Appendix B

Summary of crash-frequency and crash-severity models in highway safety

This appendix describes the historical context and offers a summary of crash-frequency and crash-severity models that have been proposed or used for analyzing highway safety data. This appendix expands on the work of Lord and Mannering (2010), Savolainen et al. (2011), Mannering and Bhat (2014), and Mannering et al. (2016).

Introduction

As discussed in Chapters 3 and 4, crash modeling is an effective approach to exploring the relationship between crash frequency or crash severity and a set of predictors from the statistical perspective. Once the relationship is established, the mean crash count or the probability of an injury type can be estimated. It is anticipated that the explanatory variables are not only statistically correlated but only logically related to crash occurrence. Such a regression method assumes the error as random noise, and the mean can be represented as the true value around which observations fluctuate.

Technically sound crash models should have the theoretical rigor and technical robustness to handle many types of data issues generated during data collection and reporting. As crashes are rare and random events, it is quite normal that individual locations do not have adequate data for drawing a valid and explicit conclusion. Crash data are often pooled from a wide range of geographic locations and at different times to enhance the analysis. Data collected at the same time and location may exhibit similarities, whereas data collected at different times and from different locations may exhibit markedly different characteristics and therefore be heterogeneous. Heterogeneity means the variance of the dependent variable changes from observation to observation and may change as the independent variable changes. The accuracy of the coefficient estimates will be compromised, and the statistics used to test the hypothesis under the Gauss-Markov assumption will not be valid if heterogeneity is not carefully considered.

The development in statistical methods for safety data has significantly improved modeling accuracy while overcoming data limitations. Appendix B presents the overview and bibliography of methodologies for crash frequency and injury severity. The reader is encouraged to review Chapters 2, 3, 4 and 5 for detailed account of methodologies and model specifications.

Crash-frequency modeling

Crash-frequency modeling focuses on establishing a quantitative relationship between crash count and factors based on the statistical significance unveiled from the data. Decades of modeling crash data reveal that crash count data have a variety of issues, including overdispersion, underdispersion, time-varying explanatory variables, temporal and spatial correlation, low sample mean and small sample size, injury-severity and crash-type correlation, underreporting, endogenous variables, unobserved heterogeneity, and different crash risk sources (e.g., driver behavior, engineering, and weather). Advancement of methodologies for modeling crashes has been propelled by emerging problems with safety data (Chapters 2 and 5). Development was tardy in the early 1950s, and it was not until the 1970s that researchers started using the Poisson distribution to model crash count. In the early 1980s, the introduction of negative binomial or Poisson-gamma distribution to address crash data overdispersion marked a developmental monument. Since then, explosive growth in safety research has been witnessed, largely due to the substantial investment on standardization, modernization, and availability of safety data, as well as the advancement in computing power. Fig. B.1 presents the timeline of when each method was introduced to crash modeling.

The nature of the data guides the selection of a model, and the selection of an appropriate model depends on limitations; therefore, the data and the methodology are inseparable. Crash frequency, for example, can be assumed to follow a Poisson distribution. When the variance of crash count is larger than the mean, crash data are said to be overdispersed. Overdispersed count data are usually modeled with a negative binomial distribution, the most popular model for analyzing crash data (Lord and Mannering, 2010). When a dataset includes an excessive number of sites with zero crashes, alternative models such as the negative binomial—Lindley or negative binomial—generalized exponential should be

