university mailing lists and other available contact lists. The inclusion criteria required respondents to hold a valid driver’s license, possess freeway driving experience, and be 18 years of age or older. To ensure data quality, incomplete survey responses were excluded from the analysis, resulting in a final sample of 220 fully completed responses.

This study analyzed a sample of 220 responses. Of the entire participant sample, the greatest percentage of participants were aged 24 to 29 years (24.1%). The majority of participants were female (85%) and Caucasian (81.4%). Nearly thirty-two percent (31.4%)

had some college credit, with no degree, and twenty (19.5%) were high school graduates. Fifty-three participants (24.1%) had a college degree, and together, approximately eight percent had a master's, professional, or doctorate degree. Fifty participants (22.7%) reported an annual income of less than \$15,000. Nearly half of the participants (45.5%) operate a sedan, with thirty percent of the participants owning their vehicle for between five to ten years. The majority (69.1%) of the participants do not have a blind spot feature in their vehicle and have more than ten years of driving experience (63.6%) in the United States. More than half (52.7%) of the participants reported driving on the freeway over two times per week.

It is critical to note that the demographic distribution of our sample is heavily skewed, particularly with regard to gender (85% female) and race (81.4% Caucasian). While convenience sampling allowed us to quickly reach a highly completed sample size of 220, this extreme imbalance limits the direct generalizability of the findings to the broader, more diverse United States driving population. The potential confounding effects of this demographic skew on our relative ranking metrics are detailed in Section 4.3.

3.4. Survey Analysis

The analysis of lane-changing factors survey includes two different steps:

- Determining the most and the least important discretionary lane-changing factors by generating z-scores in order to prioritize them for consideration for incorporation into simulation packages.
- Determining (1) the potential lane-changing clusters with a data-driven approach using EFA, (2) the appropriateness of using EFA, (3) the number of required clusters, (4) the importance of each factor within its cluster, and (5) the importance of each data-driven cluster in causing discretionary lane changes.

Prioritizing Lane-Changing Factors Using Z-Scores

This step analyzes all lane-changing factors together to determine their importance. While evaluating Likert-scale data using item means and standard deviations is common practice, it can be susceptible to individual response style biases, such as extreme responding or acquiescence bias. To control for these variations in how different participants use the scale, this study normalizes the responses by calculating within-person z-scores $((x - \mu)/\sigma)$ for each respondent. This standardization approach (ipsatization) shifts the interpretation from absolute agreement to relative importance, allowing the analysis to highlight which factors a driver prioritizes relative to their own personal baseline.

The author uses $((x - \mu)/\sigma)$, where μ and σ are the mean and standard deviation of each participant's responses to the questions (each participant had 40 questions to answer), to obtain the z-score for each participant response. Afterwards, the average of the z-scores is calculated for each lane-changing factor using $\sum(z\text{-scores})/220$. A larger z-score means that the drivers attribute greater importance to this factor than to other factors. Table 4 shows the lane-changing factors based on their importance in causing drivers to change lanes. For instance, "Changing lane because an emergency vehicle is parked or stopped on the shoulder" is the most important factor in causing drivers to change lanes. Therefore, the author prioritizes the lane-changing factors using these z-scores.

Table 4. Prioritizing lane-changing factors using z-scores.

