Comparison of an Injury Prediction Algorithm for Japan and the U.S. Using Field Accident Data

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Abstract The innovative Advanced Automatic Collision Notification (AACN) uses the URGENCY algorithm, which is studied and developed using the National Automotive Sampling System Crashworthiness Data System (NASS-CDS). The objectives of this study are to clarify the adaptation of the URGENCY algorithm to Japan and to the U.S. and to ascertain the important issues in predicting injuries. Accident data for 2000–2009 were obtained from the Institute for Traffic Accident Research and Data Analysis in-depth accident investigation database in Japan, and the NASS-CDS in the U.S. Crashes are classified as head-on crashes, frontal single-vehicle crashes, nearside (driver-side) crashes, and farside crashes.

The results of the present study show that the performance for frontal crashes is almost the same for the two countries; however, the performance for side-impact crashes is different, and the balance between the sensitivity and the rate of overtriage for Japan is worse than that for the U.S. The under- and overtriage cases include some unusual accidents that indicate a need to improve the injury prediction algorithm for both Japan and the U.S. The cutoff value of the injury prediction algorithm is important for determining the overall balance of field triage decisions, and optimization must consider the accident conditions.

Keywords Advance Automatic Collision Notification, Injury prediction, Safety, URGENCY algorithm

I. INTRODUCTION

For 2012 in Japan, the number of traffic accident fatalities is 4,411 occurring within 24 h or 5,237 occurring within 30 days; furthermore, 829,807 total casualties, which mean minor injuries and greater, occurred. The Japanese government has set a new target for traffic accidents with the aim of achieving the safest road traffic in the world: by 2015, no more than 2.8 fatalities per 100,000 people in a year. The net targets are no more than 3,000 fatalities and 700,000 total casualties per year. However, the current annual decrease in the rate of total casualties is around 5%, which is slower than it had been for the decade before. To achieve these targets, it is necessary to identify and study factors that contribute to traffic accidents and to find more effective countermeasures.

Passive safety technology, such as airbag systems or body-structure designs, helps reduce occupant injury risks; moreover, active safety technology, such as crash-avoidance systems or stability control systems, helps reduce traffic accidents. However, crashes still happen and effective rescue care provides an essential safety net. For this purpose, one of the key technologies is the Advance Automatic Collision Notification (AACN). Just after a crash of a vehicle equipped with the AACN, the severity of occupant injuries are predicted using an injury prediction algorithm, and a call is automatically placed to emergency rescue services in order to quickly determine the best method of transport of any seriously injured occupants to a suitable trauma center.

The point of interest here is the URGENCY algorithm of the AACN, which predicts injuries and initiates requests for help. This algorithm has been studied and developed using the National Automotive Sampling System Crashworthiness Data System (NASS-CDS) in the U.S. Malliaris et al. indicated 21 predictors, including delta-V, seat belt use, and crash direction, using logistic regression models as the basis of the URGENCY algorithm [1]. Augenstein et al. confirmed the algorithm using trauma center cases of frontal crashes, and indicated the validity and improvements for pole crashes and multiple crashes [2]. In the Augenstein et al. studies, regression models for multiple impacts were presented and validated using the NASS-CDS data and the Crash Injury Research and Engineering Network (CIREN) case data [3, 4]. Furthermore, Augenstein et al. studied more practical uses of the injury prediction model and discussed some useful variables [5].

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The Centers for Disease Control and Prevention of the U.S. (CDC-US) published the recommendations for the AACN and for triage of the injured patient, which state that a high risk should be considered a risk of severe injuries of 20% or greater [6]. In the U.S., the application of the AACN to some vehicles using the URGENCY algorithm has begun [7], and similar algorithm was developed with CDC-US Expert Panel [8]. In Japan, the need for the AACN combined with the Helicopter Emergency Medical Service has been increasing [9]. Many studies of injury prediction modeling have been conducted using accident data [10, 11] and simulations [12, 13]. These studies show numerous predictors with many viewpoints; however, they have not yet led to practical implementations.

The injury prediction method and influential factors in frontal crashes was examined in a previous study using the in-depth accident investigation database of the Institute for Traffic Accident Research and Data Analysis (ITARDA Micro Data) [14]. However, it is also important for validating Japanese data to compare data from the U.S. because the ITARDA Micro Data have sampling limitations. Furthermore, if a common algorithm can be confirmed for traffic accidents throughout the world, this will lead to the spread the AACN. This study investigates the similarities and differences between Japan and the U.S. for sensitivity, specificity, and outlier cases, using the injury prediction models with the URGENCY algorithm. This comparison makes it possible to clarify the adaptations of the injury prediction model and to determine the issues of accurate injury prediction for not only Japan but also the U.S. Moreover, this comparison promotes the common AACN in both countries, which indicates advantages and improvements of URGENCY algorithm.

