

Article

Modeling Informal Driver Interaction and Priority Behavior in Smart-City Traffic Systems

Alica Kalašová , Peter Fabian * , Ľubomír Černický  and Kristián Čulík 

Department of Road and Urban Transport, University of Žilina, Univerzitná 1, 01026 Žilina, Slovakia; alica.kalasova@uniza.sk (A.K.); lubomir.cernicky@uniza.sk (Ľ.Č.); kristian.culik@uniza.sk (K.Č.)

* Correspondence: peter.fabian@stud.uniza.sk

Highlights

What are the main findings?

- Traditional methodologies systematically overestimate waiting times at uncontrolled intersections because they ignore the phenomenon of psychological priority among drivers.
- Regression analysis and supplementary data demonstrated that incorporating psychological priority yields results that correspond much more closely to real traffic conditions.

What is the implication of the main finding?

- The consideration of psychological priority increases the accuracy of traffic modeling, enabling a more realistic assessment of intersection capacity and more effective transport planning in the urban environment.
- The integration of this approach into intelligent transport systems of Smart Cities will enable more accurate simulations, more flexible traffic management, and contribute to improving the quality of life of residents.



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Abstract

Accurate traffic modeling is essential for effective urban mobility planning within Smart Cities. Conventional capacity assessment methods assume rule-based driver behavior and therefore neglect psychological priority, an informal interaction in which drivers negotiate right-of-way contrary to traffic regulations. This study investigates how the absence of this behavioral factor affects the accuracy of delay and capacity evaluation at unsignalized intersections. A 12 h field observation was conducted at an intersection in Prešov, Slovakia, and 28 driver interactions were analyzed using linear regression modeling. The derived model ($R^2 = 0.83$, $p < 0.05$) demonstrates that incorporating psychological priority significantly improves the agreement between calculated and observed waiting times. Unrealistic results occurring under oversaturated conditions in standard methodologies were eliminated. The findings confirm that behavioral variability has a measurable impact on traffic performance and should be reflected in analytical and simulation models. Integrating these behavioral parameters into Smart City traffic modeling contributes to more realistic and human-centered decision-making in intersection design and capacity management, supporting the development of safer and more efficient urban mobility systems.

Keywords: psychological priority; traffic modeling; smart cities; unsignalized intersections

1. Introduction

The concept of Smart Cities represents a comprehensive and systemic approach to urban development, encompassing culture, infrastructure, environment, energy, and social services [1,2]. At its core, a Smart City can be understood as a combination of technological, organizational, and social innovations designed to improve the quality of life for urban residents through sustainable development principles [3].

Among the core components of Smart Cities is smart mobility, which focuses on optimizing the movement of people and goods while enhancing traffic safety, reducing environmental burdens, promoting alternative transport modes, and ensuring efficient use of infrastructure [4–6].

Within this context, intersections play a crucial role as microsystems of the Smart City, where technological, safety, and environmental factors converge [7].

Properly functioning intersections have a direct influence on road safety, fluency, and urban livability [8–10].

However, as noted by Nama and Pardo [3], Smart Cities cannot rely solely on technological innovations; understanding human behavior and psychological factors is equally essential. This forms the foundation for the present study, which addresses how driver behavior, specifically psychological priority, affects the accuracy of traffic modeling within the framework of smart mobility.

Psychological priority is defined as a situation in which a driver at an intersection asserts priority that is not granted by traffic regulations.

In contrast to legal priority, which arises from formal traffic regulations and right-of-way rules, psychological priority reflects spontaneous driver interaction based on perception, intuition, and social signaling. It can be observed through behavioral indicators such as eye contact, short head movements, flashing headlights, vehicle positioning, or micro-accelerations used to communicate intent. These actions represent implicit negotiation between drivers and serve as the operational basis for identifying psychological priority in real traffic observation [11].

It represents informal behavior based on expectations, experience, or assumed rules among road users. This phenomenon occurs most frequently at small uncontrolled intersections, where visual cues, narrow roadways, or traffic intensity lead to dynamic interactions between drivers [12–14]. Driver behavior is shaped by a combination of traffic regulations, visual stimuli, and implicit social signals [12].

Psychological priority arises from the following factors:

- expectations of the behavior of other participants, where the driver assumes that others will yield;
- experience and cognitive shortcuts, where the driver relies on previous situations or intuition;
- social and visual perception, such as eye contact, vehicle movements, or the speed of another car signaling available space for entry.

Psychological priority is a double-edged phenomenon:

- Positive: it contributes to greater efficiency and fluency of traffic when participants communicate through implicit signals [12].
- Negative: it represents a safety risk because it is unpredictable and may conflict with legislation [3,4].

Psychological priority differs from related concepts such as gap acceptance, social yielding, and cooperative driving. Gap acceptance focuses on measurable time or distance gaps that drivers consider safe to enter traffic, while social yielding refers to intentional courtesies or compliance with social norms. Cooperative driving involves deliberate coordi-

nation among drivers, whereas psychological priority represents spontaneous and informal decision-making, where drivers assert or yield right-of-way based on mutual perception and momentary expectation rather than explicit rules [11,15].

Recent studies emphasize that cognitive and psychological mechanisms, including perception, attention, and implicit negotiation between drivers, have a key role in sustainable and age-friendly transport systems [15]. These insights strengthen the behavioral interpretation of psychological priority in traffic modeling. Additional research highlights that nonverbal communication, eye contact, and cooperative behavior strongly influence how drivers negotiate right-of-way in real traffic environments [11].

