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A Knowledge-Based Expert System for Pedestrian Safety Improvement at Intersections

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A Knowledge-Based Expert System for pedestrian safety improvement at intersections

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By

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University of Maryland, College Park

June 2023

ABSTRACT

In response to the rising concerns about intersection safety across the United States, traffic administrators have developed various techniques to create more effective and targeted improvement projects. Among them, Knowledge-Based Expert Systems (KBESs) demonstrate the unique advantage of having low requirements for users' experience and efficient decision-making. Recognizing that existing KBESs often lack comprehensive analysis of the critical factors contributing to pedestrian-involved crashes and the capability to optimize countermeasure selection, this study proposes an enhanced KBES to assist the traffic community in efficiently generating a set of optimal cost-benefit countermeasures to address pedestrian safety risks at intersections. In the proposed KBES, the carefully designed knowledge acquisition process fills two knowledge bases: one containing well-evidenced cause-effect relationships between contributing factors and corresponding Safety Related Intersection Characteristics (SRICs), and the other storing various attributes of a comprehensive list of countermeasures. The first developed inference engine is capable of identifying the contributing factors at an intersection and innovatively quantifying the impact of each of them based on the user input of SRICs. The second inference engine optimizes the countermeasure selection to maximize the expected effectiveness in accurately targeting the impact of those contributing factors while accounting for both budget constraints and users' defined priorities among the countermeasures' attributes. The results of the performance evaluation indicate that the proposed KBES is effective in analyzing contributing factors and recommending countermeasures and can serve as an efficient tool for traffic engineers to develop safety improvement projects at intersections.

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1. Introduction

In response to the need for enhancing intersection pedestrian safety, this study introduces a Knowledge-Based Expert System (KBES) that can take advantage of valuable lessons from experienced engineers and innovative methods reported in the literature to help professionals identify effective countermeasures for minimizing intersection vehicle-pedestrian crashes. This chapter highlights the significance of focusing on pedestrian safety at intersections and emphasizes the benefits of utilizing a KBES to contend with these issues. The overall organization of this paper is first outlined in the remaining part of this chapter, followed by a brief description of the main contents and findings in each subsequent chapter.

1.1.Addressing Intersection Pedestrian Safety Concerns

The importance of intersection pedestrian safety cannot be overstated, as the frequency and severity of crashes remain alarmingly high, especially over the past decade. In the United States, motor vehicle accidents account for 7,000 pedestrian fatalities annually, translating to one pedestrian death every 75 minutes (Centers for Disease Control and Prevention, 2015). According to the National Highway Traffic Safety Administration (National Highway Traffic Safety Administration, 2019), pedestrian fatalities made up 17% of all traffic-related deaths in 2018. Intersections, where traffic conflicts are prominent, experience a non-negligible portion of these tragedies, evidenced by 1,011 deaths in 2016 and 1,048 in 2017 at unsignalized intersections. Pedestrian fatalities at signalized intersections have also increased between 2016 and 2019, with the numbers reaching 793 and 848, respectively.

Given the gravity of these statistics, it is crucial for the transportation community to tackle intersection pedestrian safety issues to reduce the frequency and severity of crashes. Doing so can also contribute to several strategic goals for promoting sustainable and healthy environments, such as enhancing urban design and livability by creating more pedestrian-friendly intersections, fostering social inclusion and equity, promoting walking and active transportation, and ultimately, protecting human lives.

Recognizing the need for improving pedestrian and intersection safety, various states and agencies have implemented programs and strategies to address these concerns. The federal government has established the Highway Safety Improvement Program (HSIP) (FHWA, n.d.) as a key mechanism for transportation funding, mandating that states allocate at least 15% of HSIP funds to bicyclist and pedestrian safety when their fatalities constitute 15% or more of traffic-related deaths (League of American Bicyclists, 2018). Additionally, many states and jurisdictions have pledged their commitments to the Vision Zero initiative, which strives to eradicate serious injuries and fatalities arising from traffic incidents (Maryland.gov, 2022, NYC.gov, n.d.), with pedestrian safety as a primary focus. These programs aim to improve pedestrian safety through the 5 E's: engineering, enforcement, education, encouragement, and evaluation. As a critical component, engineering solutions are expected to provide substantial protection to pedestrians and bicyclists, as well as other vulnerable roadway users.

1.2.Advantages of Implementing a Knowledge-Based Expert System (KBES)

Identifying effective and cost-beneficial engineering solutions is naturally a challenging task due to the uniqueness of issues at each location, the complexity of the contributing factors, and the redundancy of the available countermeasures. To develop effective safety improvement projects, various methods exist to address pedestrian safety concerns, such as systemic approaches (Hughes et al., 2015; Gandhi et al., 2007; Kumfer et al., 2019), cost/benefit analysis (Elvik, 2003), and Crash Modification Factor (CMF) analysis (Fitzpatrick et al., 2022; Gross et al., 2010; Sanejnejad & Lo, 2015). These methods are used to assist engineers in selecting the most appropriate countermeasures, such as comparing the Crash Modification Factor (CMF) values of pedestrian countdown signals and Pedestrian Hybrid Beacons (PHBs).

Other than employing those traditional systems, another viable option is to apply the Knowledge-Based Expert System (KBES), which has been widely utilized in the medical and transportation engineering fields and offers the following unique advantages for addressing safety issues:

- Efficient decision-making: With an artificial intelligence approach, KBES can account for the most viable countermeasures for intersection pedestrian safety through an efficient, automated process without extensive manual comparisons. This benefit is especially pronounced when junior traffic engineers with limited knowledge or information face the challenge of identifying the optimal countermeasure combinations within budget limits and under various operational constraints.
- Cost-effectiveness: Implementing a KBES can be more cost-effective than hiring a team of experts to analyze and address pedestrian safety issues, offering a more affordable and efficient solution to most highway agencies suffering from budget constraints.
- Consistency and accuracy: Based on the expertise/knowledge embedded in its rule sets, KBES can ensure that all generated suggestions or countermeasures have consistent logic and reasoning, contributing to increased effectiveness in addressing pedestrian safety concerns.
- Continuous learning and improvement: a KBES allows for continuous learning and enhancements by incorporating more information and knowledge about emerging advanced technologies after their benefits have been validated, ensuring that the system is always up-to-date and effective.
- Public engagement: a KBES can facilitate public involvement in the decision-making process by providing transparent and accessible information on pedestrian safety issues and explaining the reasoning behind selecting certain countermeasures or other deployable solutions. Such a tool, with its mechanism, can certainly encourage community participation in traffic agencies' efforts to provide safe intersections.

In summary, a Knowledge-Based Expert System offers a wide range of benefits that render it a valuable tool for use in addressing intersection pedestrian safety concerns.

1.3. Primary Objectives

The primary objective of this study is to develop an effective tool that can assist the traffic community in efficiently generating high-cost-benefit countermeasures to enhance pedestrian safety at intersections with different geometric features and to reduce the frequency of pedestrian-vehicle crashes. Specifically, the Knowledge-Based Expert System (KBES) developed for such an objective shall have the following functions:

- Maintaining an abundant inventory of the most up-to-date contributing factors and countermeasures for contending with intersection pedestrian crashes, including both traditional and advanced solutions;

- Recording and evaluating the intersection characteristics relevant to various crash contributing factors;
- Identifying and ranking primary contributing factors of pedestrian crashes based on location-specific conditions;
- Identifying and prioritizing individual or collective countermeasures that provide targeted solutions to the studied intersection based on available budget, targeted issues, and the expected benefits;
- Allowing high flexibility to accommodate users' preferences and knowledge on contributing factor identification and countermeasure selection.

1.4.Paper Outline

Chapter 2 provides a review of the processes involved in selecting countermeasures for pedestrian safety, examines related literature on KBESs, and identifies the strengths and potential improvements in using a KBES. Chapter 3 introduces the system’s overall structure and explains the operational flows of the proposed KBES, offering insights into its design logic and primary functions. The methodology behind the core ideas of the two inference engines that form the basis of the proposed KBES will be introduced in Chapter 4, focusing on the system's innovative design logic and its contributions. Chapter 5 presents a summary of the evaluation results, showcasing the effectiveness and potential contributions of the proposed KBES on contending with intersection pedestrian safety. Conclusions from the study and research directions for potential enhancement of the proposed KBES for intersection pedestrian safety constitute the core of Chapter 6.

2. Literature Review

This chapter first reviews literature related to intersection pedestrian safety, then presents an expert's rigorous process for addressing such concerns. The current practices conducted by traffic agencies and the available tools for doing so will then be discussed. An investigation of some vital safety issues that have not been addressed by current tools, along with recommendations on relevant research needs, constitutes the core of the remaining chapter. Concluding comments and the potential for improving intersection safety analysis with an effective knowledge-based system are summarized in the last section.

2.1.Intersection pedestrian safety concerns

Over the past several decades, most studies on pedestrian-related accidents have largely concentrated on identifying a comprehensive range of factors for impact assessment, including predicting the probability of having pedestrian accidents under given intersection and traffic scenarios. Most of these factors reported in the literature can be broadly classified into two categories: pedestrian-related and traffic-related.

Two extensively studied pedestrian-related factors are gender and age groups. Male pedestrians have been consistently found to be at a higher risk for experiencing pedestrian accidents than females (Zhu et al, 2013; Lee & Abdel-Aty, 2005; Dai, 2012; Hezaveh, 2018; Zegeer, 2012; Sandt & Zegeer, 2006), while non-elderly individuals also exhibit a higher likelihood of involvement in pedestrian accidents (Abdel-Aty, 2005; Kim & Ulfarsson, 2019; Das et al, 2019; Sandt & Zegeer, 2006). Socioeconomic factors such as education level, income, employment status, and literacy rates have also been scrutinized. For instance, one study (Cottrill & Thakuriah, 2010) posits that low-income areas have a higher probability of pedestrian accidents, but another study claims drivers yield more in low-income areas (Coughenour et al, 2017).

In addition to factors such as gender and age, the increasing popularity of technology, such as cell phones, has been linked to a rise in pedestrian accidents. Research by Sunder et al (2019), Basch et al (2014), and Wells et al (2014) indicates that pedestrians using cell phones are more likely to be involved in crashes. This finding also applies to drivers, as they tend to be more inattentive and prone to collisions with pedestrians using their cell phones (Strayer et al, 2004; Engelberg et al, 2015; Xiong et al, 2015). Pedestrian accidents are also more likely to occur when pedestrians or drivers are under the influence of alcohol (Yadav & Velaga, 2020). Lastly, drivers who engage in speeding are at an increased risk of causing pedestrian accidents (Wilmot & Khanal, 1999; Panagiotis, 2007; Haglund & Aberg, 2000).

In addition, it is recognized that the risk of incurring accidents may increase when vehicles travel at high speeds near intersections (Davis, 2001; Spainhour et al., 2006; Sun et al., 2019; Bernhardt & Kockelman, 2021). Some studies (Yue et al. 2020; Zhai et al., 2019; and Sun et al., 2019) conclude that distractions caused by adverse weather conditions can also contribute to pedestrian-vehicle crashes.

Apart from the factors mentioned above, pedestrian accident rates may also be influenced by a crosswalk's geometric features (Lee & Abdel-Aty, 2005; Pulugurtha et al., 2007). For example, wet surfaces have been reported to be associated with pedestrian accidents (Ashifur Rahman, 2022; Kopelias et al, 2007; Jung et al, 2014). Properly posted speed limits are generally considered to decrease the likelihood of speeding vehicles (Martínez et al, 2013; Wu et al, 2013) and, consequently, the crash frequency.

It is well recognized that pedestrians are a vulnerable group at an intersection, especially when exposed to various hazardous factors. For example, Zhu (2022) concluded that pedestrians are a vulnerable group under light rain conditions and at junctions controlled by traffic signals or no controls (Zhu, 2022). Additionally, intersections with higher average traffic volumes are found to experience a greater number of pedestrian accidents (Lee & Abdel-Aty, 2005). Furthermore, intersections with a higher number of right-turn-only lanes, nearby nonresidential driveway crossings, and commercial properties are also reported to have increased pedestrian crash rates (Schneider et al., 2010).

In view of these safety concerns, a vast body of countermeasures has been produced and implemented by the traffic community at various intersections to enhance pedestrian safety.

While the effectiveness of some countermeasures for pedestrian safety has been well recognized in the literature and widely implemented in practice (Pulugurtha et al, 2012; Yang et al, 2016; Chen et al, 2012; Harkey & Zegger, 2004), such affirmative conclusions are subject to certain limitations or caveats. For example, one study (Yang et al, 2016) shows that high-visibility signs and markings can help increase awareness of pedestrians at intersections, but their effectiveness is affected by the level of vehicle flows.

Technological countermeasures, such as the Pedestrian Hybrid Beacon (PHB)/HAWK (FHWA, 2010; Fitzpatrick et al, 2019), Smart Pedestrian Crosswalk (BERCMAN, n.d.), and Campbell Wave Pedestrian Station (ODOT, 2009), have been shown to effectively reduce crash rates; however, there are limitations to their use. For example, the PHB is only applicable when there are more than six lanes (Fitzpatrick et al, 2019). In addition to technological solutions, conventional countermeasures such as in-street crossing signs (Lyon et al, 2017), raised crosswalks (Harkey & Zegger, 2004), curb extensions (FHWA, 2012), and high-visibility crosswalks (Preusser et al, 2002) can also help. However, these non-technological countermeasures also have limitations. Curb extensions, for example, are most effective near parking lanes (FHWA, 2012).

2.2.Countermeasure selection for pedestrian safety

There are several strategies commonly used by the traffic community to select countermeasures that enhance pedestrian safety.

One such approach is the systemic road safety evaluation, which examines the interaction between new and existing facilities at intersections to improve pedestrian safety (Hughes et al., 2015). Additionally, Gandhi et al. (2007) designed a pedestrian protection system that predicts the likelihood of collisions by modeling pedestrian behaviors, and the Monte Carlo method shows potential for integrating pedestrian detection with collision prediction. Furthermore, Kumfer et al. (2019) developed safety performance function (SPF) crash prediction models using network-wide data from Seattle to identify potential risk factors for motor vehicle-pedestrian collisions.

Apart from systemic approaches, cost-benefit analysis can also help assess the effectiveness of road safety measures in reducing pedestrian or road casualties (Elvik, 2003). Crash modification factor (CMF) analysis is another useful tool that enhances pedestrian safety by identifying countermeasures that reduce the risk of crashes. CMF analysis calculates the safety benefits of a countermeasure based on its impact on the frequency and severity of crashes. For example, Fitzpatrick et al. (2022) found that increasing the corner radius from 10 feet to 70 feet could decrease pedestrian crashes by a factor of 1.59. Gross et al. (2010) provided a guide to help agencies apply CMFs and select the most suitable countermeasures based on reliable data. Overall, cost-benefit analysis and CMF analysis are valuable tools for choosing appropriate countermeasures to improve pedestrian safety.

2.3. *A Rigorous Process for Identifying and deploying intersection Safety Improvement Projects*

To address the raising concerns regarding pedestrian intersection safety and develop improvement strategies, it is expected that experienced experts should follow a rigorous process that leverages their expertise to identify critical safety issues and best select targeted countermeasures for improvement. This section will outline such a process for countermeasure selection and implementation.

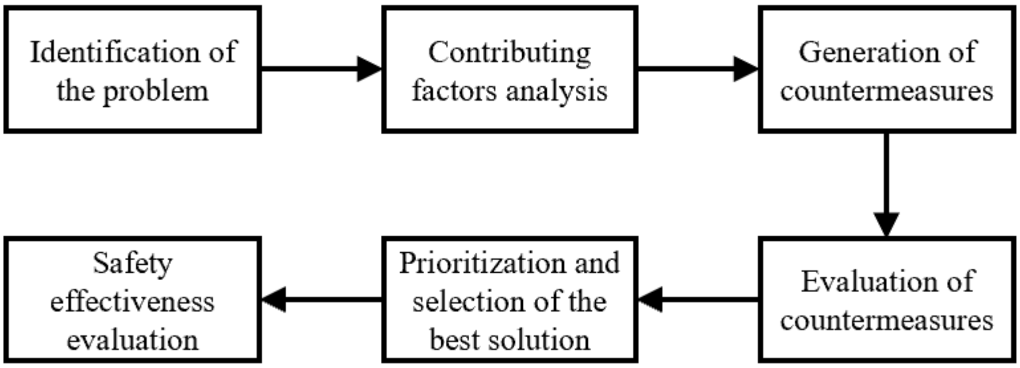


Figure 2.1. The process for intersection risk analysis and countermeasure selection

As outlined in the Federal Highway Administration (FHWA) report by Bahar et al. (2016), the process for an expert to recommend safety countermeasures typically involves six critical steps shown in Figure 2.1, including 1) identifying the problem, 2) conducting contributing factors analysis, 3) generating countermeasures, 4) evaluating countermeasures, 5) prioritizing and selecting the best solution, and 6) evaluating safety effectiveness.

The first step is **identification of the problem**. Generally, the following three stages are typically taken by a safety expert to pinpoint the issues at a specific intersection: reviewing safety data, evaluating supporting documentation, and examining field conditions (Srinivasan et al, 2016). In terms of safety data review, this process typically entails examining a summary of crash types, crash severity, event sequences, and circumstances. During the evaluation of supporting documentation, relevant materials may consist of traffic volume data, condition diagrams, construction plans, design criteria, photographs, maintenance logs, weather patterns, and recent traffic studies. As for assessing field conditions, comprehensive field observations should encompass traffic operations such as turning movements, conflicts, and operating speeds, in addition to provisions for pedestrians, cyclists, and specialized road users like elderly pedestrians. For instance, issues and intersection characteristics may include inadequate pavement markings and improperly timed signals. The output of this step will include the specific issues from all above aspects to be addressed at the target intersection.

The second step is **contributing factors analysis**. Based on the identified problems, experts typically draw upon their experience to determine the critical factors contributing to these issues (Srinivasan et al, 2016). Such a process often relies on experts' familiarity with the relationship between a certain type of crash and various issues identified in the previous step. For example, after reviewing the identified problems, responsible agencies may conclude that a combination of restricted sight distance and high approach speeds result in left-turn crashes. The task of rigorously identifying contributing factors enables agencies to maintain consistency and accuracy in choosing countermeasures targeting the root cause of the intersection's safety issues.