II. METHODS

Flow of the Study

The goal of this study is to clarify the adaptations of the injury prediction algorithm URGENCY, which was studied and developed using the NASS-CDS database in the U.S., and to determine the issues of the algorithm for not only Japan, but also the U.S., by comparing the sensitivity in Japan to that in the U.S. The flow of the study is as follows: first, accidents were sampled from each database. Second, the injury prediction algorithm was adapted to the accidents, and the sensitivity, rate of overtriage (the actual injuries were less severe than the predicted injuries), and rate of undertriage (the actual injuries were more severe than the predicted injuries) were analyzed and compared for each database. The aim of the adaptation to the U.S. database is to obtain a reference performance value for the URGENCY algorithm in the U.S. Third, cases of major under- and overtriage were extracted from both databases, and this set of unusual accident conditions were compared to the injury prediction algorithms for Japan and the U.S. Finally, an improved injury prediction algorithm was examined using additional factors based on the unusual accidents.

TABLE 1
Definition of sensitivity and rate of overtriage [15]

	Injury severity	
Prediction	Severe	Not severe
Severe	a	b
Not severe	c	d

Sensitivity = a/(a+c)
Specificity = d/(b+d)
Rate of undertriage = c/(a+c)
Rate of overtriage = b/(b+d)
O/U ratio = b/c (This is defined in this paper.)

The definitions used in this study are shown in Table 1. The overtriage rate is the same as the more generally used term, 1-specificity.

Data Sources

The subject data sources are drivers involved in crashes involving small and regular-sized passenger vehicles, vans, SUVs, and pickup trucks during the period 2000–2009. For Japan, they include Kei cars (light vehicles with an engine displacement of 660 cc or less) and Kei trucks (light trucks with an engine displacement of 660 cc or less), which are vehicles unique to Japan. The accident types analyzed are head-on crashes (H-on), frontal single-vehicle crashes (f-SVC), nearside (driver-side) crashes (Nearside), and farside crashes (Farside). These types are defined in terms of accident type and impact direction, using the Collision Deformation Classification (CDC) codes, as shown in Table 2.

TABLE 2
Data sources of Japan and the U.S.

	ITARDA Micro Data 2000 – 2009		NASS-CDS 2000 – 2009		
Accident type	CDC code	unweighted	CDC code	unweighted	weighted
H-on	11F– 01F	133	11F – 01F	678	89,126
f-SVC	11F – 01F	116	11F – 01F	1,697	431,045
Nearside	02R – 04R	93	08L – 10L	406	99,743
Farside	08L – 10L	136	02R – 04R	342	75,373
Total		478		3,123	695,287

ITARDA Micro Data for Japan: There are two major traffic accident databases in Japan: ITARDA Macro Data, which is a database of all the traffic accidents that occur throughout Japan; and ITARDA Micro Data, which is an in-depth accident investigation database. ITARDA Macro Data is based on police reports; however, it does not have specific crash outcomes, for example the delta-V, or the AIS code. ITARDA Micro Data has this specific information, but it is limited to only Tsukuba city, which is located about 60 km north of Tokyo. There is no method for weighting cases to estimate entire Japan crashes using ITARDA Micro Data. In a previous study, an injury prediction model using the ITARDA Micro Data and a model that corresponds with the documented accident data in the ITARDA Macro Data were examined [14]. Therefore, in this study, the ITARDA Micro Data is used as representative of all accidents in Japan. The total number of samples, without missing values, was 478. The number of each type of accident is shown in Table 2.

NASS-CDS Data for the U.S.: The NASS-CDS database is the largest and the most utilized database of crash outcomes in the U.S. Many researchers use it when they analyze accidents or perform statistical analyses of safety. The injury prediction algorithm URGENCY was studied and developed using the NASS-CDS. In the NASS-CDS, there is a weighting factor called the *ratio inflation factor* for each case sample, and it estimates the total number of similar accidents in the entire U.S. The *ratio inflation factor* is the estimated number of each case sample, which occurred during the year in the U.S. In this study, the NASS-CDS weighted by the *ratio inflation factor* means the estimated number of accidents in the U.S., and is used as representative of all accidents in the U.S.

Injury Prediction Model

In this study, the latest injury prediction model the URGENCY algorithm using the NASS-CDS, was used as the basis to predict injury bases on crash data in Japan and U.S. The predictors are impact direction, delta-V, multiple impact, rollover, and seat belt use. The logistic regression equation is as follows:

$$P(MAIS3+) = \frac{1}{(1+\exp(-w))} \qquad (1)$$

$$w = \beta_0 + \sum_{i=1}^{n} \beta_i\, x_i \qquad (2)$$

where P (MAIS3+) is the probability that the maximum AIS code (MAIS) is 3 or more (considered to be a serious injury level), β_0 is the intercept, β_i are the coefficients of the predictors x_i, and n is the number of predictors. These coefficients are shown in Table 3.

It is necessary to have a cutoff value for P (MAIS3+). The CDC-US recommends in their rescue handbook a cutoff value of 0.2 or more using Injury Severity Score (ISS) [6]. This means that a probability of 0.2 or more is judged as a serious injury situation. In this study, this recommended cutoff value is used with P (MAIS3+).

