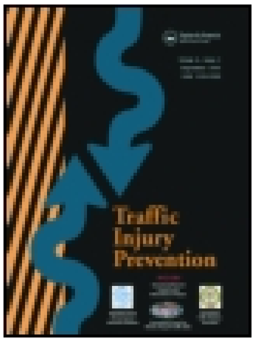

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Secondary collisions and injury severity: A joint analysis using structural equation models

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ABSTRACT

Objective: This study aims to investigate the contributing factors to secondary collisions and the effects of secondary collisions on injury severity levels. Manhattan, which is the most densely populated urban area of New York City, is used as a case study. In Manhattan, about 7.5% of crash events become involved with secondary collisions and as high as 9.3% of those secondary collisions lead to incapacitating and fatal injuries.
Methods: Structural equation models (SEMs) are proposed to jointly model the presence of secondary collisions and injury severity levels and adjust for the endogeneity effects. The structural relationship among secondary collisions, injury severity, and contributing factors such as speeding, alcohol, fatigue, brake defects, limited view, and rain are fully explored using SEMs. In addition, to assess the temporal effects, we use time as a moderator in the proposed SEM framework.
Results: Due to its better performance compared with other models, the SEM with no constraint is used to investigate the contributing factors to secondary collisions. Thirteen explanatory variables are found to contribute to the presence of secondary collisions, including alcohol, drugs, inattention, inexperience, sleep, control disregarded, speeding, fatigue, defective brakes, pedestrian involved, defective pavement, limited view, and rain. Regarding the temporal effects, results indicate that it is more likely to sustain secondary collisions and severe injuries at night.
Conclusions: This study fully investigates the contributing factors to secondary collisions and estimates the safety effects of secondary collisions after adjusting for the endogeneity effects and shows the advantage of using SEMs in exploring the structural relationship between risk factors and safety indicators. Understanding the causes and impacts of secondary collisions can help transportation agencies and automobile manufacturers develop effective injury prevention countermeasures.

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Safety analysis; secondary collisions; injury severity; endogeneity; structural relationship; structural equation model; urban area

Introduction

Research motivation

A secondary collision in this study is defined as any collision or noncollision event (e.g., overturn) that occurs after the initial collision in a traffic crash event (crashes with secondary collisions can also be referred to as multi-event crashes). It should be distinguished that the secondary "collisions" are different from the secondary "crashes" defined in previous studies such as Yang, Morgul, et al. (2014) and Yang, Ozbay, and Xie (2014). A secondary crash is an induced crash event that occurs due to the influence of the previous one, whereas a secondary collision along with the initial collision can be regarded as different phases of a single crash event. Common examples of secondary crashes include those that occur as a consequence of the queues induced by the primary crashes. Examples of secondary collisions include, but are not limited to, one vehicle striking another 2 vehicles consecutively, one vehicle hitting another vehicle first and then a pedestrian/bicyclist/fixed object, and one vehicle overturning after striking another vehicle. Secondary collisions are not rare events and are among the most injurious phases in crash events (Gabauer 2010; Ray et al. 1987). For instance, in Manhattan, New York City, about 7.5% of crash events include secondary collisions and as high as 9.3% of those secondary collisions lead to incapacitating and fatal injuries according to the historical crash data we collected.

New York City's mayor launched the Vision Zero Action Plan in 2014, which targets reducing injuries and fatalities caused by traffic crashes. To improve traffic safety, the investigation of factors contributing to secondary collisions and safety impacts of secondary collisions are both of great importance to transportation agencies. It is expected that rational and effective injury prevention countermeasures could be developed by understanding the causes and impacts of secondary collisions. Manhattan, the most densely populated urban area of New York City, is used as a case study. New York City's open data policy makes detailed

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crash data available to the public and enables data-driven safety analysis. The objectives of this study are to explore the determinants of secondary collisions and to investigate the effects of secondary collisions on injury severity using a robust quantitative method. Statistical models are proposed to capture the structural relationship between the contributing factors, presence of secondary collisions, and injury severity levels.