The third step is **generation of countermeasures**. Analysts can employ tools like the Haddon Matrix and resources such as the information in the NCHRP Report 500 series to identify targeted countermeasures so as to address or mitigate underlying contributing factors (Bahar et al, 2016). Employing the roadway safety data along with an analysis toolbox is another recommended approach for countermeasure identification. Experienced engineers may also supplement the countermeasure list with past successful implementations within or out of their jurisdictions.

The fourth step is **evaluation of countermeasures**. The safety impacts and economic benefits of countermeasures should always be data-driven, and estimated with judgement-based, behavioral-based or crash-based methods (Bahar et al, 2016). The method of professional judgement, although the least reliable, can benefit from using a multidisciplinary team that limits the influence of personal bias and takes advantage of expertise from different experts. The adoption of Data-driven behavioral-based methods may focus on performance measures such as speed, conflicts, lane keeping, and compliance with traffic control devices. This process should also involve policy-level decisions such as appropriate crash costs, discount rates, selected economic methods, and non-monetary factors associated with local conditions.

The fifth step involves **prioritizing and selecting the optimal solution**. To best use the available resources and circumvent some constraints, responsible agencies always need to finalize the priority of an optimal list of countermeasures, based on the evaluation results and available budget (Bahar et al, 2016). This process is generally used to prioritize the countermeasures according to the information from the previous step and selects the set of most cost-effective countermeasures from an extensive list of options.

The sixth step is **safety effectiveness evaluation**. The purpose is to assess the impacts of a particular treatment (or group of treatments) on the resulting safety performance (crash frequency and severity) using either before and after analysis or a cross-sectional study (Bahar et al, 2016).

2.4. The current practice

Even with this rigorous process, local agencies may often face difficulties in taking all the essential steps due to various challenges ranging from incomplete road inventory data to a lack of up-to-date information on available countermeasures. Other examples of these difficulties include the lack of reliable methods to identify contributing factors, the absence of a comprehensive set of countermeasures, and the lack of quantitative analysis methods for evaluating and selecting countermeasures. As such, many agencies may choose to follow a more practical procedure for intersection safety improvement, as summarized in the Field Guide for Selecting Countermeasures at Pedestrian Crossing Locations by FHWA (2013).

The first step in the Field Guide involves collection of pedestrian and vehicle volumes, site characteristics, and focus crash types.

The second step involves selecting appropriate countermeasures based on the analysis results conducted in the previous step and intends to engage engineers and other professionals to assist in the design and installation of the selected countermeasures. For instance, engineers at this step may recommend providing high-visibility crosswalk markings, parking restrictions on crosswalk approaches, overhead lighting, *'yield/stop for pedestrians'* signs, or yield/stop lines.

The third step is to monitor their effectiveness. This requires the safety engineer to continuously monitor the effectiveness of the implemented countermeasures to identify areas for improvement.

Note that the above process is heavily dependent on engineers' experience with various tasks, including problem identification and countermeasure selection. The effectiveness of such a judgement-dependent process might be limited by either the preference of the experts or the incomplete knowledge of novice engineers. Therefore, to enhance the accuracy and reliability of an engineer's decision-making for final safety countermeasure selection, researchers in the traffic community have developed various Knowledge-Based Expert Systems (KBES) to assume such tasks (Harkey & Zegger, 2004; De Guzman & Sigua, 2009; Frey et al, 2014; and Kindler et al, 2003).

2.5.The PEDSAFE system

In addition to following the guidelines mentioned earlier, practitioners can also utilize pre-existing tools explicitly developed to address pedestrian safety issues at intersections. One example of such tools is PEDSAFE, a knowledge-based system that suggests the most appropriate countermeasures for a targeted intersection.

PEDSAFE, developed by Harkey and Zegeer (2004), is a user-friendly expert system designed to assist traffic safety professionals and associated decision-makers in addressing pedestrian safety.

PEDSAFE employs the following steps to provide countermeasures:

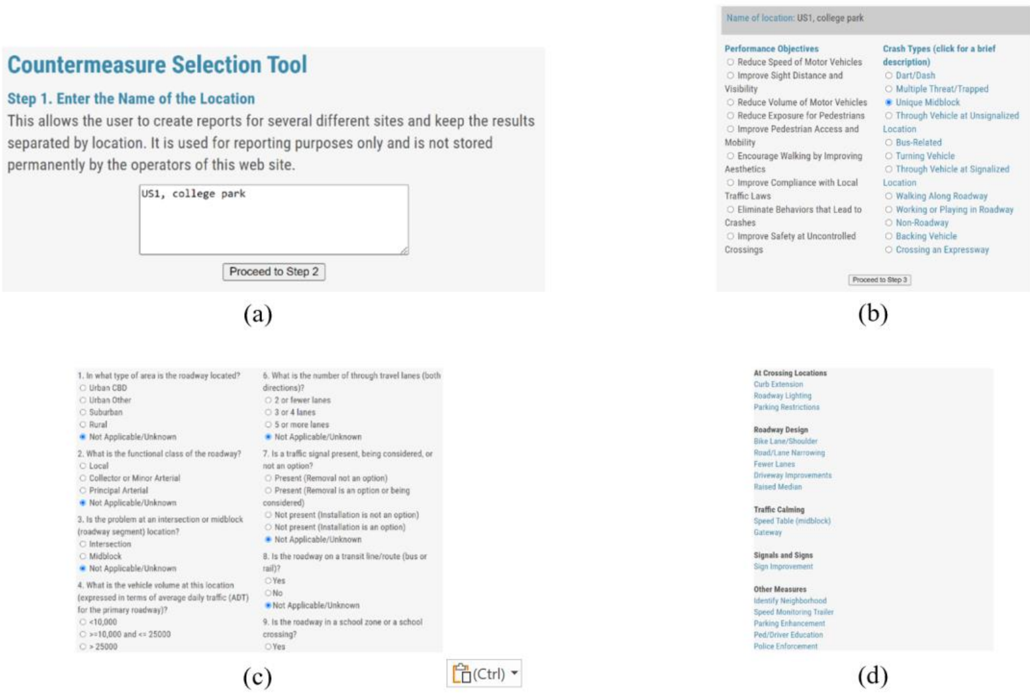


Figure 2.2. The processes of using PEDSAFE

As shown in Figure 2.2, users can provide the location, select the treatment goal (e.g., reducing traffic volumes or mitigating a specific type of pedestrian-motor vehicle collision), and describe the site's geometric and operational characteristics (e.g., type of area, vehicle volume, and travel lanes) to identify the root causes of the safety problem.

With the collected inputs, PEDSAFE can then generate a list of conventional countermeasures, such as sidewalks, shoulders, and street furniture to contend with the target safety issues as shown in Figure 2.4 (d). Additionally, the developers emphasize that the output of PEDSAFE should serve as a starting point for further analysis.

As for the evaluation of countermeasures, PEDSAFE can provide estimated costs for each countermeasure, including both furnishing and installation expenses. The effectiveness of each countermeasure on pedestrian crashes and safety has been documented in a separate report (Harkey & Zegeer, 2004), allowing users to assess the potential impact of the proposed solutions.

PEDSAFE is an exemplary Knowledge-Based Expert System (KBES) for addressing pedestrian safety issues. It encourages public engagement in identifying problems, streamlines decision-making by providing countermeasures to targeted safety issues, and evaluates countermeasures based on cost and effectiveness.

2.6.Other Expert Systems

Aside from PEDSAFE, several similar Knowledge-Based Expert Systems (KBESs) have been developed to address intersection safety. A summary of their objectives and methodologies is presented below:

The Knowledge-Based Expert System for Intersection Improvement

De Guzman and Sigua (2009) developed a system with the objective of diagnosing intersection accidents (as well as congestion) and providing suitable strategies with potential traffic control measures. Similar to PEDSAFE, this system also follows a three-step process to offer countermeasures:

The first step is to identify problems by employing a physician-patient analogy, where the problem is akin to a person being diagnosed with an unidentified illness, classified as “congestion only”, “accidents only”, or “congestion + accidents.”.

The second step is to generate a list of conventional countermeasures, such as traffic signals, roundabouts, warning signs, stop signs, and yield signs. Each countermeasure is recommended to target a specific crash type.

The third step is to evaluate the properties of countermeasures and to classify them into operational solutions, geometric modifications, or regulations/enforcement categories. Countermeasures can be selected based on their types, rather than solely on cost or effectiveness.

This KBES has effectively categorized various countermeasures to facilitate efficient decision-making when dealing with a substantial number of countermeasures.

An Expert System for Rural Unsignalized Intersections

Frey et al. (2014) created an expert system aimed at enhancing intersection safety using “IF…THEN” statements. This system, situated within the logic block, targets specific crash types and is designed to emulate the thought process of a human expert.

This system generally follows a two-step process of problem identification and countermeasure generation to recommend countermeasures.

For the identification of problems, the system recommends reviewing crash records from the past three to five years and creating a crash diagram. This step can help determine the types of crashes occurring at the target intersection.

For the generation of countermeasures with respect to the identified crash types, the system will generate a list of conventional countermeasures based on their respective costs and expected effectiveness. Examples of such countermeasures include intersection lane narrowing, all-way stop control (for angle crashes), improving intersection sight distance, and installing flashing beacons.

Intersection Diagnostic Review Module (IDRM) Expert System for Geometric Design

The Intersection Diagnostic Review Module (IDRM) is an expert system designed to detect potential geometric safety issues at intersections (Kindler et al, 2003). The system follows a two-step process.

First, the system identifies potential design deficiencies by examining geometric characteristics and design elements. Even when these elements are individually considered within good design practice, they may still cause safety issues. The IDRM addresses 111 potential design concerns (Kindler et al, 2003) on intersection configuration, horizontal alignment, vertical alignment, and intersection sight distance.

Second, based on the identified geometric concerns, the system generates a list of conventional countermeasures. Examples of these countermeasures include closing one or more legs (for multileg intersections), realigning one or more legs (for skewed intersections), and/or increasing curve radius (for horizontal curves).

This system can consider geometric conditions when identifying countermeasures to enhance the effectiveness of the recommendation.

2.7. <u>*Summary*</u>

As illustrated in the above sections, KBESs have various notable functions to assist safety engineers in effectively developing projects for intersection pedestrian safety improvement, including 1) identifying the problematic characteristics of an intersection, 2) generating a list of countermeasures, and 3) evaluating the effectiveness of selected countermeasures. In the problem identification process, both the agencies and the public can engage in the design process by providing geometric characteristics and crash-related details.

As for the process of generating countermeasures, a KBES can offer a comprehensive list of conventional and advanced countermeasures to contend with targeted crash types, and to facilitate efficient decision-making. Its final process evaluates countermeasures by assessing the cost, effectiveness, and possible combinations from the identified list to help users determine the most cost-effective option.

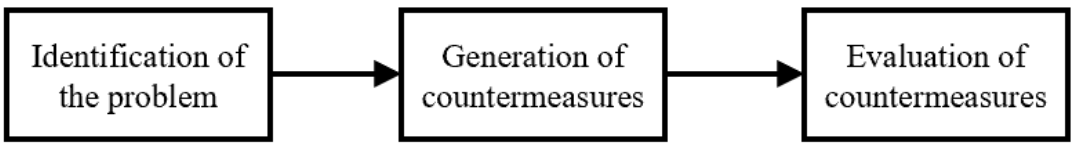


Figure 2.3. The practical procedures followed by existing KBESs

Although existing KBESs have made significant contributions, they primarily concentrate on problem identification, countermeasure generation, and evaluation as depicted in Figure 2.3. However, when compared to the more rigorous processes illustrated in Figure 2.1, these systems fail to address crucial aspects, such as analyzing contributing factors and prioritizing and selecting appropriate countermeasures.

For example, when generating countermeasures, the existing system often fails to contain a comprehensive list of available countermeasures, including both conventional and advanced ones. Moreover, existing analysis tools that rely on characteristics or crash types often provide too many countermeasures for traffic engineers to choose from. Hence, much remains to be done to perfect the process and approaches to identify the most critical contributing factors and finalize the corresponding countermeasures. More importantly, a well-designed quantitative approach to select and prioritize the countermeasures would provide users with solid support and a better grasp of the expected benefits. These limitations of existing KBESs raise the need for additional enhancements which are to be addressed in this study.

3. System structure and logic flows

3.1.System design description

This study proposes an advanced Knowledge-Based Expert System (KBES) to address the intersection pedestrian-vehicle crash issue and the discrepancies between state-of-the-art and current practices in identifying safety improvement countermeasures. The primary purpose is to offer engineers an optimized set of countermeasures in response to the key factors (e.g., Inattentive pedestrian, speeding and poor geometric conditions) causing crashes at target intersections. The developed system can automate the process for selecting safety-improvement projects that cater to pedestrian safety at intersections, enabling safety engineers to minimize efforts while ensuring the quality of analysis and the effectiveness of selected countermeasures.

To optimize the selection of safety countermeasures at intersections, engineers must fully capture not only the critical factors contributing to the target crash type, but also the individual impact of such factors in relation to the traffic, environment, and geometric features of the intersection. Moreover, the selection and prioritization of countermeasures should be closely tied to the expected impact of each contributing factor, while also considering budget limitations and engineers' priority concerns.

Design with the aforementioned requirements in mind, the proposed system features its effectiveness in exercising the following two functions:

- Identify a set of crash-contributing factors that potentially cause accidents at the target intersection and assign impact value to them based on the likelihood of their impacts; and
- Generate a list of countermeasures designed to effectively contend with the identified contributing factors, taking into account the user's preferences in countermeasure selection and the budget constraints for deployment.

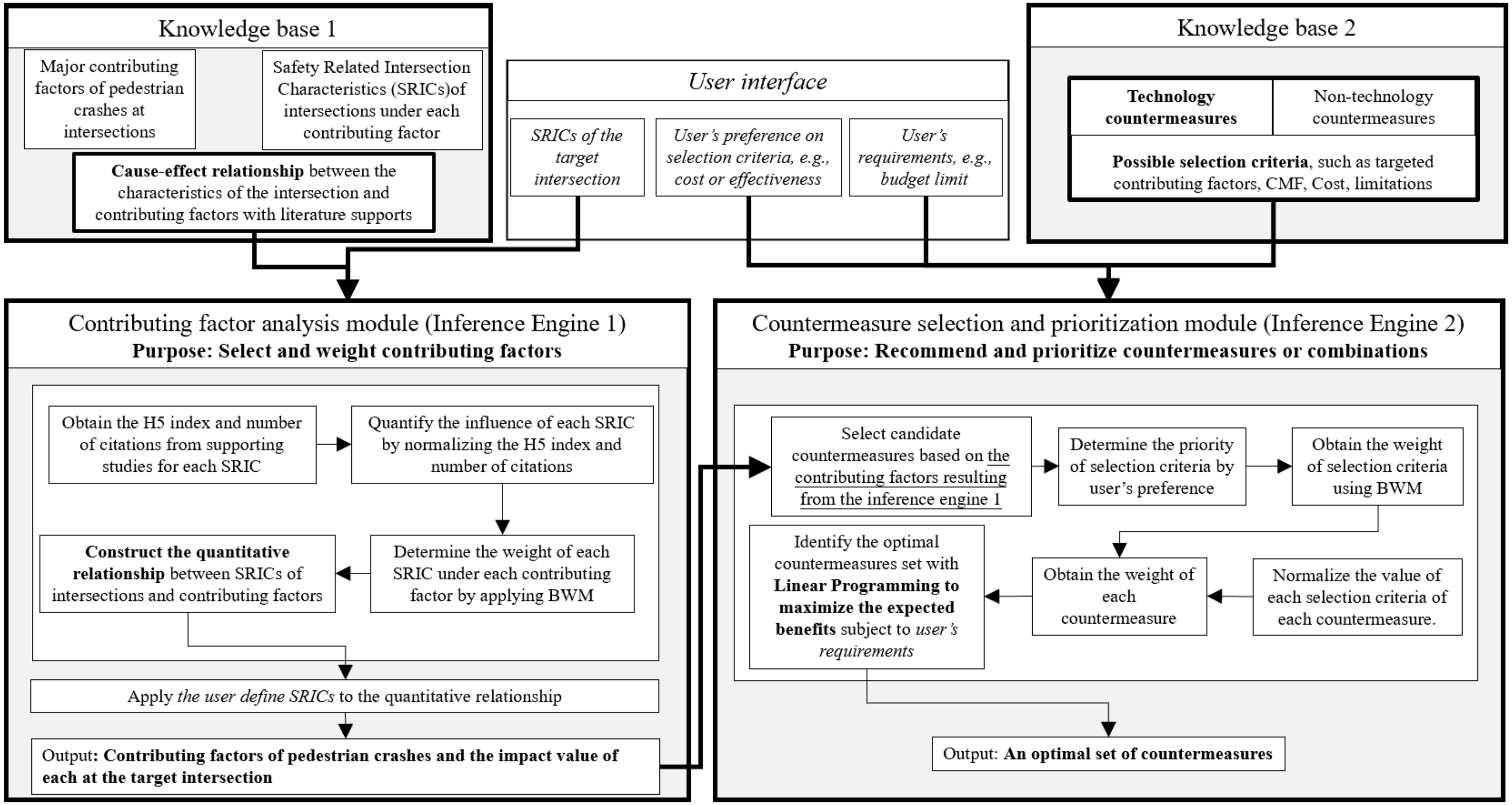
To effectively execute the above functions, this study has been designed with four essential modules, as depicted in Figure 3.1. The primary role of each module and relationship with others in the system's overall operational structure are summarized below:

- **Knowledge Base 1**: This module serves as a qualitative foundation for the Contributing Factor Analysis module. It compiles key information and data on factors potentially contributing to pedestrian-vehicle crashes, including intersection geometric features and behavioral characteristics of driving populations, and more importantly, the causal relationships between them. The sources for acquisition of such information will be discussed in the subsequent section.
- **Contributing Factor Analysis Module**: The primary objective of this module is to generate a list of the most likely contributing factors to pedestrian-vehicle crashes at target intersections. This module enables a more accurate and well-founded selection of countermeasures. Specifically, it includes a set of quantitative relationships between intersection related information (i.e., geometric features, characteristics of traffic and driving populations), named Safety Related Intersection Characteristics (SRICs) variables hereafter, and contributing factors, derived from the qualitative relationships obtained from Knowledge Base 1. These functions can be used to compute the relative impact value of each contributing factor based on all information available in the state-

of-the-art and state-of-the-practice in the traffic safety community. The impact values of the contributing factors are then used as the foundation for the analysis task executed by the Countermeasure Selection and Prioritization Module.

