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Extending the I-95 Rule-Based Incident Duration System With an Automated Knowledge Transferability Model

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Abstract

The rule-based incident duration prediction model (IDPM), covering Interstate highways I-95, I-495, and I-695, has been adopted by the Maryland Department of Transportation State Highway Administration in its daily responses to non-recurrent congestion. In light of its effectiveness and robustness in practice, expanding such a system to all other highways emerges as desirable but a challenging task, because of the need to integrate field operators' expertise in generating prediction rules and the dependence on sufficient incident records for key parameter calibration. To circumvent such a data-demanding and time-consuming process for knowledge acquisition and refinement for extending the IDPM's spatial coverage, this study has proposed a knowledge transferability analysis (KTA) method, featuring its automated process to assess, select, and transfer existing prediction rules to perform incident duration estimate for the new target highway. Evaluation of the proposed KTA with the incident records from Maryland I-70, using both transferred and customized local rules, reveals that it can achieve accuracy of 87% with the training dataset (i.e., 2016–2018) and 82% with the test dataset (i.e., 2019), comparable to the current system's performance but demanding much fewer incident records for model calibration and significantly less effort for system expansion.

Keywords

advanced traffic management systems, operations, incident management, incident management, policy and organization, executive management issues, knowledge management, knowledge management, knowledge transfer

It is well recognized that traffic incidents can result in reduction of a roadway's capacity and degradation of reliability, and also significant delays for commuters. Over the past several decades, many U.S. highway agencies have established Traffic Incident Management (TIM) systems to help mitigate such impacts and restore normal traffic conditions. A TIM system typically consists of a coordinated multi-disciplinary process to detect, respond to, and clear traffic incidents. It is expected that such a system can effectively reduce the clearance duration of detected incidents, and reduce the resulting impacts on traffic delay and safety. To do so, a TIM system first needs a reliable and robust model to predict the required duration for incident clearance operations, and then to assess its time-varying traffic queues as well as resulting delays, because such information is essential for determining the proper control strategies and the responsive traffic management tasks.

Transportation researchers have devoted significant efforts to developing incident duration prediction models (IDPMs) with a variety of techniques, including continuous statistical models (*1–20*), neural network approaches (*21–28*), discrete/classification methods (*29–34*), and hybrid modeling techniques (*35–43*). Despite the significant progress made by the traffic community on this subject, the implementation of such an imperative system to contend with non-recurrent congestion remains at the infancy stage. This is partly because of the large number of factors (see Table 1) that are critical to an incident's clearance time but difficult to collect at a desirable level of accuracy for system development. Moreover, the complex nature (e.g., discrete, continuous, or binary) of those critically associated factors and their distributions is inconsistent with the underlying assumptions of many statistical-based methods reported in the literature. In view of such constraints, Won et al. (*42*)

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Table 1. Factors Associated With the Clearance Time of a Detected Incident

Category	Variable	Classification
Incident type	Incident type	Collision with fatality (CF), Collision with personal injury (CPI), Collision with property damage (CPD)
Time	Hour indicator	Morning peak, Day time, Evening peak, Night
	Weekend indicator	Weekend, Weekday
	Holiday indicator	Holiday, Non-holiday
	Season indicator	Spring, Summer, Fall, Winter
Location	Direction indicator	Northbound, Southbound, Eastbound, Westbound
	Exit number indicator	Exit 1, Exit 2, …
Environmental conditions	Pavement condition indicator	Dry, Wet, Snow-ice, Chemical wet
	Hazard material related	Yes, No
Operation center	Center indicator	AOC, TOC3, TOC4, TOC5, SOC
Lane blockage information	# of blocked lanes	1, 2, 3, 4, …
	# of blocked shoulder lanes	0, 1, 2, 3, …
	# of blocked travel lanes	0, 1, 2, 3, …
	# of blocked auxiliary lanes	0, 1, 2, 3, …
	Travel lane blocked in tunnel	Yes, No
	Travel lane blocked in toll	Yes, No
Involved vehicle information	Vehicle status	Jack-knifed, Overturned, Lost load
	# of total involved vehicles	1, 2, 3, 4, …
	# of involved passenger cars	0, 1, 2, 3, …
	# of involved trucks	0, 1, 2, 3, …
	# of involved motorcycles	0, 1, 2, 3, …
Response unit information	# of total response units	1, 2, 3, 4, …
	# of arrived CHART	0, 1, 2, 3, …
	# of arrived police	0, 1, 2, 3, …
	# of arrived fireboard	0, 1, 2, 3, …
	# of arrived medical service	0, 1, 2, 3, …
	# of arrived tow service	0, 1, 2, 3, …
	First responder	CHART, Police, Fireboard, Medical, Tow

Note: AOC = Authority Operations Center; SOC = Statewide Operations Center; TOC = Traffic Operations Center; CHART = Coordinated Highways Action Response Team

explored the methodology of integrating the expertise of field responders and extensive information from the incident records to calibrate a rule-based IDPM. Their proposed knowledge-based model was first applied to Maryland I-95, and later extended to I-495 and I-695.

Further extension of the flexible and robust method by Won et al. (*42*) to other Maryland highways (such as I-70 and US 29), however, inevitably encounters the challenges of insufficient incident records for calibration of prediction rules and the need for significant involvement of experienced incident response operators. This study presents a knowledge transferability analysis (KTA) model, intending to explore the potential of constructing a new IDPM by transferring some of those prediction rules from existing IDPMs, based on their effectiveness, to the new target highway. With such a computerized and effective KTA model, traffic professionals would need to apply the resource-demanding method proposed by Won et al. (*42*) only to the small set of incidents that exhibit unique patterns and demand local-specific incident response resources.

The next section will first provide a brief description of the knowledge-based IDPM by Won et al. (*42*). This is followed by a detailed presentation of the proposed KTA method for new system construction. An application of the KTA to developing the IDPM for Maryland I-70 constitutes the core of its following section. Concluding comments and future research tasks are summarized in the last section.

Development of a Knowledge-Based IDPM

Figure 1 illustrates the development process proposed by Won et al. (*42*), using the association rule mining method (*44, 45*) for rule generation and statistical tests to construct prediction rules for different types of incidents.

Incident Categorization

Given the pre-processed incident dataset, first, all incident records from the target highway will be classified into several subsets based on the incident type and lane blockage information. For instance, all collisions resulting in lane closure, as shown in Figure 2, are typically divided into three categories: collision with personal injury (CPI), collision with property damage (CPD), and

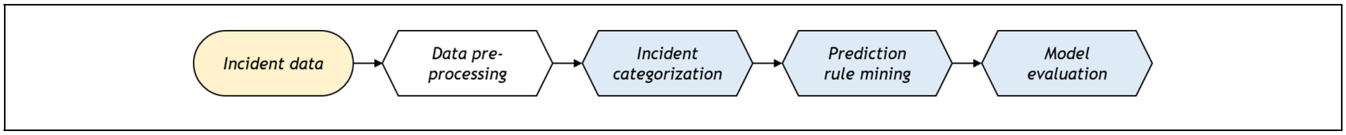

Figure 1. Development process of the knowledge-based incident duration prediction model (IDPM) (*2*).