The significance of psychological priority is most evident at small uncontrolled intersections, which are typical of historic city centers [12–14]. This phenomenon has been examined in the context of traffic behavior theories that emphasize the importance of informal traffic rules. According to Kaparias et al. and Pettitt, Christie, and Tyler, implicit social agreements are formed among drivers in urban environments, which may temporarily substitute or even outweigh official traffic regulations [16,17]. While this phenomenon has the potential to improve traffic fluency, it simultaneously introduces the risk of greater unpredictability.

Risser points out that drivers base their decisions not only on formal rules but also on cognitive shortcuts and subjective risk assessment [18]. From the perspective of traffic psychology, the expectation of other participants' behavior also plays an important role. According to Fuller, this may lead to a safety paradox: when all participants assume the same course of action, traffic becomes more fluent, yet when expectations diverge, the risk of collisions increases [19].

In the design of intersections and traffic solutions, it is necessary to take psychological priority into account. Ignoring these aspects may result in underestimating factors that significantly influence safety. The integration of insights from traffic psychology into the planning of smart mobility leads to more efficient and safer solutions.

The concept of Smart Cities emphasizes the harmonization of technological innovations with social and behavioral factors [20,21].

Although the informal negotiation of right-of-way has been addressed in previous research, the present study introduces the concept of psychological priority as a formalized and measurable behavioral factor that can be incorporated into quantitative traffic modeling. This approach extends existing knowledge by linking behavioral interaction with mathematical representation, allowing the phenomenon to be expressed statistically and applied within capacity and delay analyses.

However, most existing traffic models still rely on idealized, rule-based assumptions about driver behavior and therefore ignore psychological and behavioral aspects that occur in real traffic operations. This represents a significant research gap that limits the accuracy of current traffic modeling and motivates the present study.

Intersections, as microsystems of the Smart City, demonstrate that beyond traffic engineering parameters, it is also necessary to consider psychological patterns of behavior [3,22,23]. Traffic models are a key tool for transport planning and management, yet most of them assume strictly rational driver behavior. Real-world operation shows that drivers often apply psychological priority, which contributes to greater fluency and reduced delays at intersections. The limitation of current models is that they fail to account for this phenomenon, which may result in overestimating waiting times and underestimating capacity.

The present study is therefore grounded in behavioral traffic psychology and human factors research, emphasizing that cognitive, perceptual, and social processes fundamentally influence driver decision-making in real traffic conditions [11,15].

Research hypotheses of the article:

- H1: Traffic models that do not consider psychological priority systematically overestimate vehicle waiting times.
- H2: The consideration of psychological priority leads to improved intersection capacity and a reduction in overall delay time.

The aim of the article is to highlight this methodological shortcoming and to discuss its implications for the accuracy of traffic modeling, which constitutes a fundamental element in the development of smart mobility within Smart Cities.

2. Materials and Methods

This chapter describes the procedure of data collection, the selection of sites, and the method of processing calculations that made it possible to compare the standard approach with the adjusted computation that considers psychological priority.

2.1. Foundations of the Analysis

The analysis was based on a comparison of the results of intersection capacity assessments conducted using standard methodologies, which assume strictly rule-based driver behavior, with calculations adjusted by incorporating the factor of psychological priority. The objective was to demonstrate the difference between the idealized model approach and the actual behavior of road users [24–26].

Standard calculations were carried out in accordance with applicable technical conditions and methodological procedures used in road transport. Such an approach to evaluating intersections represents a global standard [27–29]. The adjusted calculations were derived from observations of real traffic operation and accounted for situations in which drivers allowed other vehicles to pass even when not formally required by traffic regulations.

2.2. Survey Location

The subject of the analysis was a selected uncontrolled intersection in the city of Prešov, located in a traffic-intensive area with frequent conflicts between major and minor traffic flows. Such an environment is ideal for observing the application of psychological priority by drivers, as the gap between the theoretical model and actual behavior is most pronounced in this context.

Because the analysis focused on a single intersection, the research design inherently minimized the influence of external factors such as geometry, signal control, or differences in local driver behavior. Data collection was limited to stable daytime and weather conditions to ensure consistency. Situations influenced by pedestrians, temporary obstructions, or atypical traffic events were excluded, allowing the study to isolate the behavioral effect of psychological priority as accurately as possible.

The observation lasted for a total of 12 h during regular weekday traffic. In total, 28 instances of driver interaction were classified as psychological priority based on clearly observable behavioral indicators such as eye contact, head movement, or vehicle positioning, suggesting informal negotiation. All evaluations were performed by the same observer to maintain consistency in classification and interpretation. Each event was time-stamped during observation to maintain chronological order and consistency of data recording. Outlier cases with unrealistic or ambiguous driver behavior that could not be reliably classified were excluded from further analysis.

The probability p represents the share of driver interactions in which priority was informally asserted or yielded contrary to traffic regulations. It was calculated according to the expression $p = k/n$, where n denotes the total number of observed driver–driver interactions and k the subset identified as psychological priority. Classification was based

on clearly observable behavioral indicators, including eye contact, head movement, vehicle positioning, or short accelerations indicating implicit negotiation. During the 12 h observation, a total of 28 eligible interactions were recorded, of which 22 were classified as psychological priority, resulting in $p = 22/28 = 0.79$. This value represents a full-day aggregate under comparable daytime and weather conditions, with all events influenced by pedestrians, temporary obstructions, or atypical traffic situations excluded to ensure data consistency and validity.