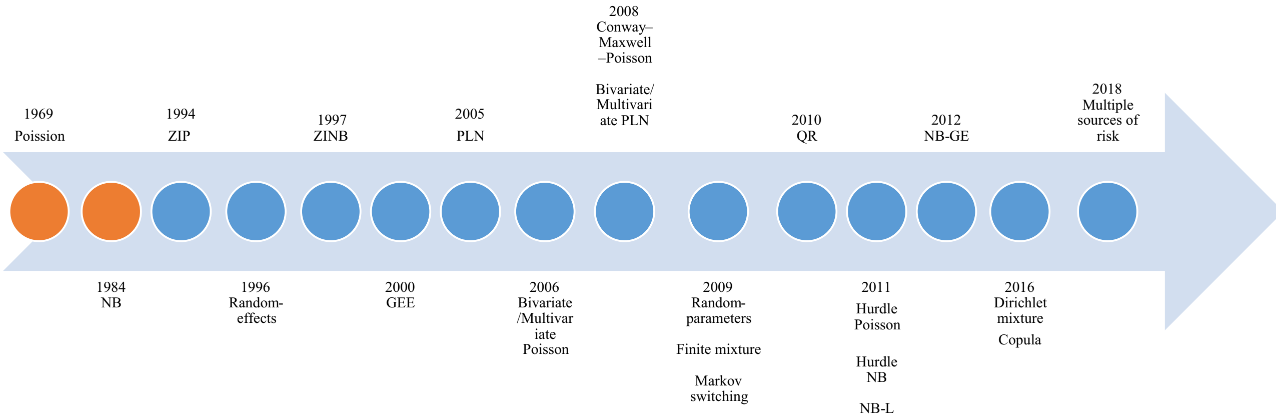

FIGURE B.1 Timeline of methodologies in crash-frequency modeling. *GEE*, generalized estimating equations; *NB*, negative binomial or Poisson-gamma; *NB-GE*, negative binomial—generalized exponential; *NB-L*, negative binomial—Lindley; *PLN*, Poisson-lognormal; *QR*, quantile regression; *ZINB*, zero-inflated negative binomial; *ZIP*, zero-inflated Poisson.

considered. When no specific probabilistic distribution form is assumed, quantile regression (QR) is an effective modeling method to handle skewed data with heterogeneity issues (Qin 2012, Qin and Reyes, 2011, Qin et al., 2010). More sophisticated models can treat the coefficient of an independent predictor as a random variable to account for the effects of omitted or missing variables. A (spatial) weight matrix or a covariance matrix can be added to the regression model to handle the autocorrelation when a temporal trend, a spatial pattern, or both are suspected in the crash data. Nevertheless, the methodologies are connected and related, illustrating a gradual and continued improvement. Fig. B.2 presents a family tree of crash-frequency models. The left figure is a family tree of Poisson-based models, and the right is a variety of other models. The negative binomial is the most widely used among Poisson-based models due to its ability to address overdispersion and its simple estimation procedure, as discussed above. Bivariate/multivariate Poisson/Poisson-lognormal has been quite popular in modeling correlations between crash types. The random effects model is widely recognized among other models due to its ability to address the spatial/temporal correlation, and the random parameters model is popular because of its ability to efficiently address unobserved heterogeneity. Zero-inflated and Hurdle models are included here for completeness, but as discussed in Chapter 3, they suffer from important methodological limitations.

Table B.1 summarizes crash-frequency methods that have been applied to analyze crash-frequency data, as well as the issues for which they can and cannot account. Based on this table, one can identify the suitable methodology corresponding to the issues presented in the crash data.

Crash-severity modeling

Equally if not more important is the task of identifying the contributing factors and their impacts on crash injury severities. The methodologies and techniques for crash-severity modeling, like their crash count modeling counterparts, are diverse. But unlike crash count that can change from zero to a large integer, the injury severity outcome has a finite number of alternatives (e.g., a KABCO scale). Moving from simple to complex, from weak to robust, the methodological evolvement of crash-severity modeling benefits tremendously from the development of econometrics and from travel demand models where highway route choice and transportation model choice are typical applications for a discrete choice model. Fig. B.3 presents the timeline of the approximate year when each method was introduced and when it gained recognition.

Prevailing issues were found during model development, including underreporting, omitted-variables bias, small sample size, endogenous variables, temporal and spatial correlation, unobserved heterogeneity, ordinal nature of crash injury severity data, and within-crash correlation.

