Leading Pedestrian Intervals – Yay or Nay? A Before-After Evaluation using Traffic Conflict-Based Peak Over Threshold Approach

Ashutosh Arun
Transportation Engineer
Advanced Mobility Analytics Group
Brisbane, QLD 4000, Australia

Md. Mazharul Haque
Professor, School of Civil and Environmental Engineering
Queensland University of Technology
Brisbane, QLD 4000, Australia

Craig Lyon
(corresponding author)
General Manager (North America)
Advanced Mobility Analytics Group
Ottawa, ON Canada
E-mail: craig@amagroup.io

Tarek Sayed
Professor, Department of Civil Engineering
University of British Columbia
Vancouver, Canada

Simon Washington
Chief Executive Officer and Managing Director
Advanced Mobility Analytics Group
Brisbane, QLD 4000, Australia

Franz Loewenherz
Mobility Planning and Solutions Manager
City of Bellevue, Washington
Bellevue, WA

Darcy Akers
Senior Transportation Engineer
City of Bellevue, Washington
Bellevue, WA

Mark Bandy
Regional Solutions Lead for Transportation Planning (America West Region)
Jacobs Engineering
Seattle, United States

Victor Bahl
Technical Fellow at Microsoft
Redmond, Washington, United States

Ganesh Ananthanarayanan
Principal Researcher at Microsoft
Redmond, Washington, United States

Yuanchao Shu
Principal Researcher at Microsoft
Redmond, Washington, United States

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1 INTRODUCTION

Pedestrian safety is of grave concern to traffic engineers. In the United States, 6,205 pedestrians were killed, and approximately 76,000 were injured in 2019. More concerning is the fact that the relative proportion of pedestrian fatalities among all crash fatalities has been steadily increasing over the past ten years (National Center for Statistics and Analysis (NCSA), 2020, December). A pedestrian was estimated to be killed every 85 minutes and injured every 7 minutes in traffic crashes in 2019. Therefore, targeted treatments for improving pedestrian safety at crucial locations such as urban intersections are needed.

Leading Pedestrian Intervals (LPI) are an innovative signalized intersection treatment involving a pre-timed allocation to allow pedestrians to begin crossing the street in advance of the next cycle of vehicle movements (AASHTO, 2014). It helps reduce the "element of surprise" for right-turning vehicles. However, the evidence from the literature on the effectiveness of the LPI treatment is mixed.(King, 2000, Van Houten et al., 2000, Fayish and Gross, 2010, Sharma et al., 2017, Goughnour et al., 2021).

Modern advancements in sensor technology offer an unprecedented opportunity to assess the effectiveness of safety treatments remotely and proactively using traffic conflict analysis (Tageldin et al., 2018, Zheng et al., 2018, Guo et al., 2020a, Guo et al., 2020b). Therefore, this study undertook a traffic conflict-based before-after type safety evaluation of a 5-second LPI treatment implemented at three signalized intersections in the city of Bellevue, Washington. The traffic conflicts were automatedly extracted from video-captured traffic movements using advanced Computer Vision and Deep Learning techniques. The study applied a bivariate peak-over threshold modelling approach to model the tail distributions of pedestrian-vehicle Time-to-collision (TTC) conflicts, with the objective of studying whether the LPI treatment leads to a reduction in such conflicts. Additionally, the study also modelled rear-end TTC conflicts between vehicles to investigate whether the LPI treatment, on the other hand, led to an increase in vehicular conflicts.