Figure 1 presents a detailed view of the analyzed intersection. For the purposes of calculations and analyses, the traffic situation was further schematically illustrated in Figure 2, where the levels of subordination and the traffic signage are indicated.



Figure 1. Location of the analyzed uncontrolled intersection [30].

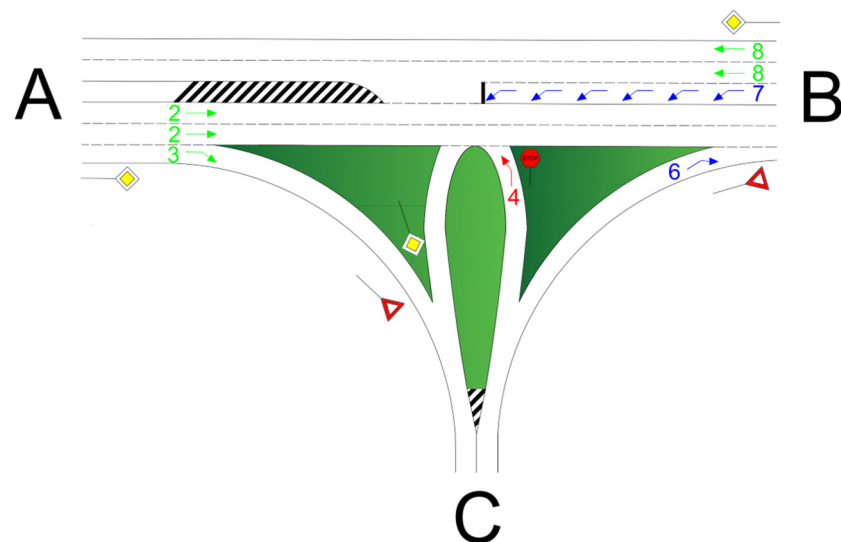


Figure 2. Schematic representation of the intersection geometry and traffic flow hierarchy [31].

Particular attention was devoted to two traffic flows in which psychological priority was most frequently observed. These flows were evaluated independently, and the results were subsequently compared with the standard calculation based on rule-compliant driver behavior.

2.3. Data Collection

An overview of the observed situations is provided in Table 1. Each row represents a single vehicle, with records including the vehicle type (PC—passenger car, HGV—heavy goods vehicle, B—bus), the time of passing through the intersection, the waiting time, and the manner of merging. In the final column, the abbreviation N (normal) is used when the vehicle merged in accordance with traffic regulations, and P (permitted) is used for cases in which the vehicle was allowed entry by another road user.

Table 1. Observed driver interactions classified by vehicle type.

Vehicle Type	Time of Arrival [hh:mm:ss]	Delay Time [hh:mm:ss]	Merging Behavior
B	6:07:53	0:00:18	N
B	6:12:22	0:00:36	P
B	6:16:15	0:00:40	P
B	6:20:17	0:00:46	P
B	6:24:15	0:00:16	P
HGV	6:26:54	0:00:14	P
HGV	6:29:52	0:00:38	P
PC	6:30:15	0:00:16	P
B	6:32:28	0:00:38	P
PC	6:33:15	0:00:09	P
PC	6:34:10	0:00:11	N
PC	6:40:33	0:00:20	P
PC	6:42:30	0:00:17	N
B	6:44:37	0:00:02	N
PC	6:46:22	0:00:53	P
B	7:00:27	0:00:13	P
B	7:14:22	0:01:00	P
PC	7:29:45	0:01:00	P
HGV	7:32:55	0:00:20	P
HGV	7:34:35	0:01:10	P
PC	7:52:30	0:01:07	P
B	7:52:35	0:00:31	P
B	7:58:33	0:01:30	P
PC	7:59:10	0:01:35	P
B	7:59:15	0:00:16	P
PC	8:22:32	0:01:27	P
PC	8:23:10	0:01:33	N
PC	8:23:15	0:01:08	N

Table 1 clearly shows that the occurrence of psychological priority is not an isolated phenomenon but recurs in a significant proportion of the observed situations. This finding highlights the gap between the theoretical model and reality, which must be considered in traffic calculations.

The choice of transport mode significantly affects the way vehicles merge as it can be observed that buses make up a considerable share of vehicles joining, thanks to psychological priority. Therefore, it can be said that these findings have the potential to influence mode choice [32].

Based on the collected data, calculations and comparisons were subsequently carried out, as presented in the Results chapter. In addition, regression analysis and supplementary data from the Google Maps application were employed to verify the relationships between parameters and to compare real traffic operation with the model-based approach.

3. Results

The research results are divided into several sections according to the assessment methods applied. The objective is to compare calculations based on the technical standard TP 102, which represents a standardized calculation process, regression analysis derived from the measured data, and estimates obtained from the Google Maps application [24]. Such a multi-level approach makes it possible not only to evaluate the accuracy of individual methods but also to demonstrate how the original calculation can be adjusted to better reflect actual driver behavior and thereby the real conditions at the analyzed intersection [24,25,33].