TABLE 3
Coefficients for URGENCY algorithm [16]

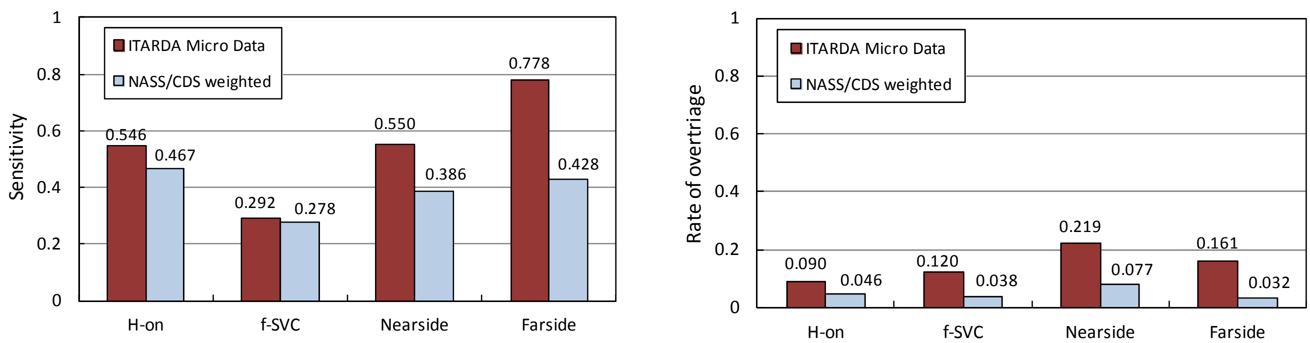
Variable	Frontal[a)]		Nearside		Farside	
Intercept	–5.2321	(p=<0.001)	–5.9529	(p=<0.001)	–5.0963	(p=<0.001)
Delta-V	0.1335	(p=<0.001)	0.2092	(p=<0.001)	0.1641	(p=<0.001)
Multiple impact	0.2743	(p=0.02)	1.0401	(p=<0.001)	0.6528	(p=0.11)
Rollover	1.5260	(p=0.001)	–0.4525	(p=<0.001)	0.8247	(p=0.74)
Seat belt use	–1.1045	(p=<0.001)	–0.5558	(p=<0.01)	–1.9522	(p=<0.001)

a) Frontal: all frontal crash modes including head-on crashes and frontal single-vehicle crashes

III. RESULTS

Sensitivity and Rate of Overtriage

Figure 1 shows the sensitivity and rate of overtriage at the cutoff ratio 0.2 for each crash type and for both the ITARDA Micro Data and the NASS-CDS data. For head-on crashes and frontal single-vehicle crashes, the sensitivity for Japan is the same as that for the U.S. The rates of overtriage are quite low in both databases; however, the rate of overtriage for Japan is about 2–3 times as large as that for the U.S. In both nearside and farside crashes, the sensitivity for Japan is about 1.5 times as large as that for the U.S.; furthermore, the rate of overtriage for Japan is about 3–5 times as large as that for the U.S. This indicates that the performance for frontal crashes is almost the same; however, the performance for side-impact crashes is different, and the balance between the sensitivity and the rate of overtriage for Japan is worse than that for the U.S.



(a) Sensitivity (b) Rate of overtriage

Fig. 1. Comparison of ITARDA Micro Data and NASS-CDS weighted for each crash type.

Undertriage Cases

Undertriage accidents are those for which no serious injuries were predicted, but in which occupants were seriously injured. Reducing the number of undertriage accidents, which can be accomplished by improving the injury prediction algorithm, saves lives. In this study, the injury prediction algorithm used a cutoff value of 0.2 to indicate the undertriage cases in both databases. Note that some accidents fall into more than one category.

Head-on Crashes: Table 4 shows the number of major undertriage cases in head-on crashes for each database. In head-on crashes, many undertriage cases have a lack of airbag deployment or the impact with a heavy truck. The current AACN is operated by an airbag deployment signal. The rate of head-on crashes where there was no airbag system was about 41% for the ITARDA Micro Data and about 25% for the NASS-CDS weighted data. The rate of undertriage cases when there was no airbag deployment system was higher than those in the sampling cases. Therefore, crashes without airbag deployment are noteworthy cases. However, these percentages of vehicles without airbag system in crashes will continue to decrease as the vehicle fleet approaches 100% with frontal airbag. It is also worth noting that many cases involving light vehicles, especially for Japanese Kei cars and short-statured female drivers, occur in Japan, and they are an accident category in Japan. In this study, the definition of short-statured female is a female with less than 155 cm height, which is close to the average – S.D. (approximately 16 percentile) of Japanese female height. Therefore, these undertriage cases are issues for the accuracy of the injury prediction algorithm in Japan.