2 METHODOLOGY

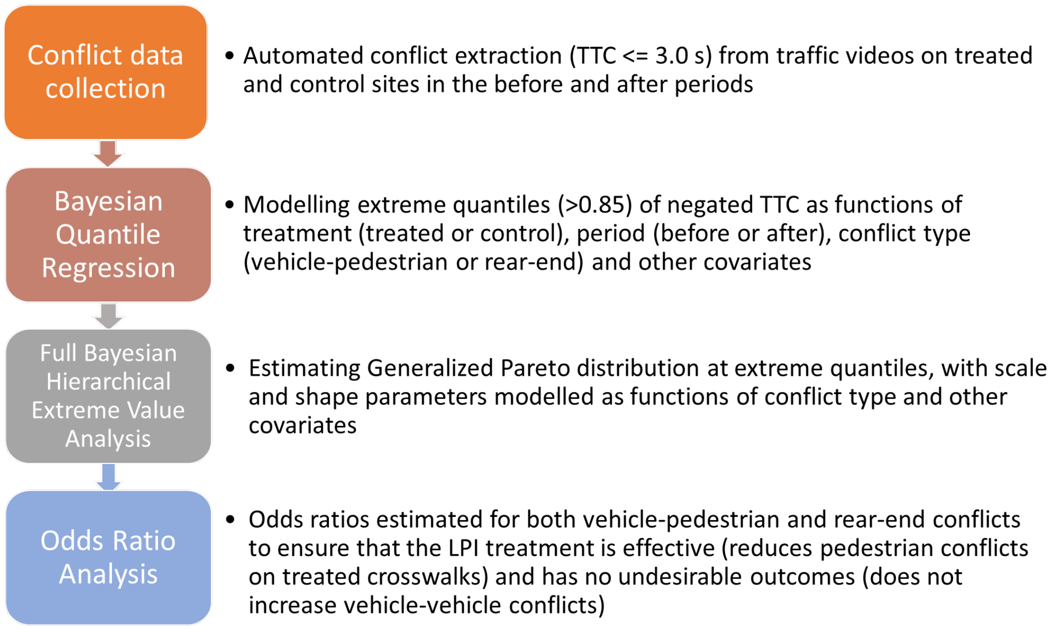

Fig. 1: The study framework

The study framework is given in Fig. 1, which details the various steps and analyses performed to reach the study's objectives. The traffic movements were video recorded and analyzed using Microsoft's proprietary computer vision platform, **Edge Video Service (EVS)**, to obtain road user trajectories. The extracted trajectories were then analyzed using Advanced Mobility Analytics Group's (AMAG) proprietary **SMART Safety™** platform to automatically extract traffic conflicts based on a bevy of conflict indicators. This study analyzed Time-to-Collision (TTC) conflicts (TTC $\leq$ 3 s) for in-depth before-and-after analysis.

In the second step, the extreme quantiles (>=0.85) of the TTC values of the conflicts were modelled using Bayesian Quantile Regression (Zheng and Sayed, 2019a) to meaningfully include the effect of important covariates in conflict threshold selection. Thereafter, peak-over threshold extreme value analysis of the TTC conflicts was conducted using the Bayesian Hierarchical analysis framework (Zheng and Sayed, 2019a, Guo et al., 2020a) to get frequency estimates of extreme rear-end and vehicle-pedestrian conflicts. The risk of extreme conflicts can be estimated as the tail probability of the negated TTC extreme value distribution over the specified extreme conflict threshold. It is known that $TTC = 0$ indicates the occurrence of a crash. Hence, the extreme conflict threshold must be near this value to indicate the most atypical interactions between the conflict participants. In this study, an extreme conflict threshold of 0.2s was adopted (Zheng and Sayed, 2019b, Guo et al., 2020a). Using extreme conflicts instead of the expected crash frequency helps overcome the zero denominator issue that can hamper odds ratio analysis.

Finally, an odds ratio analysis (Zheng and Sayed, 2019b, Guo et al., 2020a) was conducted to investigate the two research questions mentioned earlier. The safety treatment effectiveness in before-and-after type studies using a control group may be assessed using the Odds Ratio method (Autey et al., 2012). An OR less than 1 is desirable as it indicates that the intended safety benefits have been achieved. Whereas an OR equal to 1 represents no effect of the safety treatment, and a value greater than 1 indicates an undesirable effect. The OR is strictly positive and is assumed to follow a lognormal distribution. Correspondingly, a test statistic z is defined on OR that asymptotically follows a standard normal distribution. The statistical test consists of testing the null hypothesis that the safety treatment has no overall effect $H0: OR = 1$. The null hypothesis is rejected if the approximate tail probability of z is smaller than the significance level, adopted as 95% level of significance, represented by the p-value.

3 DATA

The study locations included 10 pedestrian crossings on 3 signalized intersections in Bellevue, Washington. Fig. 2 illustrates the various treated and control pedestrian crosswalks (sites) on the study intersections.