3.1. Results According to the Standard Methodology

This approach represents the official standard applied in traffic capacity assessments of intersections. Although it was developed for Slovak conditions, its logic is universal and corresponds to procedures used in many other countries. A common feature of these methodologies is the assumption of ideal driver behavior without considering psychological factors. This means that drivers strictly follow traffic regulations and do not allow other vehicles to pass beyond their formal right of way [34,35].

The methodology represents the standard approach to traffic capacity assessment of uncontrolled intersections. It is based on calculating the capacity of individual traffic flows and the average vehicle waiting times derived from it. The calculation assumes that drivers strictly adhere to traffic regulations and that no psychological yielding of other vehicles occurs [24].

An important limitation of the methodology is that the calculation of average waiting time can only be applied if the degree, of saturation $y = \frac{q}{Q} \leq 1$. When the traffic flow intensity exceeds capacity, an overloaded condition occurs, denoted as level F. In such a case, methodology no longer recommends calculating the average waiting time, as the results would yield unrealistically high values on the order of thousands or even millions of seconds. These results do not represent reality but are a consequence of applying formulas outside their valid range. Nevertheless, in this study, they are included in Table 2 below, which follows the sample calculation of a traffic flow with an acceptable outcome.

$$t_w = \frac{3600}{q} \times \frac{y}{1-y} = \frac{3600}{522} \times \frac{0.832}{1-0.832} = 34.1544 \text{ [s]} \quad (1)$$

Table 2. Results of standardized methodology.

Traffic Flow	Quality Level	Waiting Time [s]
7	F	N/A
6	D	34.1
4	F	N/A
7+8	F	N/A
4+6	F	N/A

Note: Values marked as N/A indicate cases where the calculation exceeded the valid range of the applied formula under oversaturated conditions.

The presented results clearly indicate that the methodology has significant limitations. For traffic flows with a degree of saturation $y \leq 1$, the calculation provides specific outcomes, such as 34.1 s for traffic flow 7. However, for flows with values of $y > 1$, the methodology produces unrealistically high results on the order of thousands or even millions of seconds, which do not correspond to actual traffic operation and arise from applying formulas beyond their valid range.

These findings confirm that the standard calculation without considering psychological priority systematically overestimates waiting times and does not provide a realistic picture of intersection performance. Therefore, the next section presents the results of regression analysis, which makes it possible to correct these distortions and bring the calculations closer to real values.

3.2. Results of the Regression Analysis

As the previous calculations have shown, the standardized methodology leads to unrealistic results at higher values of the degree of saturation. For this reason, regression analysis was applied in the next step, as it allows a better representation of the relationship between the observed waiting times and the values calculated.

The analysis was conducted for two observed traffic flows (4 and 7), with a separate regression model constructed for each. The outcome was a linear equation of the form.

$$t_{real} = a * t_{standard} + b \quad (2)$$

where

- t_{real} —waiting time based on observation [s],
- $t_{standard}$ —waiting time according to standardized methodology [s],
- a, b —regression coefficients determined from the measured data.

The regression model was estimated using the ordinary least squares (OLS) method based on 28 observed cases ($n = 28$). The coefficient of determination reached $R^2 = 0.83$, indicating a strong relationship between the observed and calculated values. All regression coefficients were statistically significant at the 0.05 level, confirming the reliability of the model fit.

Although the applied regression model is intentionally limited to a simple linear form with one explanatory variable, this structure was selected to demonstrate the direct proportionality between the observed and calculated waiting times. The residual analysis confirmed that the deviations were randomly distributed around zero, with no apparent trend, supporting the adequacy of the linear specification. Despite its simplicity, the model achieved a coefficient of determination $R^2 = 0.83$ and statistically significant parameters ($p < 0.05$), indicating a strong and consistent fit between the measured and predicted values.

The resulting linear regression can be expressed as $t_{real} = 0.87 t_{standard} + 3.54$, where the slope coefficient (0.87) reflects the proportional adjustment between theoretical and observed delay, and the constant term (3.54 s) represents the average systematic deviation. The model achieved a good fit quality, with residuals showing low variance and no systematic bias. The overall uncertainty of the fitted parameters remained within acceptable limits for a sample of this size ($n = 28$), confirming the stability of the regression outcome.

Sample calculation (traffic flow 7)

$$t_{real} = 0.87 \times 34.1 + 3.54 = 33.22 \text{ s}$$

The regression correction reduced the average waiting time from 34.1 s, obtained using the standardized methodology, to approximately 33.2 s according to the adjusted regression model. This value corresponds more closely to the actually observed waiting times recorded during the field survey.

The results presented in Table 3 show that regression analysis provides values closer to reality than the standardized methodology, although in some cases, deviations from the actual observed times still occur.

Table 3. Calculated waiting time.

	Interval	t_w Measured [s]	t_w Calculated [s]
Morning rush hour	7:15–7:30	33	67.93
	7:30–7:45	56	75.50
	7:45–8:00	82	67.84
	8:00–8:15	60	48.97
Afternoon rush hour	15:00–15:15	62	48.86
	15:15–15:30	59	52.00
	15:30–15:45	29	37.93
	15:45–16:00	39	20.97

The results of the regression analysis can be better illustrated through a graphical representation in Figure 3, that compares the actual observed waiting times with the values calculated using regression analysis. Such visualization makes it possible to clearly track the progression throughout the day and to reveal the differences between the individual methods.

**Figure 3.** Comparison of waiting times in traffic flow 7 between the observed time and the time calculated by regression.