ID	Lane-Changing Factors	Z-Scores
36	Emergency vehicle stopped on the shoulder	0.605
38	Debris or object in the lane	0.502
44	Roadside hazard (e.g., fire)	0.459
28	Leading vehicle braking unnecessarily or frequently	0.414
48	Stopped vehicle on the shoulder with occupants outside	0.394
46	Leading vehicle producing excessive exhaust/smoke	0.353
52	Sudden evasive action due to a vehicle malfunction	0.341
50	Leading vehicle carrying an insecure cargo load	0.331
55	Lane blockage (e.g., stalled vehicle)	0.326
26	Vehicle parked or stopped on the shoulder	0.287
34	Poor pavement condition (e.g., bumpy road)	0.200
47	Yielding the left lane to faster traffic	0.193
45	Tailgating by a trailing vehicle	0.181
16	Crossing a train track for safety/comfort	0.159
29	Presence of a police vehicle	0.156
31	Water accumulation in the current lane	0.153
18	Increasing spatial buffer on curves	0.070
23	Poor vehicle condition (e.g., steering/braking issues)	0.000
32	Moving to the middle lane to avoid merging traffic	−0.065
54	Adjacent driver using a phone	−0.065
51	Erratic behavior from occupants of another vehicle	−0.072
33	Downstream traffic congestion	−0.101
12	Anticipation of speed gain	−0.117
21	Navigating a weaving, merging, or diverging area	−0.148
39	Entering a lane with truck prohibitions	−0.173
27	Driver distraction (e.g., radio, phone, passengers)	−0.174
22	Familiarity with the road	−0.175
15	Travel time constraints (e.g., being in a rush)	−0.182
35	Heavy general traffic	−0.198
30	Adverse weather conditions (rain, snow, wind)	−0.202
53	Passenger request	−0.205
25	Driver fatigue or sleepiness	−0.222
17	Navigating sharp curves	−0.246
42	Heavy vehicle traveling in the adjacent lane	−0.276
40	Positive emotional state (e.g., excitement)	−0.281
49	Trailing vehicle flashing headlights	−0.285
43	Aggressive driving environments (e.g., specific cities)	−0.333
41	Passing a heavy vehicle regardless of its speed	−0.345
37	Vehicle maneuverability preferences (e.g., newer/smaller car)	−0.491
24	Nighttime driving conditions	−0.766

3.5. Exploratory Factor Analysis

Exploratory factor analysis (EFA) represents a data-driven approach to developing clusters of discretionary lane change stimuli. The EFA uncovers the relationship of the different factors with a latent variable, develops a scale or subscale and identifies the underlying construct of the measured factors.

Factor analysis reduces large sets of variables by grouping them based on their strong intercorrelations. Aside from dimensionality reduction, EFA can be used to compress data and visualize highly dimensional datasets. The smaller groups consist of variables that have a strong linear correlation with each other. The results of factor analysis may differ from those of other data analysis techniques such as principal component analysis (PCA) and cluster analysis [40]. Principal component analysis (PCA) converts a number of possibly correlated variables into a smaller number of variables that are linearly uncorrelated.

3.5.1. Validity of Exploratory Factor Analysis

The Bartlett test of sphericity can be used to determine if factor analysis is appropriate by examining the entire correlation matrix to determine correlations among variables (lane-changing factors). This index shows that at least a number of the variables in the matrix have significant correlations with each other, so the clustering approach can proceed. Prior to using factor analysis, the existence of a structure needs to be supported by a “strong conceptual foundation” (Hair et al. [18]). Clustering of the factors should proceed only if sufficient correlation among the variables (lane-changing factors) exists. Since Bartlett’s test observes significant correlation among the variables (the p -value is <0.0001), clustering the lane-changing factors appears reasonable.

3.5.2. Determining the Appropriateness of EFA Analysis Using the Kaiser–Meyer–Olkin Measure of Sampling Adequacy

The measure of sampling adequacy (MSA) calculates the level of intercorrelations among the variables to determine if factor analysis is appropriate. This index ranges between 0 and 1, reaching 1 when each variable can be perfectly predicted by the other variables without error. The MSA index is interpreted as follows: 0.80 or above is meritorious; 0.70 or above is middling; 0.60 or above is mediocre; 0.50 or above is miserable; and below 0.50 is unacceptable (Hair et al., 2014) [18]. To proceed with the analysis, each individual variable must have an MSA greater than 0.50. If a variable falls below this threshold, it should be removed iteratively, starting with the lowest value, until the overall model MSA also exceeds 0.50 (Hair et al., 2014) [18].

The results of the sampling adequacy test show that all forty lane-changing factors have a Kaiser-Meyer-Olkin measure greater than 0.80, with an overall model KMO of 0.891, as shown in Table 5. Consequently, all forty factors were retained for the clustering analysis.

Table 5. Results of measure of sample adequacy.