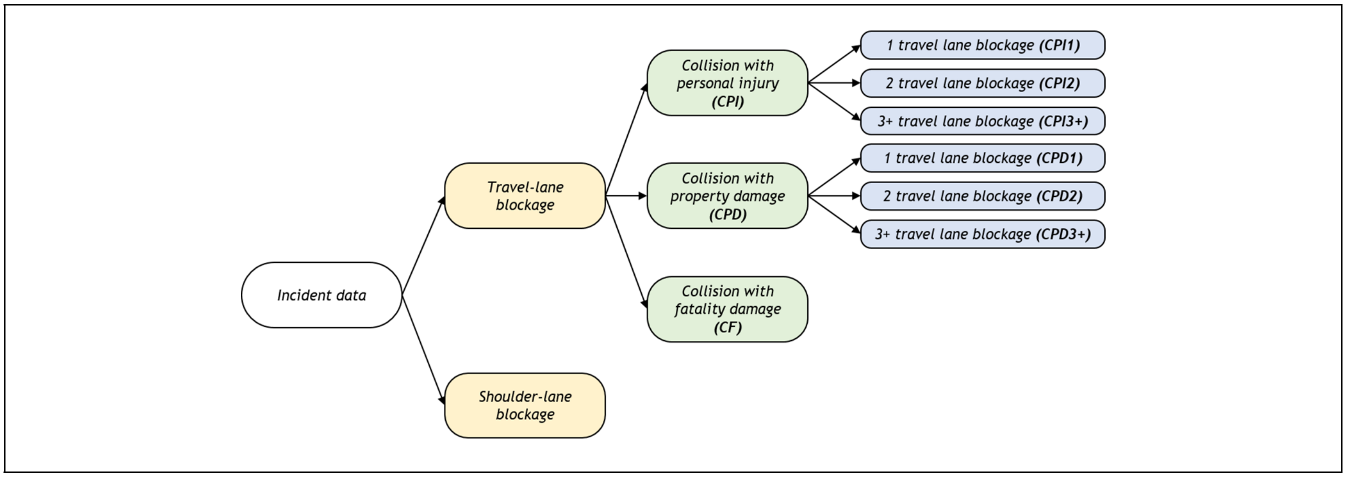

Figure 2. Incident categorization based on the incident type and lane blockage information.

collision with fatality (CF). Depending on the available incident records, one may further classify each of the three categories by the number of closed lanes. For instance, because of the small sample size and unique clearance duration pattern, all incidents in CF are grouped in one cluster. The incident records resulting in only shoulder lane blockage are not further decomposed either because the clearance times for all such incidents distribute consistently within a relatively stable and short interval.

Prediction Rules Mining Process

After the initial categorization of available incident records, one can then proceed with the following procedures to construct a set of "if-then" rules for the estimated clearance time for each of those finalized subsets of incidents:

CPI and CPD Incidents. The incident data in those six subsets of CPI and CPD would be first classified into two classes of "<30 minutes" and "$\geqslant 30$ minutes" by using the association rule mining method. The incident data classified in the class of "$\geqslant 30$ minutes" are then further divided into two groups of "<60 minutes" and "$\geqslant 60$ minutes" for searching other classification rules. With the same logic, one can then further decompose the incident data group of "$\geqslant 60$ minutes" into two clusters of "<120 minutes" and "$\geqslant 120$ minutes." Finally, based on the distribution of the incident clearance durations, three intervals of the estimated clearance duration corresponding to the confidence levels of 60%, 70%, and 80% can be produced from the sequential classification process. Figure 3 illustrates such a process by using CPI with two-lane blockage on I-95 from 2012 to 2015 as an example.

CF Incidents. Notably, compared with CPD and CPI, nearly all highways, by nature, have much fewer incidents resulting in both collisions and fatalities (CF). In view of the very small sample size for CF, Won et al. (*2*) suggested adopting a different searching process for identifying robust rules to estimate their required clearance durations. A detailed illustration of such a process is available in their works (*42, 43*).

Figure 4 presents the application process of the developed IDPM-I95 software, including its key input data, underlying classification and estimation structure, and the resulting outputs. Note that the system provides an interval-based, rather than the point-based estimate for a detected incident's duration to accommodate the data quality and availability, which are often imperfectly collected during the emergency incident response process. Additionally, such a model was later extended to I-495 and I-695; all three developed models, as shown in Table 2, have produced the expected level of performance sufficient for use in daily incident response operations.

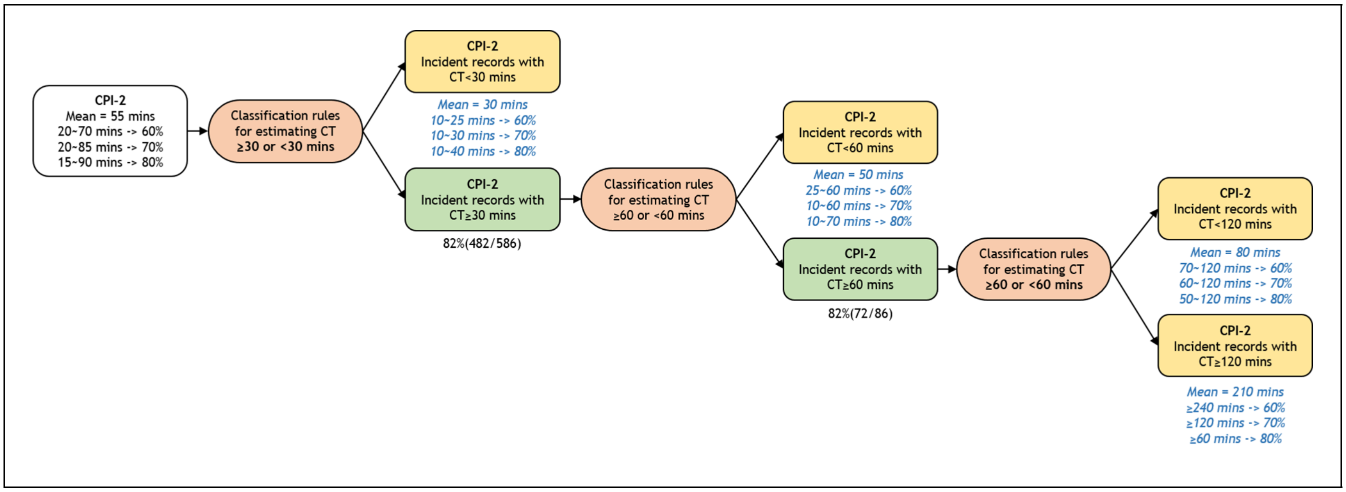

Figure 3. An example of the sequential classification process (2).