For the second function, this study has designed two additional essential modules for the KBES, as shown in Figure 3.1:

- **Knowledge Base 2**: Intending to provide a basis for the Countermeasure Selection and Prioritization module, Knowledge Base 2 contains a list of available technologies and conventional countermeasures to cope with intersection pedestrian safety issues. All related information and data such as the cost, crash modification factor, contributing factors, and constraints for deployment and maintenance are also included in this knowledge base.
- **Countermeasure Selection and Prioritization Module**: This module functions to generate the final output—an optimal set of countermeasures that can maximize expected effectiveness with respect to identified contributing factors within a limited budget based on users' preferences on selection criteria. To do so, the module is designed to comprise two functions: selecting countermeasures to match their targeted contributing factors available from the previous module and prioritizing countermeasures using their selection criteria with an optimization procedure to yield an optimal set of countermeasures.



Notes: Bold text indicates unique contributions in the proposed KBES; Italic text denotes user input; Underline text indicates input from the inference engine 1; BWM stands for Best-Worst method

Figure 3.1 Structure of the proposed KBES for countermeasure selection

3.2.<u>Development methodology for each module</u>

This section details the core logic and the development procedure for each module in the proposed system, including data requirements and expected outputs.

Knowledge Base 1

To ensure that Knowledge Base 1 contains comprehensive and reliable information for all subsequent analyses, it is developed with the following procedures, as illustrated in Figure 3.2.

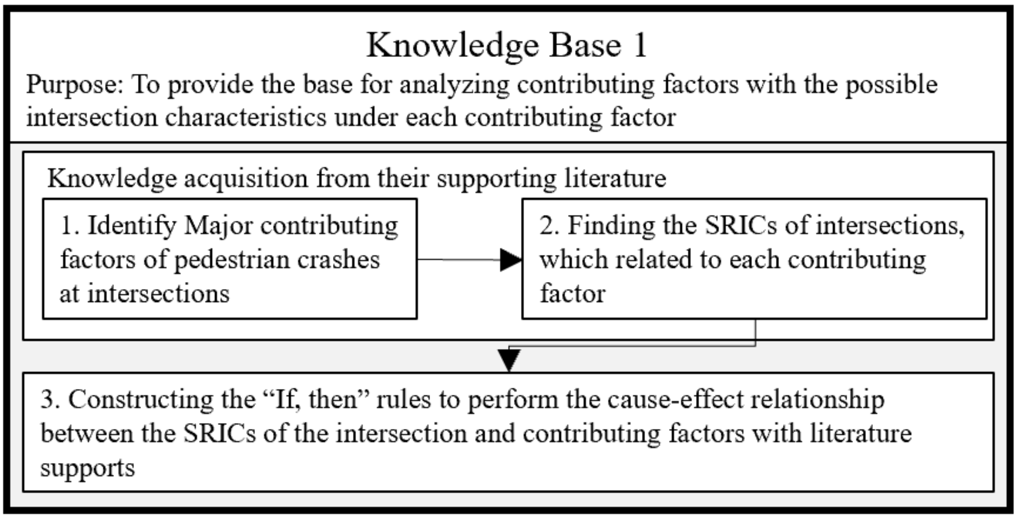


Figure 3.2. The development processes of the Knowledge Base 1

1. **Identify major contributing factors of pedestrian crashes at intersections**. The process begins with identifying a set of factors that contribute to pedestrian crashes from various publications and quality safety journals such as "Accident Analysis & Prevention," "Transportation Research Record," and "Journal of Transport & Health”. Furthermore, to ensure that these major contributing factors can sufficiently reflect the major causes of most intersection pedestrian-vehicle crashes, such information, documented in the crash record systems, are extracted from several state reports, including the VDOT Traffic Engineering Division (2017), California Highway Patrol (2002), Texas Department of Transportation (2012), National Highway Traffic Safety Administration (2020), Georgia Department of Public Health (2021), and Maryland Open Data Portal (2022). Lastly, to further verify the validity of major contributing factors, all data associated with intersection pedestrian-vehicle crashes have been extracted from the database of Maryland Statewide Vehicle Crashes (Maryland Open Data Portal, 2022). The percentage of intersection crashes attributable to any of the major contributing factors can serve as the base for assessing the effectiveness of the identified contributing factors.
2. **Find the possible relations between Safety Related Intersection Characteristics (SRICs) variables (i.e., geometric features and behavioral characteristics of the driving populations) and each contributing factor**. The intersection’s geometric features and any characteristics of driver behavior that may be related to each contributing factor will be identified based on the analysis results reported in

relevant studies. For example, if "Inattentive Pedestrian" is considered a major contributing factor and some studies (Sunder et al, 2019; Basch et al, 2015) suggest that pedestrians using cell phones become more inattentive and that more pedestrians are inattentive at busy intersections, then one can conclude that "many pedestrian-involved crashes are likely to involve cell phone use, especially at busy intersection environments." Such behavior related SRICs can then also be identified as associated with this contributing factor. It is important to note that each major contributing factor may have more than one type of relations with the SRICs variables (i.e., geometric features or behavioral characteristics of its driving populations), and such relations may be reported consistently in different sources.

3. **Construct the "If-then" rules to demonstrate the cause-effect relationship between each contributing factor and its associated SRICs variables identified in the last step.** Under such rules, related behavioral characteristics and/or geometric features are considered causes, and major contributing factors are regarded as effects. For example, following the scenario in step 2, the "if-then" rule for "Inattentive Pedestrian" would be constructed as follows: if the intersection has its populations with the behavioral SRICs related to "many pedestrian-involved crashes involving cell phone use" or "busy intersection environments", then one can conclude that "Inattentive Pedestrian" is likely to be a major contributing factor to intersection pedestrian-vehicle crash. A set of such rules will be generated and summarized in an organized format to facilitate further analysis.

Contributing factor analysis module (Inference Engine 1)

To compute the impact value of each contributing factor at the target intersection based on the user input, the relationship between each contributing factor and its associated SRICs variables, identified in Knowledge Base 1, must be properly quantified to reflect its reliability when depicting the nature and causes of the target pedestrian-vehicle crashes. To do so, this study has first conducted a comprehensive review of related studies discussing such relationships and then investigated the validity of their conclusions. This is followed by the adoption of the H5 index (Google Scholar, n.d.) and number of citations of those studies as the basis for such findings' reliability and quality assessment.

More importantly, to facilitate further comparison and ranking of these quantitative relationships and determine their relative impacts on safety, the statistical approach known as the Best-Worst Method (BWM) (Rezaei, 2020) has been adopted. BWM demonstrates simplicity, exceptional flexibility, definitive ranking of alternatives, an efficient data collection process, and most importantly, its capability to conduct pairwise evaluations of the effects of SRICs (Rezaei, 2020).

The core logic for guiding the above ranking and comparison analysis is summarized below:

1. **Obtain the H5 index and the number of citations from supporting studies for each item of information associated with each contributing factor**. The H5 index and the number of citations of those studies serve as the basis for assessing the reliability of the relationship between each contributing factor and its potentially related SRIC variables. For example, as mentioned in Knowledge Base 1, a study by Sunder et al (2019) concluded that cell phone usage often causes pedestrians to be more inattentive. The H5 index and the number of citations of this study will be used as the data to support the hypothesis that "pedestrians using cell phones when crossing an intersection

are more likely to cause a crash with vehicles.”

2. **Quantify the influence of each set of SRIC variables by normalizing the H5 index and the number of citations.** This step converts the H5 index and the number of citations of each study associated with each set of SRIC variables related to the contributing factor into quantitative values.
3. **Determine the weight for each set of SRIC variables related to the contributing factor by applying the Best-Worst Method (BWM)**. This is due to the fact that different SRIC variables may have different weights of impact on the contributing factor. The input for BWM consists of the normalized H5 index and the normalized citation numbers from each SRIC. The output is the weight of each SRIC variable on the contributing factor.
4. **Construct the quantitative relationship between an intersection's SRIC variables and each contributing factor.** Since the weights of all SRICs have been obtained, the quantitative relationship or the transformation function can be expressed as:

   *Impact value of each contributing factor = (Weight of related SRIC 1) * (Variable of related SRIC 1) + (Weight of related SRIC 2) * (Variable of related SRIC 2) + …… + (Weight of related SRIC n) * (Variable of related SRIC n)*

   If the related SRIC variable exists at the target intersection, the variable will be 1; otherwise, it is 0.
5. **Apply user-defined additional SRIC variables to the quantitative relationship** to reflect local-specific needs and issues. The output of this module is the impact values of all contributing factors. It is important to note that the higher the impact value of a contributing factor, the more critical we expect the contributing factor to be with respect to safety at the target intersection.

Additionally, it is important to note that the database is expandable, as managing the numerical weight of SRIC variables and contributing factors is quite convenient. In addition, all essential information, data, and results are currently collected and stored in an Excel spreadsheet. As such, the impact values of even a large number of contributing factors can be calculated efficiently with the proposed optimization method. Furthermore, the quantitative relationships between SRICs and contributing factors can be easily migrated into other database formats.

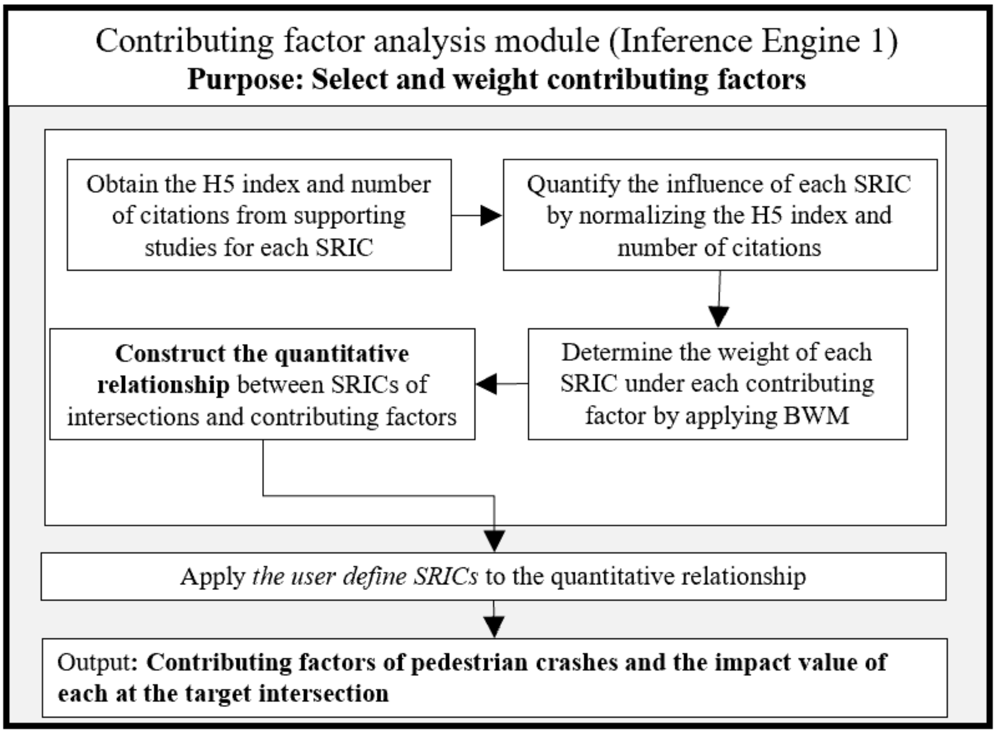


Figure 3.3. The development processes of the contributing factor analysis module

Knowledge Base 2

To ensure that Knowledge Base 2 contains comprehensive and reliable information for further analysis, the following processes are employed:

1. **Identify technologies and conventional countermeasures**. Technologies and countermeasures can be identified from leading technology companies (e.g., TAPCO and Lanelight), authoritative patent offices (e.g., the US Patent Office), and publications about pedestrian crash countermeasures. Conventional countermeasures can be identified from publications and state reports from major states about pedestrian crashes. For instance, TAPCO company (TAPCO, 2021) introduced the "High Water Warning System" as a countermeasure.
2. **Determine the value under each selection criterion**, including targeted contributing factors, Crash Modification Factors (CMFs), the types (including operational, geometric, and regulatory) and limitations. Such information can be obtained from the source related to the corresponding countermeasure. For example, the "High Water Warning System" costs about $30,000 and can warn drivers under adverse weather conditions. Therefore, its targeted contributing factor is "Adverse Weather," and its cost is "$30,000."
3. **Construct a list of countermeasures with the user-defined criteria**. In this list, the columns are the selection criteria. The rows are the countermeasures. Therefore, details about each countermeasure can be reviewed row by row.

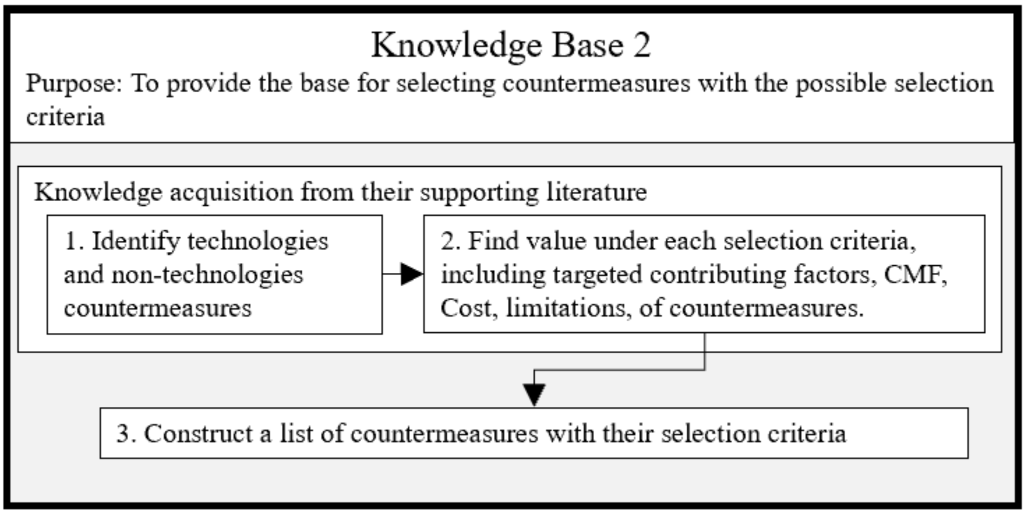


Figure 3.4. The development processes of the Knowledge Base 1

Countermeasure Selection and Prioritization module (Inference Engine 2)

The Countermeasure Selection and Prioritization module (Inference Engine 2) shortlists the optimal set of countermeasures from a long list in Knowledge Base 2 by matching the identified set of contributing factors and the set of countermeasures designed to contend with each of such factors. To produce an optimal set, a Linear Programming formulation is constructed with an objective function of maximizing the expected effectiveness of countermeasures subject to the constraints defined by user requirements, such as budget limits and the number of countermeasures allowed. Note that since a specified weight represents the cost-effectiveness from the user's viewpoint, the user's preference, including effectiveness (CMF) and cost criteria, is collected, and used to construct the weight for each countermeasure. Following the same logic of generating weights for contributing factors, the proposed system will apply BWM as a tool to convert the user's preference on the comparison of cost and CMF into associated weights.

To finalize the optimal set of countermeasures, the proposed system will take the following actions:

1. **Select candidate countermeasures based on the contributing factors obtained from Inference Engine 1**. The Contributing Factor Analysis Module (Inference Engine 1) will identify all contributing factors associated with pedestrian crashes at the target intersection. Each Countermeasure in Knowledge Base 2 is classified with its effectiveness in contending with some contributing factors for intersection crashes. Therefore, the recommended set of countermeasures can be generated by matching contributing factors of pedestrian crashes at the target intersection with the possible contributions from each countermeasure. Additionally, some limitations associated with each countermeasure and the target intersection conditions, such as the number of lanes and types, should be considered in finalizing the selection.
2. **Determine the priority of the selection criteria based on the user preference**. The user can decide whether the cost or effectiveness (CMF) is more important by assigning their scores from 1 to 5.
3. **Obtain the weight of selection criteria using the Best Worst Method (BWM).** The input consists of the scores of each target's contributing factors, cost, and effectiveness (CMF) where the target contributing factor is specified with the highest score since eliminating the contributing factors that cause

pedestrian crashes is the top priority. The output is the set of relative weights for the target contributing factors, cost, and CMF.

4. **Normalize the value of each criterion for selecting each countermeasure and obtain its associated weight** using the following transformation function:

Weight of countermeasure n = (Weight of "target contributing factors")(Total impact value of its targeted contributing factors) + (Weight of "cost")*(1 - Normalized value of its cost) + (Weight of "CMF")*(1 - Normalized value of its CMF)*

Countermeasures can be prioritized based on their weight.

5. **Identify the optimal set of countermeasures** using Linear Programming to maximize the expected benefits, subject to user requirements. Its objective function is to maximize the total weight of selected countermeasures. Proper constraints can be added according to the user's requirements, such as budget and quantity constraints. The simplex method can be used to solve linear programming equations.

The output of linear programming is the finalized set of countermeasures, which will have the highest total weight, meaning they are the most cost-effective countermeasures. Note that the entire processes executed in this module are expandable. For example, more countermeasures with details can be added row by row to an Excel spreadsheet and then be directly adopted as the input of the mathematical programming.