Lane-Changing Factor ID	MSA	Lane-Changing Factor ID	MSA	Lane-Changing Factor ID	MSA	Lane-Changing Factor ID	MSA
12	0.886	26	0.897	36	0.913	46	0.908
15	0.876	27	0.864	37	0.881	47	0.846
16	0.862	28	0.954	38	0.897	48	0.929
17	0.914	29	0.829	39	0.823	49	0.844
18	0.869	30	0.847	40	0.886	50	0.894

Table 5. Cont.

Lane-Changing Factor ID	MSA	Lane-Changing Factor ID	MSA	Lane-Changing Factor ID	MSA	Lane-Changing Factor ID	MSA
21	0.911	31	0.888	41	0.843	51	0.817
22	0.884	32	0.865	42	0.851	52	0.938
23	0.820	33	0.919	43	0.878	53	0.916
24	0.905	34	0.919	44	0.931	54	0.899
25	0.895	35	0.881	45	0.839	55	0.950
KMO							0.891

3.5.3. Determining the Number of Clusters in Exploratory Factor Analysis

While the factors identified in the focus groups were qualitatively categorized, this phase uses EFA to group them quantitatively based on their underlying correlations. To determine the optimal number of clusters, we applied the Latent Root Criterion (Kaiser criterion), which dictates that only factors with an eigenvalue greater than 1.0 should be retained. The underlying logic is that any significant cluster must explain at least the variance of a single variable. This criterion is highly reliable when the number of variables is between 20 and 50 (Hair et al., 2014) [18]. With forty variables in our analysis, the Latent Root Criterion is highly appropriate. As shown in Table 6, the first three latent factors exhibit eigenvalues greater than 1.0, suggesting that a three-factor solution is optimal for clustering the discretionary lane-changing stimuli.

Table 6. Potential lane-changing clusters and the associated eigenvalues.

Potential Cluster	Eigenvalue
F1	9.907
F2	4.969
F3	1.108
F4	0.838
F5	0.787
F23	0.008

3.5.4. Identifying Lane-Changing Clusters Using EFA Technique

The previous exploratory analysis indicated that the forty different lane-changing factors could be grouped into three categories, as shown in Tables 7–9. The third column of each table shows the z-scores associated with each factor, indicating its relative exploratory importance in triggering a discretionary lane change. It is important to emphasize that these EFA-derived clusters represent preliminary taxonomic findings. Because they have not yet been structurally verified through secondary confirmatory analyses, they must be treated as exploratory conceptual constructs requiring independent validation with a new driver sample. The authors assigned descriptive labels to these three clusters based on the conceptual coherence of the comprised factors: “Hazard & Evasive” factors, “Situational & Environmental” factors, and “Operational & Efficiency” factors.

Table 7. Factors in the “Hazard & Evasive” cluster.

Factor ID	Factors in “Hazard & Evasive” Cluster	Z-Score
36	Changing lane because an emergency vehicle is parked or stopped on the shoulder	0.60
38	Changing lane because of an object in your lane. (e.g., seeing a dead animal or a piece of lumber)	0.50
44	Changing lane to avoid a hazard such as fire along one side of a road	0.46
28	Changing lane because a vehicle in front of you keeps braking or brakes for no reason	0.41
48	Changing lane because a car is parked or stopped on the shoulder (because of a flat tire or something is wrong with their cars) and people are observed outside the vehicle	0.39
46	Changing lane because the car in front of you produces lots of smoke and blocks your view	0.35
52	Changing lane to go to shoulder of freeway or exit from freeway when something suddenly happens to your car	0.34
50	Changing lane if a truck with something in it like a mattress is in front of you and you do not feel safe	0.33
55	Changing lane because of lane blockage (e.g., stalled car in your lane)	0.33
26	Changing lane because a car is parked or stopped on the shoulder	0.29
34	Changing lane because of bad pavement condition or because the road is bumpy	0.20
47	Changing lane to provide the left lane for other vehicles to pass you	0.19
45	Changing lane because somebody is tailgating you	0.18
31	Changing lane to avoid being in the rightmost lane when water is accumulated in that lane because of rain	0.15
54	Changing lane because another driver is on the phone	−0.07
33	Changing lane when there is congestion downstream in your lane (Lane Density matters)	−0.10
21	Changing lane because of being in a weaving, merging or diverging area	−0.15
Average of z-scores		0.26

Table 8. Factors in the “Situational & Environmental” cluster.