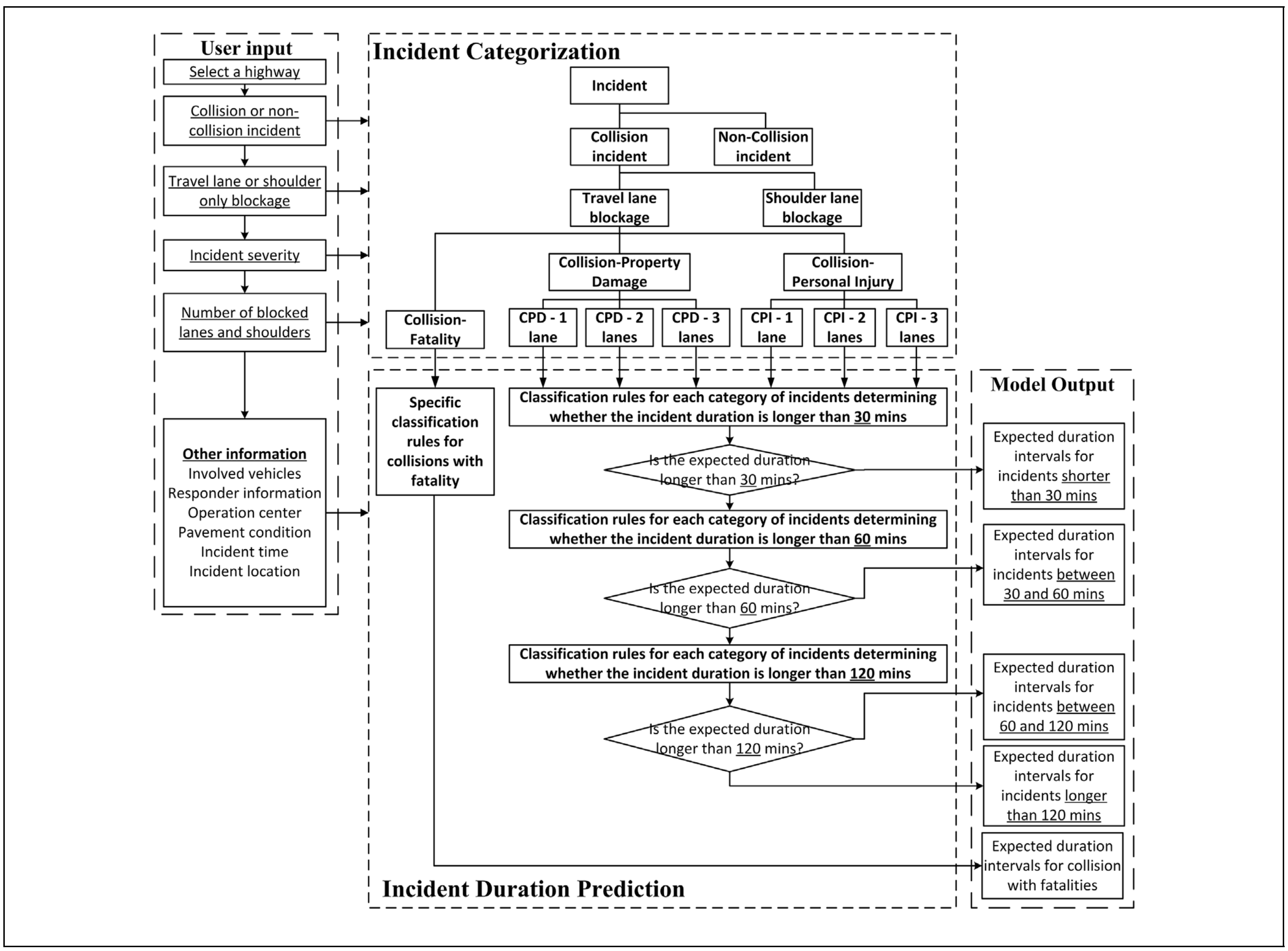

Figure 4. The application process of the developed incident duration prediction model (IDPM)–I-95 software (*42, 43*).

KTA Methodology

The primary functions of the KTA model are, first, to assess the transferability of available prediction rules, and then to identify their respective priorities in the transferring sequence. This is because the complex inter-relations between the existing prediction rules—such as

Table 2. Performance of Incident Duration Prediction Models (IDPMs) for I-95, I-495, and I-695 by Incident Type and Blocked Lane

Highway	Collision with travel lane blockage						
	CPI 1	CPI 2	CPI 3 +	CPD 1	CPD 2	CPD 3 +	Total
I-95 (2012–2017)	77.2%[a] (446/578)	84.6% (203/240)	78.8% (82/104)	74.3% (795/1070)	80.5% (177/220)	83.7% (41/49)	77.1% (1744/2261)
I-495 (2015–2018)	78.7% (392/498)	78.7% (295/375)	61.7% (113/183)	79.8% (631/791)	81.6% (301/369)	79.2% (95/120)	80.0% (2018/2523)
I-695 (2016–2019)	85.6% (297/347)	82.4% (150/182)	78.7% (59/75)	87.0% (842/968)	87.6% (219/250)	82.7% (43/52)	85.9% (1610/1874)

Note: CPI = collision with personal injury; CPD = collision with property damage.
[a]The percentage of incident durations which were correctly predicted the 80% confidence interval.

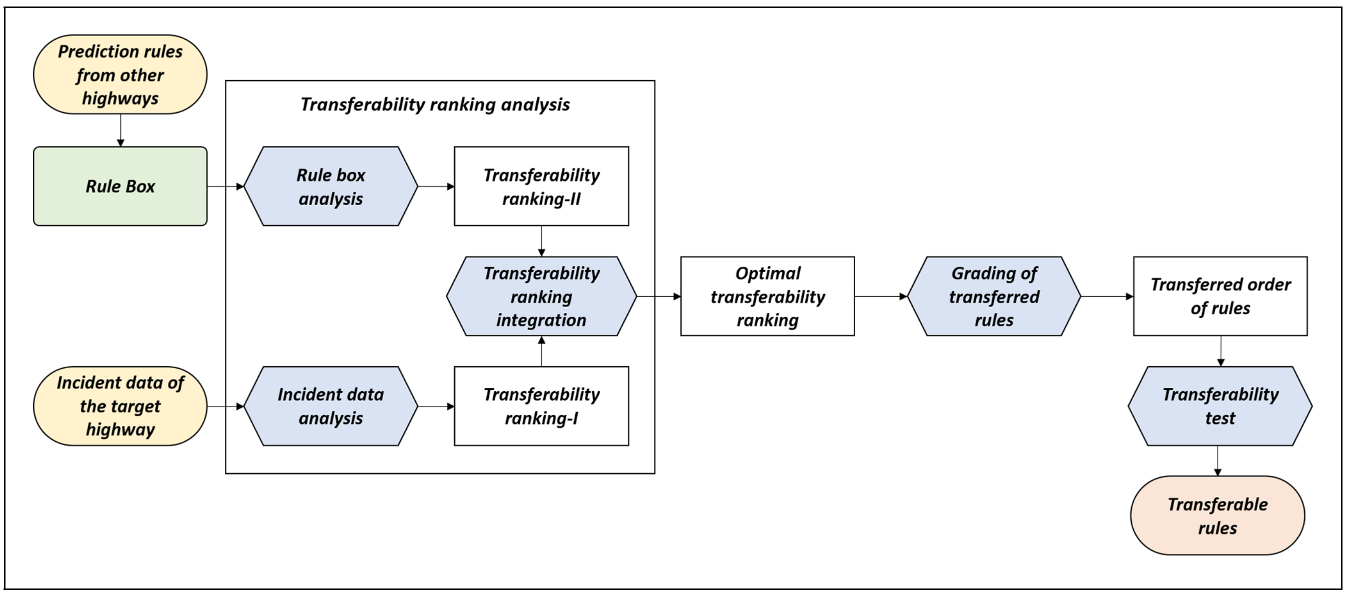

Figure 5. Illustration of the transferability analysis in the knowledge transferability analysis (KTA) model.

those mutually exclusive or supplementary in nature—may render the effectiveness dependent not only on which rules to adopt, but also their sequence of execution in the decision structure. Figure 5 illustrates the process for the rule transferability analysis including: (i) generation and update of the Rule Box to include available prediction rules from existing systems; (ii) ranking of key factors for constructing available prediction rules; (iii) identification of the transferring priority for available prediction rules, and (iv) effectiveness assessment with respect to all transferred prediction rules.

Rule Box Generation and Update

The primary function of the Rule Box is to house all effective prediction rules from existing IDPMs for assessing their transferability to a highway of similar features and incident patterns. As such, all well-calibrated prediction rules for the IDPMs for I-95, I-495, and I-695 are collected and classified into six categories, as shown in Figure 6, based on the nature of the incident and the resulting number of blocked lanes. Depending on their usage for incident duration prediction, such rules in each category are further divided into six types with three pre-specified thresholds for classifying incident durations (i.e., 30, 60, and 120 min).