Literature review

There are a few studies on secondary collisions in the literature. Bryden and Fortuniewicz (1986) examined a total of 3,302 barrier crashes in New York State and found that secondary collisions were present in about 25% of all cases and accounted for nearly 90% of fatalities. Ray et al. (1987) collected barrier crash data from New York State and North Carolina and investigated the impacts of secondary collisions on injury severity. They found that occupants often suffered from severe injuries in secondary collisions after their vehicles were redirected from the longitudinal barriers and the risk of severe injuries was nearly 3 times greater when second collisions were present. More recently, Gabauer (2010) examined the risk of secondary collisions following an initial barrier impact, based on 12-year crash data from NASS-CDS. Two binary logistic regression models were used to predict the presence of secondary collisions and severe injuries, respectively. Vehicle type and barrier penetration were found to be significantly associated with the involvement of secondary collisions, and secondary collisions were expected to increase the risk of severe injuries by a factor of 3.53, close to the safety effect of seat belt use. In a following study by Gowat and Gabauer (2013) that used a similar data source and statistical methods, barrier lateral stiffness, postimpact vehicle trajectory, vehicle type, and pre-impact tracking condition were found to influence the occurrence of secondary collisions significantly, and secondary collisions were predicted to raise the likelihood of severe injuries by a factor of 6.98 versus crashes without secondary collisions. Kononen et al. (2011) found that crashes with multiple impacts were associated with higher risk of serious injuries. Daniello and Gabler (2011) investigated the fatality risk in motorcycle crashes with more than one impact event and concluded that "collisions with fixed objects are more harmful to motorcyclists than collisions with the ground" (p. 1167).

Factors contributing to secondary collisions (e.g., one vehicle hitting another 2 vehicles consecutively or one vehicle hitting another vehicle and then a pedestrian) have not been fully explored in the literature. In addition, previous studies did not account for the endogeneity of the presence of secondary collisions in explaining injury severity. In econometrics, the endogeneity occurs when an explanatory variable is correlated with the error term (Wooldridge 2010). Endogeneity can arise as a result of various causes such as omitted variables, measurement error, and simultaneity (Greene 2003). In this study, the presence of secondary collisions is likely to be endogenous to the injury severity due to the possible existence of confounding variables (e.g., speeding, alcohol, and fatigue) that can impact both secondary collisions and injury severity levels. Ignoring the endogeneity may lead to overestimated effects of a secondary collision on injury severity.

Methods

Crash data and descriptive analysis

Three-year crash record data (May 1, 2008 to April 20, 2011) were obtained from the New York State Department of Transportation (https://www.dot.ny.gov). Factors contributing to crashes such as speeding, alcohol, and fatigue can be obtained from historical crash record with a total of 43,149 reportable crashes; 3,245 crash events (involving 7,586 parties) involved secondary collisions, accounting for about 7.5% of the total. Secondary collisions recorded include collisions with motor vehicles, bicyclists, pedestrians, and fixed objects after the initial collision and noncollision events such as overturning. Secondary collisions with motor vehicles (5,328) and fixed objects (1,810) account for about 94.1% of the total.

Regarding injury severity, crashes were classified into 5 types: no injury (39.0%), possible injury (45.8%), nonincapacitating injury (9.8%), incapacitating injury (5.0%), and fatality (0.3%). The injury severity level of a crash is the worst severity sustained by any occupant involved in the crash. For example, if a motor vehicle hit a pedestrian and led to incapacitating injury to the pedestrian and nonincapacitating injury to the driver, the injury severity level for this crash event is incapacitating injury. The proportion of serious crashes (including incapacitating injuries and fatalities) is 5.0% when secondary collisions are not present, and the proportion increases sharply to 9.3% when secondary collisions are present. Empirically, secondary collisions tend to raise the likelihood of severe injuries in crash events.

Driver, vehicle, road, and environmental features with the potential to affect the occurrence of secondary collisions and injury severity were extracted from the crash record files. Driver features mostly describe risky driving behaviors such as speeding, following closely, driving under the influence of alcohol, and using cell phones while driving. Vehicle features include brake defects, oversized vehicle, and the vehicle types involved in the collision. Road features provide information mainly about the pavement, traffic control, and location where each crash occurred. Environmental features include weather (e.g., cloudy, rain, and snow) and the time period (e.g., nighttime or daytime). The descriptions and descriptive statistics of data are listed in Appendix A (see online supplement).