The graph clearly shows that during the morning and afternoon rush hour periods, the observed values (orange curve) are significantly higher than the average in other time intervals. The regression analysis (green curve) smooths these fluctuations and provides values that, in most intervals, are closer to real traffic operation than the standardized methodology. Deviations appear mainly in intervals with very high or very low waiting times, but the overall trend demonstrates that regression analysis can effectively eliminate extreme overestimations.

These results confirm that the regression model provides a more realistic representation of the traffic situation at the intersection and serves as a suitable tool to complement traditional calculation methods.

3.3. Results According to Google Maps

As a supplementary source of information, data from the Google Maps application was used, providing travel time estimates based on a combination of real-time and historical traffic flow data. This tool is widely accessible and frequently used by both drivers and transport planners, and therefore represents a suitable independent validation of the obtained results [36,37].

For the selected intersection, times were obtained during the morning and afternoon rush hour periods, when traffic load is highest and the differences between the individual methodological approaches are most evident. These values were subsequently compared with the actually observed waiting times and with the results of the regression analysis. Addressing rush hours is a standard in traffic evaluation, as the conditions during this time are the least favorable [37,38].

The results showed that the deviations between the Google Maps data and the actual measured times were within only a few seconds. In some intervals, the values were almost identical, confirming the high accuracy of the application's estimates. A graphical representation of the results is provided in Figure 4, which illustrates the relationships between the Google Maps values and the observed data for the individual traffic flows.

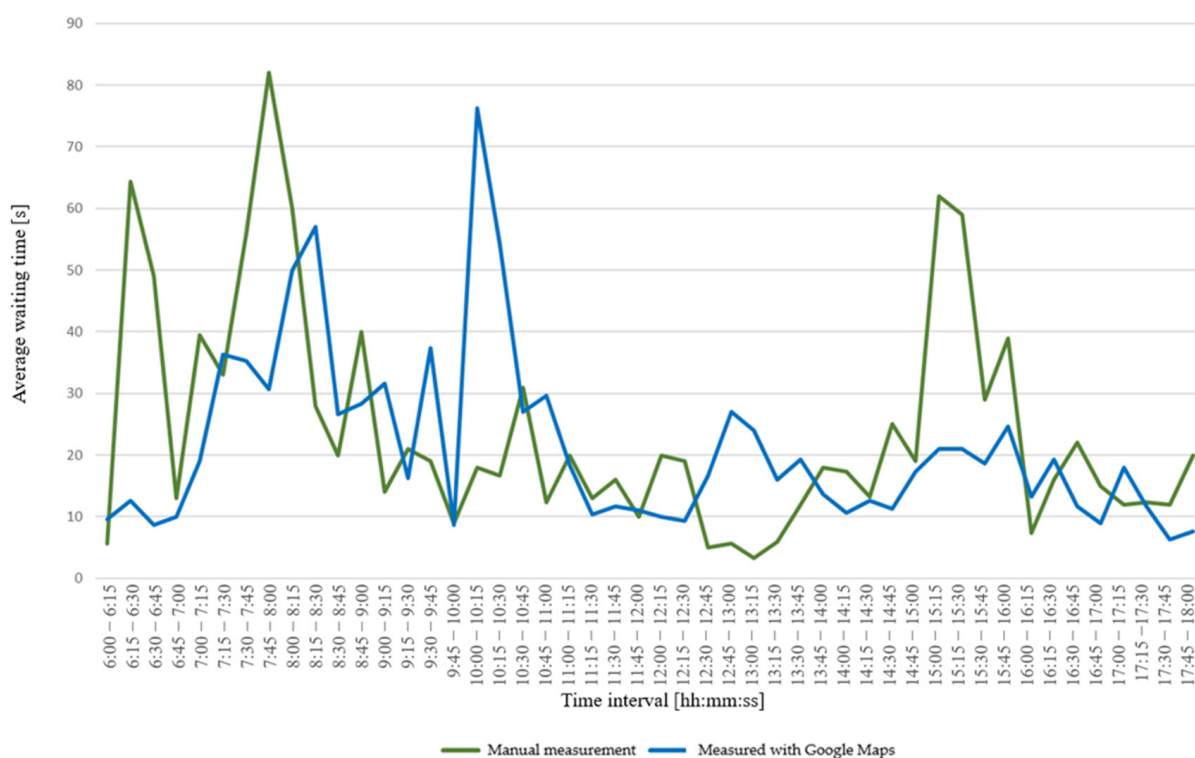


Figure 4. Comparison of waiting times in traffic flow 7 between the observed time and the time measured by Google Maps.

The graph shows that the progression of both curves is similar. The Google Maps times (blue line) in most intervals are close to the values measured directly in the field (green line). Deviations appear mainly at extreme values during the morning rush hour, where Google Maps estimates slightly lower delays than those actually observed.

The differences are caused by the fact that Google Maps processes a large amount of data collected from a wide range of smartphones. As a result, the data are not entirely accurate, since this method of data collection shows certain limitations [23].

The data obtained through Google Maps were compared with the results of the regression analysis, which was carried out based on the actual measured data. Figure 5 illustrates

the progression of waiting times in traffic flow 7, displaying the values calculated by regression analysis together with the confidence interval, as well as the estimates provided by Google Maps. This approach makes it possible to verify the extent to which an independent external data source corresponds to the values derived from the statistical model.