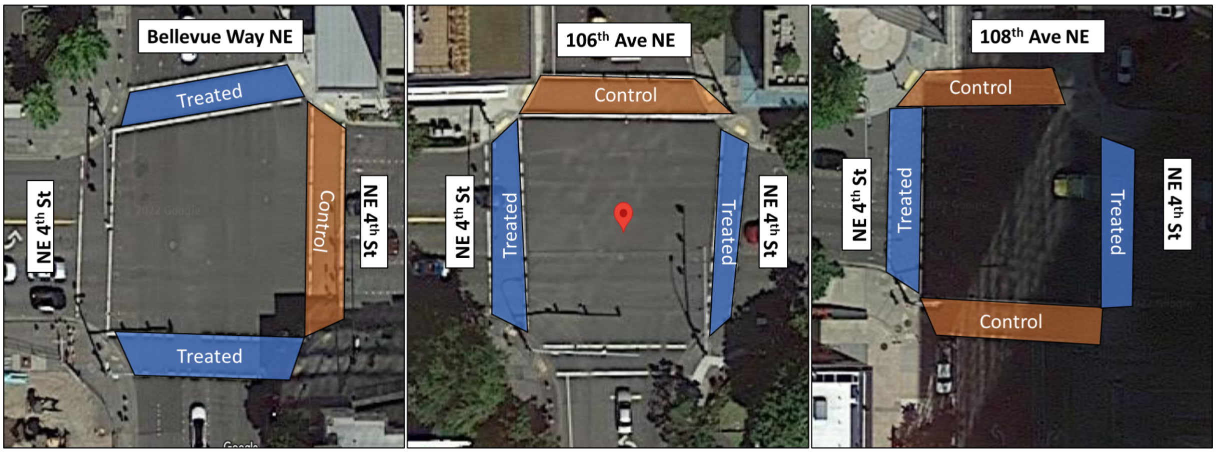

Fig. 2: Study locations showing the treated and control pedestrian crossings

The primary data used in the study consisted of video-recorded traffic movements, captured using cameras mounted on signal heads to capture the treated and control pedestrian crosswalks (Fig. 3).


Fig. 3: An screenshot from the traffic movement captured by the video camera mounted on the signal head at the Bellevue Way – NE 4th St Intersection

The data were collected for one full week (Monday – Sunday) in both before and after periods at each intersection. 12 hours of video data were recorded for each day. Table 1 summarizes the video data collection schedule to observe traffic movements.

Table 1: Summary of traffic movement observations

Intersection Name	**Treated Crosswalks**	**Control Crosswalks**	**Before Date**	**After Date**	**Before Duration**	**After Duration**
Bellevue Way & NE 4th St	North, South	East	9th-15th Oct 2020	30th Oct-5th Nov 2020	06:00-18:00	06:00-18:00
106th Ave & NE 4th St	East, West	North	9th-15th Oct 2020	30th Oct-5th Nov 2020	06:00-18:00	06:00-18:00
108th Ave & NE 4th St	West, East	North, South	9th-15th Oct 2020	30th Oct-5th Nov 2020	06:00-18:00	06:00-18:00

Video analytics for the study was performed using Microsoft's proprietary video platform, named Edge Video Service (EVS). EVS is a highly extensible software stack to empower everyone to build practical real-world live video analytics applications for object detection and counting/alerting with cutting edge machine learning algorithms. Using a video pipeline built on C# .NET Core, EVS allows for model plug-ins from TensorFlow and PyTorch, GPU and VPU acceleration, and Docker containerization and Kubernetes orchestration. EVS pipelines are used to detect objects and their trajectories (e.g., of cars and people on the street), either on live videos in real-time or on stored videos. For this study, we used the Yolo V3 object detection model and the DeepSORT object tracker. EVS has been built upon years of research on video analytics by Microsoft in Project Rocket (http://aka.ms/rocket). EVS makes the analysis of videos to be efficient, low-cost, and amenable to edge compute deployments.

The road user trajectories were then analyzed using Advanced Mobility Analytics Group's (AMAG) SMART Safety^{TM} platform, which uses Deep Learning and advanced econometrics to handle Big Data and automatically extract conflicts (see Fig. 3) based on several conflict indicators, including Time-to-Collision (TTC). The system is developed based on extensive previous research conducted at the University of British Columbia, Canada, the Queensland University of Technology, Australia, and the University of Queensland, Australia (Autey et al., 2012, Zaki et al., 2016, Arun et al., 2021).

