

Article

Risk Assessment of Human Errors in Interaction Design Using Fuzzy Fault Tree Analysis

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Abstract

User experience constitutes an essential element of effective interaction design. To enhance the user experience, it is necessary to identify the primary root causes related to human errors and then initiate actionable interventions for the high-priority root causes. Risk assessment of human errors in interaction design is characterized by subjective uncertainties and a lack of precise numerical values. However, very little attention has been given to these issues when assessing human errors. In this paper, a fuzzy fault tree analysis approach is proposed to execute risk assessment of human errors in interaction design. First, the system is analyzed, and a fault tree diagram is constructed. Subsequently, probabilities for each basic event are derived through the combination of fuzzy set theory and the similarity aggregation method. Then, the minimal cut sets (MCSs) are identified. Following this, the failure probability of the top event is determined, and the MCSs are ranked in accordance with their respective importance values. Finally, the results are evaluated, and the recommendations for corrective actions are provided for the high-priority MCSs. A practical case study of the in-vehicle information system in heavy trucks was conducted to demonstrate the feasibility and effectiveness of the proposed approach. The findings suggest that this approach can effectively address the subjective and even subconscious aspects of risk assessment related to human errors in interaction design, providing accurate results for risk evaluation. Furthermore, it can effectively address the situations where the probabilities related to human errors are imprecise, inadequate, and ambiguous. The proposed approach can be universally applied to enhance the user experience in interaction design.

Keywords: risk assessment; human errors; interaction design; fuzzy fault tree analysis; similarity aggregation method

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1. Introduction

In recent years, the wave of digital transformation has led to rapid advancements in human–computer interaction (HCI). HCI is the field dedicated to studying and designing interactions between systems and users. It seeks to understand how human users engage with computer technology in order to design systems that effectively meet users' needs [1]. A primary goal of HCI is to foster positive interactions between humans and technology, making systems more user-friendly and accessible. Systems encompass a wide variety of machines, as well as computerized systems and software. Human errors is an inherent aspect of system performance [2,3]. One of the most common reasons for human-

induced errors is that individuals are often required to perform tasks and processes that exceed human capabilities [4]. Approximately 75% to 95% of industrial accidents are attributed to human errors, which can be broadly defined as any action that hinders a user from completing a task in the most efficient manner [5]. A significant portion of a HCI design project involves addressing human errors [6].

Human errors are fundamentally a design problem to some extent. Designers should identify the root causes of errors and either enhance or redesign the system to prevent their occurrence. Common types of errors in HCI include behaviors that impede task completion, execution of actions in an incorrect sequential order, misinterpretation of relevant content, and failing to notice critical information [7]. Some changes implemented to address specific human errors may inadvertently introduce new errors [8]. Therefore, it is crucial to identify and eliminate the most significant human errors to enhance the user experience in interaction design. Numerous studies have been conducted on this issue. Mandal et al. [9] integrated hierarchical task analysis (HTA) with systematic human error reduction and prediction approach (SHERPA) for the identification of human errors, and then employed fuzzy VIKOR technique to rank the errors. Li and Zhu [10] used failure mode and effect analysis to analyze the risk factors of human errors, and then employed fuzzy logic to rank the errors. These studies employed a bottom-up approach to evaluate component-level failures, and effectively identified and eliminated the significant errors; however, they did not thoroughly investigate the mechanisms underlying the causes of errors. In the field of interaction design, mechanisms are often analyzed based on the subjective judgments of designers. When these mechanisms are complex, a systematic technique is essential for effective analysis.

There are several techniques that can be used to explore the mechanisms behind the causes of errors. Fault tree analysis (FTA) is one such well-recognized technique for analyzing complex systems and ascertaining the mechanisms that drive error causation [11]. It uses a top-down, deductive approach that begins with an undesired event and then analyzes the causes that led to this event [12]. In the conventional FTA, probability of the top event was estimated using combinations of basic events, each with precise failure probabilities. However, in practice, the probabilities associated with human errors are often imprecise, inadequate, and ambiguous. To address the difficulties and limitations in the conventional FTA, many studies have integrated fuzzy set theory with FTA [13,14]. The concept underlying fuzzy FTA has found extensive application in diverse professional fields [15,16]. For example, Gürgen et al. [17] adopted fuzzy FTA to investigate the root causes of accidents leading to the loss of a ship's steering ability, and the linguistic judgments of experts were utilized to derive the failure probabilities of each basic event in the fault tree. However, to the best of the authors' knowledge, very little research has been dedicated to the application of fuzzy FTA for the risk assessment of human errors in interaction design.