Ranking of Key Factors Used in Constituting Prediction Rules

As stated previously, the rule transferring priority concurrently determines not only which rules to transfer but also the execution structure of the new IDPM. Therefore, the set of prediction rules having the highest transferring priority shall have the following properties:

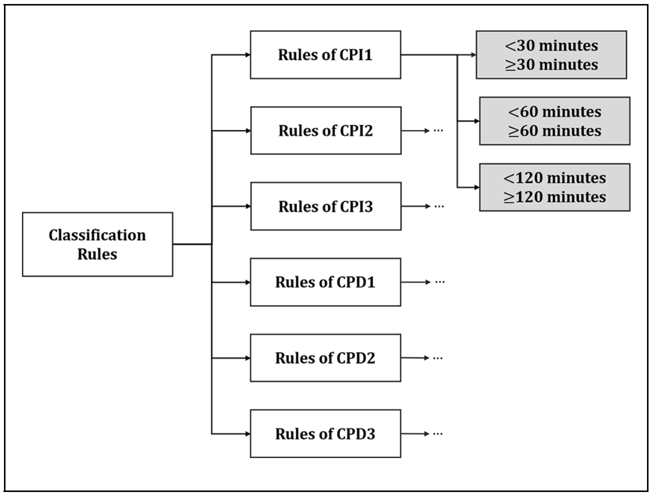

Figure 6. Classification of the prediction rules in the Rule Box.

- their included factors for prediction are also the most critical set of contributors to the incident durations on the target new highway; and
- they have achieved the highest level of prediction effectiveness with respect to incidents on their own highways.

The methodology for assessing the transferability priority for each set of available rules in the Rule Box, based on the above two essential properties, is presented below. First of all, all key factors contributing to the required incident duration are initially classified into the following seven categories, as shown in Table 3.

Transferability Ranking-I Analysis. The purpose of this task is to identify the relative impacts of the above seven categories of factors on the resulting incident durations revealed in the target new system's incident records. To do so, this study has adopted the permutation-based variable-importance measure (*46*) for ranking analysis, and provided a brief description of its core logic below:

Given a set of n incident records for p contributing factors and the incident clearance duration $\boldsymbol{Y}$, then, let $\boldsymbol{X}$ denote the matrix of p columns and n rows, and the

Table 3. List of the Incident Duration's Key Contributing Factors Classified by Category

Category	Description	Item
Category-1 (# of responders)	The number of different responders at the incident scene	# of total response units # of arrived CHART # of arrived police # of arrived fireboard # of arrived medical service # of arrived tow service
Category-2 (First arrived responder)	Type of the first-arriving responders	Police first arrived Medical service first arrived Tow service first arrived CHART first arrived Fireboard first arrived
Category-3 (Vehicle status)	The number and the type of vehicles involving in incidents and their damage levels	Overturned, lost load, jack-knife # of total involved vehicles # of involved passenger cars # of involved trucks # of involved motorcycles
Category-4 (Pavement conditions)	Indicators for the pavement conditions	Wet, dry, snow-ice, chemical wet, hazard material related
Category-5 (Lane blockage)	Indicators to denote the lane blockage conditions	# of blocked lanes # of blocked shoulder lanes # of blocked travel lanes # of blocked auxiliary lanes Travel lane blocked in tunnel Travel lane blocked in toll
Category-6 (Operation center)	Indicators reflecting different incident response centers	AOC, TOC3, TOC4, TOC5, SOC
Category-7 (Time)	Temporal-related indicators associated with an incident	Morning peak, evening peak, daytime, night Weekday, weekend Holiday, non-holiday Spring, Summer, Fall, Winter

Note: AOC = Authority Operations Center; SOC = Statewide Operations Center; TOC = Traffic Operations Center; and CHART = Coordinated Highways Action Response Team column vector of $\underline{\boldsymbol{y}}$ show the observed values of $\boldsymbol{Y}$. As such, $\underline{\widehat{\boldsymbol{y}}} = (f(^{-}x_1), \ldots, f(^{-}x_n))'$ denotes the corresponding vector of predictions from the random forest (*46*) for $\underline{\boldsymbol{y}}$ for model $f()$, and $\mathcal{L}(\underline{\widehat{\boldsymbol{y}}}, \underline{\boldsymbol{X}}, \underline{\boldsymbol{y}})$ is a loss function to quantify the goodness-of-fit. The core algorithm can then be summarized into the following steps:

Step-1: Compute $L^0 = \mathcal{L}(\underline{\widehat{\boldsymbol{y}}}, \underline{\boldsymbol{X}}, \underline{\boldsymbol{y}})$ (i.e., the value of the loss function for the original data). Then, for each contributing factor X^j included in the model, repeat steps 2–5.
Step-2: Create a matrix $\underline{\boldsymbol{X}}^{*j}$ by permuting the j *-th* column of $\underline{\boldsymbol{X}}$, that is by permuting the vector of observed values of X^j.
Step-3: Compute the model's predicted $\underline{\widehat{\boldsymbol{y}}}^{*j}$ based on the modified data $\underline{\boldsymbol{X}}^{*j}$.
Step-4: Compute the value of the loss function for the modified data: $L^{*j} = \mathcal{L}(\underline{\widehat{\boldsymbol{y}}}^{*j}, \underline{\boldsymbol{X}}^{*j}, \underline{\boldsymbol{y}}^{*j})$.
Step-5: Quantify the importance of X^j (vip^j_{Ratio}) by calculating $vip^j_{Ratio} = L^{*j}/L^0$.

With the computed importance of each contributing factor, one can do the ranking analysis based on the factor with highest importance in each category. For instance, if "the total number of responders" is identified to be the most important factor, then the category (i.e., Category-1) having this factor would be assigned with the highest rank of 1. By excluding all other factors in Category-1 from the ensuing comparisons, if the next one with the highest importance in the remaining list is "number of trucks involved," then the category (i.e., Category-3) having this factor shall be assigned with the rank of 2. The same procedures can be iteratively executed to identify the proper rank for each of the remaining categories.

Transferability Ranking-II Analysis. The core of ranking-II analysis is to rank the importance associated with each category of factors from the perspective of how often they have been used in the existing IDPMs' prediction rules and the resulting effectiveness. The measurements proposed for such an analysis are defined below:

Coverage: For a given category of factors, its coverage is measured by the total number of incident records in the base dataset (i.e., total incident records from I-495, I-95, and I-495 for their model developments) that have been predicted by any set of rules which contain one or more factors from this category. For instance, the set of 134 rules that contain either one or more factors from the category of "# of responders" has been used to predict the duration for 2,979 incidents in the base dataset.

Accuracy: The total number of correctly predicted incidents out of the total "coverage" associated with each category. For instance, the group of "the number of responders" is assessed to yield the "accuracy" level of 83.42%, based on their applications to 2,797 incidents.

Proportion of conjunctive rules: The number of rules constituted with the command "AND" out of the total rules (defined as frequency) associated with each of those seven pre-classified groups of factors.

With these measurements, one can compute the resulting rank for each category of factors under Rank-II analysis with the following data envelopment analysis method (*47*), in which the objective function is to maximize the total positive measurements for each category:

$$\begin{aligned} &\text{Maximize} \\ &\text{Subject to} \sum\nolimits_{r=1}^{s} u_r y_{rk} - \sum\nolimits_{i=1}^{m} v_i x_{ik} \leqslant 0 \\ &\sum\nolimits_{r=1}^{s} v_i x_{ik} = 1 \\ &u_r \geqslant 0,\ r = 1, \ldots, s \\ &v_i \geqslant 0,\ i = 1, \ldots, m \end{aligned} \tag{1}$$

where E_k denotes the relative effectiveness of category k among all categories ($k = 1, \ldots, 7$), u_r and v_i represent weights for the rth positive measurement (i.e., coverage and accuracy levels) and ith negative measurement (i.e., *proportion of conjunctive rules*), respectively; y_{rk} is the standardized value for the rth measurement in category k, and x_{ik} is the standardized value for its ith negative measurement computed from the base dataset.