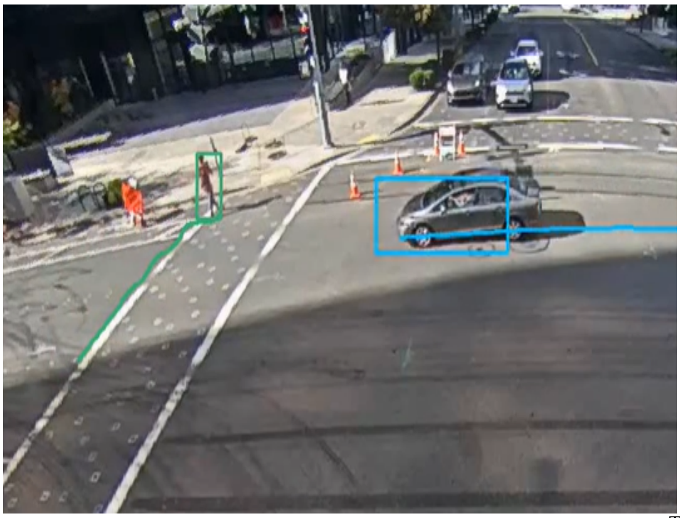

Fig. 3: Example of a conflict detected using the SMART Safety^{TM} Platform

Table 2 describes the various types of conflicts the SMART Safety platform extracted in the before-and-after periods at the study intersection. This study used only the rear-end and vehicle-pedestrian conflicts below the TTC screening threshold of 3.0 s for further analysis.

Table 2: Descriptive statistics of traffic conflicts observed at the study intersections in the before and after periods

Intersection Name	**Period**	**Conflict Type**	**Conflict Counts**	**TTC (s)**			
				Mean	SD	Min	Max
Bellevue Way & NE 4th St (Site_1)	Before	AA	329	1.61	0.55	0.32	2.55
		LTOD	201	1.19	0.51	0.10	2.13
		RE	2393	1.21	0.38	0.10	2.40
		LC	54	1.15	0.48	0.29	2.38
		P	99	0.91	0.41	0.32	1.65
		B	6	-	-	-	-
	After	AA	318	1.50	0.64	0.13	2.49
		LTOD	201	1.26	0.36	0.41	1.94
		RE	2613	1.19	0.37	0.11	2.45

Intersection Name	Period	Conflict Type	Conflict Counts	TTC (s)			
				Mean	SD	Min	Max
		LC	60	1.26	0.49	0.30	2.82
		P	57	1.19	0.54	0.48	2.29
		B	4	1.88	0.15	1.77	1.99
106th Ave & NE 4th St (Site_2)	Before	AA	399	1.75	0.58	0.04	2.61
		LTOD	94	1.41	0.47	0.81	2.37
		RE	1075	1.75	0.48	0.00	2.79
		LC	2	1.04	0.32	0.81	1.26
		P	58	1.02	0.53	0.40	2.13
		B	1	1.05	-	1.05	1.05
	After	AA	326	1.75	0.61	0.42	2.62
		LTOD	110	1.15	0.57	0.42	2.03
		RE	1043	1.76	0.44	0.11	2.65
		LC	2	0.95	0.41	0.66	1.24
		P	34	1.00	0.50	0.41	2.08
		B	4	0.90	0.62	0.46	1.33
108th Ave & NE 4th St (Site_3)	Before	AA	167	1.50	0.63	0.58	2.58
		LTOD	48	0.92	0.46	0.39	1.55
		RE	1888	1.73	0.32	0.15	2.61
		P	11	1.63	0.37	1.37	1.89
		B	8	1.06	0.42	0.53	1.77
	After	AA	138	1.66	0.77	0.30	2.45
		LTOD	54	0.89	0.45	0.34	1.67
		RE	1095	1.67	0.36	0.11	2.73
		LC	1	0.22	-	0.22	0.22
		P	14	1.10	0.37	0.83	1.36
		B	6	0.85	0.27	0.42	1.09

Notations:
AA: Angled conflict between vehicles from adjacent approaches; LTOD: Conflict between Left turning vehicles and thru travelling vehicles from opposite approaches; RE: Rear-end conflicts; LC: Lane changing conflicts between vehicles from the same approach; P: Pedestrian-vehicle conflicts; B: Bicycle-vehicle conflicts