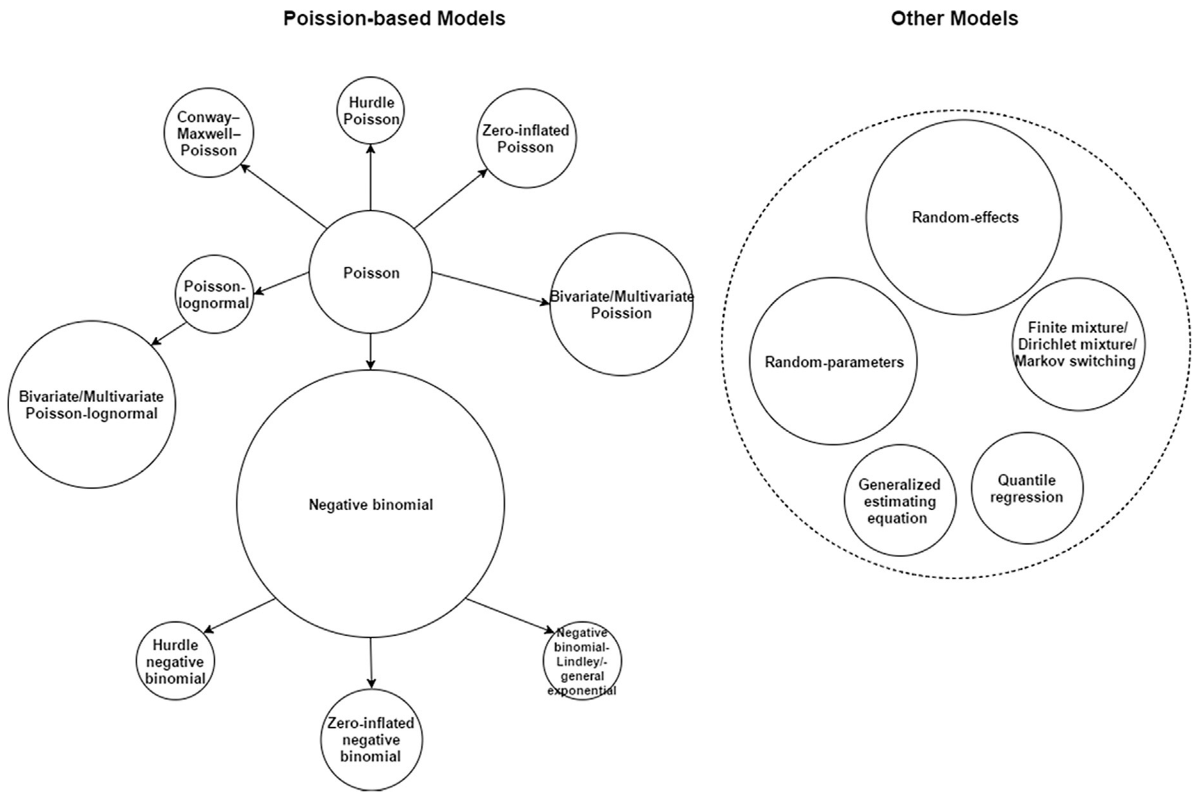

FIGURE B.2 Family tree of crash-frequency methodologies (*circle* size indicates the relative popularity of one methodology).

TABLE B.1 Summary of crash-frequency methods.

	Issue type						
Model type	**Overdispersion**	**Underdispersion**	**Low sample mean**	**Small sample size**	**Temporal/ Spatial correlation**	**Injury-severity and crash-type correlation**	**Unobserved heterogeneity**
Poisson	No[a]	No	No	No	–	No	–
Negative binomial	Yes[b]	No	No	No	–	No	–
Poisson-lognormal	Yes	No	Yes	Yes	–	No	–
Conway–Maxwell–Poisson	Yes	Yes	No	No	–	No	–
Zero-inflated/Hurdle[d]	–[c]	–	–	–	–		–
Hurdle	–	–	Yes	–	–	No	–
Negative binomial–Lindley/ negative binomial–general exponential	Yes	No	Yes	–	–	No	–
Generalized estimating equation	–	–	–	–	Yes	No	–
Random effects models	–	–	–	–	Yes	No	Yes
Bivariate/multivariate models	–	–	–	–	–	Yes	–
Random parameters models	–	–	–	–	Yes	No	Yes
Finite mixture/Markov switching/Dirichlet mixture	Yes	No	–	–	–	No	Yes
Quantile regression	–	–	Yes	–	–	No	–

[a] *Indicates the model cannot account for the issue.*
[b] *Indicates the model can account for the issue.*
[c] *Indicates whether the methodology can address this issue or not is unknown or depends on the model specification.*
[d] *Included for completeness. See Chapter 3 for a discussion about important methodological deficiencies related to these models.*