The computed effectiveness value for each category will then serve as an indicator for ranking the effectiveness of the seven categories of factors used by the existing IDPMs.

Transferability Ranking Integration. Given the rank assessment from both perspectives, one can then take the following steps to produce the final ranking list for the seven categories of factors:

Let δ_i^* be the optimal rank for category i; r_i^1 denotes the resulting rank from Rank-I test for category i; r_i^2 represents the resulting rank from Rank-II test for category i; and w_i stands for the number of existing rules using one or more factors from category i. Then, with the objective function shown in Equation 2, one can employ the method for rank aggregation by Pihur et al. (*48*) to produce the final optimized ranking list for all categories.

$$Min \sum_{i=1}^{7} (|\delta_i^* - r_i^1| + |\delta_i^* - r_i^2|) \times w_i \tag{2}$$

The final ranking for the categories will be in a descending order where the category ranked at the top of the list indicates that it contains the set of contributing factors with the most impacts on a detected incident's resulting clearance duration. However, it is noticeable that the Rule Box, because of the contributions from several well-developed IDPMs, may contain multiple prediction rules for the same category of incidents, but with different categories of factors. Thus, the following process has been proposed in this study to finalize the optimal transferring priority for such rules.

Prioritizing Candidate Rules for Transferability Analysis

For convenience of assessing the transferring priority, all candidate rules based on their logic structure and target incident types are characterized into four types, and each is assigned a customized score. For example, let Category-1 (i.e., # of responders) be the category with the computed rank of 1 and Category-7 (i.e., time) with the computed rank of 5, one can then follow the rules presented below to assign the weights for each type of rules, and subsequently determine their priority in the transferring sequence:

Type-A rules: Assigning a score for each of those rules with a simple "if-then" statement for estimating the lower bound of an incident's clearance duration, based on the rank of the category that includes the factor embedded in the rule. For instance, the rule, *"IF [more than 8 response units arrived], THEN the duration >120 minutes"* will be assigned the score of "1" because the condition variable of "8 response units" is one of the Category-1 factors.

Type-B rules: Assigning a score for those with a simple "if-then" statement for estimating the upper bound of an incident's clearance duration, based on the rank of the group that comprises the factor constituting the rule and an additional status score of "200" to ensure that all such rules will be assessed and transferred after all other types of rules. For instance, the rule, *"IF [no tow service arrived], THEN the duration <30 minutes"* will be assigned the assessment score of "201" because its condition variable of "no tow service" belongs to Category-1 factors.

Type-C rules: Assigning a score for those rules constituted with a nest of "if-then" statements and the relation of "and", based on the sum of scores computed from the rank of the group associated with the factor constituting each "if-then" statement in the entire set of rules connected with "and." For instance, the rule of *"IF on [holiday] AND [tow service arrived], THEN the duration >60 minutes"* will be assigned the assessment score of "6" because its two condition variables, [holiday] and [tow service arrived], belong to factors in Category-7 and Category-1, respectively.

Type-D rules: Assigning the score for those rules with a nest of "if-then" statements and the relation of "or" based on the sum of its assigned priority status score of "100" and the lowest rank among those categories which include the factors embedded in all "if-then" statements connected with "or." As such, the rule of *"IF on [weekend] OR [police arrived], THEN the duration >30 minutes"* will be assigned the assessment score of "101", because its two condition variables, [weekend] or [police arrived], belong to Category-7 and Category-1, respectively. Thus, the final assessment score for this rule shall be the sum of "100" plus "1."

Transferability Effectiveness Test

As with the standard practice for transferability analysis, this study adopts the following two measures of effectiveness for assessing each candidate rule's performance with respect to the incident records from the target roadway: (i) the *confidence level* that demonstrates the accuracy of a candidate rule and (ii) the *support level* that shows the percentage of incident records that are consistent with the set of "if" conditions in an identified prediction rule.

Conceivably, those prediction rules yielding a sufficiently high *confidence level* and having a reasonable *support level* will be deemed transferable. As illustrated in Figure 7, the entire process for transferability effectiveness assessment with respect to all candidate prediction rules in the Rule Box can be illustrated with the following steps:

Step-1: Determine the minimum *confidence level* ($X\%$) and the lower bound ($S_L\%$) as well as the upper bound ($S_U\%$) of the *support level*, based on the information in the Rule Box and the available incident records from the target highway.

Step-2: Utilize the incident data in each subset of CPI and CPD on the target highway to verify the effectiveness of each candidate rule with respect to its applicable incident group.

Step-3: Transfer the prediction rule to the new model if it can achieve the *confidence level* and the *support level* specified at Step-1.

Step-4: Filter out the incident records already successfully classified by a prediction rule from the target incident dataset, and proceed with the same transferability analysis process with the remaining incident records.

Step-5: Stop the transferring process if no more classification rule can be transferred; otherwise, go to Step-2.

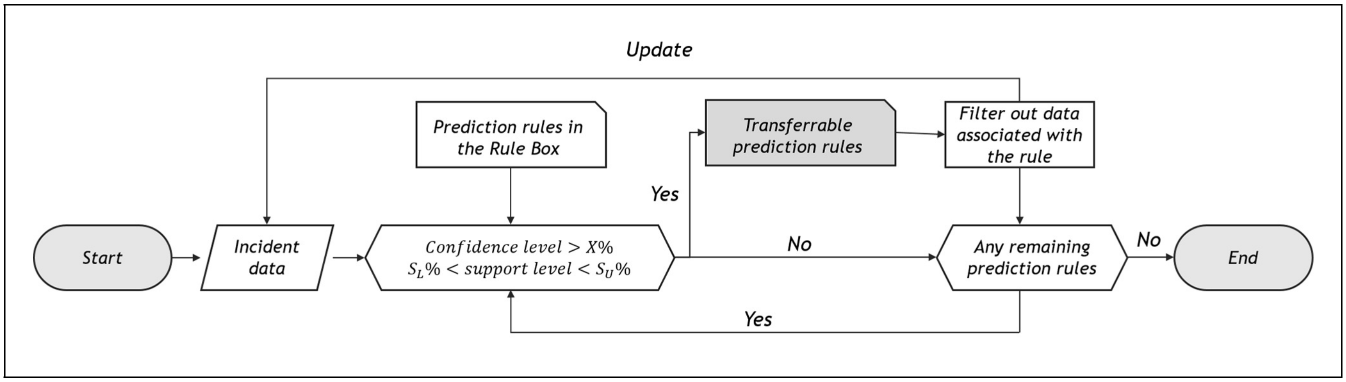

Figure 7. Flow chart of the transferability test in the classification rules transferring process.