Factor ID	Factors in “Situational & Environmental” Cluster	Z-Score
16	Changing lane because of crossing a train track in order to be in a better and safe situation	0.16
29	Changing lane on seeing a police car (e.g., police care with radar on the shoulder or police car moving in a freeway)	0.16
18	Changing lane on curves in order to have more space and be safe	0.07
32	Changing to the middle lane to avoid other vehicles’ lane-changing or merging	−0.07
51	Changing lane because people in another vehicle are fighting or crying (you think their behavior might not be normal)	−0.07
39	Changing lane for going to the lanes that are not allowed for trucks	−0.17
27	Changing lane because of any kind of distraction (listening to the radio, using GPS, seeing billboards, talking on the phone, someone is talking to you, etc.)	−0.17
22	Changing lane due to being familiar with the road	−0.17
35	Changing lane in heavy traffic	−0.20
30	Changing lane when the weather is rainy, snowy or windy	−0.20
53	Changing lane based on what other people in your car ask you to do	−0.20

Table 8. Cont.

Factor ID	Factors in “Situational & Environmental” Cluster	Z-Score
25	Changing lane when sleepy (e.g., in the morning when you go to work and you are sleepy)	−0.22
17	Changing lane because there are a lot of sharp curves	−0.25
42	Changing lane when a truck or a heavy vehicle is beside you in the adjacent lane	−0.28
40	Changing lane because of having a good mood (e.g., listening to a music or being excited)	−0.28
49	Changing lane because a vehicle behind you flashes its headlights	−0.28
41	Changing lane in order to pass a truck or a heavy vehicle even if those vehicles go fast	−0.35
37	Changing lane with a newer car or a smaller and more flexible car (type or model of the car matters)	−0.49
24	Changing lane at nighttime	−0.77
	Average of z-scores	−0.20

Table 9. Factors in the “Operational & Efficiency” cluster.

Factor ID	Factors in “Operational & Efficiency” Cluster	Z-Scores
23	Changing lane when your car is not in a good condition (when the car does not steer or brake well)	0.00
12	Changing lane in order to gain speed	−0.12
15	Changing lane because of being in a rush; I need to be someplace soon (e.g., in the morning for going to work)	−0.18
43	Changing lane in areas where drivers are more aggressive such as New York or Mexico City (Location matters)	−0.33
	Average of z-scores	−0.16

The “Hazard & Evasive” factors represent the external, safety-critical reasons that force drivers to initiate a discretionary lane change (e.g., avoiding an object in the lane or responding to an emergency vehicle). The “Situational & Environmental” factors represent context-driven conditions such as weather, traffic density, and road geometry, as well as situational driver-state variables that influence lane-changing comfort. Finally, the “Operational & Efficiency” factors represent motives related to vehicle performance, travel goals (e.g., being in a rush or needing to gain speed), and navigating specific traffic environments.

Z-scores are used to rank the factors within each cluster. They show the relative standing of each factor versus the other factors in each cluster. For each cluster, the mean and the standard deviation of the factors’ scores in that cluster are used to calculate the z-score of each factor.

3.5.5. Significant Differences Between EFA Clusters

We also looked into the statistical differences between clusters. This attempt can shed light on the relative importance of the categories through the lens of discriminant analysis.

To conduct the significant difference between the lane-changing clusters, two of each cluster were compared (based on their z-scores) with each other using a two-sample z-test. The interpretation of the test is as follows:

H0. *The difference between the means is equal to 0.*

Ha. *The difference between the means is lower than 0.*

The results summarized in Table 10 show that the mean of the “Hazard & Evasive” cluster is significantly greater than the other two clusters (p -value < 0.0001), with no significant difference between the means of the “Situational & Environmental” and “Operational & Efficiency” clusters. However, because this comparison utilized item-level z -scores—treating them as independent observations rather than accounting for the nested nature of the respondent data—this finding must be treated strictly as a preliminary and exploratory indication. It does not constitute definitive statistical proof of cluster dominance or absolute superiority. Based strictly on these exploratory tests, the “Hazard & Evasive” cluster tentatively appears to be the most influential trigger for discretionary lane changes in this specific cohort, but this ranking remains highly speculative until validated through robust, repeated-measures statistical techniques on a representative dataset.