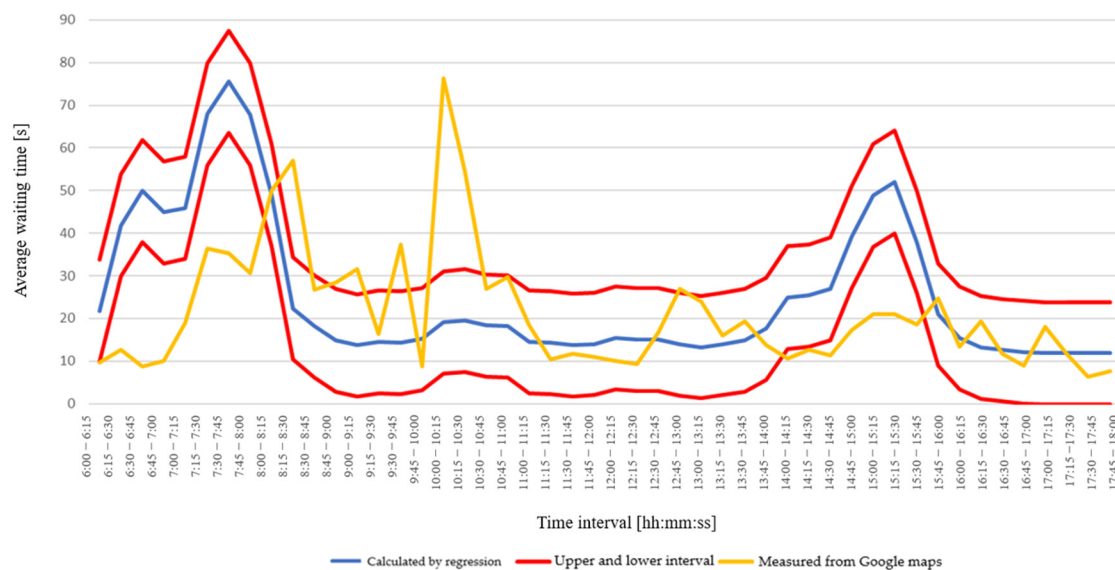


Figure 5. Comparison of waiting times in traffic flow 7 between the calculated time and the time measured by Google Maps.

The graph shows that the progression of waiting times calculated by regression analysis (blue line) follows the trend of real traffic conditions and displays higher values during rush periods. The confidence interval of the model (red lines) defines the range within which the real values are expected to occur. The Google Maps data (yellow line) in most cases fall within this interval, confirming their consistency with the regression model.

The largest deviations can be observed during the morning rush hour, when Google Maps estimated lower waiting times than those indicated by the regression analysis. In the afternoon rush hour, by contrast, the values approached the upper boundary of the interval. Overall, however, the differences amounted to only a few seconds, confirming that the data from Google Maps are suitable for validating the accuracy of regression-adjusted results. Nevertheless, it is important to note that Google Maps data represent aggregated travel-time estimates influenced by multiple intersections, speed limits, and route-level conditions rather than direct measurements of intersection delay. Therefore, this method should be interpreted only as indicative validation, useful primarily for trend comparison rather than precise calibration. Despite these limitations, the consistency between the application's estimates and the regression-based results confirms the robustness of the proposed behavioral model.

The results revealed significant differences between the individual approaches to assessing waiting times at the intersection. The standardized methodology calculations systematically overestimated average waiting times and, at higher levels of saturation, even produced unrealistically high values beyond the range of real conditions. The reason lies in the methodology's assumption that drivers behave strictly according to traffic regulations and do not apply psychological priority, which does not hold true in practice.

The regression analysis, carried out on the basis of real measurements, provided results that corresponded much more closely with the observed traffic operation. This approach was able to eliminate extreme overestimations and bring the calculations closer to actual values.

The comparison with Google Maps data confirmed the validity of the regression model. The values obtained from this independent application in most cases fell within the confidence interval of the regression analysis, indicating a high level of consistency between the two approaches.

Based on these findings, it can be concluded that while the standardized methodology does not reflect actual driver behavior and leads to overestimation of waiting times, the combination of regression analysis and validation using Google Maps provides a realistic representation of intersection operation. This confirms the need to extend traditional calculation methods with elements that take into account the psychological factors of driver behavior.

4. Discussion

The results presented in the previous chapter clearly demonstrated that the methodology for assessing uncontrolled intersections systematically overestimates waiting times and, in the case of oversaturated flows, even produces unrealistically high values. The reason lies in the assumption of ideal driver behavior, which is not fulfilled in practice, as road users frequently apply so-called psychological priority. In contrast, the regression analysis based on real data provided results that corresponded substantially better with the observed traffic operation, and their validity was further supported by the data obtained from Google Maps.

These findings are of fundamental importance for transport planning and traffic management in the context of Smart Cities. When methodologies that do not reflect actual driver behavior are applied, this may lead to an overestimation of problems, misjudgment of intersection capacity, and consequently inappropriate investment decisions [39,40].

Regression analysis made it possible to quantify these deviations and to develop a correction model. By comparing calculated and actually observed values, it was shown that regression can eliminate extreme overestimations and bring the results closer to reality. The deviations between the real values and the regression model were within a few seconds, which represents an acceptable level of accuracy in traffic modeling.