This paper presents a fuzzy FTA approach for conducting risk assessment of human errors in interaction design. The main contribution of this study lies in the integration of heterogeneous methodological approaches across different disciplines into a cohesive analytical framework, as well as its application to interaction design—a research field in which this type of approach has not previously been utilized. In this framework, fault tree analysis is employed to conduct a risk assessment of human errors. Furthermore, fuzzy linguistic variables and the similarity aggregation method (SAM) are combined to aggregate the possibilities derived from expert assessments. This novel approach enables effective management of the subjective and subconscious components of human errors while accurately prioritizing the basic events associated with it. Moreover, it can effectively address the probabilities associated with human errors, which are often imprecise, inadequate, and ambiguous.

The remainder of this paper is organized as follows. Section 2 provides a theoretical background of the research. Section 3 provides a thorough presentation of our proposed methodology. Section 4 demonstrates the procedures through a case study, and the results are discussed in Section 5. Finally, we summarize the main conclusions in Section 6.

2. Theoretical Background

This paper presents a fuzzy fault tree analysis approach for conducting risk assessments of human errors in interaction design. The theoretical background of the proposed approach encompasses interaction design, fault tree analysis, and fuzzy set theory.

2.1. Interaction Design

HCI is an interdisciplinary field that centers on the design, study, implementation, and evaluation of interactions between users and computers [18]. Interaction design involves designing HCI systems to support the ways that people communicate and interact in their everyday lives [19]. The interaction design process should consider every possible action that a user is likely to take and understand the user's expectations at each step. Generally, a human error in interaction design is an action that results in a user's deviation from the path to successful completion. A well-designed interaction system organizes the behaviours most commonly adopted by users, making these elements accessible and usable in the simplest way possible [6].

User experience is fundamental to interaction design. It encompasses two distinct categories of qualities [20]. The first comprises pragmatic qualities, which correspond to usability goals tied to the tasks users perform to accomplish their objectives—key factors include task suitability, efficiency, and error tolerance. The second category consists of hedonic qualities, which relate to experience goals centered on the subjective impressions of a user's overall interaction with the system, encompassing elements like aesthetic appeal, emotional resonance, and novelty [1,18,21]. Measuring user experience focuses on ensuring that interaction design is appropriate and effective [22]. There are various questionnaires that can be used to measure user experience, such as system usability scales, computer system usability questionnaires, and user experience questionnaires [23]. System usability scales have been widely utilized in the field of HCI, encompassing desktop applications, websites, and interactive products [7]. In this study, we employed a system usability scale to assess the user experience of interaction design.

2.2. Fault Tree Analysis

FTA is an essential tool that provides a clear and direct visualization of various combinations of failure events, enabling an accurate estimation of the probability of an undesired outcome [24]. FTA can be used to assess the reliability of complex systems; it allows for the examination of various types of factors that can lead to malfunctions or accidents within these systems [25]. FTA begins with an undesired event and identifies the contributing factors. In FTA, the top event represents the undesired event. Intermediate events, which are not directly observable, are defined in relation to the basic events. Basic events represent the most fundamental level of events in a fault tree.

FTA is based on Boolean logic, utilizing logic gates such as AND and OR to illustrate the relationships between events [26]. From the probability values of each basic event, we can derive the probability that the top event will occur. For events involving AND and OR gates, the probability values can be calculated using Equations (1) and (2), respectively [27].

$$P(E_0) = \prod_{i=1}^m P(E_i) \quad (1)$$

$$P(E_0) = 1 - \prod_{i=1}^m (1 - P(E_i)) \quad (2)$$

A fault tree offers crucial insights into the various combinations of basic events that can lead to a top event. A combination of these basic events is referred to as a cut set; a minimal cut set (MCS) is one that cannot be reduced without losing its status as a cut set [28]. The primary objectives of an FTA include identifying all possible combinations of basic events that could trigger a hazardous event in the system, along with the identification of system aspects requiring enhancement to mitigate the probability of such hazardous occurrences [29]. In this study, to investigate the human errors that are characterized by subjective uncertainties and a lack of precise numerical values [30], we combined FTA with fuzzy set theory.

2.3. Fuzzy Set Theory

Fuzzy set theory, developed by Zadeh [31], is a valuable tool for addressing concepts that involve uncertainty, imprecision, and nonlinearity. It emphasizes that human reasoning depends on linguistic terms or labels instead of numerical values, which helps in addressing the complexities of real-world situations more effectively. Fuzzy set theory can be integrated with user experience in various aspects, including the treatment of uncertainty, expert judgment, and performance-shaping factors [32].