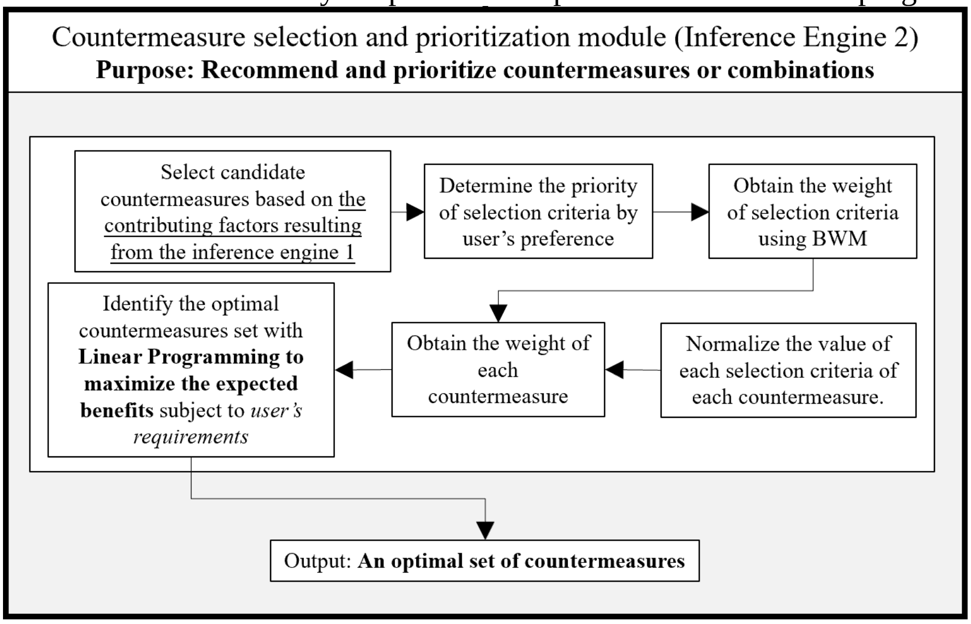


Figure 3.5. The development processes of the Countermeasure selection and prioritization module

***3.3.** *Contributions*

The proposed KBES addresses several deficiencies mentioned in Chapter 2, including the use of conventional countermeasures, the lack of contributing factor analysis, and an excessive number of candidate countermeasures. Additionally, the KBES incorporates methods for selecting countermeasures, providing an efficient and reliable means to address most concerns often raised in practice.

The proposed logic flows for finalizing the optimal set of countermeasures can be extended to the broader scope of contending with all types of intersection crashes, such as rear-end collisions and angle crashes. Further, the method proposed in this study to quantify the impact value of each contributing's impact on pedestrian crashes and the optimization process designed to produce the optimized set of effective countermeasures within user-specified constraints have collectively offered a new avenue to strengthen the quality and effectiveness of a knowledge-based system.

4. Design methodology for core system modules

This chapter will present the core methodology used in developing each of the four critical modules of the proposed KBES, namely, Knowledge Base 1, Knowledge Base 2, the Contributing Factor Analysis module, and the Countermeasure Selection and Prioritization module.

The primary purpose of Knowledge Base 1 and the Contributing Factor Analysis module (Inference Engine 1) is to identify and rank the key contributing factors directly causing pedestrian crashes at an intersection. Note that Knowledge Base 1 functions to document all evidence and relevant information regarding the impacts of the seven major contributing factors on pedestrian-vehicle crashes. Such a module also contains information associated with all Safety Related Intersection Characteristics (SRICs) (e.g., geometric features and behavioral characteristics of driving populations) and their relations with each contributing factor. The module, named Inference Engine 1, features its unique method to construct the quantitative relationship between each contributing factor and its associated qualitative and quantitative SRICs.

The objectives of Knowledge Base 2 and the Countermeasure Selection and Prioritization module are to identify and prioritize the most cost-effective set of countermeasures for a target intersection's pedestrian-vehicle crash pattern. The module of Knowledge Base 2 is designed to produce a comprehensive list of technological and conventional countermeasures based on their Crash Modification Factors (CMFs), costs, limitations, and the target contributing factors for which each countermeasure is designed. The Countermeasure Selection and Prioritization module (Inference Engine 2) is embedded with an innovative optimization method that enables traffic safety professionals to effectively and efficiently finalize the optimal set of countermeasures within all preset constraints based on the relative impacts of those identified contributing factors on the target intersection resulting crashes.

The primary development process for each of these key modules is presented in the remaining sections of this chapter.

4.1. The Knowledge Base 1

The core idea of Knowledge Base 1 is to establish the cause-effect relationship between Safety Related Intersection Characteristics (SRICs) and critical factors affecting pedestrian safety at the intersection. The primary challenge of Knowledge Base 1 lies in ensuring that the list of contributing factors is sufficiently comprehensive for further analysis but not so excessive as to burden or confuse potential system users. Additionally, it is crucial to identify all SRIC variables associated with each potential contributing factor through a rigorous knowledge acquisition process.

Identifying and Verifying the safety impacts of Contributing Factors

The major task in developing this module, as mentioned in the previous chapter, is to identify all potential contributing factors to pedestrian-vehicle crashes from the state-of-the-practice and various publications and reports. Examples of such publications reviewed for this study include safety journals, such as "Accident Analysis &

Prevention," "Transportation Research Record," and "Journal of Transport & Health". These identified factors are then cross-referenced with similar findings available from several state reports, including the VDOT Traffic Engineering Division (2017), California Highway Patrol (2002), Texas Department of Transportation (2012), National Highway Traffic Safety Administration (2020), Georgia Department of Public Health (2021), and Maryland Open Data Portal (2022). Additionally, they are tested with crash cases from the Maryland Database (Maryland Open Data Portal, 2022).

Note that the results of the extensive literature review reveal seven main contributing factors associated with pedestrian-vehicle crashes as shown in Table 4-1, where Inattentive pedestrians and Inattentive drivers are on the top five factors by Bernhardt & Kockelman (2021). Several studies indicate that high speeds increase the severity of pedestrian injuries and that urban areas with high-speed limits are more likely to cause pedestrian crashes (Davis, 2001; Spainhour et al., 2006; Sun et al., 2019; Bernhardt & Kockelman, 2021). As such, **speeding** is recognized as one major contributing factor.

Jaywalking, including crossing outside designated areas, has been identified as a contributing factor to pedestrian crashes by Yue et al. (2020). Additionally, **adverse weather** is generally viewed as a factor contributing to pedestrian crashes, as reported by Yue et al. (2020), Zhai et al. (2019), and Sun et al. (2019). Their studies conclude that various adverse weather conditions, including rain, fog, and darkness, increase the risk and severity of pedestrian crashes.

Moreover, **turning right on red** is found to be another major contributing factor to pedestrian-vehicle crashes because some drivers may conflict with pedestrians who assume that they are given the right of way when turning right on red (Yue et al., 2020; Preusser et al., 2002).

In addition, **poor geometric conditions**, such as poorly designed intersections and roads, are identified as a contributing factor to pedestrian crashes. Several studies in traffic safety have highlighted the need to improve roadway and intersection design to enhance pedestrian safety (Lee & Abdel-Aty, 2005; Pulugurtha et al., 2007).

To ensure that the aforementioned seven major contributing factors from the safety literature are consistent with the state-of-the-practice, this study has verified them with those indicated in project reports and databases from various states, including VDOT Traffic Engineering Division (2017), California Highway Patrol (2002), Texas Department of Transportation (2012), National Highway Traffic Safety Administration (2020, 2005), Georgia Department of Public Health (2021), and Maryland Open Data Portal (2022). The concluding findings are that almost all direct and indirect contributing factors identified in the state of practices are encompassed by these seven contributing factors, as shown in Table 4-1. The right columns in the table show all similar contributing factors adopted by different state highway agencies in selection of effective countermeasures.

Table 4-1 Contributing factors and their similar contributing factors adopted by different states' highway agencies.

Direct contributing factors	Similar contributing factors from other states
Inattentive pedestrian/ Inattentive drivers	● Under Influence of Drugs ● Under Influence of Alcohol ● Under Influence of Medication ● Under Combined Influence ● Physical/Mental Difficulty etc.
Inattentive drivers	● Improper Turn

	● Improper Lane Change ● Improper Backing ● Improper Passing ● Improper Signal etc.
Inattentive pedestrian	● Bicycle Violation ● Approaching or leaving motor vehicle ● Darting in roadway ● Improper crossing ● Clothing not visible etc.
Speeding	● Exceeding Safe Speeds for Conditions ● Exceeded the Speed Limit
Adverse weather	● Smog, Smoke ● Sleet, Hail, Freezing Rain ● Blowing Sand, Soil, Dirt ● Severe Crosswinds ● Rain, Snow etc.
Jaywalk	● Hitchhiking ● Jaywalking
Turning right on red	● Improper Right Turn on Red ● Turning Right on Red
Poor geometric conditions	● Wet surface ● Icy or Snow-covered ● Debris or Obstruction ● Ruts, Holes, Bumps ● Road Under Construction/Maintenance etc.

Note: More similar contributing factors from state practice are shown in the appendix.

In Table 4-1, the right column includes alternative contributing factors from different states' practices which can be categorized into Inattentive Pedestrians/Inattentive Drivers. For instance, Driving Under the Influence (DUI) / Driving While Impaired (DWI) are classified into the category of Inattentive pedestrians/Inattentive drivers. The table also highlights several instances of improper driving behaviors that, while too detailed to explicate individually, can be broadly categorized as inattentive drivers. Furthermore, the results from the table indicate that various inattentive actions are considered inattentive pedestrians.

As shown in table 4-1, speeding can be defined as either exceeding safe speeds under the given traffic conditions or exceeding the speed limit. Likewise, adverse weather conditions may include smog, blowing sands, severe crosswinds, rain, snow, and other similar conditions. Note that jaywalking is named differently in different states; turning right on red is also considered as a contributing factor in many states. Lastly, poor geometric conditions are referred to as both inadequate road surfaces and physical obstructions.

To verify the adequacy of using the seven classified contributing factors in selection of countermeasures, this study has conducted an in-depth investigation of the contributing factors documented in all pedestrian-vehicle accident reports available from the Maryland crash dataset, called the Maryland Statewide Vehicle Crashes.

Table 4-2 shows the percentage of crashes attributed to each contributing factor among all intersections' pedestrian-vehicle crashes from 2015 to 2022 from Maryland Statewide Vehicle Crashes (Maryland Open Data Portal, 2023). Noticeably, a total of 89% of Maryland's crashes can be attributed to one of the seven classified contributing factors.

Table 4-2 Crash proportion occupied by contributing factors.

Contributing factors	# accidents	Proportions
Inattentive pedestrian & Inattentive drivers	5583	64%
Poor geometric condition	1137	13%
Adverse weather	763	9%
Speeding	58	1%
Turning right on red	52	1%
Jaywalk	41	1%
Others	20	1%
Unknown	619	7%
Total	8273	100%

Note: The data is organized from Maryland Statewide Vehicle Crashes (Maryland Open Data Portal, 2023)

To summarize, this section has identified seven major contributing factors which will be utilized to establish relationships between all information and data associated with the intersection (e.g., geometric features, traffic, and behavioral characteristics) and each contributing factor.

Identification of all possible SRICs

To identify possible Safety Related Intersection Characteristics (SRICs), this study has conducted a systematic review of related articles published in those journals listed in Table 4-3, which are all peer-reviewed journals and have been available in the traffic community for at least ten years.

Table 4-3 List of journals referred to for identifying the SRICs variables.

Country of Publishers	The US	The UK	Netherland
Journal titles	1. Transportation research record, 2. The International Journal of Aging and Human Development 3. Accident Analysis & Prevention 4. Injury prevention 5. Human factors 6. Public Health Report 7. Weather, climate, and society 8. ITE journal 9. The Journal of Social Psychology	1. Journal of safety research 2. Transport Reviews 3. Traffic injury prevention 4. Journal of Transport Geography 5. International journal of road safety 6. International journal of injury control and safety promotion 7. Journal of safety research	1. Journal of Transport & Health 2. Safety science 3. Physica A: Statistical Mechanics and its Applications 4. Journal of community health

Noticeably, the results of extensive literature review will produce a list of well-recognized cause-effect relationships between SRICs variables and each of the seven contributing factors. For example, a study by Basch et al. (2014) investigated the distracted walking behaviors in Manhattan, concluding that technology played a significant role, and many involved in accidents were using cell phones. Consequently, "Considerable percentage of crashes involving cell-phone-use pedestrians" can be regarded as a SRIC of the contributing factor, named inattentive pedestrians.

Table 4-4 lists the Safety Related Intersection Characteristics (SRICs) identified to associate with each of the seven contributing factors from the relevant citations. For example, the findings regarding inattentive pedestrians indicate that such a contributing factor is likely to exist at the target intersection if an intersection is characterized with the following Safety Related Intersection Characteristics (SRICs): a high frequency of crashes involving elderly pedestrians, a high frequency of crashes involving pedestrians using cell phones, and a busy intersection environment.

Table 4-4 The identified list of Safety Related Intersection Characteristics (SRICs) for each of those seven major contributing factors

Major Contributing Factor	SRICs	Citation
Inattentive pedestrians	Many elderly pedestrian-involved crashes	Knoblauch et al., 1996; Harrell, 1991
	Considerable fraction of crashes involving cell phone use pedestrian	Sundfer et al., 2019; Basch et al, 2014; Wells et al, 2018; Horberry et al, 2019
	The intersection at a busy environment	Basch et al, 2015
Inattentive drivers	Many cell-phone use drivers-involved crashes	Strayer et al, 2004; Engelbery et al, 2015; Xiong et al, 2015
	Many nighttime crashes-involved crash	Stimpson et al, 2013; Tefft, 2012
	Busy interchanges at that area	Zhai et al, 2019; Smiley et al, 2005
Speeding	Many exceeding speed limits-involved crash	Wilmot & Khanal, 1999; Panaioannou, 2007; Haglund & Aberg, 2000
	Wider street widths	Gårder, 2004
	Many taxi-involved crash	Huang et al, 2018; Prince et al, 2019; Tseng, 2013
	Many crashes with under the influence of alcohol	Yadav & Velaga, 2020
	High posted speeds	Matírnez et al, 2013; Wu et al, 2013
Jaywalk	Corner with business stores	Dai, 2012; Spainhour, 2006
	Intersections with bus stops	Zegeer & Bushell, 2012; Wang et al, 2021
	Many crashes under adverse weather conditions	Zhai et al, 2019
	Narrow crossing distances	Spainhour et al, 2006; Harrell, 1991
	Many crashes with pedestrians under influence of alcohol	Spainhour et al, 2006; Kim et al, 2008
	No pedestrian crossing	Wang et al, 2010; Rasouli & Kotseruba, 2022
Adverse weather	Many heavy rain-involved crash	Zhai et al, 2019
	Many hot or cold weather-involved crash	Lobo et al, 2020; Li & Fernie, 2010
	Many hurricane-involved crash	Samerei et al, 2021; Xie et al, 2015
Turning right on red	Many right turn crashes without “No turn on red” sign	Retting et al, 2002; Zegger & Cynecki, 1985; Chadda & Schonfeld, 1985
	Many teenaged male bicyclist involved crashes	Preusser et al, 1982
	Many median age drivers crashes involved crash	Preusser et al, 1982
Poor geometric	Many wet surfaces involved crashes	Ashifur Rahman, 2022, Kopelias et al, 2007, Jung et al, 2014

conditions	Road markings defects	Papadimitriou et al, 2019
	Road defects (e.g., bumps, rots, holes)	Baireddy et al, 2018

Developing the cause-effect relationship between each contributing factor and associated SRICs

Table 4-5 summarizes the findings between each contributing factor and its associated SRICs from the extensive review of safety literature and related reports.

Table 4-5 The cause-effect relationship between each contributing factor and SRICs.

If the SRICs of an intersection contain:	Then the contributing factor may include:
Many elderly pedestrians-involved crash (C) / Considerable fraction of crashes involving cell phone use pedestrian (C)/ The intersection at a busy environment	Inattentive pedestrians
Many cell-phone use drivers-involved crash (C) / Many nighttime crashes-involved crash (C)/ Busy interchanges at that area	Inattentive drivers
Many exceeding speeds limits-involved crash (C) Wider street widths/ Many taxi-involved crash (C)/ Many crashes with under the influence of alcohol (C)/ High posted speeds	Speeding
Corners with business stores/ Intersections with bus stops/ Many crashes under adverse weather conditions (C)/ Narrow crossing distances/ Many crashes with pedestrians under influence of alcohol (C)/ No pedestrian crossing	Jaywalk
Many heavy rain-involved crash (C)/ Many hot or cold weather-involved crash (C)/ Many hurricane-involved crash (C)	Adverse weather
No "No turn on red" sign-involved crash/ Many teenaged male bicyclists involved crashes (C)/ Many median age drivers' crashes involved crashes (C)	Turning right on red
Many wet surfaces involved crashes (C)/ Road markings defects/ Road Defects (e.g., Ruts, holes or bumps)	Poor geometric conditions

Note: SRICs marked with (C) are identified using crash data, while others are based on intersection geometry or environmental characteristics

4.2. The operating logic for the Inference Engine 1

Inference Engine 1, embedded in the Contributing Factor Analysis module, is designed to construct the relationship between each contributing factor and its associated SRICs. Note that a target intersection for safety analysis may not possess all related SRICs for each contributing factor's reported in the literature. For instance, the contributing factor of "Inattentive pedestrian" is associated with the following three SRICs: many elderly pedestrian-involved crashes; considerable fraction of crashes involving cell phone use pedestrian; the intersection is at a busy environment. Then, the challenge lies in how to estimate the relative impact weight for each of these three SRICs which are postulated to constitute their common associated contributing factor.

Given the estimated weights for all SRICs, one can then decide that only 75 percent of the contributing factor's impact needs to be accounted in the selection of countermeasures, because one of its SRICs, for example, with the weight of 0.25 does not exist at the target intersection. Note that since all justifications and supporting results from publications or reports about the safety impact of each contributing factor's SRICs are qualitative in nature and are also subject to differences in quality and reliability, the following method is thus proposed to overcome such challenges.