Table 10. Summary of clusters’ significance tests.

Cluster Comparisons	p -Value of z -Test for Two Independent Samples
Hazard & Evasive and Situational & Environmental	<0.0001
Operational & Efficiency and Situational & Environmental	0.31
Hazard & Evasive and Operational & Efficiency	<0.0001

4. Discussion

4.1. Theoretical Implications

The transition from raw focus group dialogue to the structured EFA clusters highlights the multifaceted nature of driver decision-making. By moving beyond traditional trajectory data and actively identifying the “Hazard & Evasive,” “Situational & Environmental,” and “Operational & Efficiency” clusters, this study theoretically bridges the gap between mechanical traffic flow theory and traffic psychology. It demonstrates that a discretionary lane change is rarely a singular calculation of speed gain; rather, it is a complex response to a hierarchy of external constraints, contextual comfort levels, and operational goals.

4.2. Modeling and Computational Implications

From a computational and decision sciences perspective, identifying these latent clusters provides a highly structured framework for parameterizing driver behavior in microscopic simulations and autonomous vehicle controllers. While traditional microscopic traffic models rely strictly on kinematic inputs, the proposed conceptual clusters offer clear utility for expanding simulation parameters.

For instance, “Hazard & Evasive” factors (e.g., debris, stalled vehicles) can be modeled as high-priority, deterministic constraint overrides ($\Lambda_n(t)$) in autonomous optimization algorithms. Conversely, “Situational & Environmental” variables (such as adverse weather or road geometry) can be incorporated as dynamic, stochastic weights ($X_{i,n}(t)$) within the utility functions of existing gap-acceptance models, allowing for more realistic, heterogeneous traffic flow simulations. Finally, factors from the “Operational & Efficiency” cluster (such as travel time constraints or vehicle preferences) can be conceptualized as driver-type modifiers ($Y_{j,n}(t)$). These modifiers dynamically scale a simulated vehicle’s sensitivity parameters, adjusting its target speed, desired following distance, and aggressiveness parameters to reflect the underlying heterogeneity in human driver states.

To bridge the gap between behavioral findings and microscopic traffic flow simulation, we propose a concrete mathematical framework to integrate the three identified clusters (Hazard & Evasive, Situational & Environmental, and Operational & Efficiency) into standard discretionary lane-changing decision-making architectures.

Let $U_n(t)$ be the latent utility of driver n executing a discretionary lane change at time t . In a standard discrete choice utility framework, we can model this decision as:

$$U_n(t) = \beta_0 + \beta_1 \Delta v_n(t) + \sum_i \gamma_{i,n} X_{i,n}(t) + \sum_j \theta_j Y_{j,n}(t) - \Lambda_n(t)$$

where:

- $\Delta v_n(t)$ represents the expected velocity gain in the target lane (the traditional kinematic stimulus);
- $X_{i,n}(t)$ represents environmental variables from the Situational & Environmental cluster (e.g., adverse weather, lane water accumulation, poor pavement condition);
- $Y_{j,n}(t)$ represents operational variables from the Operational & Efficiency cluster (e.g., driver distraction, emotional state, travel time constraints);
- $\Lambda_n(t)$ represents a deterministic priority override function driven by the Hazard & Evasive cluster.