TABLE 4
Undertriage cases in head-on crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Without airbag deployment (including no airbag)	7	46.7%	3,810	34.7%
Heavy truck impacts	3	20.0%	3,276	29.9%
Kei cars (or light vehicle < 900kg)	8	53.3%	115	1.0%
Short-statured female drivers (<155cm)	4	26.7%	594	5.4%
Total	15		10,966	

Frontal Single-Vehicle Crashes: Table 5 shows the major undertriage cases in frontal single-vehicle crashes for each database. Many undertriage cases are due to the lack of an airbag deployment system, which is also the case for head-on crashes. A pole impact crash is a common example, especially in the U.S., of a frontal single-vehicle crashes that is also likely to be an undertriage case. The reason for the higher rate of overtriage of frontal pole impact crashes in the U.S. may depend on the rate of the sampling cases. The rate of the frontal pole impact crashes in the frontal single-vehicle crashes is about 35% for the ITARDA Micro Data and about 48% for the NASS-CDS weighted data. Comparing these rates of sampling frontal pole impact crashes with the rates of undertriage cases of frontal pole impact crashes in each database, the rates of undertriage cases of frontal pole impact crashes are higher in the U.S. The accuracy of the injury prediction algorithm for frontal pole impact crashes is one of the issues in Japan and the U.S. Augenstein et al. indicate that pole impact crashes have some errors in the injury prediction [2]. In an earlier work [17], the frontal pole impact crashes using the ITARDA Micro Data and the ITARDA Macro Data in Japan exampled. The frontal pole impact crashes have high injury risks if the vehicle collides with an unbroken pole at the right or left corner of front end. The sensitivity of injury prediction for frontal single-vehicle crashes can be improved by the consideration of impact position and breakage of a pole. However, it would be difficult for the AACN to measure these factors automatically after crashes at the moment.

TABLE 5
Undertriage cases in frontal single-vehicle crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Without airbag deployment (including no airbag)	9	52.9%	15,501	46.5%
Frontal pole impacts (pole, tree)	3	17.6%	20,040	60.2%
Kei cars (or light vehicle < 900kg)	7	41.2%	186	0.6%
Short-statured female drivers (<155cm)	1	5.9%	1,254	3.8%
Total	17		33,300	

Nearside Crashes: Table 6 shows the major undertriage cases in nearside crashes for each database. Many of these undertriage cases involve heavy truck side impacts and SUV side impacts or elderly drivers (55 or older). In nearside crashes, the impacts with larger and heavier trucks cause larger deformation of doors and pillars; therefore, they result in higher risks for the driver. The predictor delta-V represents the risk of vehicle deformation; however, the URGENCY algorithm does not include the intrusion factor directly. One of the reasons for the undertriage of elderly occupants is the reduced skeletal resistance as compared to younger occupants, in particular, the resistance of older ribs is less than that of younger ones [18]. The influence of occupant age occurs primarily in side-impact crashes because the occupants tend to sustain their rib fractures from vehicle's side panels. Occupant age is thus an important factor for the injury prediction algorithm. Undertriage of short-statured female drivers is also observed in nearside crashes in Japan; however, the result has a large uncertainty because the total number of cases is quite small.

TABLE 6

Undertriage cases in nearside crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Heavy truck impacts	5	55.6%	1,522	24.6%
SUV impacts	2	22.2%	1,559	25.2%
Elderly drivers (55+ yrs old)	5	55.6%	4,601	74.2%
Short-statured female drivers (<155cm)	1	11.1%	109	1.8%
Total	9		6,198	

Farside Crashes: Table 7 shows the major undertriage cases for farside crashes for each database. As for the nearside crashes, many undertriage accident cases involve heavy truck side impacts, SUV side impacts, and elderly drivers. The rate of undertriage for elderly drivers in farside crashes is smaller than that in nearside crashes. One of the reasons is that there is no direct contact the driver's chest from the side panels since the impacts are on the opposite side of the vehicle. An undertriage case involving short-statured female drivers also is observed in farside crashes in Japan; however, the number of the abstracted cases is quite small.

TABLE 7

Undertriage cases in farside crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Heavy truck impacts	2	50.0%	304	17.9%
SUV impacts	2	50.0%	558	34.6%
Elderly drivers (55+ yrs old)	2	50.0%	748	44.0%
Short-statured female drivers (<155cm)	1	25.0%	13	0.8%
Total	4		1,701	

Overtriage Cases

Overtriage cases are those for which serious injuries were predicted but in which no occupants were seriously injured. These cases are important for the rescue care capacity. Some overtriage should be accepted in the field; however, a high rate of overtriage overtaxes the emergency medical system. Therefore, it is important to balance the sensitivity and control the rate of overtriage for the AACN. In this study, the injury prediction algorithm used a cutoff value of 0.2 to indicate the overtriage cases for each database.