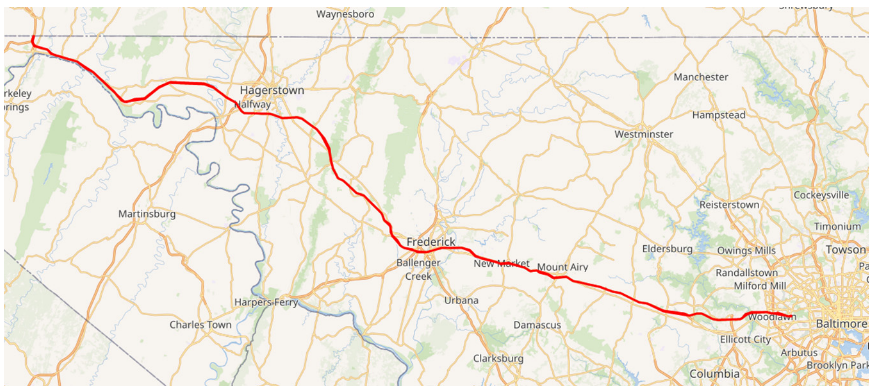

Figure 8. Spatial scope of the incident duration prediction model (IDPM)–I-70.

Case Study: I-70 in Maryland

For illustration and evaluation of the proposed KTA method, this study has selected I-70 in Maryland for the case study. The 2016–2018 incident records from the CHART II Database were used for model calibration, and those from 2019 served for performance evaluation. As illustrated in Figure 8, the system covers I-70 from Exit 1 to Exit 94 in Maryland.

Incident Categorization

Figure 9 shows the results of the initial incident categorization, including the mean for each categorized group and the range of its variation within the confidence intervals of 60%, 70%, and 80%. Note that because of the lack of sufficient samples, CPI3 and CPD3 are merged with CPI2 and CPD2, respectively.

Transferability Ranking-I

Figure 10 shows the results of ranking-I transferability analysis, where the relative importance of the seven categories is based on the factor of highest rank included in each category. For instance, "# of total responders" is identified to be the most important factor, thus the category (i.e., Category-1: # of responders) including this factor would be assigned the highest rank of 1. Then, by excluding all other factors in Category-1 from the list for comparison, the next one with the highest importance is "# of involved trucks." Therefore, Category-3 (i.e., Vehicle status), containing this factor, shall be assigned the rank of 2.

Transferability Ranking-II

Table 4 presents the properties of seven categories of factors used to construct the prediction rules from the existing IDPMs. The results of transferability ranking analysis with respect to their effectiveness, where those categories with higher E-values are given higher priorities in the sequence of the transferability assessment.

Finalized Ranking for Transferability Assessment

Table 5 reports the finalized ranking results, reflecting the relative importance of those categories of factors in the transferability assessment. For instance, those

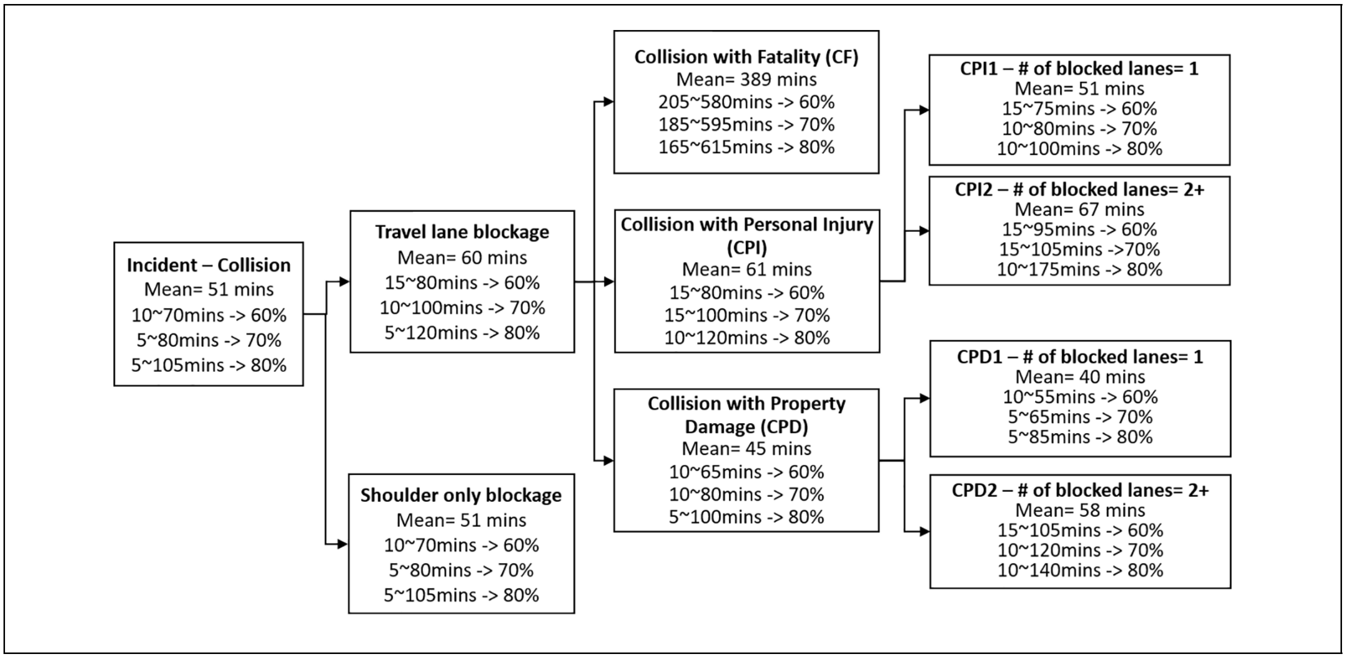

Figure 9. Initial incident categorization and estimated clearance duration for I-70.