Structural equation modeling

Addressing the endogeneity issue is gaining increased attention in studies on traffic safety modeling. In this study, we focus on endogeneity caused by uncontrolled confounding variables (either observed or unobserved. Another common cause of endogeneity, simultaneity—at least one explanatory variable is simultaneously influenced by the response variable—is not discussed in this study.) To account for this type of endogeneity, a structural model specification is generally suggested. The conceptual framework of the proposed structural equation model (SEM) is shown in Figure 1. Secondary collision propensity is a function of driver, vehicle, road, and environmental features. A secondary collision is predicted to occur once the secondary collision propensity is over a certain threshold. The presence of secondary collisions as well as driver, vehicle, road, and

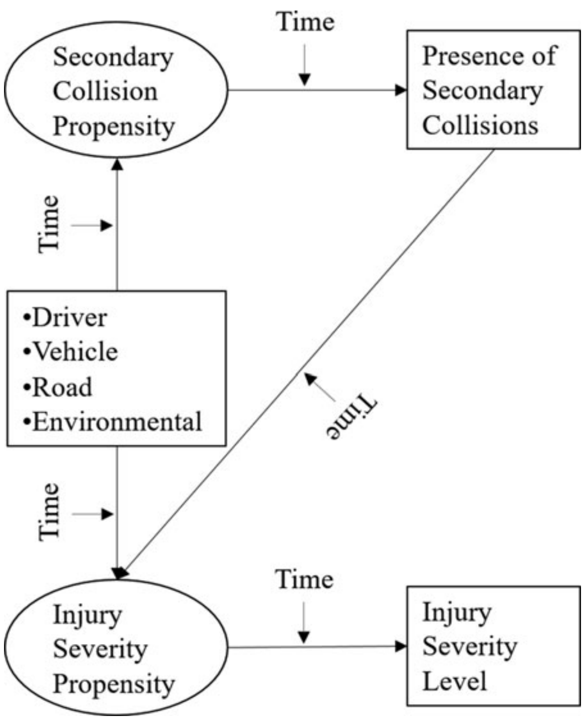

Figure 1. Conceptual path diagram of the proposed SEM.

environmental features are used to estimate the injury severity propensity, which is associated with injury severity outcome. To assess the temporal effects, the variable time (0 for daytime and 1 for nighttime) is used as a moderator in the proposed SEM framework. Crash events are classified into daytime and nighttime groups. The model parameters including the coefficients of explanatory variables and thresholds can be constrained to be the same or allowed to vary between groups. The types of constraints we used are described in the Modeling Results section.

The formulation for the proposed SEM is expressed as

$$\begin{aligned} sc_i^* &= \boldsymbol{\alpha}'\mathbf{z}_i + \nu_i \\ sc_i &= 1, if sc_i^* > \varphi, sc_i = 0, otherwise \\ y_i^* &= \boldsymbol{\beta}'\mathbf{x}_i + \gamma sc_i + \varepsilon_i \\ y_i &= k, if \eta^{k-1} < y_i^* < \eta^k, \end{aligned} \tag{1}$$

where i $(i = 1,\ 2, \ldots, N)$ is an index for crashes, sc_i^* is the latent secondary collision propensity in crash i, sc_i is the secondary collision indicator with 1 indicating the presence of secondary collisions, $\mathbf{z}_i$ is an (M $\times$ 1) vector of exogenous variables that explains the presence of secondary collisions in crash i, $\boldsymbol{\alpha}$ is an (M $\times$ 1) vector of coefficients corresponding to $\mathbf{z}_i$, ν_i is a normally distributed error term with mean 0 and variance σ_ν^2, φ is the threshold corresponding to the presence of secondary collisions, y_i^* is the latent injury severity propensity for crash i, y_i is the observed injury severity level (1 for no injury, 2 for possible injury, 3 for nonincapacitating injury, 4 for incapacitating injury, and 5 for fatality) for crash i, $\mathbf{x}_i$ is an (N $\times$ 1) vector of exogenous variables that affects the injury severity propensity, $\boldsymbol{\beta}$ is an (N $\times$ 1) vector of coefficients corresponding to $\mathbf{x}_i$, γ is the effect of the presence of secondary collisions on the injury severity, ε_i is a normally distributed error term with mean 0 and variance σ_ε^2, k $(k = 1,\ 2, \ldots, K)$ is an index to represent injury severity outcome, and η^k is the upper threshold corresponding to the injury severity outcome k (with $\eta^0 < \eta^1 \cdots < \eta^5$, $\eta^0 = -\infty$, $\eta^5 = +\infty$).