Head-on Crashes: Table 8 shows the number of major overtriage cases for head-on crashes for each database. Many head-on crashes involve young drivers (less than 30 years old). This indicates that the URGENCY algorithm shows a higher probability of serious injury for young drivers. Therefore, the injury prediction algorithm could be improved by considering the factor of occupant age. The algorithm studied by Augenstein et al. involved a predictor of occupant age [3]; however, it is difficult for the AACN to judge occupant age automatically, and so the occupant age factor was removed from the AACN in practice. In the U.S., there are cases of large (185 cm or taller) and heavy (90 kg or heavier) people. In ITARDA Micro Data, heavier occupants have lower injury risks; however, taller occupants have higher injury risks [14]. It needs further studies on the injury mechanism for larger occupants. Cases with seatbelts, airbag deployment, and a delta-V of over 75 km/h, are sometimes overtriage cases in Japan. Accidents with a delta-V of 75 km/h or more are rare in Japan, compared to the U.S. This may be why they are overtriage cases in Japan.

TABLE 8
Overtriage accident cases in head-on crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Young drivers (<30 yrs old)	7	77.8%	1,066	33.8%
Belted with airbag and delta-V 75km/h+	2	22.2%	128	4.1%
Large drivers (185cm+ and 90kg+)	0	0%	1,228	38.9%
Total	9		3,157	

Frontal Single-Vehicle Crashes: Table 9 shows the major overtriage cases for frontal single-vehicle crashes for each database. As is true for head-on crashes, many cases of frontal single-vehicle crashes involving young drivers (less than 30 years old) are cases of overtriage. In the U.S., large drivers are observed. In Japan, traffic barrier impacts, including guardrail impacts, occur. These structures are designed to mitigate impacts and prevent departure from the lane. They reduce the risks to the occupants, compared to other structures. Cases with seat belts, airbag deployment, and delta-V of 75 km/h or more are not often observed in Japan.

TABLE 9
Overtriage cases in frontal single-vehicle crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Young drivers (<30 yrs old)	5	45.5%	10,868	73.6%
Belted with airbag and delta-V 75km/h+	1	9.1%	315	2.1%
Large drivers (185cm+ and 90kg+)	0	0%	2,437	16.5%
Traffic barrier impacts (including guardrail)	3	27.3%	326	2.2%
Total	11		14,764	

Nearside Crashes: Table 10 shows the major overtriage cases for nearside crashes for each database. Many nearside crashes with multiple impacts are overtriaged. This indicates that URGENCY overestimates the risk of multiple impacts in the case of nearside crashes. Also, young drivers are frequently observed in nearside crashes. Furthermore, short-statured female drivers and vehicles with heavier curb weight (1,300 kg or heavier) are frequently observed in nearside crashes. There are cases of short-statured female drivers both in under- and overtriage cases. There are likely errors in these results because the number of cases is small, except for the overtriage cases in the NASS-CDS weighted data.

TABLE 10
Overtriage cases in nearside crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Multiple impacts	12	75.0%	3,050	44.1%
Young drivers (<30 yrs old)	6	37.5%	4,487	64.9%
Short-statured female drivers (<155cm)	4	25.0%	1,536	22.2%
Vehicle curb weight 1,300kg+	4	25.0%	4,117	59.6%
Total	16		6,910	

Farside Crashes: Table 11 shows the major overtriage cases for farside crashes for each database. As for nearside crashes, many farside crashes with multiple impacts are overtriage cases. Also, young drivers in farside crashes are common, as are cases of unbelted drivers. In farside crashes, the driver can be moved inside the vehicle during the crash; therefore, seat belt use is effective for preventing this movement or contact with parts of a vehicle. The effect of seat belt use in farside crashes in the URGENCY algorithm is estimated to be higher than that in nearside crashes. Cases of short-statured female drivers are found in overtriage cases in Japan, and there are likely errors due to the small sample size.

TABLE 11
Overtriage cases in farside crashes

	ITARDA Micro Data		NASS-CDS weighted	
	Number	%	Number	%
Multiple impacts	14	73.7%	2,200	94.2%
Unbelted	10	52.6%	1,676	71.8%
Young drivers (<30 yrs old)	3	15.8%	747	32.0%
Short-statured female drivers (<155cm)	3	15.8%	27	1.2%
Total	19		2,335	

Improvement of Injury Prediction Model

In under- and overtriage cases, occupant age is sometimes a factor. Therefore, one of the improvements considered in this study is adding an occupant age factor to the injury prediction algorithm. In order to ascertain the effect of age, the age factor was added to the current injury prediction algorithm URGENCY, but the other coefficients were left unchanged.

The occupant age factor is calculated by the odds ratio of the defined age regions using the NASS-CDS weighted data [13]. The drivers in accidents were categorized into three groups: 16–29 years old, 30–54 years old, and 55 or older. Statistically analyzed odds ratios for each crash type are shown in Table 12.