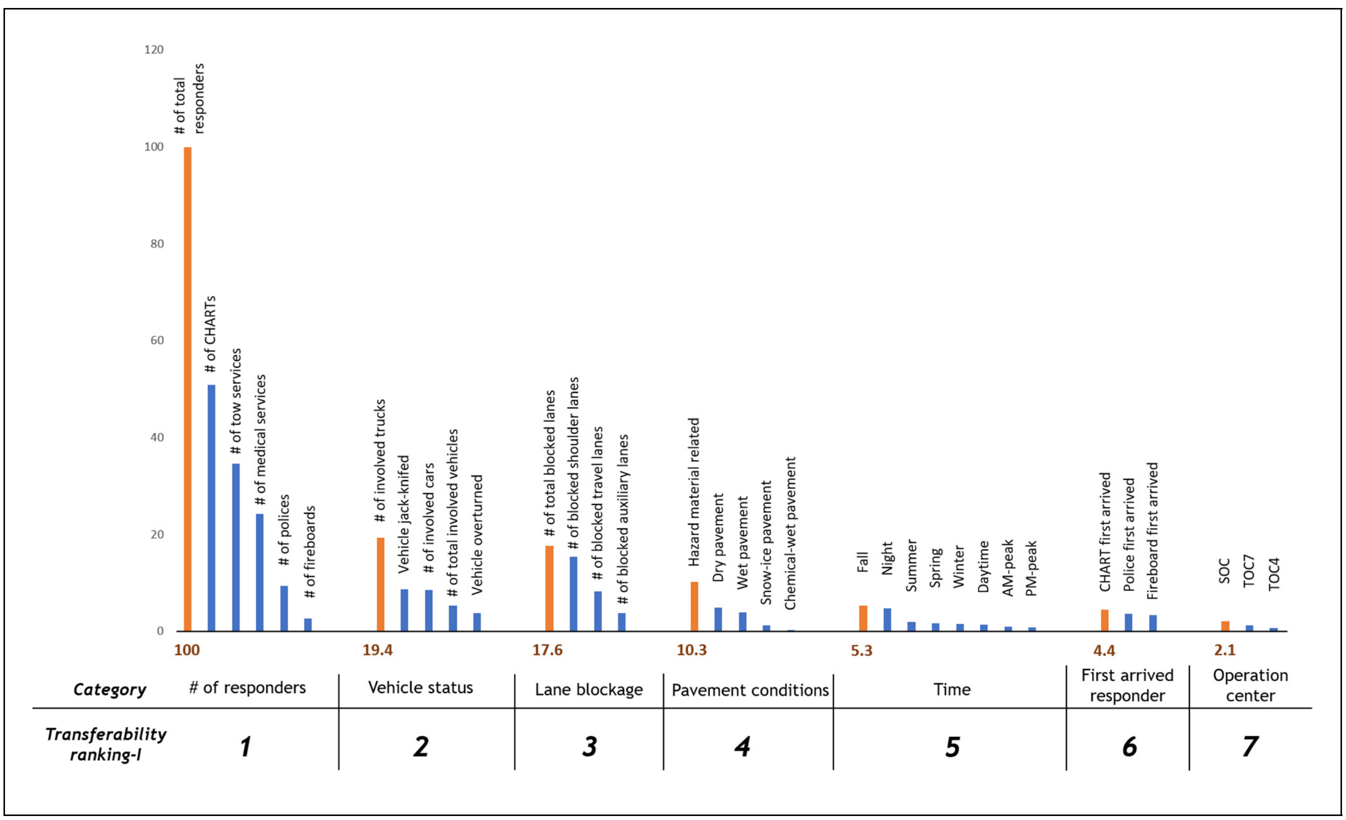

Figure 10. Results of transferability ranking-I analysis for I-70.

candidate prediction rules, comprising factors from the category "# of responders" should be given the highest priority in the sequence of transferring effectiveness assessment for I-70.

Transferring and Generation of Prediction Rules

Overall, 36 out of the total 54 prediction rules in the IDPM–I-70 are transferred from existing IDPMs for I-

Table 4. Results of Transferability Ranking-II Analysis for I-70

	# of responders	First arrived responder	Vehicle status	Pavement conditions	Lane blockage	Operation center	Time
Coverage (no. of cases)	2979/0.665[a]	247/0.074	1478/0.640	1220/0.203	343/0.154	596/0.079	684/0.268
Accuracy (mean)	83%/0.377	75%/0.341	85%/0.383	89%/0.404	88%/0.398	82%/0.370	82%/0.371
Proportion of conjunctive rules	0.59/0.331	0.80/0.449	0.64/0.357	0.39/0.246	0.68/0.380	0.69/0.386	0.81/0.457
E-val	1.000	0.411	0.642	1.000	0.567	0.521	0.444
Rank	1	7	3	1	4	5	6

[a]The left-hand side of the number is the measurement (e.g., 2,979), while the right-hand side is the normalized measurement (e.g., 0.665).

Table 5. Final Ranking Analysis Results for all Categories of Factors

	# of responders	First arrived responder	Vehicle status	Pavement conditions	Lane blockage	Operation center	Time
Frequency	134	15	129	41	31	16	54
Transferability ranking-I	1	6	2	4	3	7	5
Transferability ranking-II	1	7	3	1	4	5	6
Optimal transferability ranking	1	7	2	4	3	6	5

95, I-495, and I-695, and the remaining 18 rules were calibrated with the same method by Won et al. (*42*) to reflect some local-unique incident patterns. Figure 11 illustrates the example of the rule-generation process for CPI2 and its application with all embedded "if-then" rules. Table 6 lists the prediction rules of IDPM–I-70 transferred from IDPMs for I-95, I-495, and I-695.

Model Evaluation

The evaluation results of the IDPM for I-70 with both transferred and customized local rules are shown in Table 7. Noticeably, the IDPM–I-70 constituted mostly of transferred rules (i.e., 36 out of 54 rules) can achieve the accuracy level of 87% with the training dataset (i.e., 2016–2018) and 82% with the test dataset (i.e., 2019). Its level of performance is comparable with existing IDPMs, but demands much less resource with an automated computer program and does not need to be constrained by the available size of incident records.

Table 8 shows the comparison results between the IDPMs for I-70 with and without the KTA model, where the former yields a better accuracy despite both models having similar training accuracy. This is because, even though one can find the common prediction rules among incident records in the training dataset to fit with a sufficient level of accuracy, such rules may be too location-specific (e.g., overfit), because of the lack of enough data samples, to capture those incident records in the test dataset. In contrast, the proposed KTA model relies on empirical rules from previously-developed IDPMs which have demonstrated their reliability in field applications. Thus, it can be more robust in providing an acceptable and even better accuracy, especially for those incidents with insufficient incident records for model calibration.

Conclusion

To circumvent the demanding development efforts and the need for an extensive dataset for calibration of an IDPM's prediction rules, this study has developed an innovative KTA model that allows the construction of a new system to take advantage of existing IDPMs' embedded rules with an automated process. The proposed model features its use of a series of transferability analysis methods with respect to the existing IDPMs to identify the effectiveness and transferring priority of those adopted prediction rules.

The effectiveness of the proposed model has been evaluated with the incident data from I-70 in Maryland. The result of extensive evaluation with multi-year incident records indicates that the performance of the IDPM for I-70, with 67% of transferred rules, can yield a prediction accuracy comparable with existing IDPMs that demand much more development resources. Although a more extensive assessment of the proposed KTA method can be done for other highways in different regions, the preliminary results from the I-70 case study seem to offer a promising avenue for responsible highway agencies to cope with the difficulty of insufficient incident records in the IDPM development for some highways.

Table 6. Prediction Rules of the incident duration prediction model (IDPM) for I-70 Transferred from I-95, I-495, and I-695

Transferred rules description—CPI1			
IF	[Tow service arrived]	THEN	$\geqslant$ 30
IF	[More than 3 vehicles involved]	THEN	$\geqslant$ 30
IF	[More than 1 CHART arrived] AND [Police first arrived]	THEN	$\geqslant$ 30
IF	[Peak hour] AND [More than 2 vehicles involved]	THEN	$\geqslant$ 30
IF	[Car overturned] AND ([Weekend] OR [Tow service arrived])	THEN	$\geqslant$ 30
IF	[Fireboard first arrived]	THEN	$<$ 30
IF	[Snow-ice pavement] OR [More than 1 truck involved] OR [More than 7 response units arrived] OR [AOC center]	THEN	$\geqslant$ 60
IF	[No tow service arrived] AND [No truck involved]	THEN	$<$ 60
IF	[Less than 4 response units] OR [No truck involved]	THEN	$<$ 120
Transferred rules description—CPI2			
IF	[Tow service arrived]	THEN	$\geqslant$ 30
IF	[More than 4 response unit arrived]	THEN	$\geqslant$ 30
IF	[Dry pavement]	THEN	$<$ 30
IF	[More than 6 response units arrived]	THEN	$\geqslant$ 60
IF	[More than 1 Fireboard arrived] OR [Snow-ice pavement]	THEN	$\geqslant$ 60
IF	[No tow service arrived] OR [No truck]	THEN	$<$ 60
IF	[More than 7 response units arrived] OR [More than 5 vehicles involved]	THEN	$\geqslant$ 120
IF	[More than 1 truck involved] OR [More than 3 vehicles involved] OR [Hazard materials related] OR [More than 7 response units arrived]	THEN	$\geqslant$ 120
IF	[More than 4 vehicles involved] OR [Wet pavement]	THEN	$\geqslant$ 120
Transferred rules description—CPD1			
IF	[Tow service arrived] AND [Fireboard arrived]	THEN	$\geqslant$ 30
IF	[More than 2 CHART arrived] AND [CHART first arrived]	THEN	$\geqslant$ 30
IF	[Wet pavement] AND [More than 1 police arrived] AND [Auxiliary lane blocked] AND [Shoulder lane blocked]	THEN	$\geqslant$ 30
IF	[More than 2 CHART arrived] OR ([More than 4 response units arrived] AND [Wet pavement])	THEN	$\geqslant$ 30
IF	([Daytime] AND [More than 4 response units arrived]) OR ([Truck involved] AND [More than 1 police arrived])	THEN	$\geqslant$ 30
IF	[Dry pavement]	THEN	$<$ 30
IF	[More than 6 response units arrived] OR [Truck overturned] OR [Bus involved] OR [Vehicle lost load]	THEN	$\geqslant$ 60
IF	[Truck involved] AND ([More than 5 response units arrived] OR [Auxiliary lane blocked])	THEN	$\geqslant$ 120
IF	[Snow-ice pavement] OR ([Auxiliary lane blocked] AND [Chemical wet pavement])	THEN	$\geqslant$ 120
Transferred rules description—CPD2			
IF	[Tow service arrived] AND [Fireboard arrived]	THEN	$\geqslant$ 30
IF	[Snow-ice pavement] OR [Chemical wet pavement] OR [Truck jack-knifed] OR [More than 6 response units arrived]	THEN	$\geqslant$ 30
IF	([Night] OR [More than 4 response units arrived]) AND [More than 1 police arrived]	THEN	$\geqslant$ 30
IF	[Car overturned] OR [More than 1 shoulder lane blocked] OR ([Truck involved] AND [Pickup involved])	THEN	$\geqslant$ 30
IF	[More than 1 tow service arrived]	THEN	$\geqslant$ 60
IF	[Truck involved] AND [More than 5 response units arrived]	THEN	$\geqslant$ 60
IF	([Truck involved] OR [More than 2 vehicles involved]) AND [Night]	THEN	$\geqslant$ 60
IF	[More than 1 tow service arrived]	THEN	$\geqslant$ 120
IF	[No truck involved]	THEN	$<$ 120