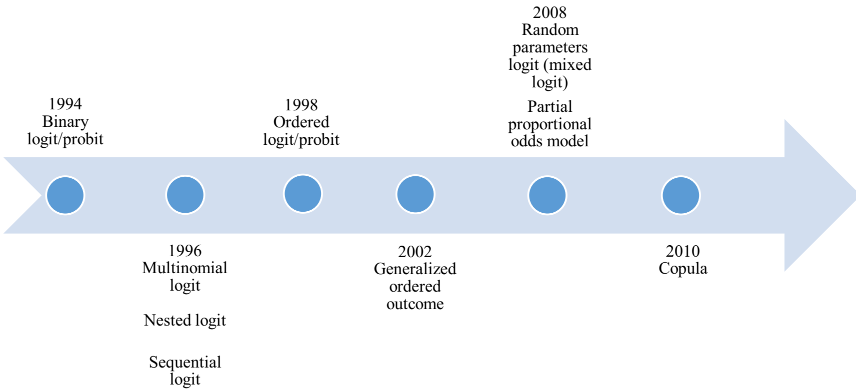

FIGURE B.3 Timeline of methodologies in crash injury severity modeling.

The first seven issues have been discussed in detail in the crash-frequency analysis, as the causes of the problems are the same. The last two issues are specific to crash-severity data: (1) the ordinal scale is that the injury severity levels (i.e., fatal injury or killed, incapacitating injury, non-incapacitating injury, possible injury, and property damage only) are ordered from the highest level to the lowest. There may be correlation among severity levels, and the correlation should be stronger between two closer levels; and (2) within-crash correlation exists among injury levels of drivers or of most severely injured persons in all vehicles involved in a multivehicle crash due to the unobserved shared factors such as speed.

Various modeling techniques have been proposed to account for the above issues, ranging from unordered to ordinal discrete choice models, from fixed parameters to mixed logit models. Fig. B.4 presents a family tree of crash injury severity methodologies, and the circle size represents the relative popularity of each methodology. The binary logit/probit model is the base of all the other models. Ordered logit/probit is the most popular among ordered discrete outcome models due to its ability to account for the ordinal nature of crash injury severity and its easy estimation procedure. The multinomial logit model is most widely recognized among unordered discrete outcome models because of its relaxation of the effects of contributing factors across all injury severities. The nested logit model is also popular as the violation of independence of irrelevant alternatives makes it is an appropriate model when the multinomial logit model fails. The mixed logit model has been gaining ground due to its ability to account for unobserved heterogeneity.

Table B.2 summarizes the major modeling differences from the technical perspective. The table can help guide the selection of appropriate modeling methodology corresponding to the issues presented in the crash-severity data.