TABLE 12
Population and odds ratio for occupant age groups using NASS-CDS weighted

Age groups		H-on	f-SVC	Nearside	Farside
16-29	MAIS3+	8,258	13,472	2,218	683
	MAIS<3	32,649	218,355	32,075	32,059
	OR_{29-}	0.740	0.350	1.200	0.782
30-54	MAIS3+	7,954	22,278	1,938	668
	MAIS<3	23,278	126,390	33,623	24,510
	Reference of odds ratio	1	1	1	1
55+	MAIS3+	4,367	10,399	5,941	1,623
	MAIS<3	12,619	40,146	23,947	15,830
	OR_{55+}	1.013	1,470	4.304	3.760

The equations of the odds ratios of OR_{29-} and OR_{55+}, for reference of the middle age group, are shown as follows:

$$OR_{29-} = \frac{P_{29-}/\ (\ 1 - P_{29-})}{P_{ref}\ /\ (1 - P_{ref}\ )} \qquad (3)$$

$$OR_{55+} = \frac{P_{55+}/\ (\ 1 - P_{55+})}{P_{ref}\ /\ (1 - P_{ref}\ )} \qquad (4)$$

where P_{29-} , P_{55+}, and P_{ref} are the probability of serious injury for the youngest group, oldest group, and middle age group. These probabilities are transformed using the standard probability P_{ref}, as follows:

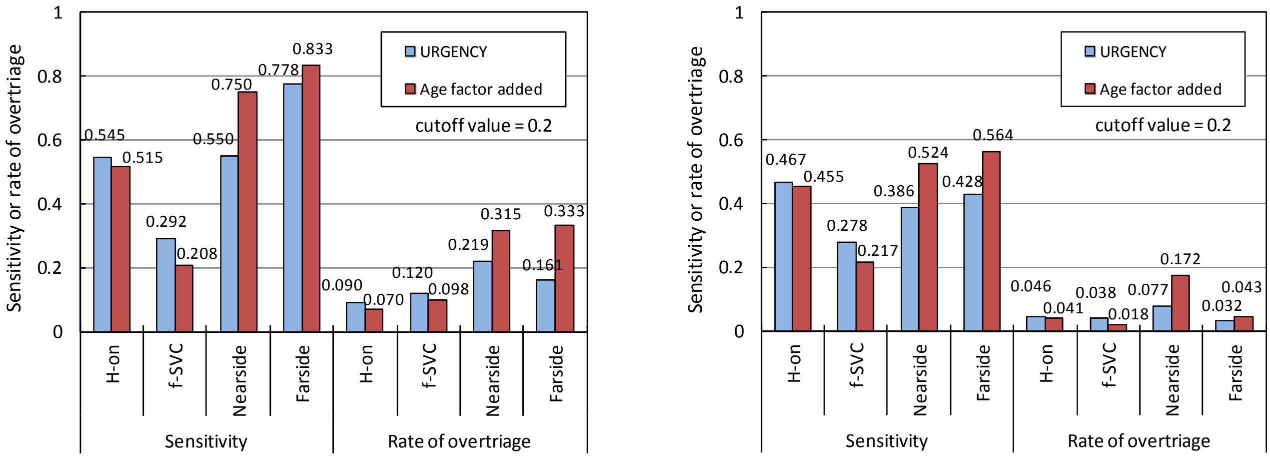
$$P_{29-} = \frac{OR_{29-} \cdot P_{ref}}{1 - P_{ref} + OR_{29-} \cdot P_{ref}} \qquad (5)$$

$$P_{55+} = \frac{OR_{55+} \cdot P_{ref}}{1 - P_{ref} + OR_{55+} \cdot P_{ref}} \qquad (6)$$

Equations (5) and (6) are the new injury prediction algorithms with the occupant age factor. The sensitivity and rate of overtriage are analyzed using this algorithm for each crash. Figure 2 shows the performance of the new algorithm for each database.

This new algorithm with an occupant age factor can improve the sensitivity, especially for nearside crashes and farside crashes. However, small increases were observed in the rate of overtriage. This is discussed below.

On the other hand, in frontal crashes, the rate of overtriage decreased; however, the sensitivity was not improved. One of the reasons is that the odds ratios for older occupants in head-on crashes and frontal single-vehicle crashes are smaller than those for nearside crashes and farside crashes (Table 12). This study used the age factor using the NASS-CDS weighted data. Different age factor using Japanese data could improve the sensitivity for Japan.



(a) For ITARDA Micro Data (b) For NASS-CDS weighted

Fig. 2. Effect of occupant age factor added to URGENCY algorithm.