In fuzzy set theory, fuzzy numbers can effectively represent knowledge using linguistic terms [33]. A fuzzy number refers to a quantity with an imprecise value, in contrast to the exactitude of crisp numbers. Fuzzy numbers encompass various types, such as triangular, trapezoidal, and sigmoid variants. Among these, the trapezoidal fuzzy number features a relatively simple structure that aligns with human reasoning; additionally, it unifies crisp numbers, interval numbers, and triangular numbers [34]. Consequently, this study adopts the trapezoidal fuzzy number, whose membership function is defined by Equation (3).

$$\mu_M(x) = \begin{cases} 0, & x < n_1 \\ \frac{x-n_1}{n_2-n_1}, & n_1 \leq x < n_2 \\ 1, & n_2 \leq x < n_3 \\ \frac{x-n_4}{n_3-n_4}, & n_3 \leq x \leq n_4 \\ 0, & x > n_4 \end{cases} \quad (3)$$

3. Proposed Methodology

This paper presents an approach for assessing the risk of human errors in interaction design. The flowchart of the proposed approach is presented in Figure 1, and the methodology consists of seven distinct stages: analysing the system, constructing the fault tree diagram, deriving the probabilities for each basic event, identifying the MCSs, calculating the failure probability for the top event, ranking the MCSs according to their values of importance, and evaluating the results and providing advice.

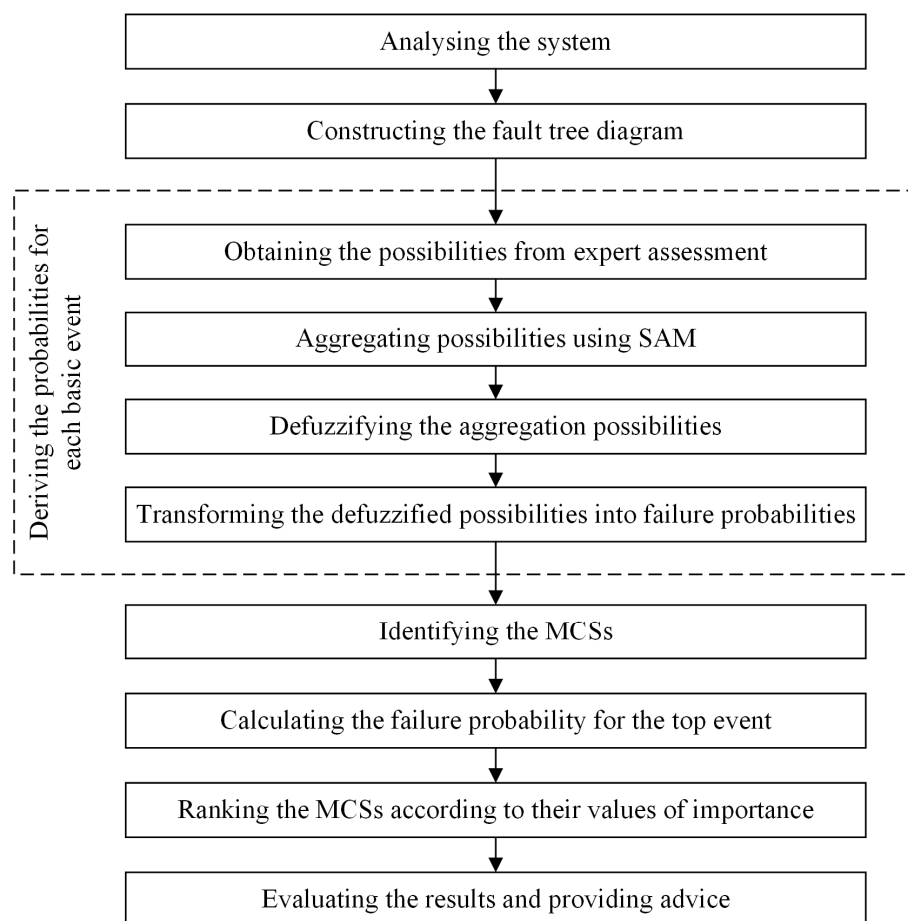


Figure 1. Flowchart of the proposed methodology.

3.1. Analysing the System

The proposed methodology begins with analyzing the system. During this analysis, it is essential to consider typical usage scenarios to define the system's boundaries and identify undesired events or human errors that will serve as the top event.

3.2. Constructing the Fault Tree Diagram

Constructing the fault tree diagram is carried out after identifying the top event. The top event is decomposed into intermediate events that contribute to its occurrence. These intermediate events are further broken down into basic events that directly contribute to the emergence of the top event. Next, logic gates and symbols are employed to represent the relationships between the events, resulting in the creation of the fault tree diagram. The fault tree diagram illustrates the sequence of events leading to the top event.

3.3. Deriving the Probabilities for Each Basic Event

3.3.1. Obtaining Possibilities Using Expert Assessment

When precise data on human errors during interaction design is unavailable, expert judgment-based possibility acquisition is a feasible practical strategy. In our methodology, experts offer their judgments on every basic event. Because the weight of each expert's opinion on a given attribute may not be uniform, the final assessments are influenced by the perceived importance assigned to each expert. Ramzali et al. [35] introduced weighting scores to represent the relative quality of different experts. Table 1 illustrates the weighting scores for the experts. The weighting scores are determined based on factors such as professional position, job experience, education, and years of using system. Each factor can be categorized into multiple levels, with each level assigned a specific score. If

some experts are regarded as more knowledgeable than others, the more knowledgeable experts may be assigned greater weight scores.