It is also worth noting that the method proposed to quantify the relationship between a contributing factor and its related SRICs from the literature is based on the assumption that the quality and reliability of the findings from a publication is correlated with its impact factor (H5 index) and its citation counts (from 2012-2023)

A step-by-step description of the Inference Engine 1's development process is presented below:

Step 1: obtain the H5 index and number of citations from the studies listed in Table 4-4.

Step 2: quantify the influence of each SRIC by normalizing the H5 index and number of citations (H_n and N_n): $I_i = \sum H_n N_n$, where I_i denotes the converted impact of SRIC i.

Step 3: determine the relative weights of all SRICs that constitute each contributing factor by applying the Best-Worst Method (BWM) (Rezaei, 2020) and using the converted impact of I_i for each SRIC as the input:

Step 4: construct the quantitative relationship between each contributing factor and its associated SRICs with the resulting weights from BWM as follows:

$Y_j = \sum U_i W_i$, where U_i denote a binary variable which equals 1 if SRIC i exists at the intersection; and Y_j is the resulting impact value for contributing factor j.

Note that the method of BWM features its strengths of simplicity, exceptional flexibility, definitive ranking of alternatives, and efficient data collection process. It is an effective ranking technique that can facilitate the comparison of all SRICs by utilizing the most and least significant attributes (Rezaei, 2020).

An example of using the contributing factor of "Inattentive pedestrian" to illustrate the above transformation process is presented below.

As shown in Knowledge Base 1, the contributing factor of inattentive pedestrians is recognized to comprise the following three SRICs: many elderly-involved crashes, a considerable fraction of crashes involving a cell-phone-use pedestrian, and busy intersections. Then, the process used to convert the quality information about each of such SRICs into the quantitative impact on its associated contributing factor from the research results published in seven studies is presented below :

The first step is to assess the quality and reliability of the research results associated with the target SRIC and the contributing factors with the H5 index and the number of citations. Table 4-6 displays the H5 index, and the number of citations associated with each study.

Table 4-6 H5 index and number of citations associated with each study.

Supporting Studies	SRICs	H5 index	#citaion	Citation
Study 1	Many elderly pedestrian-involved crashes	51	293	Knoblauch et al, 1996
Study 2	Many elderly pedestrian-involved crashes	-24	-10	Harrell, 1991
Study 3	Considerable fraction of	74	45	Sundfer et al, 2019

	crashes involving cell phone use pedestrian			
Study 4	Considerable fraction of crashes involving cell phone use pedestrian	36	38	Basch et al, 2014
Study 5	Considerable fraction of crashes involving cell phone use pedestrian	42	57	Wells et al, 2018
Study 6	Considerable fraction of crashes involving cell phone use pedestrian	58	45	Horberry et al, 2019
Study 7	The intersection at a busy environment	42	45	Basch et al, 2014

The second step is to normalize the H5 index and number of citations associated with each SRIC as follows: $I_i = \sum \quad H_n N_n$, where I_i is the quantified impact for SRIC i. and the normalized results are shown in Table 4-7.

The third step is to calculate the relative weight of each SRIC's impact, denoted as Wi, on its associated contributing factor, based on its normalized reliability score, with the Best-Worst Method (BWM). The resulting weight computation for this example is shown in Table 4-8.

Table 4-7 Normalized results based on H5 index and number of citations.

Study n	H5 index of journals	H_n	#Citation	N_n
Study 1	51 (Elderly)	0.765	293 (Elderly)	1.000
Study 2	-24 (Elderly)*	0.000	-10 (Elderly)	0.000
Study 3	74 (Phone)	1.000	45 (Phone)	0.182
Study 4	36 (Phone)	0.612	38 (Phone)	0.158
Study 5	42 (Phone)	0.673	57 (Phone)	0.221
Study 6	58 (Phone)	0.837	45 (Phone)	0.182
Study 7	42 (Busy)	0.673	45 (Busy)	0.182

Note: the negative value indicates that the study disagrees that the SRIC is related to the contributing factor.

Table 4-8 Input and Output of BWM

SRIC (i)	Input ($I_i = \sum \quad H_n N_n$)	Output (W_i)
Elderly pedestrian	0.765	0.472
Phone using	0.579	0.444
Busy intersection	0.122	0.083

Given those weights for all SRICs, **the fourth step** is to assess whether the target intersection's pedestrian-vehicle crashes can be attributed, to what extent, to each of those seven well-recognized contributing factors, based on the available input information by the users. For example, the transformation function of the impact value of "Inattentive pedestrians" is specified as follows:

Impact value of Inattentive pedestrians = 0.472 (Many elderly pedestrians-involved crash) + 0.444 (Considerable fraction of crashes involving cell phone use pedestrian) + 0.083 (The intersection at a busy environment)

As such, with the above transformation function, one can then assess if the target intersection’s pedestrian-vehicle crashes can indeed be attributable to this particular contributing factor based on the presence of its associated SRICs inputted by the users. In this example, the resulting impact value for the contributing factor of “Inattentive pedestrians” is quantified with the function as = 0.472(1) + 0.444(0) +0.083(1) = 0.555. If none of the three associated SRICs exist at the target intersection, then the resulting impact from the contributing factor based on the function would equal “zero”, and thus imply that all pedestrian-vehicle crashes that occurred at this target intersection has nothing to do with this factor.

By the same token, one can compute the transformation function for each of those seven contributing factors used in this study as follows:

(a) *Impact value of Inattentive pedestrians = 0.472 (Many elderly pedestrians-involved crash) + 0.444 (Considerable fraction of crashes involving cell phone use pedestrian) + 0.083 (The intersection at a busy environment)*

(b) *Impact value of Inattentive drivers = 0.4 (Many cell-phone use drivers-involved crash) + 0.2 (Many nighttime crashes-involved crash) + 0.4 (The intersection at a busy environment)*

(c) *Impact value of Speeding = 0.465(Many exceeding speed limits-involved vehicles) + 0.246(Wider Street widths) + 0.055(Many taxi-involved crash) + 0.070(Many crashes with under the influence of alcohol) + 0.164(High posted speeds)*

(d) *Impact value of Jaywalk = 0.125 (Corners with business stores) + 0.386 (Intersections with bus stops) + 0.167(Many crashes under adverse weather conditions) + 0.02(Narrow crossing distances) + 0.125(Many crashes with pedestrians under influence of alcohol) + 0.167(No pedestrian crossing)*

(e) *Impact value of Adverse Weather = 0.563 (Many heavy rain-involved crash) + 0.313(Many hot or cold weather-involved crash) + 0.125(Many hurricane-involved crash)*

(f) *Impact value of Turning right on red: 0.053(No “No turn on red” sign-involved crash) + 0.474(Many teenaged male bicyclist involved crashes) + 0.474(Many median age drivers crashes involved crashes)*

(g) *Impact value of Poor geometric conditions = 0.1(Many wet surfaces involved crashes) + 0.8(Road markings defect) + 0.1(Road Defects (e.g., Ruts, holes or bumps))*

In summary, the importance of a contributing factor increases with its impact value, whereas an impact value of 0 renders the factor’s impacts non-existent at the target intersection.

4.3.The Knowledge Base 2

The core of Knowledge base 2 consists of a comprehensive list of technologies and conventional countermeasures, and their associated Crash Modification Factors (CMFs), costs, limitations, and target contributing factors to pedestrian-vehicle crashes. It also includes an Inference Engine 2 that functions to produce the optimal set of countermeasures under the available budget to contend with crash risks attributed to those contributing factors.

Recognizing that information regarding available countermeasures is always fragmented and stored in different databases, this study has identified countermeasures from diverse sources, including technology companies and patent offices for technology-related countermeasures, state reports, and PEDSAFE information for conventional countermeasures. Tables 4-9 and 4-10 show the comprehensive list of 41 countermeasures in Knowledge base 2 for mitigating intersection pedestrian-vehicle crashes, including 24 technological countermeasures and 17 conventional countermeasures along with associated Crash Modification Factors (CMFs), cost, operational requirements (such as Operational, Geometric, and Regulatory/Enforcement), target contributing factors of crashes, potential limitations, and relevant citations:

Table 4-9 The list of 24 technologies countermeasures

Countermeasures	CMF	Cost	Type	Targeted contributing factor(s)	Limitation	References
Automatic Pedestrian Detection for Display of Walk Signal	0.60	$10,000 per crosswalk	Operational	Inattentive pedestrians, turning right on red	Pedestrian signals should be installed	(PEDSAFE, n.d.), (Hughes et al, 2000)
Smart Lighting	NA	$2500	Operational	Inattentive pedestrians, turning right on red, Inattentive drivers	Streetlight should be installed.	(Engoplanet, 2017), (Nambisan, 2009)
Pedestrian Hybrid Beacon (PHB)/HAWK	0.543	$23000	Operational	Inattentive drivers, Speeding	The number of lanes should be more than 6.	(Virginia Department of Transportation, 2021), (FHWA, 2010), (Fitzpatrick et al, 2019)
Smart Pedestrian Crosswalk (SPC)	NA	NA	Operational	Inattentive pedestrians, Inattentive drivers, Speeding		(BERCMAN,2022)
In Road Flashing Crosswalk Light	0.45	NA	Operational	Inattentive drivers		(LaneLight, 2020), (MnDOT, 2005)
Campbell Wave Pedestrian Station	0.54	NA	Operational	Inattention pedestrians	Pedestrian signal should be already installed	(PEDsafety, n.d.), (ODOT, 2009), (FHA, 2010)
RRFB Pedestrian Crosswalk System	0.53	$4,500	Operational	Inattentive drivers		(FWHA, 2018)
Smart intersections	0.1	$9,950,000	Regulation	Inattentive drivers, Inattentive pedestrian, Speeding, jaywalk, adverse weather, turning right on red		(Lynch, 2021), (Khosravi et al, 2018)
On-Board Unit (OBU) on pedestrian, bicyclist, drivers	NA	NA	Regulation	Inattentive drivers, turning right on red		(Krings & Abdel-Rahim, 2021)
A laser-based fiber-coupled wide-spectrum light system	NA	NA	Regulation	Inattentive pedestrian, Inattentive driver, Adverse weather		(The United States Patent and Trademark Office, 2019)
Recognizing Assigned Passengers For Autonomous Vehicles	NA	NA	Regulation	Inattentive driver, Speeding		(RAND Corporation, 2017), (Waymo LLC, 2018),)
Pedestrian Warning	NA	NA	Regulation	Inattentive drivers		(Pedestrian Warning Systems, 2019)

System						
I-see System And Method	NA	NA	Regulation	Inattentive drivers		(Waheed & Farashta, 2015)
Pedestrian Tracking At A Traffic Intersection	NA	NA	Operational	Inattentive drivers		(Whiting et al, 2017)
System And Method Of Use For Safety Of Drivers And Pedestrians In Traffic Circles	NA	NA	Regulation	Inattentive drivers, Inattentive pedestrian		(Tannenbaum, 2019)
Driver biometric monitoring and impairment detection	NA	NA	Regulation	Inattentive drivers		(Khattak et al, 2020)
Two microwave-based systems for matching locations of vehicles.	NA	$7,000	Operational	Adverse weather		(Medina et al, 2012)
Roadway Weather Information Systems (RWIS)	NA	NA	Operational	Adverse weather		(Kumar & Gkritza, 2019)
High water warning system	NA	$30,000	Operational	Adverse weather		(TAPCO, 2021)
Speed Awareness Sign	NA	NA	Operational	Speeding		(TAPCO, n.d.)
Icy Road Warning	NA	NA	Operational	Adverse Weather		(TAPCO, n.d.)
Emergency Responder Warning Systems	NA	NA	Operational	Inattentive drivers, Speeding	Many emergency vehicles involved	(LaneLight, n.d.)
Early warning and collision avoidance	NA	NA	Regulation	Inattentive drivers, Speeding, Turning right on red, Jaywalk		(The United States Patent and Trademark Office, 2019),
Automatic High Beams	NA	NA	Regulation	Adverse weather, Inattentive drivers		(National Highway Traffic Safety Administration, n.d.)

Note: The first citation will include information about the cost of each countermeasure if the countermeasure has a cost. This also applies to Table 4-10. And the references are in the right column.

Table 4-10 The list of 17 conventional countermeasures

Countermeasures	CMF	Cost	Type	Target Contributing factor(s)	Limitation	References
Pedestrian Push-Button & Pedestrian signals	0.723	$800	Operational	Inattentive driver	Not necessary at intersections with automatic pedestrian signal intervals	(PEDSAFE, n.d.)
In-street crossing sign	0.886	$240	Operational	Inattentive drivers		(PEDSAFE, n.d.)
Bike Boulevard	0.37	NA	Geometric	Speeding , Inattentive drivers		(NACTO, 2014), (Weigand et al, 2013), (Minikel, 2012)
Bike Lane	0.734	NA	Geometric	Speeding, Inattentive drivers		(NACTO, n.d.), (Avelar et al, 2021)
Green Pavement Markings	NA	$85,000	Geometric	Inattentive drivers, Inattention pedestrians, adverse weather	Using on exist bicyclist lanes/boulevard	(VDOT, 2021)
Raised Crosswalk	0.55	$7,110	Geometric	Inattentive drivers		(Federal Highway Administration, 2018)
Curb Extension	NA	$2,000	Geometric	Inattentive pedestrians, Inattentive drivers, turning right on red, Speeding	Intersection near parking lane	(PEDSAFE, n.d.)
Curb Ramps	NA	$3600	Geometric	Inattentive pedestrians, Inattentive drivers, turning right on red		(PEDSAFE, n.d.)
High-visibility crosswalks	NA	$2540	Geometric	Inattentive drivers, adverse weather, and speeding		(Federal Highway Administration, n.d.)
Reduced speed limits	0.57	NA	Operational	Inattentive drivers, Speeding		(FHWA, 2010)
Pedestrian countdown signals	0.71	$20000	Operational	Jaywalk, Inattentive drivers, Exceeding safe speed at conditions	No pedestrian signals	(PEDSAFE, n.d.)
Improved lighting	0.58	NA	Operational	Inattentive pedestrian, Inattentive drivers		(Federal Highway Administration, n.d.)
Roundabouts (Independent countermeasure)	0.63	$250,000	Geometric	Inattentive drivers, jaywalk, turning right on red	Enough space to construct a circle roundabout	(Federal Highway Administration, 2010)

Median barriers	0.7	$125,000 per mile	Geometric	Jaywalk		(Minnesota Department of Transportation, 2011), (Elvik et al., 2009)
Pedestrian Island	0.68	$13,520	Geometric	Jaywalk, inattentive drivers, adverse weather		(Federal Highway Administration, 2018)
Pedestrian warning sign	NA	$220	Operational	Speeding, Inattentive drivers		(PEDSAFE, n.d.)
High Friction Surface Treatments (HFST)	0.43	$25 to $50 per square yard	Geometric	Poor geometric conditions		(Federal Highway Administration, n.d.)

In summary, the complete inventory of countermeasures is presented in Table 4-9 and Table 4-10.

4.4. The development of the Inference Engine 2

Inference Engine 2, embedded in the Countermeasure Selection and Prioritization module, is developed to select appropriate countermeasures from Knowledge Base 2 by aligning their target contributing factors with those identified by Inference Engine 1 and the users' requirements from the interface. Because some countermeasures, different in nature and costs, may share similar functions or can concurrently address multiple critical safety issues caused by more than one contributing factors, this module is further designed with the capability of providing the most cost-effective set of countermeasures under the user-specified constraints from an extensive list of options for the target intersection.

The development process for such an inference engine, named Inference Engine 2, is summarized in figure 4.1:

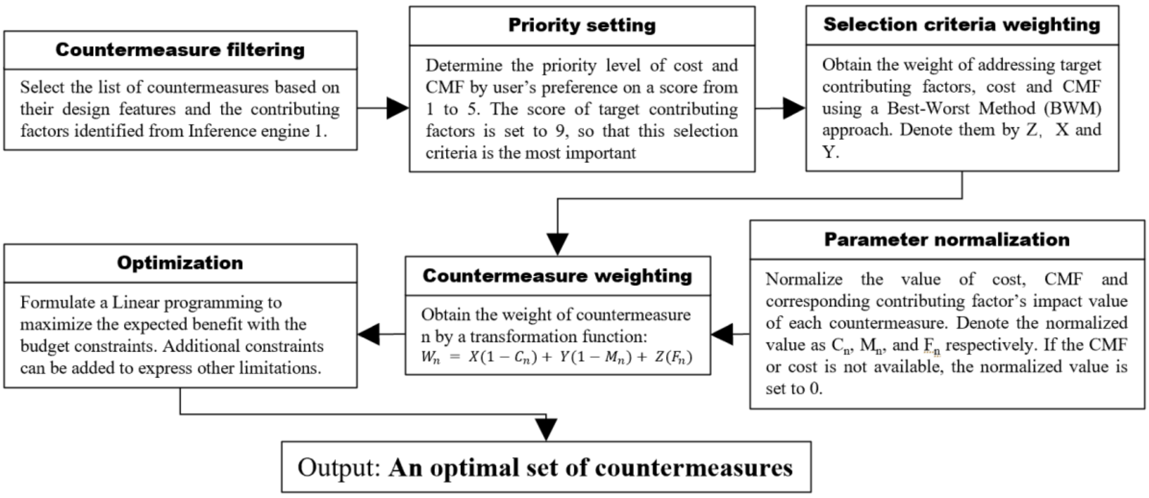


Figure 4.1. The processes of Inference Engine 2

A sample case with a hypothetical intersection is provided to illustrate the process of determining the optimal set of countermeasures as illustrated in figure 4.1. In this case, it is assumed that the outcomes from Inference Engine 1 are Speeding with an impact value of 0.8 and Turning Right on Red with an impact value of 0.3. **The first step** involves selecting a list of countermeasures based on their design features and the presence of contributing factors identified by Inference Engine 1. This process effectively filters out non-relevant countermeasures from the comprehensive list in Knowledge Base 2, enabling more efficient countermeasure selection. For the sample case, the identified countermeasures are presented in Table 4-11, as they specifically target the contributing factors of "Turning Right on Red" and "Speeding". Consequently, these issues can be effectively addressed through the implementation of these countermeasures' functions.