The Google Maps data supported this conclusion. Their progression in most cases remained within the confidence interval defined by the regression analysis, indicating consistency between the two approaches. Minor differences appeared mainly during rush hours, which can be explained by the different methods of data processing. Google Maps relies on historical and real-time data from GPS devices, whereas regression analysis is based directly on observations of the specific intersection.

It follows that standardized methodology overestimates waiting times because it does not reflect the psychological behavior of drivers, whereas regression and Google Maps indirectly capture this behavior. The results, therefore, confirm the need to extend traditional methodologies with factors that better represent reality.

4.1. Adjustment of the Calculation

The principle of the adjustment lies in incorporating the probability of a vehicle being allowed to pass in conflict situations. This probability was determined based on the survey at the selected intersection and reflects the percentage of cases in which drivers applied psychological priority. Instead of evaluating all situations as strictly rule-based, the adjusted calculation considers a portion of vehicles as permitted to proceed, which reduces the resulting average waiting time and increases the capacity of the intersection.

Mathematically, the adjustment can be expressed as follows:

$$t_{w,adjusted} = (1 - p) \times t_{w,standard} + p t_{w,real} \quad (3)$$

where

- $t_{w,adjusted}$: average waiting time after the adjustment;
- $t_{w,standard}$: average waiting time according to the standardized methodology;
- $t_{w,real}$: observed or regression-derived average value;
- p : probability of a vehicle being allowed to proceed.

By applying this approach, the waiting time values became significantly closer to real conditions, as confirmed by the results of the regression analysis and the comparison with Google Maps data. The adjusted calculation thus eliminates extreme deviations in oversaturated flows and provides a more realistic representation of the traffic situation.

4.2. Sample Adjusted Calculation (Traffic Flow 7)

From the calculation for traffic flow 7 in the given interval, the average waiting time is, approximately,

$$t_{w,TP102} \approx 34.1 \text{ s}$$

From the behavioral survey: during the morning and afternoon rush periods, 79 percent of mergers occurred through yielding by other drivers, while 21 percent followed the standard rule-based procedure.

$$p = 0.79$$

After incorporating the probability of psychological priority into the adjusted calculation, the resulting waiting time is obtained.

$$t_{w,adjusted} = (1 - 0.79) \times 34.1 + 0.79 \times 29.1 = 30.15 \text{ s}$$

The result shows that the original value of 34.1 s according to the methodology was adjusted to 30.15 s, thereby approaching the real value of 29.1 s. The difference compared to actual driver behavior was thus significantly reduced, and the outcome is methodologically more accurate. This approach confirms that considering psychological priority makes it possible to eliminate the systematic overestimation of waiting times and to provide a more realistic representation of intersection operation.

Based on the regression analysis and the incorporation of the psychological priority factor, new average waiting time values were calculated. These results are presented in Tables 4 and 5, which compare four approaches: the original values, the measured times, the values after regression adjustment, and the estimates provided by Google Maps.

Table 4. Summary of results for traffic flow 4.

Traffic Flow 4	Manually Measured [s]	Calculated with Regression [s]	Measured with Google Maps [s]	Standardized Methodology [s]
Morning rush hour	51	46	43	N/A
Afternoon rush hour	39	44	47	N/A

Note: Values marked as N/A indicate cases where the calculation exceeded the valid range of the applied formula under oversaturated conditions.

Table 5. Summary of results for traffic flow 7.

Traffic Flow 7	Manually Measured [s]	Calculated with Regression [s]	Measured with Google Maps [s]	Standardized Methodology [s]
Morning rush hour	57	65	39	N/A
Afternoon rush hour	46	40	29	N/A

Note: Values marked as N/A indicate cases where the calculation exceeded the valid range of the applied formula under oversaturated conditions.

The tables show that the standardized methodology significantly overestimates waiting times. In the case of traffic flow 4, the values reached the order of hundreds of millions of seconds, which is a consequence of applying the methodology beyond its valid range. These results are unrealistic and do not reflect actual traffic conditions. In the case of traffic flow 7, the standardized methodology values were lower but still considerably overestimated.

In contrast, the values obtained from the regression analysis were close to the actual measured times. For flow 4, the morning rush hour was 46 s compared to the observed 51 s, and for flow 7, it was 65 s compared to 57 s. In the afternoon rush hour, the regression model even matched the observations very closely (traffic flow 4: 44 s compared to 39 s, traffic flow 7: 40 s compared to 46 s). These results confirm that incorporating psychological priority significantly reduces the discrepancies between calculations and reality.

The supplementary comparison with Google Maps data showed that the application's estimates in most cases fell within the confidence interval of the regression model. For example, in traffic flow 4 during the morning rush hour, the Google Maps time was 43 s, which is very close to the observed 51 s and the regression-adjusted 46 s, similarly, in traffic flow 7.

Overall, it can be concluded that the adjusted calculation provides a more realistic representation of intersection performance than the original methodology. The consideration of psychological priority eliminated unrealistic overestimations and brought the results closer to both real traffic operation and independent external data. This approach, therefore, represents a practical improvement of traditional methodologies and may serve as a suitable basis for planning traffic measures in the context of Smart Cities.

This finding is not limited to Slovak conditions, as similar methodological frameworks across Europe and beyond are based on comparable assumptions of strictly rule-based driver behavior. Therefore, the adjustment proposed in this study can be considered relevant for a wider range of urban contexts and traffic environments.