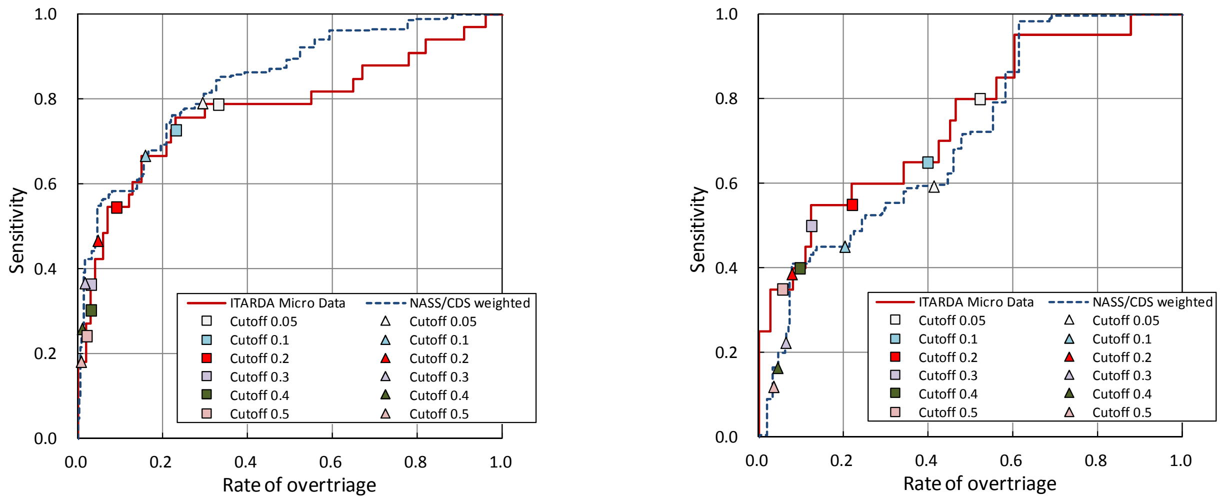
IV. DISCUSSION

Comparison of ROC Curve for Japan and the U.S.

The balance of sensitivity and rate of overtriage is important for the AACN. Increased sensitivity saves more occupants' lives, and a decreased rate of overtriage makes a better emergency medical system for everyone. This depends on the receiver operating characteristic (ROC) curve of the injury prediction model. The ROC curve is a plot of the sensitivity versus the 1-specificity (the rate of overtriage), and shows the cutoff value by which to judge a serious injury to occupants. The issues of the balance are indicated in the comparison between Japan and the U.S.; therefore, the ROC curve performances are compared between the ITARDA Micro Data and the NASS-CDS weighted data. Figure 3 shows the results of this comparison for head-on crashes and nearside crashes. These figures confirm the adaptation of the injury algorithm URGENCY and the optimal cutoff value for each database.

Figure 3(a) illustrates that, for head-on crashes, the ROC curve for Japan is similar to that for the U.S., and the optimal cutoff value is around 0.1 for each database. The optimal cutoff value is determined by the point of minimum distance from the Ideal ROC Point (IRP), which is the (0, 1) point in the ROC graph (this will be discussed below).

For nearside crashes, as shown in Figure 3(b), the ROC curve for Japan is almost the same as the one for the U.S; however, the positions of the cutoff values are different. The optimal cutoff value is 0.2 for Japan, and 0.1 for the U.S. Heavy truck impacts and SUV impacts are observed in nearside crashes with undertriage; therefore, the difference in the distribution of vehicle types between Japan and the U.S. results in different performances.



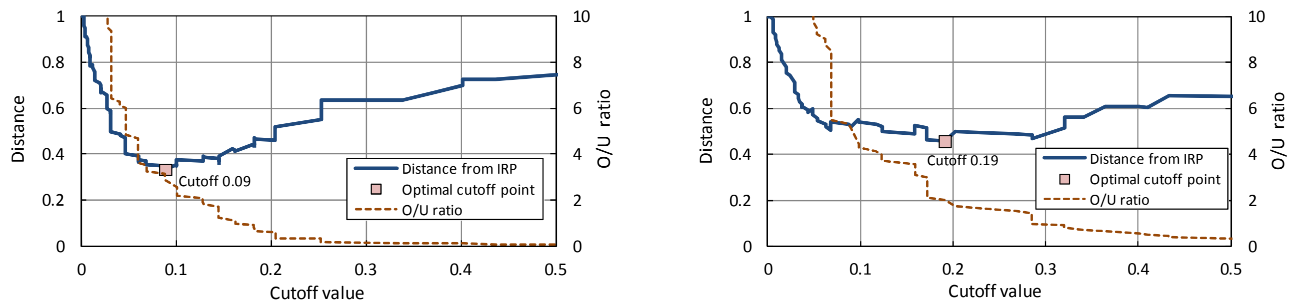
(a) Head-on crashes (b) Nearside crashes

Fig. 3. Comparison of ROC curve of ITARDA Micro Data and NASS-CDS weighted.

Optimization of Cutoff Value

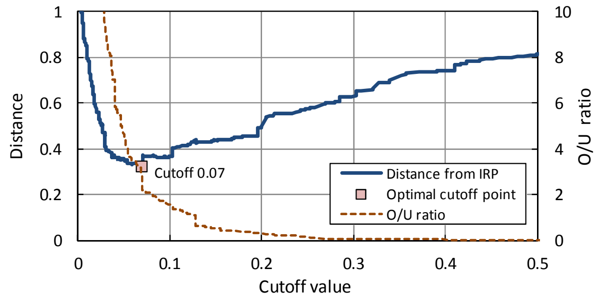
The CDC-US recommends that the cutoff value is 0.2 for a field triage decision scheme [6]. In this study, the results of the comparison show there are differences in the optimal cutoff value for each accident type and each country because the distribution of accident conditions is different. One idea is to optimize the cutoff values to correspond to the different conditions, e.g., to have different cutoff values for different accident types or countries.