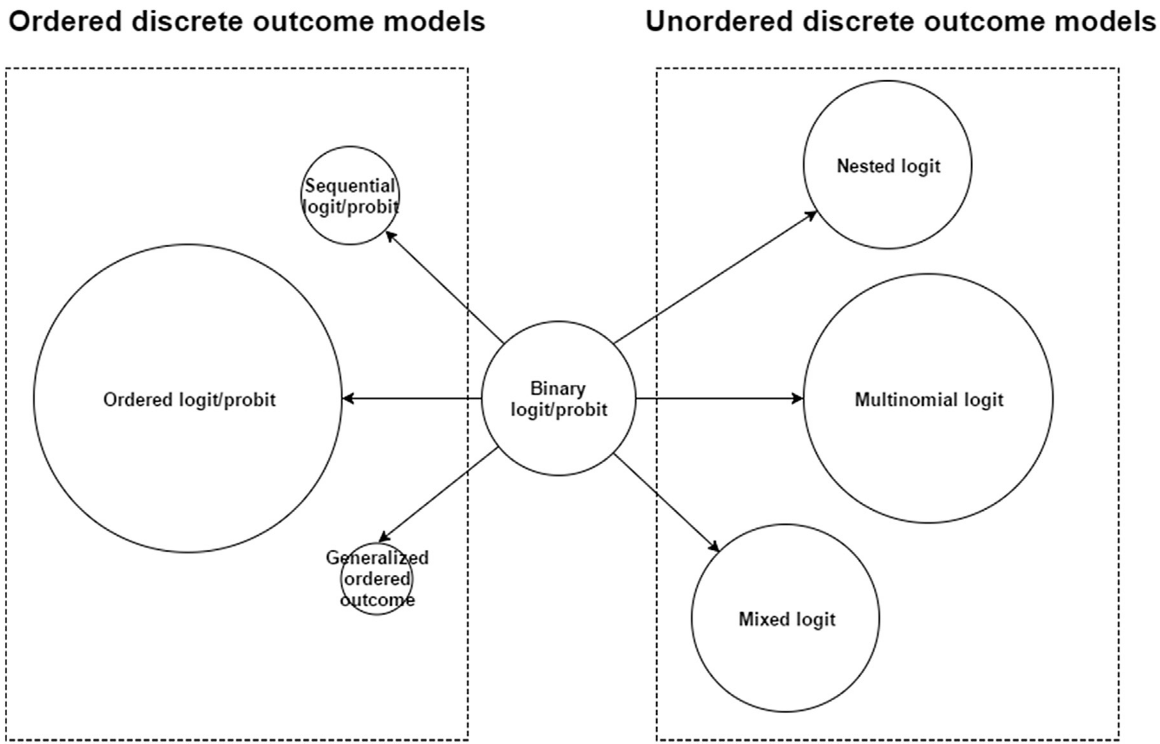

FIGURE B.4 Family tree of crash injury severity methodologies (*circle* size indicates the relative popularity of one methodology).

TABLE B.2 Summary of crash-severity methods.

Model type	Ordered/ Unordered	Variable restriction by severity
Binary logit/probit	–	–
Multinomial logit	Unordered	No
Nested logit	Unordered	No
Mixed logistic	Unordered	No
Ordinal logit/probit	Ordered	Yes
Sequential logit	Ordered	No
Generalized ordered logit	Ordered	No

Crash modeling by model type

Tables B.3 and B.4 provide a summary of some previous research for crash-frequency data and crash-injury severity data, respectively. The list may not be complete and up to date. In addition, a paper may be assigned to a different category because the paper can contain multiple models or a combination of models. Readers are suggested to use the tables for their information.

TABLE B.3 Summary of previous research analyzing crash-frequency data.

Model type	Previous research
Poisson	Erlander et al. (1969), Jovanis and Chang (1986), Joshua and Garber (1990), Jones et al. (1991), Miaou and Lum (1993), Miaou (1994)
Negative binomial	Maycock and Hall (1984), Hauer et al. (1988), Brude and Larsson (1993), Bonneson and McCoy (1993), Miaou (1994), Shankar et al. (1995), Poch and Mannering (1996), Milton and Mannering (1998), Karlaftis and Tarko (1998), Carson and Mannering (2001), Miaou and Lord (2003), Lord et al. (2005), El-Basyouny and Sayed (2006), Lord (2006), Kim and Washington (2006), Lord and Mahlawat (2009), Malyshkina and Mannering (2010), Daniels et al. (2010), Cafiso et al. (2010), Geedipally and Lord (2010), Lao et al. (2011), Geedipally and Lord (2011), Lord and Kuo (2012), Meng and Qu (2012), Ye et al. (2013), Aryuyuen and Bodhisuwan (2013), Qin et al. (2013), Vangala et al. (2015), Rahman Shaon and Qin (2016), Naznin et al. (2016), Qin et al. (2016)

(*Continued*)