Although the present research does not directly employ sensor networks, simulation environments, or digital urban infrastructure, its findings are highly relevant for Smart City development. The quantified behavioral factor of psychological priority can be integrated into microscopic and macroscopic traffic models, improving the accuracy of digital twins and intelligent transport systems that rely on real-time or predictive data. By incorporating behavioral variability into analytical and simulation-based tools, the results contribute to a more human-centered and realistic approach to Smart City traffic management.

5. Conclusions

The aim of this study was to highlight the limitations of traditional methodologies in the assessment of uncontrolled intersections and to propose an adjustment of the calculation that reflects actual driver behavior through the phenomenon of psychological priority. Based on regression analysis and the incorporation of this factor, new average waiting time values were calculated, which were significantly closer to the actual measured data, and their validity was further confirmed through comparison with Google Maps data. The adjusted calculation thus eliminates extreme deviations and provides a more realistic representation of intersection performance.

The results confirmed both hypotheses of the study:

- H1: The standardized methodology systematically overestimates average waiting times at intersections,
- H2: The incorporation of psychological priority through regression analysis provides results that are significantly closer to real conditions.

These findings have practical implications for transport planning in the context of Smart Cities. If aspects of driver psychological behavior are not considered in the assess-

ment of intersection capacity, there is a risk of misinterpreting the traffic situation and consequently making suboptimal investment decisions [41,42]. The adjusted methodology, therefore, provides a suitable basis for more accurate modeling of traffic conditions and may contribute to more efficient traffic management in cities.

The phenomenon of psychological priority reflects informal driver interactions that occur spontaneously in real traffic situations, where drivers negotiate right-of-way contrary to formal regulations. While such behavior is not defined or permitted by traffic law, it represents a real and measurable aspect of road user dynamics. The present study does not endorse or encourage such actions but seeks to understand them as part of human behavior that influences intersection performance. Recognizing these patterns enables planners and engineers to design control strategies and infrastructure that account for actual driver responses, reduces the potential for unsafe situations, and ensures that behavioral factors are addressed without promoting unsafe or extra-legal practices in Smart City environments.

The study was carried out at a specific urban intersection, which introduces certain contextual limitations. The conclusions are based on the local setting, yet the quantifiable difference between the traditional and adjusted calculations indicates that a similar effect is highly likely to occur at other intersections as well. Psychological priority was analyzed during rush periods, which confirmed its importance, particularly under conditions of increased traffic intensity.

The study was conducted at a single intersection, which represents a contextual limitation. However, the observed gap between standardized calculations and actual driver behavior is systematic in nature and has been documented in multiple international studies. For this reason, the results can be regarded as indicative of a broader methodological shortcoming rather than a purely local phenomenon.

One of the limitations of the study is that it did not focus on pedestrians. In such cases, psychological priority may be influenced by additional factors such as reduced mobility, age, or other individual characteristics, which could further shape interactions at intersections and affect overall traffic dynamics [43]. Future research could therefore also focus on this topic, with particular attention to the role of psychological priority in pedestrian behavior and its impact on intersection performance.

Future research should focus on extending the analysis to multiple intersections, diverse traffic conditions, and different cultural contexts. A promising direction is also the use of more advanced regression models, nonlinear approaches, and the integration of data from sensors or traffic applications. Such integration would enable continuous validation of calculations and their calibration according to the actual behavior of road users.

The study achieved its main objective of demonstrating that incorporating driver behavior, specifically the phenomenon of psychological priority, significantly improves the accuracy of waiting time estimation and capacity assessment at unsignalized intersections. The results confirmed that conventional calculation methods systematically overestimate delay when behavioral factors are ignored, whereas the proposed regression-based correction aligns more closely with observed traffic conditions.

Nevertheless, several limitations should be acknowledged. The research was conducted on a single intersection, without replication under different geometric or traffic conditions, and did not include a full sensitivity analysis. The model uncertainty was assessed only through residual variance and confidence intervals derived from regression results, which provide indicative rather than comprehensive bounds of reliability.

Future research should therefore extend this approach to multiple urban contexts, apply larger datasets, and incorporate simulation or sensor-based validation to further verify the behavioral correction proposed in this study. Such efforts would enhance the gen-

eralizability of the findings and strengthen their applicability for smart mobility planning in Smart Cities.

An important contribution of the study is the identification of a fundamental shortcoming of traditional traffic capacity methodologies, namely the absence of consideration of psychological priority. For the field of Smart Cities, this highlights the need to supplement traffic models with aspects of human behavior so that assessment results more accurately reflect reality. The integration of these elements into intelligent transport systems will enable more precise planning, more efficient traffic management, and contribute to improving the quality of life of urban residents.

For comparison, various methodologies across Europe were also identified, and it was found that the Slovak Republic is not an exception in disregarding psychological priority. In addition to the Slovak Republic [24], psychological priority was not considered in any of the methodologies of Germany [25], the Netherlands [44,45], or the United Kingdom [26].

Although the empirical data were collected in a single Slovak city, the behavioral mechanisms analyzed in this study are not geographically specific. Informal priority negotiation and driver interaction patterns are observable in urban environments worldwide, especially at unsignalized intersections where regulation and perception intersect. The methodological framework and regression-based adjustment proposed here can therefore be applied to diverse urban contexts, providing a transferable foundation for integrating behavioral variability into Smart City traffic modeling on an international scale.

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