A set of statistical indices can be used to assess the performance of the SEMs. Widely used measures of SEMs include chi-square (χ^2), root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the Tucker-Lewis index (TLI) measure (Kline 2015). Generally, a model with RMSEA less than 0.05 and CFI/TLI above 0.9 is favored (Hu and Bentler 1995). The chi-square difference statistic (χ_D^2) measures the statistical significance of the decrement/improvement in model overall fit as free parameters are eliminated/added (Kline 2015). It is appropriate to use chi-square difference statistics to compare 2 hierarchical SEMs estimated with the same data, even if the sample size is large.

Results

The proposed SEMs were used to model the presence of secondary collisions and injury severity levels. To test parameter constraints over groups, 3 SEMs were developed with equal thresholds (the threshold estimates are constrained to be the same for the daytime crash model and the nighttime crash model), equal regressions (the regression coefficients are constrained to be the same for the daytime crash model and the nighttime crash model), and no constraint (the thresholds and regression coefficients of the daytime and nighttime crash models are set to be different). For variable selection, we only kept the variables that are significant at the 5% level in at least one SEM and significant at the 10% level in all 3 SEMs. Each SEM has the same selection of explanatory variables so that effective model comparison can be performed. Statistical indices of these 3 SEMs are reported in Table 1.

Considering the great number of samples ($N = 43{,}419$) used for model development, the significant results of chi-square tests can be ignored. All of the SEMs have RMSEAs less than 0.05, suggesting a good fit to the data. Additionally, the CFIs and TLIs of all the SEMs are greater than 0.9, except the TLI for the SEM with equal thresholds (0.895), which is slightly lower than the acceptance criteria. Chi-square difference tests were conducted to compare the 3 SEMs developed. The SEM with no constraint can result in a smaller chi-square at the expense of lower degrees of freedom. The chi-square of the SEM with no constraint is 72.788 (417.710–344.922), less than that of the SEM with equal thresholds, with degrees of freedom decreasing by 3 (23–20). The P value of the chi-square difference statistic is greater than .99, $\chi^2(72.788,\ 3) > 0.99$, which indicates that the SEM with

Table 1. Statistical indices of SEMs with equal thresholds, equal regressions, and no constraint.

	SEMs		
	Equal thresholds	Equal regressions	No constraint
Chi-square statistics			
Chi-square	417.710	432.345	344.922
Degrees of freedom	23	49	20
P value	.000	.000	.000
RMSEA	0.028	0.019	0.027
CFI	0.969	0.970	0.975
TLI	0.895	0.952	0.901

no constraint has a significantly smaller chi-square and a better fit than the SEM with equal thresholds. Similarly, it is found that the SEM with no constraint outperforms the SEM with equal regressions by presenting a significantly lower chi-square, $P = \chi^2(87.423,\ 29) > 0.99$.

Discussion

Due to its relatively better performance, the SEM with no constraint is used for variable interpretation and its estimates of parameters are presented in Table 2. The contributing factors to severe injuries have been fully explored in the literature, but limited studies are available on the determinants of the secondary collisions. According to Table 2, 13 explanatory variables are found to contribute to the presence of secondary collisions and 16 affect the injury severity of crashes. The effects of driver, vehicle, road, and environmental features on secondary collisions and severe injuries are discussed in the following paragraphs.