TABLE B.3 Summary of previous research analyzing crash-frequency data.—cont'd

Model type	Previous research
Poisson-lognormal	Miaou et al. (2005), Lord and Miranda-Moreno (2008), Aguero-Valverde and Jovanils (2008), Aguero-Valverde (2013), Dong et al. (2016), Guo et al. (2017)
Conway–Maxwell–Poisson	Lord et al. (2008, 2010), Geedipally and Lord (2011), Giuffrè et al. (2011), Francis et al. (2012), Lord and Guikema (2012)
Zero-inflated Poisson and negative binomial[a]	Miaou (1994), Shankar et al. (1997), Carson and Mannering (2001), Lee and Mannering (2002), Kumara and Chin (2003), Shankar et al. (2003), Qin et al. (2004), Lord et al. (2007), Malyshkina and Mannering (2010), Jang et al. (2010), Dong et al. (2014), Cai et al. (2016)
Hurdle Poisson and negative binomial[a]	Son et al. (2011), Hosseinpour et al. (2013), Hosseinpour et al. (2014), Cai et al. (2016)
Negative binomial–Lindley and negative binomial–generalized exponential	Lord and Geedipally (2011), Geedipally et al. (2012), Aryuyuen and Bodhisuwan (2013), Vangala et al. (2015), Rahman Shaon and Qin (2016), Shaon et al. (2018)
Generalized estimating equation	Lord and Persaud (2000), Lord et al. (2005), Wang and Abdel-Aty (2008), Lord and Mahlawat (2009), Mohammadi et al. (2014), Cools and Moons (2016)
Copula-based models	Nashad et al. (2016), Yasmin et al. (2018), Wang et al. (2019), Zou et al. (2019)
Random effects	Johansson (1996), Shankar et al. (1998), Chin and Quddus (2003), Miaou and Lord (2003), Flahaut et al. (2003), Miaou et al. (2003), MacNab (2004), Miaou et al. (2005), Wang and Abdel-Aty (2006), Aguero-Valverde and Jovanils (2008), Li et al. (2008), Quddus (2008), Guo et al. (2010), Aguero-Valverde and Jovanis (2010), Mitra and Washington (2012), Castro et al. (2012), Narayanamoorthy et al. (2013), Aguero-Valverde (2013), Yu et al. (2013), Mohammadi et al. (2014), Xie et al. (2014), Naznin et al. (2016), Hou et al. (2018)
Bivariate/multivariate	Maher (1990), Miaou and Lord (2003), Miaou and Song (2005), Bijleveld (2005), Song et al. (2006), Ma and Kockelman (2006), Park and Lord (2007), Bonneson and Pratt (2008), Ma et al. (2008), Depaire et al. (2008), Ye et al. (2009), Geedipally and Lord (2010), Aguero-Valverde and Jovanis (2009), El-Basyouny and Sayed (2009), Park et al. (2010), Wang et al. (2011), Lao et al. (2011), Pei et al. (2011), Anastasopoulos et al. (2012), Castro et al. (2012), Narayanamoorthy et al. (2013), Chiou and Fu (2013), Caliendo et al. (2013), Yu and Abdel-Aty (2013), Dong et al. (2014), Barua et al. (2014), Lee et al. (2015), Serhiyenko et al. (2016), Wang et al. (2017), Cheng et al. (2018), Alarifi et al. (2018), Hosseinpour et al. (2018), Shaon et al. (2019)

TABLE B.3 Summary of previous research analyzing crash-frequency data.—cont'd

Model type	Previous research
Finite mixture/Markov switching/Dirichlet mixture	Park and Lord (2009), Malyshkina et al. (2009), Park et al. (2010), Peng and Lord (2011), Malyshkina and Mannering (2010), Zou et al. (2013, 2014), Buddhavarapu et al. (2016), Park et al. (2016), Heydari et al. (2016), Shirazi et al. (2016)
Random parameters	Anastasopoulos and Mannering (2009), El-Basyouny and Sayed (2009), Garnowski and Manner (2011), Venkataraman et al. (2011), Ukkusuri et al. (2011), Mitra and Washington (2012), Wu et al. (2013), Bullough et al. (2013), Castro et al. (2012), Narayanamoorthy et al. (2013), Bhat et al. (2014), Venkataraman et al. (2013), Chen and Tarko (2014), Barua et al. (2016), Buddhavarapu et al. (2016), Hou et al. (2018), Afghari et al. (2018)

[a]*Included for completeness. See Chapter 3 for a discussion about important methodological deficiencies related to these models.*

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TABLE B.4 Summary of previous research analyzing crash-injury severities.