Table 4-11 The selected countermeasures

Countermeasures	CMF	Cost	Types	Targeted Contributing factors	Limitation

				(impact value)	
Automatic Pedestrian Detection for Display of Walk Signal	0.6	10,000	Operational	Turning right on red (0.3)	Pedestrian signals are already installed
Smart Lighting	NA	2500	Operational	Turning right on red (0.3)	Pedestrian signals and streetlight are already installed.
Pedestrian Hybrid Beacon (PHB)/HAWK	0.543	21,000	Operational	Speeding (0.8)	More than 6 lanes
Smart Pedestrian Crosswalk (SPC)	NA	NA	Operational	Speeding (0.8)	

The second step involves determining the priority of "Cost" and "CMF" based on the user's preference using a score ranging from 1 to 5. In this example, the "target contributing factor" has a score of 9, making them the most crucial selection criteria. It is assumed that users prioritize the criterion of effectiveness over the budget constraints. Consequently, the scores assigned to CMF and cost are 5 and 1, respectively, reflecting the greater emphasis placed on the effectiveness of the countermeasures.

The third step involves determining the weights of "Targeted Contributing Factors," "Cost," and "CMF" from the user's perspective using the Best-Worst Method (BWM) approach. In this context, let Z, Y, and X represent the weights assigned to contributing factors, CMF, and cost, respectively. In this example, the weights Z, X, and Y are calculated to be 0.617, 0.067, and 0.317, respectively. This allocation of weights reflects the user's priorities and preferences as defined in the previous step.

The fourth step involves normalizing the values of CMF and cost for each countermeasure. This is necessary because CMF and cost have different units and will be used as the core elements of the transformation function in the subsequent step. Let's assume the normalization values of cost, CMF, and weights of contributing factors for countermeasure *n* are denoted by C_n, M_n, and F_n, respectively. If CMF or cost data is unavailable, they are assumed to be the highest in their selected countermeasures group, and the corresponding normalized value is set to be 1 so that those countermeasures would not outperform any other one on these two aspects. The normalized CMF and cost for the sample case are illustrated in Table 4-12.

Table 4-12 Normalized values of CMF and cost

Countermeasures	CMF	Cost	Normalized CMF	Normalized Cost
Automatic Pedestrian Detection for Display of Walk Signal	0.6	10,000	1	0.405
Smart Lighting	0.6 (Assumed)	2500	1	0
Pedestrian Hybrid Beacon (PHB)/HAWK	0.543	21,000	0	1
Smart Pedestrian Crosswalk (SPC)	0.6 (Assumed)	21,000 (Assumed)	1	1

After completing the fifth step, the impact weight of countermeasure *n* on the target intersection's crash risk can be determined by applying the following transformation function: $W_n = X(1 - C_n) + Y(1 - M_n) + Z(F_n)$. Therefore, the impact weight of each countermeasure will be:

Automatic Pedestrian Detection for Display of Walk Signal = (0.617)(0.3) + (0.067)(1-0.405) + (0.317)(1-1)=0.225

Smart Lighting= (0.617)(0.3)+(0.067)(1-0)+(0.317)(1-1)=0.252,

Pedestrian Hybrid Beacon (PHB)/HAWK = (0.617)(0.8) + (0.067)(1-1) + (0.317)(1-0) = 0.811

Smart Pedestrian Crosswalk (SPC) = (0.617)(0.8) + (0.067)(1-1) + (0.317)(1-1) = 0.494

In the sixth step, a linear programming model can be employed to maximize the total effective weight, which represents the effectiveness of countermeasures, subject to the user-input constraints such as budget and quantity. For instance, consider a user who has set a budget constraint of $31,000, then the optimal selection of countermeasure can be determined as follows.

$$Max\, Z = 0.225(x_1) + 0.252(x_2) + 0.811(x_3) + 0.494(x_4)$$

$$\text{s.t., } 10{,}000x_1 + 2{,}500x_2 + 21{,}000x_3 + 21000x_4 \leq 31{,}000.$$

$$x_1,\ x_2,\ x_3,\ x_4 = 1,\ 0$$

The optimal solution is X_1 =01, X_2 =1, X_3 = 1, X_4 = 0, indicating that Smart Lighting (X_2) and Pedestrian Hybrid Beacon (PHB)/HAWK (X_3) are countermeasures in the optimal result.

4.5.<u>Summary</u>

This chapter presents the system's core methodology and development process, from identifying Safety Related Intersection Characteristics (SRICs) to finalizing an optimal set of countermeasures. Knowledge Base 1 establishes the relationship between SRIC and contributing factors based on findings from publications and expert knowledge. The proposed system employs Inference Engine 1 to process user-input SRICs and select their associated contributing factors using the H5 index and citations from publications. In addition, the system uses the specially designed Knowledge Base 2 to offer a list of countermeasures extracted from all available sources to improve safety by targeting contributing factors. Knowledge Base 2 then executes an optimization method to produce the optimal set of countermeasures based on all criteria and constraints specified. Using this system, a traffic safety engineer with limited experience and time can effectively finalize the set of countermeasures that need to be deployed in the same phase to minimize the risk of pedestrian-vehicle crashes attributed to those identified contributing factors.

5. System performance evaluation

The primary aim of the performance evaluation is to assess the efficacy of the KBES as an expert resource. This evaluation will specifically compare the contributing factors and countermeasures produced by Inference Engine 1 and Inference Engine 2 of the proposed KBES for various intersections against the professional perspectives and intersection safety projects already designed and implemented by local traffic agencies. Practical project information has been gathered from state reports available from several agencies, such as NYC DOT and DC DOT, which serve as reliable sources of expert knowledge. These reports chronicle intersection improvement projects, outlining the features of intersections and crashes, the contributing factors of pedestrian accidents, and safety enhancement measures. Presuming that the contributing factors and countermeasures presented in these reports are the optimal solutions for their deployments, they will be considered as benchmarks. The contributing factors and countermeasures generated by the inference engines will be compared with those found in the reports. Subsequent sections will provide further details, focusing on the evaluation of Inference Engine 1 and Inference Engine 2.

5.1.Performance Evaluation of Inference Engine 1

The performance evaluation of Inference Engine 1 will utilize Safety Related Intersection Characteristics (SRIC) from state reports as input and then subsequently generate a list of contributing factors. These factors will then be compared to those identified by experts in the reports. The comparison will result in one of three possible outcomes, as illustrated in Table 5-1.

Table 5-1. Criteria for evaluating the proposed Inference Engine 1

Comparison output	Conclusion
Results from the proposed system match the expert's produced contributing factors	Equivalent to experts' conclusions
The generated contributing factors include experts' contributing factors	Similar to experts' conclusions
All other possible situations	Not supported by experts' conclusions

As depicted in Table 5-1, when the proposed system generates the same contributing factors as the experts, its analysis is considered to be as comprehensive and accurate as that from experts. If the proposed system identifies the most critical contributing factors which are in agreement with those form the experts and also provides additional factors, its analysis function is deemed akin to that from experts. In any other scenario, the analysis function of the proposed system is regarded as unsubstantiated.

This section will commence by presenting two contrasting samples– one that aligns with the experts' conclusions and another that does not. This will be followed by a display of the evaluation results derived from 38 validation cases.

Sample case 1 - Comparison of the analysis results by safety experts with concluding findings for Inference Engine 1

The intersection used in Sample case 1 is located at Blair Road and Cedar Street in Washington D.C., as illustrated in Figure 5.1.

Figure 5.1: A sample of Intersection Location (DC DOT, n.d.) for evaluation

The input for Inference Engine 1 comprises the following target intersection's safety related characteristics:

- Numerous crashes involving vehicles exceeding speed limits have occurred. The speed analysis findings indicate that the 85th percentile speed is documented at 32 mph, which is significantly above the posted speed limit of 25 mph (for Cedar St).
- A narrow crossing distance exists.
- The corner features a variety of bars, restaurants, and shops, reflecting significant commercial activity at the intersection.
- A bus station and Metro station are located near Cedar St, resulting in an increase in pedestrian and bicycle traffic in the area.

By applying the equations in Inference Engine 1 for calculating the weight for each contributing factor, one can have the following results:

Speeding = 0.465(Many exceeding speed limits-involved vehicles) + 0.246(Wider Street widths) + 0.055(Many taxi-involved crash) + 0.070(Many crashes with under the influence of alcohol) + 0.164(High posted speeds) = 0.465(1) + 0.246(0) + 0.055(0) + 0.070(0) + 0.164(0) = 0.465

Jaywalk = 0.125 (Corners with business stores) + 0.386 (Intersections with bus stops) + 0.167(Many crashes under adverse weather conditions) + 0.02(Narrow crossing distances) + 0.125(Many crashes with pedestrians under influence of alcohol) + 0.167(No pedestrian crossing) = 0.125 (1) + 0.386 (1) + 0.167(0) + 0.02(1) + 0.125(0) + 0.167(0) = 0.531

The weights of other contributing factors are zero, indicating that "Speeding" and "Jaywalk" are the two main factors causing pedestrian crashes, with scores of 0.465 and 0.531, respectively. The remaining contributing factors have a negligible impact with scores of 0. The expert reports (DC DOT, n.d.) also emphasize that excessive speeding and jaywalking are significant contributors to pedestrian crashes. As such, one can conclude that **the findings produced from the proposed system with respect to the contributing factors of the target intersections crashes are aligned with that identified by safety experts**.

Sample case 2 - Comparison of the analysis results by safety experts with concluding findings for Inference Engine 1

Another improvement project at the intersection of Cooper Ave and 64th Pl in New York City, Figure 5.2, is used as the second sample case for the proposed system's performance evaluation.

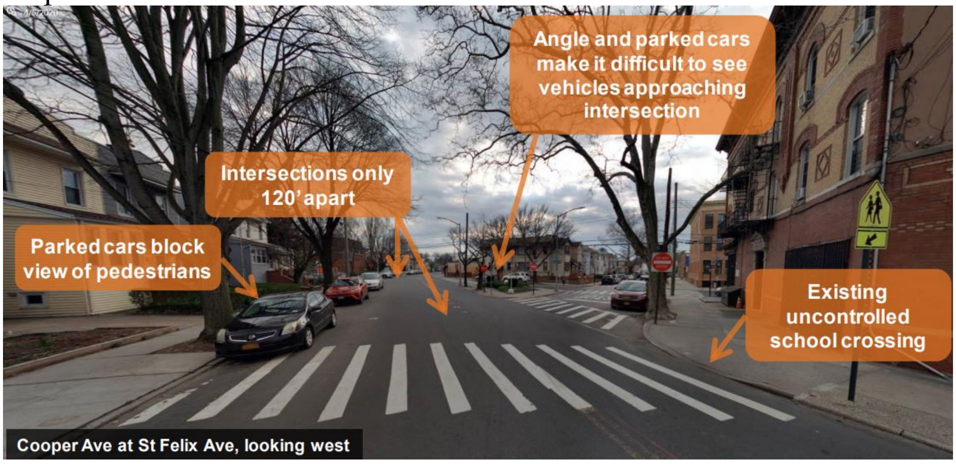


Figure 5.2: Study Intersection Location (NYC DOT, 2022)

The input (characteristics of intersections) for Inference Engine 1 for this location is listed below:

- There are two bus stops for B13 and Q39 bus routes.
- Many students are observed crossing the intersection and the nearby intersections.
- There are no control devices for pedestrian crossings on Cooper Ave between Cypress Ave and 64th St.
- The roadway is narrow for crossing.

As in the previous case, by inputting the safety related characteristics of the target intersection, the weights of Jaywalk are calculated as follows:

Jaywalk = 0.125 (Corners with business stores) + 0.386 (Intersections with bus stops) + 0.167(Many crashes under adverse weather conditions) + 0.02(Narrow crossing distances) + 0.125(Many crashes with pedestrians under influence of alcohol) + 0.167(No pedestrian crossing) = 0.125(0) + 0.386(1) + 0.167(0) + 0.02(1) + 0.125(0) + 0.167(1) = 0.573

According to Inference Engine 1, other contributing factors have a minimal impact, with scores of 0. As a result, the analysis results from Inference Engine 1 indicate that "Jaywalk" is the primary contributing factor to pedestrian crashes, with a score of 0.573. However, the expert report (NYC DOT, 2022) highlights that excessive speeding is a significant contributor to pedestrian crashes. Therefore, **the proposed system's result is not aligned with the assessment by safety experts.**

Extended evaluation with respect to Inference Engine 1

Table 5-2 showcases 38 intersection improvement projects collected from reports from various agencies, encompassing each intersection's characteristics, the experts' identified contributing factors for each project, and the contributing factors produced by Inference Engine 1. By comparing the generated factors with those from the experts, 17 projects reveal that the generated results are equivalent to the experts' conclusions.

The additional 17 projects show that the generated results are similar to the experts' evaluations. Only the results of 4 projects are not compatible with that safety experts' assessment.

In summary, about 89 percent of the results produced by Inference Engine 1 are consistent with those from safety experts' recommendations, reflecting the potential for such an inference engine to be used in practice.

Table 5-2 Intersection improvement case for validating Inference Engine 1

Location	Characteristics of an intersection	Contributing factors from experts' analysis	Contributing factors from the proposed system (Weight)	Rank	Citation
E 170th ST & TELLER AVE, NYC	No crossing, bus stops at the intersection, business stores at the corner, Narrow crossing distance.	Jaywalk	Jaywalk (0.698)	Equivalent to an expert	NYC DOT, 2015
Bronxdale Avenue and Bronx Park East	Many exceeding speeds limits-involved vehicle, Wider street widths, Road markings defects.	Speeding	Speeding (0.711), Poor geometric conditions (0.8)	Similar to an expert	NYC DOT, 2021
E 165th St, E & Intervale Ave	Wider street widths.	Speeding	Speeding (0.246)	Equivalent to an expert	NYC DOT, 2021
East 180th St & East 179th St	Many exceeding speed limits-involved vehicle, Wider street widths.	Speeding	Speeding (0.711)	Equivalent to an expert	NYC DOT, 2022
Eastchester Road & Westchester Avenue	Wider street widths.	Speeding	Speeding (0.246)	Equivalent to an expert	NYC DOT, 2021
Greystone Avenue & West 242 nd Street	No crossing, Road markings defects.	Jaywalk, Poor geometric conditions	Jaywalk (0.167), Poor geometric conditions (0.8)	Equivalent to an expert	NYC DOT, 2021
Mosholu Pkwy and Southern Blvd	High posted speed, Many exceeding speed limits-involved vehicles, Wider street widths, No crossing.	Speeding, Jaywalk	Speeding (0.875), Jaywalk (0.167)	Equivalent to an expert	NYC DOT, 2015
Soundview Ave and Lafayette Ave	Wider street widths.	Speeding	Speeding (0.246)	Equivalent to an expert	NYC DOT, 2022
86th Street and Bay Pkwy	Bus stops, unstandardized pedestrian signs,	Jaywalk, Inattentive pedestrians, Inattentive drivers,	Jaywalk (0.511), Inattentive pedestrians (0.083),	Equivalent to an expert	NYC DOT, 2022

	Business store at corner, Busy intersection, Poor roadway conditions Road surface (Ruts, holes or bumps) defects.	Poor geometric conditions	Inattentive drivers (0.4), Poor geometric conditions (0.1)		
Ashland Pl & Navy St	Wider street widths High posted speed limit, Business at the corner.	Speeding, Jaywalk	Speeding (0.41), Jaywalk (0.125)	Equivalent to an expert	NYC DOT, 2022
Atlantic Ave and its nearby intersections	Wider street widths, Narrow crossing distance, some intersections have no pedestrian crossing.	Speeding, Jaywalk	Speeding (0.246), Jaywalk (0.187)	Equivalent to an expert	NYC DOT, 2018
Fountain Ave to Shepherd Ave	High posted speed Road markings defects.	Speeding	Speeding (0.164), Poor geometric conditions (0.8)	Similar to an expert	NYC DOT, 2022
Dumont Ave, and Shephard Ave	No crossing, low visibility, Busy intersection.	Inattentive drivers	Inattentive driver (0. 4), jaywalk (0.167	Similar to an expert	NYC DOT, 2022
Cozine Ave and Louisiana Ave	Wider street widths, Busy intersection.	Speeding, Inattentive drivers	Inattentive drivers (0.4), Speeding (0.246)	Equivalent to an expert	NYC DOT, 2022
W 188st and Amsterdam Ave	Wide Street with Long Crossing Distances High posted speeds.	Speeding	Speeding (0.41)	Equivalent to an expert	NYC DOT, 2021
Riverside Dr and Henry Hudson Parkway ramps	No pedestrian crossing, No sidewalk, Narrow crossing distances, Many exceeding speed limits-involved crash Road markings defects.	Speeding, Poor geometric conditions	Speeding (0.465), Jaywalk (0.187), Poor geometric conditions (0.8)	Similar to an expert	NYC DOT, 2022
2 Ave and E 30 st,	The intersection at a busy environment, Narrow crossing distances.	Inattentive pedestrians	Inattentive pedestrians (0.083), Jaywalk (0.02)	Similar to an expert	NYC DOT, 2020

149th street and 25th drive	School zone (The intersection at a busy environment), Wider street widths, Many exceeding speed limits-involved crash, No pedestrian crossing, Road markings defects.	Speeding, Inattentive drivers, Poor geometric conditions	Speeding (0.711). Inattentive pedestrians (0.083), Inattentive drivers (0.4), Poor geometric conditions (0.8)	Similar to an expert	NYC DOT, 2021
21 st street at side street	The intersection at a busy environment, Intersections with bus stops, Busy interchanges at that area.	Jaywalk	Inattentive pedestrian (0.083), Inattentive drivers (0.4), Speeding (0.246)	Not accurate	NYC DOT, 2022
21 st street at Astoria Blvd	The intersection at a busy environment, Intersections with bus stops, Busy interchanges at that area, Corners with business stores, No pedestrian crossing.	Jaywalk	Jaywalk (0.678), Inattentive pedestrian (0.083), Inattentive drivers (0.4)	Similar to an expert	NYC DOT, 2022
Cooper Ave, 80th Ave to 64th Pl	High posted speeds, Intersections with bus stops.	Speeding	Jaywalk (0.573)	Not accurate	NYC DOT, 2022
Hempstead Avenue and 217th Street	No pedestrian crossing, Road markings defects.	Jaywalk, Poor geometric conditions	Jaywalk (0.167), Poor geometric conditions (0.8)	Equivalent to an expert	NYC DOT, 2022
Rockway Beach Blvd at Beach 84th st	Wider street width, High posted speeds, Corners with business shops, No pedestrian crossing.	Speeding	Speeding (0.41), Jaywalk (0.292)	Similar to experts	NYC DOT, 2015
144th Road to Farmers Blvd	Wider street width,	Inattentive drivers	Speeding (0.246),	Not accurate	NYC DOT, 2020