Note: CPI = collision with personal injury; CPD = collision with property damage; CHART = Coordinated Highways Action Response Team.

Table 7. Results of Model Evaluation for IDPM–I-70

Evaluated by groups of incident records						
	CPI1	CPI2	CPD1	CPD2	CF	Overall
Training set (2016–2018)	87.80% (36/41)	85.37% (35/41)	86.17% (81/94)	87.50% (35/40)	100% (6/6)	86.94% (193/222)
Test set (2019)	100.00% (10/10)	68.75% (11/16)	78.26% (18/23)	90.00% (9/10)	100% (1/1)	81.67% (49/60)

Note: CPI = collision with personal injury; CPD = collision with property damage; CF = collision with fatality. Numbers in parentheses represent "the number of data whose clearance time is correctly estimated by the model/the total number of incident records in the group."

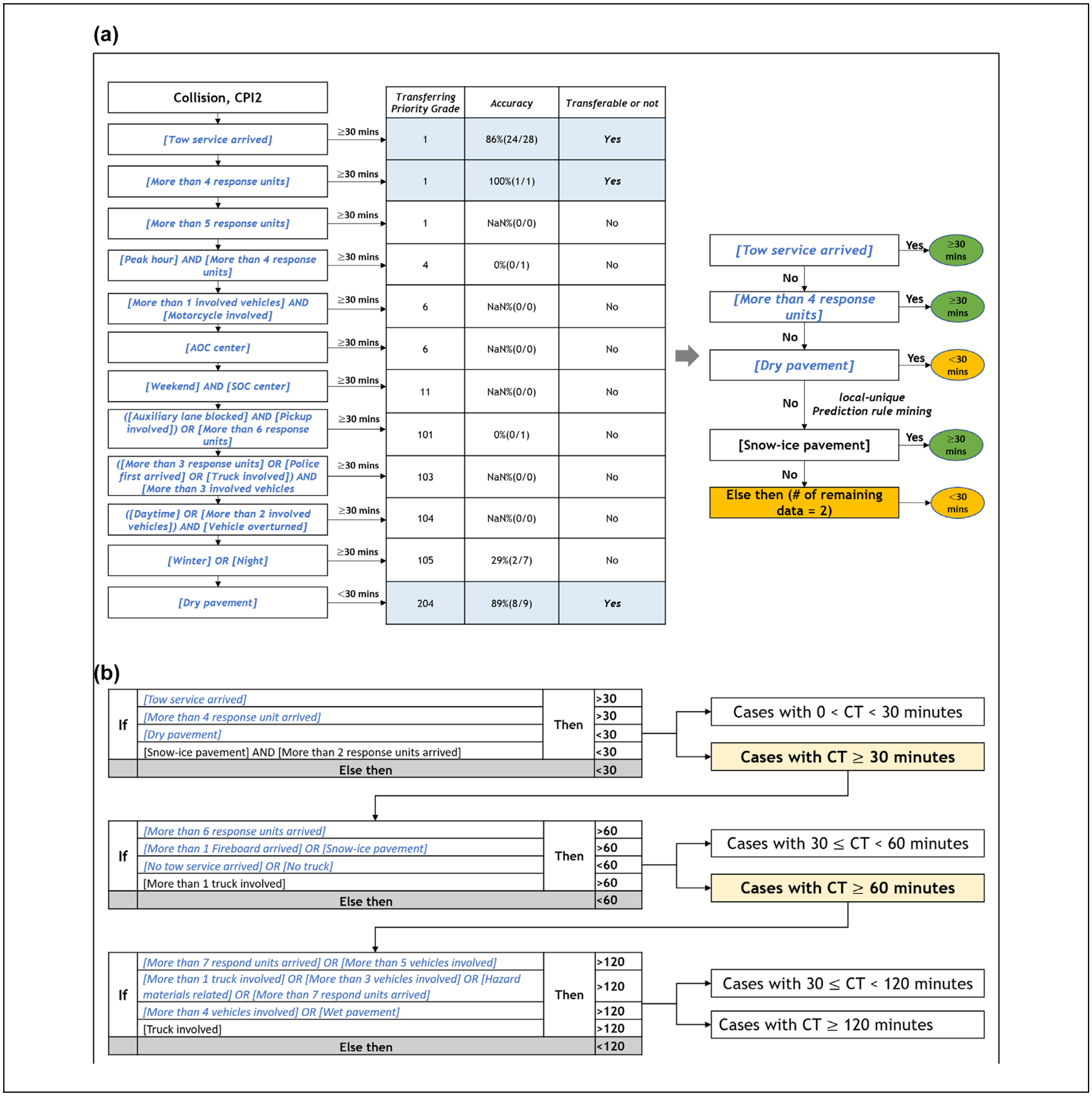

Figure 11. An example of an application for collision with personal injury (CPI) with two-travel-lane blockage: (*a*) the generation process of the prediction rules and (*b*) the application process.

Table 8. Comparison Between the Models Developed With and Without the Knowledge Transferability Analysis (KTA) Model

	Model 1	Model 2
KTA model	Yes	No
Training accuracy (%)	86.94	83.84
Testing accuracy (%)	81.67	69.05
Total number of rules	54	31

Future research along this line includes: (i) extending the KTA model's application to major signalized arterials mostly with a small sample of well-documented incident records, and (ii) constructing a supplemental module to enhance the efficiency and robustness of the rule-based IDPMs.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Y.-L. Huang, Y.-T. Lin, G.-L. Chang; data collection: Y.-L. Huang; analysis and interpretation of results: Y.-L. Huang and Y.-T. Lin; draft manuscript preparation: Y.-L. Huang, Y.-T. Lin, and G.-L. Chang. All authors reviewed the results and approved the final version of the manuscript.

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