Drivers under the influence of alcohol are more likely to get involved with secondary collisions relative to those who are sober, presumably because the alcohol would affect the judgment, reasoning, and reaction of drivers. It is also found that drinking alcohol may lead to aggressive driving and thus severe injuries, consistent with earlier studies such as Abay et al. (2013), Eluru and Bhat (2007), Khattak et al. (2003), and Kim et al. (1995). Similar to the impact of alcohol, taking drugs would make drivers lose consciousness and result in more secondary collisions and severe injuries. Consistent results have been obtained in previous studies such as Khattak et al. (2003) and Kim et al. (1995). For crashes caused by driver inattention, the likelihoods of secondary collisions and severe injuries are expected to be higher. Neyens and Boyle (2008) found a higher likelihood of severe injuries for passengers of teenage drivers when their drivers were distracted by devices or passengers. Zhu and Srinivasan (2011) also found that driver distraction was associated with higher severity levels. Inexperienced drivers are prone to a higher risk of secondary collisions, possibly due to their inability to control the vehicle after the initial collisions. Injury severity levels rise substantially for drivers who suffer from illness, because they are in vulnerable situations. The impact of illness was also considered in the study by Zhu and Srinivasan (2011), but an insignificant relation was found between illness and severe injuries. From their perspective, the insignificant relation they found could be caused by their missing data issue. If drivers fail to yield the right of way, the risk of being severely injured would increase. It is intuitive that drivers who fall asleep can lead to more chances of secondary collisions because they cannot react in time even after the initial collision. If drivers disregard traffic control devices, it is more likely that secondary collisions and severe injuries will occur. Speeding is predicted to increase the likelihood of secondary collisions, presumably because speeding vehicles cannot be slowed down immediately and present a higher possibility of striking multiple objects. Speeding is also found to be associated with greater severe injury propensity, a result observed in previous studies such as Abdel-Aty (2003) and Chang and Mannering (1999). Fatigued drivers are prone to higher risks of secondary collisions and severe injuries, possibly because they are unable to make

Table 2. Estimates of the SEM with no constraint.

	Daytime				Nighttime			
	Secondary collision		Injury severity		Secondary collision		Injury severity	
	Estimate	*P* value	Estimate	*P* value	Estimate	*P* value	Estimate	*P* value
Secondary collision	—	—	0.243	.000	—	—	0.217	.000
Driver								
Alcohol	0.866	.000	0.370	.000	0.593	.000	0.407	.000
Drugs	0.800	.001	0.800	.000	0.657	.037	0.399	.049
Inattention	0.236	.000	0.061	.001	0.156	.000	0.080	.003
Inexperience	0.431	.000	—	—	0.384	.000	—	—
Yield	—	—	0.061	.035	—	—	0.139	.001
Sleep	0.486	.019	—	—	0.555	.015	—	—
Illness	—	—	1.668	.000	—	—	1.192	.000
Control disregarded	0.290	.000	0.456	.000	0.328	.000	0.405	.000
Speeding	0.730	.000	0.374	.000	0.637	.000	0.318	.000
Fatigue	0.436	.034	0.502	.002	0.450	.034	0.480	.002
Cell phone	—	—	0.507	.000	—	—	0.480	.043
Vehicle								
Brake defects	0.574	.000	0.473	.000	0.673	.000	0.405	.004
Motorcycle involved	—	—	1.265	.000	—	—	1.144	.000
Bike involved	—	—	1.498	.000	—	—	1.232	.000
Pedestrian involved	− 0.498	.000	1.496	.000	− 0.666	.000	1.329	.000
Road								
Pavement defects	0.470	.000	0.178	.000	0.396	.000	0.229	.000
Intersection	—	—	0.149	.000	—	—	0.080	.000
Limited view	0.426	.001	—	—	0.361	.027	—	—
Environmental								
Rain	0.124	.001	—	—	0.101	.017	—	—
Threshold								
η^1	—	—	0.246	.000	—	—	0.028	.117
η^2	—	—	1.899	.000	—	—	1.605	.000
η^3	—	—	2.599	.000	—	—	2.243	.000
η^4	—	—	3.922	.000	—	—	3.420	.000
φ	1.441	.000	—	—	1.219	.000	—	—

a quick reaction. The safety effect of fatigue was investigated in the study by Zhu and Srinivasan (2011). Although variables related to fatigue turned out to be insignificant predictors of injury severity, they stated that the effect of fatigue could be partially captured by variables such as time of day and crash type (Zhu and Srinivasan 2011). In addition, the use of cell phones would lead to a high risk of severe injuries. According to the study by McEvoy et al. (2005), cell phone use caused a 4-fold increase in crash injuries resulting in hospitalization. Neyens and Boyle (2008) found that teenage drivers had an increased likelihood of severe injuries if distracted by cell phones.