	No sidewalk, No pedestrian crossing.		Jaywalk (0.167)		
Seagirt Blvd and Beach 13th St	Many elderly pedestrians-involved crash, Wider street widths, High posted speeds Many exceeding speed limits-involved crash.	Inattentive pedestrians	Inattentive pedestrians (0.472), Speeding (0.875)	Similar to an expert	NYC DOT, 2022
Thomson Av and Van Dam St	Corners with business stores, Intersections with bus stops, Narrow crossing distance.	Jaywalk	Jaywalk (0.531)	Equivalent to an expert	NYC DOT, 2016
Polhemus Ave and Fern Pl	Intersections with bus stops, Narrow crossing distances, Road markings defects.	Jaywalk	Poor geometric conditions (0.8); Jaywalk (0.511)	Similar to an expert	NYC DOT, 2022
Goethals Rd N and Fahy Av	Busy interchanges at that area, Narrow crossing distances.	Jaywalk	Inattentive drivers (0.4), Jaywalk (0.02)	Similar to an expert	NYC DOT, 2022
Blair Road and Cedar Street	Many exceeding speed limits-involved crash, Narrow crossing distances, Business stores at corner, Bus stations.	Speeding, Jaywalk	Jaywalk (0.531), Speeding (0.465)	Equivalent to an expert	DC DOT, n.d.
14th St NW and Colorado Ave NW	Intersections with bus stops, Busy interchanges at that area.	Driver Inattention	Inattentive drivers (0.4), Jaywalk (0.386)	Similar to an expert	DC DOT, 2020
New Hampshire Ave NW and Whittier St NW	High posted speeds, Corners with business stores, Narrow crossing distances.	Speeding	Speeding (0.164), Jaywalk (0.145)	Similar to an expert	DC DOT, 2017
Florida Ave NE and 1st St NE	The intersection at a busy environment,	Inattentive pedestrian, Inattentive drivers	Speeding (0.465), Jaywalk (0.386),	Similar to an expert	DC DOT, 2019

	Busy interchanges at that area, Intersections with bus stops, Many exceeding speed limits-involved crash.		Inattentive drivers (0.4), Inattentive pedestrian (0.083)		
Beacon St at Berkeley and Mass Ave	High posted speeds, Wider street widths.	Speeding	Speeding (0.41)	Equivalent to an expert	City of Boston, 2017
W Fullerton Ave, N Damen Ave and N Elston Ave	The intersection at a busy environment, Busy interchanges at that area.	Inattentive pedestrian, inattentive pedestrian	Inattentive pedestrian (0.083), Inattentive drivers (0.4)	Equivalent to an expert	Chicago DOT, 2022
Bronxdale Ave and Unionport Rd	Busy interchanges at that area, Intersections with bus stops, No sidewalk, No pedestrian crossing.	Jaywalk	Inattentive pedestrian (0.083), Inattentive drivers (0.4), Speeding (0.41)	Not accurate	NYC DOT, 2020
Roosevelt Ave, 90 St, Canse St at Elmhurst Ave	The intersection at a busy environment, Busy interchanges at that area, Wider street widths, High posted speeds.	Inattentive pedestrian, Inattentive drivers	Speeding (0.41), Inattentive drivers (0.4), Inattentive pedestrian (0.083)	Similar to an expert	NYC DOT, 2018
Burke Ave and White Plains Rd	The intersection at a busy environment, Busy interchanges at that area, Intersections with bus stops.	Inattentive drivers	Inattentive driver (0.4), Jaywalk (0.386), Inattentive pedestrian (0.083)	Similar to the expert	NYC DOT, 2017
26th Ave, Francis Lewis Blvd and 169th St	Wider street widths, Corners with business stores, No pedestrian crossing.	Jaywalk	Jaywalk (0.292), Speeding (0.246)	Similar to the expert	NYC DOT, 2018

5.2. Performance Evaluation of Inference Engine 2

The input for Inference Engine 2 comprises the contributing factors generated by Inference Engine 1, their associated countermeasures, and deployments related to the constraints of the intersection. The performance of Inference Engine 2 is evaluated based on the consistency between the KBES-generated countermeasures and the countermeasures that have been planned or implemented at the intersection.

To demonstrate the proposed method’s ability to account for budget constraints, a budget of $160,000 is assumed in the ensuing case studies based on the average cost of pedestrian safety improvement projects at intersections from New York City Department of Transportation (2023). It is also assumed that the project director's primary concern is for the proposed countermeasures to address all identified factors contributing to the pedestrian crash, while other aspects (e.g., cost and CMF) are not deemed critical. The countermeasures generated by Inference Engine 2 will be compared to the experts' countermeasures for each intersection improvement project. If the results include the expert's recommendations and additional countermeasures, then one can conclude that the proposed system’s effectiveness is comparable to that of experts. Otherwise, the proposed system's analysis results are deemed inconsistent with those used in practice.

The first two parts of this section present two distinct sample cases – one generates a countermeasure list in line with the experts' analysis, and another produces an inconsistent list. The third part highlights a collection of 24 intersection improvement cases input into Inference Engine 2, and their comparison results with those adopted in practice.

Sample case 3 - Demonstration of a validation consistent with expert analysis for Inference Engine 2

Sample case 3 applies the safety-related data from the same intersection used in sample case 1, i.e., the intersection of Blair Road and Cedar Street in Washington D.C. The results from each step of the execution with Inference Engine 2 are summarized below:

Step 1: Select countermeasures based on the contributing factors resulting from Inference Engine 1. The contributing factors in the case identified from Inference Engine 1 are Jaywalking and Speeding, and their weights are 0.531 and 0.465, respectively. Additional limitations to be accounted for in the countermeasure selection process include:

1. Only a few bike crashes occurred at the intersection.
2. Has installed pedestrian countdown signal.
3. The number of travel lanes is less than 6.
4. Not enough space to construct a roundabout at the intersection.
5. Only operational or geometric related countermeasures will be adopted.

Based on the impacts of identified contributing factors and limitations, the list of selected countermeasures from Knowledge Base 2 is shown in Table 5-3.

Step 2: Determine the priority between costs and CMF with user input based on a scale of 1 to 5. In this sample case, it is assumed that users are not concerned with either cost or CMF. Therefore, the marks of CMF and cost are both 1.

Step 3: compute the relative weights for cost, CMF, and target contributing factors with the Best-Worst Method (BWM) approach, which are 0.091, 0.091, and 0.818, respectively.

Step 4: Normalize the value of CMF and cost, as indicated in table 5-3.

Step 5: Obtain the effectiveness weight for each countermeasure using the following equation:

Weight of countermeasure n = (Weight of target contributing factors)(Total weight of its targeted contributing factors) + (Weight of cost)*(1 - Normalized value of its cost) + (Weight of CMF)*(1 - Normalized value of its CMF)*

The weight of each countermeasure is listed in Table 5-3.

Table 5-3 The list of selected countermeasures for Case 3, their normalized values, and effective weights from Steps 1, 4, and 5.

Countermeasures	Step 1			Step 4		Step 5
	CMF	Cost ($)	Weights of Target factors	Normalized CMF	Normalized Cost	Effective Weight of each countermeasure
Raised Crosswalk	0.550	7110	0.465	0	0.055	0.557
Curb Extension	NA	2000	0.465	1	0.014	0.470
High-visibility crosswalks	0.900	7110	0.465	0	0.055	0.557
Reduced speed limits	0.570	NA	0.465	0.125	1	0.460
Median barriers	0.700	125000	0.531	0.938	1	0.440
Pedestrian Island	0.680	13250	0.531	0.813	0.10	0.532
Pedestrian warning sign	NA	220	0.465	1	0	0.471
Smart Pedestrian Crosswalk (SPC)	NA	NA	0.465	1	1	0.380
Speed Awareness Sign	NA	NA	0.465	1	1	0.380

Step 6: Identify the optimal countermeasure set using Linear Programming:
Let the set of binary variables ($i.e., x_1,\ x_2,\ x_3 \ldots\ldots\ x_n, where\ n = 9\ in\ this\ case$)). denote the candidate list of countermeasures with respect to the identified contributing factors as follows:

$$Max\ Z = 0.557(x_1) + 0.557(x_2) + 0.532(x_3) + 0.471(x_4) + 0.470(x_5) + 0.460(x_6) + 0.440(x_7) + 0.380(x_8) + 0.380(x_9)$$

$$s.t.,\ 7110(x_1) + 7110(x_2) + 13250(x_3) + 220(x_4) + 2000(x_5) + 125000(x_6) + 125000(x_7) + 125000(x_8) + 125000(x_9) \leq 160{,}000.$$

$$x_1,\ x_2,\ x_3 \ldots\ldots\ x_9 = 1,\ 0$$

The optimal solution is $x_1 = x_2 = x_3 = x_4 = x_5 = x_6 = 1$ are 1, and $x_7 = x_8 = x_9 = 0$, indicating that Raised Crosswalks, High-visibility crosswalks, Pedestrian Islands, Pedestrian warning signs, Curb Extensions and Reduced speed limits are recommended countermeasures at the intersection.

Notably, the experts' recommendations in the report are the “Stop Here for Pedestrians" sign and "Repainting Crosswalk". The "Pedestrian Warning Sign" selected by Inference Engine 2 is equivalent to the "Stop Here for Pedestrians" sign, and "High-Visibility Crosswalk" can be considered as "Repainting Crosswalk." **Therefore, in this validation case, the system's analysis function can be considered similar to that of an expert.**

Sample case 4 - Demonstration of a validation inconsistent with expert analysis for Inference Engine 2

All safety-related intersection data used in sample case 4 are from the sample intersection used in sample case 2, that is, the junction of Cooper Ave and 64th Pl in New York City. The execution results with Inference engine 2 are summarized below:

Step 1: The contributing factor identified from Inference Engine 1 is only Jaywalking, and its impact weight is 0.573. Other limitations are identical to those in Case 3:

According to the contributing factors and limitations, the selected countermeasures from Knowledge Base 2 is listed in table 5-4:

Step 2: In this sample, it is assumed that users are not concerned with either cost or CMF, so both are assigned with marks of 1.

Step 3: The weights of cost, CMF, and contributing factors computed with BWM are 0.091, 0.091, and 0.818, respectively.

Step 4: Normalize the value of CMF and deployment cost, as indicated in table 5-4.

Step 5: Obtain the effectiveness weight of each countermeasure using the following equation:

Weight of countermeasure n = (Weight of target contributing factors)(Total weight of its targeted contributing factors) + (Weight of cost)*(1 - Normalized value of its cost) + (Weight of CMF)*(1 - Normalized value of its CMF)*

Their weights are presented in Table 5-4.

Table 5-4 The list of selected countermeasures for Case 4, their normalized values, and weights on Step 1, 4, and 5

Countermeasures	Step 1			Step 4		Step 5
	CMF	Cost ($)	Weights of Target factors	Normalized CMF	Normalized Cost	Weight of each countermeasure
Pedestrian countdown signals	0.710	20000	0.573	1	0.060	0.554
Median barriers	0.700	125000	0.573	0.667	1	0.499
Pedestrian Island	0.680	13250	0.573	0	0	0.651

Step 6: Identify the optimal countermeasure set using Linear Programming:
Let the set of variables, x_1, x_2, x_3, denote the countermeasures of pedestrian island, pedestrian countdown signals and median barriers, respectively, then, the optimal selection can be done as follows:

$$Max\ Z = 0.651(x_1) + 0.554(x_2) + 0.499(x_3)$$

$$\text{i.e., } 13250(x_1) + 20000(x_2) + 125000(x_3) \leq 160{,}000.$$

$$x_1,\ x_2,\ x_3 = 1,\ 0$$

The optimal solution is $x_1 = x_2 = x_3 = 1$, indicating that Pedestrian Island, Pedestrian countdown signals, and Median barriers are countermeasures in the optimal list.

However, there are additional recommendations from the expert, such as curb extension, sidewalk expansion, concrete island, and reconstruction. Hence, **the system's performance for case 4 is considered inferior to that by an expert.**

Extensive evaluations for Inference Engine 2

Table 5-5 lists 24 intersection improvement projects from the NYC DOT and DC DOT's reports along with their adopted countermeasures and expert recommendations. The proposed system has yielded the same recommendations as those from experts for 18 projects. However, for the remaining 6 projects, the system's recommended list is not as comprehensive as those from experienced safety experts.

In conclusion, the results of the study indicate that Inference Engine 2 is able to produce equivalent or similar results to those of the experts for around 75% of the projects examined. This suggests that although the proposed Knowledge-Based Expert System (KBES) is at the infancy of its development, it has the potential for use in practice to address the issues of countermeasure selection for intersection safety improvement.

Table 5-5 Summary of Extensive evaluation results for Inference Engine 2

Location	Type	Contributing factors from inference engine 1 (Weights)	Constraints	Countermeasures recommended by experts	Countermeasures generated by inference engine 2	Rank	Citation
86th Street, and the nearby intersection.	Geometric	Jaywalk (0.511), Inattentive pedestrians (0.083), Inattentive drivers (0.4), Poor geometric conditions (0.1)	4 lanes, Pedestrian signal available	Curb extensions	Pedestrian Island, Raised Crosswalk, High-visibility crosswalks, Curb Extension, Curb Ramps, Median barriers	Similar to an expert	NYC DOT, 2022
Ashland Pl & Navy St	Geometric	Speeding (0.41), Jaywalk (0.125)	4 lanes, Signal available, many bike accidents	Bike path, curb extension, pedestrian island	Raised Crosswalk, High-visibility crosswalks, Curb Extension, Bike Lane, Pedestrian Island	Similar to an expert	NYC DOT, 2022
Atlantic Ave and its nearby intersections	Geometric	Speeding (0.246), Jaywalk (0.187)	6 lanes, signal available, many bike accidents	Provide crossing, Bike Lane	Raised Crosswalk, High-visibility crosswalks, Curb Extension, Pedestrian Island, Bike Lane	Similar to an expert	NYC DOT, 2018
Brownsville and East New York School	Operational, Geometric	Speeding (0.164), Poor geometric conditions (0.8)		Speed humps, Signage improvements	High Friction Surface Treatments (HFST), Pedestrian warning sign, Curb Extension, Raised Crosswalk, High-visibility crosswalks, Reduced speed limits, Smart Pedestrian Crosswalk (SPC), Speed Awareness Sign	Similar to an expert	NYC DOT, 2022
Dumont Ave, Fountain Ave to Shephard Ave	Geometric	Inattentive driver (0.4), jaywalk (0.167)	2 lanes, signal not available	Curb extension, Adding crosswalk	Pedestrian Island, Raised Crosswalk, High-visibility crosswalks, Curb Extension, Curb Ramps, Median barriers	Similar to an expert	NYC DOT, 2022
W 188 St, W 190 St and Amsterdam Ave	Geometric	Speeding (0.41)	School zone	Curb extensions, Pedestrian Island	Curb Extension, Raised Crosswalk, High-visibility crosswalks	Not accurate	NYC DOT, 2021

Riverside Dr and Henry Hudson Parkway ramps	Geometric	Speeding (0.465), Jaywalk (0.187), Poor geometric conditions (0.8)	Ramp	Add crosswalk, Curb extension, Delineators, Pedestrian ramps	High Friction Surface Treatments (HFST), Curb Extension, Raised Crosswalk, High-visibility crosswalks, Median barriers, Pedestrian Island (Usually delineators)	Similar to an expert	NYC DOT, 2020
2 Ave and E 30 St,	Geometric	Inattentive pedestrians (0.083), Jaywalk (0.02)		Realign crosswalk, Median	Curb Extension, Curb Ramps, Median barriers, Pedestrian Island	Not accurate	NYC DOT, 2020
149th street at 25th drive	Geometric	Speeding (0.711). Inattentive pedestrians (0.083), Inattentive drivers (0.4), Poor geometric conditions (0.8)	School zone, many bike accidents	Protected Bike Lane with concrete islands, Shorten crossing distance	Curb Extension (Shorten crossing distance), Raised Crosswalk, High-visibility crosswalks, Bike Lane High Friction Surface Treatments (HFST), Curb Ramps, Pedestrian Island	Similar to an expert	NYC DOT, 2021
21st street at side street	Geometric	Inattentive pedestrian (0.083), Inattentive drivers (0.4), Speeding (0.246)		Pedestrian island, Curb Extension	Curb Extension, Raised Crosswalk, High-visibility crosswalks, Curb Ramps, Pedestrian Island	Similar to an expert	NYC DOT, 2022
21st street at Astoria Blvd	Operational	Jaywalk (0.678), Inattentive pedestrian (0.083), Inattentive drivers (0.4)		Camera Enforcement, Signal Timing	Smart Lighting, Improved lighting, RRFB Pedestrian Crosswalk System, Pedestrian Push-Button & Pedestrian signals, Pedestrian warning sign	Not accurate	NYC DOT, 2022
Beach Channel Dr at Beach 108 St	Geometric	Jaywalk (0.573)		Improve pedestrian crossings	Median barriers, Pedestrian Island	Not accurate	NYC DOT, 2019
Cooper Ave and 64th Pl	Geometric	Jaywalk (0.573)	Close intersections	Curb Extension Pedestrian refuge island; Sidewalk expansion;	Pedestrian Island, Pedestrian countdown signals, and Median barriers	Not accurate	NYC DOT, 2022

				Concrete island reconstruction			
Rockway Beach Blvd at Beach 84th st	Geometric	Speeding (0.41), Jaywalk (0.292)		Shorten crossing distance	Curb Extension (help to shorten the crossing distance), Raised Crosswalk, High-visibility crosswalks, Median barriers, Pedestrian Island	Similar to an expert	NYC DOT, 2015
144th Road to Farmers Blvd	Geometric	Speeding (0.246), Jaywalk (0.167)		Shorten crossing distance	Curb Extension, Raised Crosswalk, High-visibility crosswalks, Median barriers, Pedestrian Island	Similar to an expert	NYC DOT, 2020
Seagirt Blvd and Beach 13th St	Geometric	Inattentive pedestrians (0.472), Speeding (0.875)		Painted Pedestrian Space, Narrowing of roadway to discourage speeding	Curb Extension, raised median for pedestrians, Raised Crosswalk, High-visibility crosswalks, Curb Ramps	Similar to an expert	NYC DOT, 2022
Thomson Av and Van Dam St	Geometric	Jaywalk (0.531)	School zone	Sidewalk expansion, Narrow north sidewalk	Curb Extension, Raised Crosswalk, High-visibility crosswalks, Curb Ramps	Not accurate	NYC DOT, 2016
Polhemus Ave and Fern Pl	Geometric	Poor geometric conditions (0.8); Jaywalk (0.511)	School zone	Increase Pedestrian Space	High Friction Surface Treatments (HFST), Median barriers, Pedestrian Island	Similar to an expert	NYC DOT, 2022
Goethals Rd N to Fahy Av	Geometric	Inattentive drivers (0.4), Jaywalk (0.02)		Narrow one travel lane	Curb Extension, Curb Ramps, Pedestrian Island, Raised Crosswalk, High-visibility crosswalks, Median barriers	Similar to an expert	NYC DOT, 2022
Blair Road and Cedar Street	Operational, Geometric	Jaywalk (0.531), Speeding (0.465)		Stop Here for Pedestrians Sign, Repainting crosswalk	Raised Crosswalk, High-visibility crosswalks, Pedestrian Island, Pedestrian warning sign, Curb Extension and Reduced speed limits	Similar to an expert	DC DOT, n.d.