To reflect unobserved driver heterogeneity, the sensitivity parameters $\gamma_{i,n}$ and θ_j can be modeled as random parameters following a normal distribution:

$$\gamma_{i,n} \sim N(\mu_{\gamma_i}, \sigma_{\gamma_i}^2) \text{ and } \theta_j \sim N(\mu_{\theta_j}, \sigma_{\theta_j}^2)$$

Furthermore, *Hazard & Evasive* factors act as deterministic constraints rather than marginal trade-offs. We model this as an immediate utility override:

$$\Lambda_n(t) = \begin{cases} -\infty & \text{if a critical hazard exists in the target lane (e.g., debris or stalled car)} \\ +\infty & \text{if an immediate hazard exists in the current lane forcing an evasive maneuver} \\ 0 & \text{otherwise} \end{cases}$$

In microscopic simulation packages, this model can be operationalized via a threshold-activation algorithm. A driver will initiate a lane change if the utility of doing so exceeds an activation threshold τ_n :

$$P(\text{Lane Change}_{n,t}) = P(U_n(t) > \tau_n)$$

By scaling the random parameters ($\gamma_{i,n}$ and θ_j) and defining the priority override ($\Lambda_n(t)$), simulation developers can move beyond simplistic speed-gain algorithms, dynamically adjusting gap-acceptance and lane-changing behavior based on simulated environmental and driver state variables.

4.3. Limitations and Future Validation

The findings of this study must be interpreted within the context of several methodological limitations. First, the quantitative survey relied on a non-probability convenience sample, resulting in a significant demographic imbalance (85% female and 81.4% Caucasian), which restricts the generalizability of the findings across the broader U.S. driving population. Specifically, this heavy demographic skew likely acts as a confounding variable that inherently biases the resulting z-score rankings, potentially suppressing the relative prioritization of aggressive or efficiency-driven motives found within the “Operational & Efficiency” cluster. Furthermore, this study relies entirely on stated-preference survey data, which inherently differs from revealed on-road kinematic behavior. Stated subjective motives may not always perfectly align with actual traffic execution, necessitating future cross-validation of these survey-based clusters against real-world trajectory datasets. Second, due to data retention constraints, the complete statistical outputs for the EFA (including the rotated factor-loading matrix, communalities, and variance explained) were

unavailable for secondary evaluation, meaning the proposed clusters must be treated strictly as preliminary theoretical constructs. Furthermore, the use of respondent-level standardization (z-scores) shifted the interpretation from absolute agreement to relative importance, and the cluster significance tests utilized item-level z-scores, which did not account for the nested, repeated-measures nature of the survey data. Finally, relying on the latent root criterion revealed a borderline third eigenvalue (1.108), suggesting potential instability in the “Operational & Efficiency” cluster.

Additionally, regarding the qualitative data collection, the use of specific situational probes during the focus groups (e.g., asking about tailgating or pavement conditions) carries an inherent risk of priming participants; therefore, the final list of forty stimuli should be understood as a combination of both purely spontaneous participant-generated motives and participant-endorsed scenarios.

Future research must prioritize conducting demographically stratified, large-scale surveys to secure a representative sample. Utilizing these representative samples, subsequent studies should conduct subgroup regressions and moderation analyses to rigorously investigate how socio-demographic factors—such as age, income, and driving experience—moderate driver sensitivity to these different lane-changing stimuli. Furthermore, utilizing robust statistical methodologies—such as Confirmatory Factor Analysis (CFA), Structural Equation Modeling (SEM), and mixed-effects models—alongside alternative clustering techniques will be essential to rigorously validate the structural integrity and relative dominance of these lane-changing dimensions.

A primary limitation of the quantitative analysis lies in the demographic composition of our sample, which features a heavy female (85%) representation. In traffic safety and travel behavior literature, driver gender represents a key moderating factor in risk perception, safety valuation, and lane-changing behavior. Prior empirical research consistently shows that female drivers, on average, demonstrate higher levels of risk aversion, are more compliant with safety buffers, and are more sensitive to roadside hazards than male drivers. Because within-person standardized z-scores measure relative prioritization, this severe demographic skew likely acted as a major confounding variable in our final rankings. The overrepresentation of female participants likely inflated the relative baseline importance of the Hazard & Evasive cluster (e.g., yielding to emergency vehicles, avoiding road debris), while potentially suppressing or underrepresenting speed-seeking or aggressive driving triggers associated with the Operational & Efficiency cluster. Due to the conclusion of this study’s active data-collection phase and other data retention issues, raw participant-level datasets are no longer accessible to perform post hoc statistical corrections such as post-stratification weighting. Consequently, the reported z-scores and rankings must be interpreted strictly as preliminary, exploratory values reflective of this specific, highly safety-conscious cohort. Future research must prioritize demographically stratified, large-scale probability sampling to perform post-stratification corrections and validate these findings across a representative driving demographic.