4 RESULTS

4.1 Quantile Regression analysis for threshold selection

Only the models corresponding to the 90th and 95th quantile converged to a solution as reported in Table 3. From Table 3, the treatment indicator (1 = treated, 0 = control) was significant at both quantiles, with its effect increasing at the higher quantile representative of more extreme conflicts. The period indicator (1 = after, 0 = before) and the conflict-type indicator (1 = rear-end, 0 = vehicle-pedestrian) were not significant in both models. Importantly, the site-specific indicator for Site_1 was significant in both models (Site_3 was used as the base category), indicating that site-specific heterogeneities played a significant role in the occurrence of extreme conflicts. The non-stationarity in conflict occurrence was addressed using the N_TTC variable, which gave a scaled value of the number of conflicts with TTC <= 1.5s and was found significant in both models.

Table 3: Quantile regression results

Variables	Quantile = 0.9			Quantile = 0.95		
	Mean	2.5%	97.5%	Mean	2.5%	97.5%
(Intercept)	-0.755	-1.082	-0.349	-0.610	-1.030	0.075
Treat	-0.317	-0.460	-0.181	-0.438	-0.611	-0.283
Period	0.017	-0.033	0.067	0.036	-0.029	0.117
Type	-0.198	-0.611	0.132	-0.153	-0.837	0.264
Site_1	0.263	0.179	0.344	0.337	0.229	0.437

Variables	Quantile = 0.9			Quantile = 0.95		
Site_2	0.003	-0.055	0.061	0.052	-0.039	0.193
N_TTC	0.323	0.278	0.369	0.353	0.294	0.416

Notations:
Treat – Treated site indicator (1 = treated, 0 = control)
Period – Analysis period indicator (1 = after, 0 = before)
Type – Conflict type indicator (1 = rear-end, 0 = vehicle-pedestrian)
Site_1 – Site indicator (1 = Bellevue Way & NE 4th St, 0 = otherwise)
Site_2 – Site indicator (1 = 106th Ave & NE 4th St, 0 = otherwise)
N_TTC – No. of conflicts with TTC <= 1.5 s, standardised using the series mean and standard deviation
Mean – Mean of the parameter posterior density estimates
2.5% - Lower credible interval (95% sigificance level)
97.5% - Upper credible interval (95% sigificance level)

4.2 Bayesian hierarchical extreme value analysis

Only the best non-stationary (with covariates) models are reported for the 95th quantile in Table 4, which only included the conflict-type indicator (1 = rear-end, 0 = vehicle-pedestrian) as the significant predictor.

Table 4: Extreme value model estimation results

Parameter	Covariates	Quantile = 0.95					
		Model-1			Model-2		
		Mean	2.5%	97.5%	Mean	2.5%	97.5%
Conflict threshold $(\boldsymbol{u})$		-0.682					
Scale $(\widehat{\boldsymbol{\sigma}})$	$\widehat{\boldsymbol{\sigma_0}}$	0.424	0.379	0.473	-1.206	-1.351	-1.019
	$\widehat{\boldsymbol{\sigma_{Type}}}$	-	-	-	0.376	0.185	0.472
Shape $(\widehat{\boldsymbol{\xi}})$	$\widehat{\boldsymbol{\xi_0}}$	-0.719	-0.809	-0.629	-0.743	-0.828	-0.661
Exceedances		510					
Deviance Information Criterion (DIC)		-1769.348			-1800.249		

Notations:
Type - Conflict type indicator (1 = rear-end, 0 = vehicle-pedestrian)
Model-1 – Stationary model
Model-2 – Best non-stationary model
Mean – Mean of the parameter posterior density estimates
2.5% - Lower credible interval (95% sigificance level)
97.5% - Upper credible interval (95% sigificance level)

4.3 Odds ratio analysis

The odds ratio analysis was performed for the estimated 95th quantile of negated TTC. First, the 95th quantile threshold was estimated using the quantile regression model in Table 3. The extreme value distribution was obtained by substituting the corresponding values for the conflict type indicator in the Bayesian hierarchical model in Table 4. Thus, extreme conflict estimates were obtained for both vehicle-pedestrian (Table 5) and rear-end conflicts (Table 6). The odds ratio analysis showed that while the LPI treatment effectively reduced the frequency of extreme vehicle-pedestrian conflicts at all the intersections (total Odds Ratio = 0.577, p-value<0.001), with a treatment effect of 42.3% (=(1-0.577)x100), it had no significant effect on the frequency of extreme rear-end conflicts (p-value>0.05). These results are discussed in detail in the next section.