Burke Ave and White Plains Rd	Geometric	Inattentive driver (0.4), Jaywalk (0.386), Inattentive pedestrian (0.083		Bus-Boarding islands with pedestrian space	Pedestrian Island (Similar to this island), Raised Crosswalk, High-visibility crosswalks, Curb Extension, Curb Ramps, Median barriers	Similar to an expert	NYC DOT, 2017
E 165th St, E & Intervale Ave	Geometric	Speeding (0.246)	Many bike accidents	Standard Bike Lane	Raised Crosswalk, Curb Extension, High-visibility crosswalks, Bike Lane	Similar to an expert	NYC DOT, 2021
Mosholu Pkwy and Southern Blvd	Geometric	Speeding (0.875), Jaywalk (0.167)	Many bike accidents	Concrete island, Bike path, Enhanced crossing, Concrete curb extension	Raised Crosswalk, High-visibility crosswalks, Curb Extension, Bike Lane, Pedestrian Island	Similar to an expert	NYC DOT, 2015
14th street NW at R st NW	Geometric	Inattentive drivers (0.4), Jaywalk (0.386)		Curb and ramp extension.	Pedestrian Island, Curb Extension, Curb Ramps, Median barriers, Raised Crosswalk, High-visibility crosswalks	Similar to an expert	DC DOT, 2018

5.3. <u>Discussion</u>

The proposed system's functions for analyzing contributing factors and recommending countermeasures have demonstrated its potential to yield 89% and 75% consistency with the recommendations given by experienced safety professionals. The proposed system could benefit from further training and evaluations with more deployment cases, involving other contributing factors and more technological countermeasures.

Lastly, it is recommended that users consider other practical concerns not included in the system when finalizing the selected countermeasures. While the proposed system provides more countermeasures than those from safety experts — typically offering four to five countermeasures in intersection improvement projects compared to the two to three recommended by experts — users should carefully take other considerations into account, such as public awareness, roadway design consistency, educational efforts, and relevant enforcement.

6. Conclusion and Future Study

6.1.Conclusions

While existing Knowledge-Based Expert Systems (KBESs) for intersection safety project development have made notable advancements, much remains to be addressed, especially in the analysis of critical factors contributing to pedestrian-involved crashes and the optimization of countermeasure selection within the defined constraints. Hence, this study has presented an enhanced KBES designed to assist the traffic community in efficiently generating a set of optimal cost-benefit countermeasures. This tool aims to improve pedestrian safety at intersections with varying geometric features and to reduce pedestrian-vehicle crashes.

The proposed KBES comprises four main components: Knowledge Base 1, Inference Engine 1, Knowledge Base 2, and Inference Engine 2. Inference Engine 1 serves to identify and weight contributing factors by utilizing user-identified SRICs and cause-effect relationships between SRICs and pedestrian crash factors from Knowledge Base 1. Specifically, research findings are transformed from traffic safety literature and state-of-the-practice reports to establish quantitative relationships between crash-contributing factors and SRICs using both the H5 index and citation counts of relevant studies as well as the Best-Worst Method. These values associated with each contributing factor's SRIC are used as the basis for assessing the contributing factors' impact level pedestrian-vehicle crashes at the target intersection.

Inference Engine 2 provides an optimal set of countermeasures from a comprehensive list based on the user's defined priorities regarding cost, Crash Modification Factors (CMF), and impact values. This engine employs a flexibly designed linear programming formulation to achieve the maximum effectiveness with mutually compatible countermeasures within user-specified constraints.

The key contributions of the proposed KBES include: 1) Recommending cost-effective countermeasure sets using an innovative approach that integrates multiple selection criteria and maximizes the benefits; and 2) developing a method for analyzing contributing factors by quantifying their impact values using the Best-Worst Method, which takes into account the quality and reliability of available information sources.

To assess the effectiveness of the developed KBES, this study has conducted analyses at intersections plagued by pedestrian-vehicle crashes in various states and compared the identified contributing factors and the developed countermeasure lists with those from experts and those reported in the literature. Inference Engines 1 and 2 have both yielded analysis results that were consistent with expert decisions in 89% and 75% of the projects, respectively, demonstrating the potential of the proposed system for use in practice. Although much remains to be improved as shown in the evaluation process, it seems promising that the proposed KBES can serve as a robust foundation to effectively address pedestrian safety concerns at intersections with more refinement and extensive learning from more related quality studies.

6.2.Future research

Grounded in the progress made in this study, future research subjects along this line shall include:

- The list of contributing factors should be expanded to encompass those associated with other crash types.

- Additional advanced countermeasures and relevant selection criteria, such as life span and public awareness, should be explored to augment the functions of the KBES.
- An enhanced method for quantifying the relationships between contributing factors and SRICs should be developed to encompass public opinions and recommendations from a panel of experts.
- The inference mechanisms should be refined to integrate the experiences and preferences of local engineers so that the recommendations of the KBES can fully reflect the concerns and preferences of local residents and safety professionals.
- More advanced artificial intelligence models, such as language models using machine learning, to review multiple safety improvement projects could be incorporated into the countermeasure identification and selection module to enhance its accuracy and effectiveness.

In summary, future research shall focus on refining the methodology of the proposed KBES, broaden its target applications, and integrate the latest advancements in technology to further improve its overall effectiveness on pedestrian safety at intersections.

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Appendix

<u>More similar contributing factors stem from state practices</u>

Table A1 More similar contributing factors for Inattentive drivers

Direct contributing factors	Similar contributing factors from states practices
Inattentive drivers	• Improper Turn • Improper Lane Change • Improper Backing • Improper Passing • Improper Signal • Improper Parking • Improper Lane Usage • Failed to Yield Right of Way • Failed to Obey Stop Sign • Failed to Obey Traffic Signal • Failed to Obey Other Traffic Control • Failed to Keep Right of Center • Failed to Stop for School Bus • Disregarding Road Markings • Disregard Stop Sign - Flashing Red • Disregard Yield Sign - Flashing Yellow • Wrong Way on One Way Road • Stopping in Lane/Roadway • Followed Too Closely • Over correcting over steering • Swerved or avoided vehicle or object in road • Operated motor vehicle in erratic reckless manner • Backup due to prior crash • Backup due to prior nonrecurring incident • Backup due to regular congestion • Over Center Line • Headlight Violation • Improper right turn

Table A2 More similar contributing factors for Inattentive pedestrians/Inattentive drivers

Direct contributing factors	Similar contributing factors from states practices
Inattentive pedestrian/Inattentive drivers	• Under Influence of Drugs • Under Influence of Alcohol • Under Influence of Medication • Under Combined Influence • Physical/Mental Difficulty • Fell Asleep, Fainted, Etc. • Failed to Give Full Time and Attention • Operator Using Cellular Phone

	• Interference/Obstruction by passengers • Interference/Obstruction by outside vehicle • Driver Operating Hands-free Wireless Telecommunications • Driver Adjusting Audio or Entertainment System • Driver Smoking • Driver Eating or Drinking • Driver Reading or Writing • Driver Grooming

Table A3 More similar contributing factors for Inattentive pedestrians

Direct contributing factors	Similar contributing factors from states practices
Inattentive pedestrian	• Bicycle Violation • Darting in roadway • Wrong side of road • Disregarded Pedestrian Traffic Controls • Failed to Yield Right of Way to Vehicle • Failure to Use Crosswalk • Ran Off the Road • Disregarded Other Road Markings • Swerved or Avoided Vehicle or Object in Road • Other Improper Action • Inattentive pedestrian • Failure to Obey Officer • Wrong Side of Road

Table A4 More similar contributing factors for Adverse weather

Direct contributing factors	Similar contributing factors from states practices
Adverse weather	• Smog, Smoke • Sleet, Hail, Freezing Rain • Blowing Sand, Soil, Dirt • Severe Crosswinds • Rain, Snow • Vision Obstruction (including blinded by sun) • Other environmental

Table A5 More similar contributing factors for Poor geometric conditions

Direct contributing factors	Similar contributing factors from states practices
Poor geometric conditions	• Wet • Icy or Snow-covered • Debris or Obstruction • Ruts, Holes, Bumps • Road Under

	Construction/Maintenance ● Traffic Control Device Inoperative ● Shoulder Low, Soft, High ● Physical Obstruction(s) ● Worn, Travel-polished Surface ● Road marking Defects ● Other road condition

<u>The Python code for running a case study with Inference Engine 2</u>

```
import pandas as pd

def get_countermeasures(types, contributing_factors):
    df = pd.read_excel("file.xlsx") # Knowledge base 2 (The list of countermeasures)
    contributing_factors = contributing_factors.split(', ') # Split the user input into a list of
contributing factors
    if types == "Operational":
        mask = ((df['Types'] == "Operational")  & (df['Contributing factors'].apply(lambda x: any(f
in x for f in contributing_factors))))
    elif types == "Operational, Geometric":
        mask = ((df['Types'] == "Operational") | (df['Types'] == "Geometric")) & (df['Contributing
factors'].apply(lambda x: any(f in x for f in contributing_factors)))
    elif types == "Geometric":
        mask = (df['Types'] == "Geometric") & (df['Contributing factors'].apply(lambda x: any(f in x
for f in contributing_factors)))
    elif types == "All":
        mask = (df['Contributing factors'].apply(lambda x: any(f in x for f in contributing_factors)))
    else:
        return "Invalid type"
    selected_countermeasures = df.loc[mask, ['CMF', 'Budget', 'Types', 'Contributing factors',
'Limitation', 'Countermeasures']]
    selected_countermeasures.to_excel("selected_countermeasures.xlsx", index=False)
    return selected_countermeasures
Types = input("Please enter the types: ")
Factors = input("Please enter the factors: ")
import pandas as pd

# Load the selected countermeasures excel file
df = pd.read_excel("selected_countermeasures.xlsx")

# Ask the user about pedestrian countdown signals
ped_countdown = input("Do you have a pedestrian countdown signal? (yes/no) ")

# Cancel the "Pedestrian countdown signals" if the user has it
if ped_countdown.lower() == "yes":
    df = df[df['Countermeasures'] != "Pedestrian countdown signals"]

# Ask the user about space for roundabouts
space_for_roundabout = input("Do you have space for designing a roundabout? (yes/no) ")

# Cancel the "Roundabouts" if the user doesn't have space for it
if space_for_roundabout.lower() == "no":
    df = df[df['Countermeasures'] != "Roundabouts"]

space_for_emergency = input("Many emergency car crash?")

if space_for_emergency.lower() == "no":
```

```
    df = df[df['Countermeasures'] != "Emergency Responder Warning System"]

space_for_bike = input("Can bicycle occupy whole lane?")

if space_for_bike.lower() == "no":
    df = df[df['Countermeasures'] != "Bike Boulevard"]

space_for_bike = input("Many bike accidents?")

if space_for_bike.lower() == "no":
    df = df[df['Countermeasures'] != "Bike Lane"]

space_for_phb = input("Is the lane number more than 6?")

if space_for_phb.lower() == "no":
    df = df[df['Countermeasures'] != "Pedestrian Hybrid Beacon (PHB)/HAWK"]

# Save the updated excel file
df.to_excel("selected_countermeasures.xlsx", index=False)

# Read the DataFrame from the original Excel file
df = pd.read_excel("selected_countermeasures.xlsx")

# Iterate over the columns of the DataFrame
for col in df.columns:
    # Check if the column contains empty values
    if df[col].isna().sum() > 0:
        # Convert non-numeric values to NaN and calculate the maximum value
        max_val = pd.to_numeric(df[col], errors='coerce').max()
        # Replace empty values with the maximum value in that column
        df[col] = df[col].fillna(max_val)

# Write the updated DataFrame to a new Excel file
df.to_excel("updated_selected_countermeasures.xlsx", index=False)

def normalize_countermeasures():
    df = pd.read_excel("updated_selected_countermeasures.xlsx")
    df.loc[df['CMF'] == 0, 'CMF'] = df['CMF'].max() # Replace 0 values in the "CMF" column with
the maximum value
    df.loc[df['Budget'] == 0, 'Budget'] = df['Budget'].max() # Replace 0 values in the "Budget"
column with the maximum value
    df['CMF'] = (df['CMF'] - df['CMF'].min()) / (df['CMF'].max() - df['CMF'].min()) # Normalize
the "CMF" column
    df['Budget'] = (df['Budget'] - df['Budget'].min()) / (df['Budget'].max() - df['Budget'].min()) #
Normalize the "Budget" column
# Normalzied value
    df.to_excel("real_normalized_countermeasures.xlsx", index=False)
# 1-Normalzied value to fit the equation of weight
    df['CMF'] = 1 - df['CMF'] # Invert the values in the "CMF" column
    df['Budget'] = 1 - df['Budget'] # Invert the values in the "Budget" column
    df.to_excel("normalized_countermeasures.xlsx", index=False)
    return df

# Load data
df = pd.read_excel("normalized_countermeasures.xlsx")

# Get contributing factors
```

```
contributing_factors = ['Inattentive_driver', 'Inattentive_pedestrian', 'Jaywalk', 'Turning_right',
'Adverse_weather', 'Speeding', 'Poor_geometric']
contributing_weights = {}

# Ask user for weights
for factor in contributing_factors:
    weight = float(input(f"Please enter the weight for {factor}: "))
    contributing_weights[factor] = weight

# Calculate the total weight for each row
for index, row in df.iterrows():
    row_factors = row["Contributing factors"].split(", ")
    row_weight = 0
    for factor in row_factors:
        row_weight += contributing_weights[factor]
    df.at[index, "Contributing factors"] = row_weight

# Save the result to a new excel file
df.to_excel("contributing_factors_weights.xlsx", index=False)

def prioritize_countermeasures(): #Reminder: Change contributing values
    df = pd.read_excel("contributing_factors_weights.xlsx")
    df['Weight'] = df['CMF'] * 0.09090909 + df['Budget'] * 0.09090909 + df['Contributing factors']
* 0.81818182
    df = df.sort_values(by='Weight', ascending=False)
    df.to_excel("prioritized_countermeasures.xlsx", index=False)
    return df

def match_countermeasure_costs():
    prioritized_countermeasures = pd.read_excel("prioritized_countermeasures.xlsx")
    cost_df = pd.read_excel("updated_selected_countermeasures.xlsx")
    cost_df = cost_df.set_index("Countermeasures")
    prioritized_countermeasures["Budget"] = [cost_df.loc[countermeasure, "Budget"] for
countermeasure in prioritized_countermeasures["Countermeasures"]]
    prioritized_countermeasures.to_excel("prioritized_countermeasures_with_costs.xlsx",
index=False)
    return prioritized_countermeasures

prioritize_countermeasures()
match_countermeasure_costs()

from scipy.optimize import linprog

import pulp
B = float(input("Please enter the budget (B): "))
# Load data
prioritized_countermeasures = pd.read_excel("prioritized_countermeasures_with_costs.xlsx")

# Create a list of countermeasures and costs
countermeasures = prioritized_countermeasures['Countermeasures'].tolist()
weights = prioritized_countermeasures['Weight'].tolist()
budgets = prioritized_countermeasures['Budget'].tolist()

# Create the optimization model
model = pulp.LpProblem("Combination of Countermeasures", pulp.LpMaximize)

# Create binary variables for each countermeasure
```

```
x = pulp.LpVariable.dicts("countermeasure", countermeasures, lowBound=0, upBound=1,
cat=pulp.LpInteger)

# Objective function
model += sum([weights[i] * x[countermeasures[i]] for i in range(len(countermeasures))])

# Constraints
model += sum([budgets[i] * x[countermeasures[i]] for i in range(len(countermeasures))]) <= B,
"Budget Constraint"

# Solve the optimization problem
model.solve()

# Print the results
total_cost = 0
print("Selected Countermeasures:")
for i in range(len(countermeasures)):
    if x[countermeasures[i]].value() == 1.0:
        print(countermeasures[i])
        total_cost += budgets[i]
print("Total cost: {:.2f}".format(total_cost))
print("Budget constraint: {:.2f}".format(B))
```