Vehicles with brake defects tend to be exposed to secondary collisions and severe injuries, because they cannot stop fast enough. Khattak et al. (2003) and Chen and Chen (2011) found that defective truck brakes were significantly associated with severe injuries. It is found that pedestrian crashes are less likely to have secondary collisions. Crashes involving motorcycles, bikes, and pedestrians are prone to a higher risk of severe injuries, because motorcyclists, bicyclists, and pedestrians are vulnerable road users relative to vehicle occupants. Chang and Wang (2006) stated that motorcyclists, bicyclists, and pedestrians received less protection and were expected to have a greater likelihood of severe injuries compared to automobile drivers. Valent et al. (2002) found that crashes involving motorcyclists, bicyclists, and pedestrians were associated with high risk of death.

Regarding the road features found significant, secondary collisions are more likely to happen on roads with pavement defects and limited view. Pavement defects can also increase the risk of severe injuries. Chang and Wang (2006) found that injury severity had a serious correlation with pavement condition. Milton et al. (2008) found that increasing pavement friction led to more severe injuries. However, an opposite finding was presented in Clifton et al. (2009). Furthermore, crashes occurring at intersections tend to result in severe injuries in comparison with those occurring at road mid-blocks. A study by Yamamoto and Shankar (2004) suggested lower driver injury risk at intersections for vehicle-fixed object crashes, because of the lower driving speed and greater attention by drivers when approaching intersections. However, in this study, which considers all types of crashes, head-on and right-angle crashes are far more likely to occur at intersections than at mid-blocks, and these crash types are associated with a high risk of severe injuries (Ye et al. 2008).

Furthermore, in rainy days, more secondary collisions are found to occur due to slippery roadways and affected views. However, no weather feature was found to significantly impact injury severity in this study. Different results were obtained in the literature on the safety impacts of weather. Eluru et al. (2008) found crashes occurring under adverse weather conditions increased the likelihood of fatal injuries. On the contrary, Abdel-Aty (2003) found that drivers were less likely to experience severe injuries under adverse weather conditions, because drivers tended to slow down and kept a safe distance from other vehicles.

Considering the temporal effects, the parameter estimates of the daytime and nighttime models are compared. Explanatory variables including sleep, control disregarded, fatigue, brake defects, and pedestrian involved have greater impacts on the likelihood of secondary collision at nighttime compared to during the daytime. On the other hand, the effects of explanatory variables including alcohol, inattention, yield, and pavement defects on likelihood of severe injury are found to be greater at nighttime compared to during the daytime. According to the threshold parameters (φ) that map the secondary collision propensity to the observed secondary collision occurrence, the smaller threshold value in the nighttime secondary collision model implies that secondary collisions are more likely to occur at nighttime. Similarly, the threshold for each injury severity level (η^k) is lower for nighttime crashes than daytime crashes, indicating that severe injuries are more likely to be sustained at night. The study by Abdel-Aty (2003) also revealed an increased severity risk for crashes occurring at night. Kockelman and Kweon (2002) found that driving later at night on Friday, Saturday, and Sunday exhibited a high likelihood of severe injuries.

In summary, 13 explanatory variables are found to contribute to the presence of a secondary collisions, including alcohol, drugs, inattention, inexperience, sleep, control disregarded, speeding, fatigue, defective brakes, pedestrian involved, defective pavement, limited view, and rain, and 16 were expected to increase the risk of severe injuries, including the presence of a secondary collision, alcohol, drugs, inattention, yield, illness, control disregarded, speeding, fatigue, cell phone, defective brakes, motorcycle involved, bike involved, pedestrian involved, defective pavement, and intersection. Considering the temporal effects, the parameter estimates of the daytime and nighttime models are compared, and the results indicate that secondary collisions and severe injuries are more likely at night. Understanding the causes and impacts of secondary collisions can help transportation agencies and automobile manufacturers develop effective injury prevention countermeasures. For example, results showed that pavement conditions could affect the occurrence of secondary collisions and severe crashes, so pavement should be well maintained in a timely manner. In addition, defective brakes were found to contribute to higher risks of both secondary collisions and severe crashes. Automobile manufacturers should pay close attention to manufacturing errors that can result in brake defects.

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