Figures 4 and 5 show the optimal cutoff values for the ITARDA Micro Data and the NASS-CDS weighted data for head-on crashes and nearside crashes. The optimal cutoff value is determined by the IRP, the (0, 1) point in the ROC chart, as previously mentioned. In addition, the over- to undertriage cases ratios (O/U ratios) defined in Table 1 are shown in these same graphs. A higher O/U ratio means more overtriage cases compared to undertriage cases, so this ratio balances the social cost. If the O/U ratio is higher, the cost of emergency rescue services is more, but if the O/U ratio is lower, more lives are lost. At the point of the optimal cutoff value, the O/U ratio is around 4, which means there are 4 times as many overtriage cases as undertriage cases. The AACN should be implemented in such a way as to achieve this balance between overtriage and undertriage. It is difficult to determine what the optimal cutoff value is for each occupant or each trauma center; however, the best solution for the overall occupants should be considered. There is a limitation of current injury prediction algorithm; moreover, various cutoff values would cause some confusion. However, not only improvements in the accuracy of the injury prediction method, but also the correct total balance in field triage will lead to safer traffic.

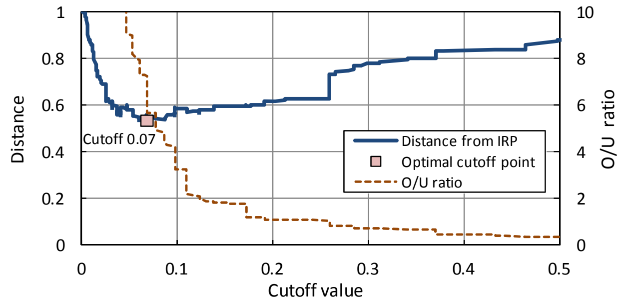


(a) Head-on Crashes (b) Nearside crashes

Fig. 4. Optimal cutoff value and O/U ratio in ITARDA Micro Data.



(a) Head-on Crashes



(b) Nearside crashes

Fig. 5. Optimal cutoff value and O/U ratio in NASS-CDS weighted.

Issue of Sampling Number

In this study, comparison is done by investigation using the ITARDA Micro Data and the NASS-CDS. The NASS-CDS data have a lot of sampling cases of around 10,000 a year, and weighting factors to estimate national data. On the contrary, the ITARDA Micro Data have fewer sampling cases of around 250 a year, and no official weighting factor; however, the ITARDA Micro Data can be validated by the ITARDA Macro Data, which is a database of all the traffic accidents that occur throughout Japan and have 800,000 cases a year. Therefore, the ITARDA Micro Data is used as representative of all accidents in Japan, and can be compared significantly.

However, lower sampling number may cause larger error of prediction, especially for outlier cases. Larger sampling has more advantages in statistical analysis. The error of ratio is generally in inverse proportion to the square root of sampling number. It is considered that there are some limitations because of fewer sampling in ITARDA Micro Data. This is an issue that needs further investigation.

It is better for statistical accident analysis to investigate more accidents in real field; however, it needs more time and higher cost. It is helpful for accident analysis to utilize accident databases in other countries by comparing them and making up for each other.

V. CONCLUSIONS

This study compares the sensitivity of the injury prediction algorithm URGENCY using the ITARDA Micro Data for Japan and the NASS-CDS for the U.S. The comparison of cases of under- and overtriage in accidents in Japan and the U.S. has led us to improvements in the injury prediction algorithm. The conclusions of this study are as follows:

(1) The sensitivity and the rate of overtriage in Japan are the same as that in the U.S. for head-on crashes and frontal single-vehicle crashes; however, for nearside crashes and farside crashes, the sensitivity and the rate of overtriage in Japan are different from that in the U.S., i.e., they are higher than that in the U.S.

(2) In both Japan and the U.S., the most frequent undertriage cases are frontal pole impacts or involve elderly drivers (55+ yrs old) in side-impact crashes. In addition, in Japan, many undertriage accident cases also involve light vehicles in frontal crashes and short-statured female drivers in side-impact crashes.

(3) In both Japan and the U.S., the most frequent overtriage cases involve young drivers (<30 yrs old) or multiple impacts in side-impact crashes. Other overtriage cases involve traffic barrier impact for single-vehicle crashes in Japan, and large drivers (185+ cm and 90+ kg) in frontal crashes in the U.S.

(4) The outlier cases indicate that occupant age is an important factor for improving the accuracy of the injury prediction algorithm. A model including a factor for occupant age can improve the sensitivity for side-impact crashes but not for frontal crashes.

(5) The cutoff value of the injury prediction algorithm is important for the balance of sensitivity and rate of overtriage. Optimization of the cutoff value needs to consider the conditions, including the type of accident and country it occurs.

(6) Lower sampling is one of issues in statistical accident analysis, it is helpful to utilize the other accident databases by comparing them and making up for each other.

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