Model type	Previous research
Binary logit/probit	Shibata and Fukuda (1994), Farmer et al. (1997), Khattak et al. (1998), Krull et al. (2000), Al-Ghamdi (2002), Bedard et al. (2002), Toy and Hammitt (2003), Ballesteros et al. (2004), Chang and Yeh (2006), Sze and Wong (2007), Lee and Abdel-Aty (2008), Pai and Saleh (2008), Rifaat and Tay (2009), Haleem and Abdel-Aty (2010), Peek-Asa et al. (2010), Kononen et al. (2011), Moudon et al. (2011), Santolino et al. (2012), Altwaijri et al. (2012), Weiss et al. (2014), Olszewski et al. (2015), Haleem (2016)
Ordered logit/probit	Khattak et al. (1998), Klop and Khattak (1999), Renski et al. (1999), Khattak (2001), Kockelman and Kweon (2002), Khattak et al. (2002), Quddus et al. (2002), Abdel-Aty (2003), Austin and Faigin (2003), Kweon and Kockelman (2003), Zajac and Ivan (2003), Khattak and Rocha (2003), Yamamoto and Shankar (2004), Donnell and Mason Jr. (2004), Khattak and Targa (2004), Abdel-Aty and Keller (2005), Lee and Abdel-Aty (2005), Shimamura et al. (2005), Garder (2006), Oh (2006), Siddiqui et al. (2006), Pai (2009), Gray et al. (2008), Chimba and Sando (2009), Wang et al. (2009), Pai (2009), Haleem and Abdel-Aty (2010), Jung et al. (2010), Quddus et al. (2010), Ye and Lord (2011), Zhu and Srinivasan (2011), Ferreira and Couto (2012), Abay (2013), Jiang et al. (2013), Eluru (2013), Mergia et al. (2013), Yasmin and Eluru (2013), Ye and Lord (2014), Sasidharan and Menéndez (2014), Zhao and Khattak (2015), Osman et al. (2016), Chen et al. (2016), Pour-Rouholamin and Zhou (2016), Jalayer et al. (2018), Shaon and Qin (2020)

(Continued)

TABLE B.4 Summary of previous research analyzing crash-injury severities.—cont'd

Model type	Previous research
Sequential logit/probit	Saccomanno et al. (1996), Dissanayake and Lu (2002), Dissanayake and Lu (2002), Helai et al. (2008), Yamamoto et al. (2008), Jung et al. (2010), Xu et al. (2013)
Generalized ordered logit	Wang and Abdel-Aty (2008), Srinivasan (2002), Eluru et al. (2008), Quddus et al. (2010), Castro et al. (2013), Eluru (2013), Yasmin and Eluru (2013), Yasmin et al. (2014a,b), Eluru and Yasmin (2015), Chen and Shen (2016), Osman et al. (2016), Pour-Rouholamin and Zhou (2016)
Multinomial logit	Shankar and Mannering (1996), Carson and Mannering (2001), Abdel-Aty and Abdelwahab (2004), Ulfarsson and Mannering (2004), Khorashadi et al. (2005), Islam and Mannering (2006), Kim et al. (2007), Malyshkina and Mannering (2008), Savolainen and Ghosh (2008), Schneider et al. (2009), Malyshkina and Mannering (2008), Malyshkina and Mannering (2010), Rifaat et al. (2011), Ye and Lord (2011), Eluru (2013), Yasmin and Eluru (2013), Ye and Lord (2014), Sasidharan and Menéndez (2014), Roque et al. (2015), Zhao and Khattak (2015), Shea et al. (2015), Osman et al. (2016), Wu et al. (2016)
Nested logit	Shankar et al. (1996), Chang and Mannering (1998, 1999), Lee and Mannering (2002), Abdel-Aty and Abdelwahab (2004), Holdridge et al. (2005), Savolainen and Mannering (2007), Haleem and Abdel-Aty (2010), Hu and Donnell (2010), Patil et al. (2012), Wu et al. (2013), Yasmin and Eluru (2013), Wu et al. (2016), Osman et al. (2016)
Copula-based models	Eluru et al. (2010), Yasmin et al. (2014), Wang et al. (2015), Wali et al. (2018)
Mixed logit/random parameters logit	Milton et al. (2008), Kim et al. (2008, 2010), Malyshkina and Mannering (2010), Anastasopoulos and Mannering (2011), Moore et al. (2011), Ye and Lord (2011), Morgan and Mannering (2011), Chen and Chen (2011), Chiou et al. (2013), Kim et al. (2013), Aziz et al. (2013), Manner and Wuensch-Ziegler (2013), Yasmin and Eluru (2013), Ye and Lord (2014), Cerwick et al. (2014), Behnood and Mannering (2015), Wu et al. (2014), Quddus (2015), Roque et al. (2015), Behnood and Mannering (2016), Wu et al. (2016), Li et al. (2019), Waseem et al. (2019), Chang et al. (2019)

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