A second key methodological limitation stems from the transition between exploratory modeling and rigorous structural verification. While Exploratory Factor Analysis (EFA) successfully identified a preliminary three-cluster taxonomy (Hazard & Evasive, Situational & Environmental, and Operational & Efficiency), these clusters represent exploratory constructs rather than fully verified scales. Standard psychometric validation typically requires the evaluation of scale reliability via internal consistency coefficients (e.g., Cronbach’s alpha) and structural validation using Confirmatory Factor Analysis (CFA) on an independent sample.

Due to data retention constraints following the conclusion of this study’s active research phase, the original, raw participant-level survey datasets are no longer accessible for

secondary statistical re-evaluation. Consequently, we were unable to calculate Cronbach's alpha coefficients or run structural equations to test the goodness-of-fit for the three-factor model. This leaves our proposed clusters as preliminary conceptual frameworks. Future studies must collect new, independent driving datasets to perform CFA, establish construct and discriminant validity, and report robust reliability metrics to formally standardize this proposed lane-changing propensity scale.

Furthermore, it is essential to distinguish between the Stated Preference (SP) methodology utilized in this study and Revealed Preference (RP) behavior observed on real-world roadways. The lane-changing priorities identified in Table 4 reflect drivers' cognitive, retrospective evaluations of what would motivate them to change lanes in a hypothetical scenario. While SP surveys are uniquely capable of capturing latent psychological, emotional, and environmental triggers (such as driver mood, distraction, or passenger requests) that cannot be easily measured via traffic cameras, they are inherently susceptible to hypothetical bias. In actual driving environments, split-second, reactive kinesthetics—such as dynamic gap availability, relative velocities of surrounding vehicles, and immediate braking thresholds—govern revealed lane-changing execution. Therefore, a driver's stated intent to change lanes due to a poor pavement surface may be entirely overridden in practice by traffic density or a tight adjacent gap. Future research must bridge this gap by cross-validating these SP-derived clusters with vehicle trajectory datasets (RP) to observe how stated psychological thresholds map onto physical trajectory paths.

5. Conclusions

Research in fields such as consumer and organizational behavior has long examined stated motives behind human decision-making; however, traffic behavior research has traditionally given limited attention to the underlying psychological motives of discretionary lane-changing. This study applied a mixed methodological approach, utilizing focus groups to identify forty specific discretionary lane-change stimuli. Exploratory factor analysis (EFA) subsequently revealed three preliminary latent clusters: Hazard & Evasive, Situational & Environmental, and Operational & Efficiency factors, with initial tests indicating that Hazard & Evasive factors exert the strongest influence on lane-changing behavior.

By identifying and clustering these motives, this study provides a structured foundation for developing a comprehensive lane-changing propensity scale. While future research is required to statistically validate these clusters using robust, large-scale modeling, these findings offer a foundational behavioral basis. This grounded understanding of driver decision-making will allow transportation researchers to systematically conceptualize how non-traditional, heterogeneous behavioral elements might ultimately be integrated into advanced microscopic simulations and autonomous vehicle systems.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. For the focus groups, a written consent form detailing research procedures, confidentiality, and voluntary rights was read and signed by all participants prior to commencing sessions. For the online survey, digital informed consent was strictly obtained from all respondents; individuals were required to review the study parameters and click an “I Accept” button to provide digital consent before being granted access to the questionnaire.

Data Availability Statement: New data were created and analyzed in this study, including qualitative focus group findings and quantitative stated-preference survey responses. However, due to data retention issues following the conclusion of this study’s active research phase, the original raw participant-level survey datasets and audio recordings are no longer publicly accessible. All aggregated findings, extracted lane-changing factors, and final cluster configurations are fully reported within this manuscript.

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