Table 5: Odds ratio analysis results for extreme vehicle-pedestrian conflicts

Intersection Name	**Period**	**Treatment Type**	**Annual Extreme Conflicts (TTC<=0.2 s) Estimate**	**Site-wise Odds Ratio**	**Total Odds Ratio (p-value)**
Bellevue Way & NE 4th St	Before	Treated	86.517	0.689	
		Control	104.286		
	After	Treated	59.633		
		Control	104.286		
106th Ave & NE 4th St	Before	Treated	104.286	0.398	
		Control	51.955		
	After	Treated	58.904		
		Control	73.646		
108th Ave & NE 4th St	Before	Treated	70.042	0.880	
		Control	13.111		
	After	Treated	74.590		
		Control	15.862		
Total	**Before**	**Treated**	**260.845**	**-**	**0.577 (<0.001)**
		Control	**169.351**		
	After	**Treated**	**193.126**		
		Control	**193.793**		

Table 6: Odds ratio analysis results for extreme rear-end conflicts among vehicles

Intersection Name	**Period**	**Treatment Type**	**Annual Extreme Conflicts (TTC<=0.2 s) Estimate**	**Site-wise Odds Ratio**	**Total Odds Ratio (p-value)**
Bellevue Way & NE 4th St	Before	Treated	89.264	0.997	
		Control	100.709		
	After	Treated	89.380		
		Control	101.135		
106th Ave & NE 4th St	Before	Treated	60.824	1.034	
		Control	94.659		
	After	Treated	60.324		
		Control	90.770		
108th Ave & NE 4th St	Before	Treated	61.105	1.019	
		Control	87.800		
	After	Treated	61.300		
		Control	86.415		
Total	**Before**	**Treated**	**211.193**	**-**	**1.015 (0.55)**
		Control	**283.167**		
	After	**Treated**	**211.003**		
		Control	**278.319**		

5 DISCUSSION

The Time-to-Collision (TTC) conflicts for rear-end and vehicle-pedestrian events were analyzed in this study. Through Bayesian quantile regression, this study showed that the treatment type, whether treated or control, had a significant effect on the 90^{th} and 95^{th} quantile negated TTC values, with a larger negative effect at the higher quantile. Zheng and Sayed (2019a) observed that negative values of predictors meant that the negated TTC values were further away from the crash zone (negated TTC ≥ 0). Thus, the LPI treatment reduced the probability of extreme conflicts and crashes by shifting the

Generalized Pareto distribution away from the crash area. The before or after periods did not significantly affect the modelled quantiles.

The quantile regression and extreme value modelling were combined to estimate the frequencies of extreme rear-end and vehicle-pedestrian conflicts at the treated and control sites in the before and after periods. These estimates were then analyzed using the Odds Ratio analysis typically used in before-and-after type studies. The odds ratio analysis showed that the LPI treatment significantly reduced the occurrence of extreme vehicle-pedestrian conflicts at the treated locations. The treatment effect was computed as a reduction of 42.3%.

Some important conclusions and recommendations from the findings of this study are:

- Leading Pedestrian Intervals (LPI) are a low-cost safety treatment that can be quickly implemented at a site. This study further lends weight to the evidence mounting in support of the validity of this treatment in reducing vehicle-pedestrian crash probability. Moreover, this study categorically found that LPI implementation does not adversely affect (increase) the occurrence of vehicle-vehicle conflicts.
- The long term effects of LPI treatment safety need to be investigated, particularly in light of assertion by certain researchers (Näätänen and Summala, 1974, Summala, 1988, Wilde, 1998) that road users adapt to the safety treatments over time. The Computer Vision-based automated traffic conflict analysis method used in this study could be a game-changer in this regard. Conflict observation videos from a long enough time period (say, 1 or 2 years *ceteris paribus*) after the initial observations can again be analyzed through the system to gain insights into any behavioral adaptation by the users and whether that returns the treated site to the original level of crash risk.

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