Table 1. Weighting scores based on expert traits.

Factor	Classification	Score
Professional position (F1)	Senior academic	5
	Junior academic	4
	Engineer	3
	Advanced user	2
	Ordinary user	1
Job experience (F2)	More than 30 years	5
	20–30	4
	10–19	3
	6–9	2
	Less than 6	1
Education (F3)	PhD	5
	Master	4
	Bachelor	3
	College diploma	2
	High school	1
Years of using system (F4)	More than 20	4
	11–20	3
	5–10	2
	Less than 5	1

To determine the weight assigned to each expert, Equation (4) is used.

$$w_i = \frac{\sum_{k=1}^m s_{ik}}{\sum_{j=1}^n \sum_{k=1}^m s_{jk}} \quad (4)$$

where w_i is the weight of the i th expert, s_{ik} is the weighting score of the i th expert for the k th weighting factor, j is the expert number, with values ranging from 1 to n , and k is the weighting score, with values ranging from 1 to m .

Linguistic judgments obtained from experts are converted into equivalent fuzzy values. The linguistic terms and their associated fuzzy numbers are listed in Table 2 [36], and the fuzzy ratings along with their membership functions are depicted in Figure 2 [37]. These definitions have been given in many studies [38], and have been successfully used in the field of risk assessment [39].

Table 2. Fuzzy numbers for linguistic terms.

Linguistic Term	Fuzzy Numbers
Very low (VL)	(0, 0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.2, 0.3)
Medium low (ML)	(0.2, 0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
Medium high (MH)	(0.5, 0.6, 0.7, 0.8)
High (H)	(0.7, 0.8, 0.8, 0.9)
Very high (VH)	(0.8, 0.9, 1.0, 1.0)

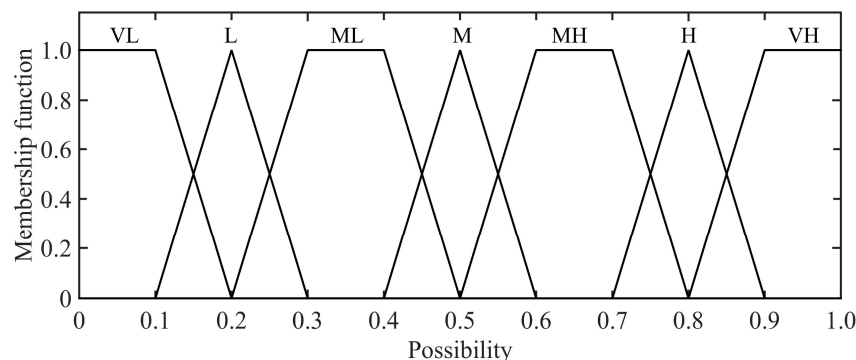


Figure 2. Fuzzy ratings and their corresponding membership functions.

3.3.2. Aggregating Possibilities Using SAM

For aggregating fuzzy opinions, we adopt SAM, which was introduced by Hsu and Chen [40]. The specific steps for applying SAM are outlined as follows [41,42].

Step 1. Calculate the similarity degree.

Each failure probability is quantified and represented through a membership function. The degree of overlap between these membership functions indicates the level of similarity, which is calculated as follows:

$$S(\tilde{R}_i, \tilde{R}_j) = \frac{\int_x \left(\min \{ \mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x) \} \right) dx}{\int_x \left(\max \{ \mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x) \} \right) dx} \quad (5)$$

where $\tilde{R}_i$ and $\tilde{R}_j$ are the fuzzy opinions of the i th expert and the j th expert, respectively; the membership functions of these opinions are denoted as $\mu_{\tilde{R}_i}(x)$ and $\mu_{\tilde{R}_j}(x)$, respectively; the similarity degree between the two experts is indicated by $S(\tilde{R}_i, \tilde{R}_j)$, with a higher $S(\tilde{R}_i, \tilde{R}_j)$ indicating stronger similarity between their opinions.

Step 2. Establish the similarity matrix SM .

$$SM = \begin{bmatrix} 1 & S_{12} & \cdots & S_{1j} & \cdots & S_{1n} \\ \vdots & \vdots & & \vdots & & \vdots \\ S_{i1} & S_{i2} & \cdots & S_{ij} & \cdots & S_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nj} & \cdots & 1 \end{bmatrix} \quad (6)$$

where if $i \neq j$, then $S_{ij} = S(\tilde{R}_i, \tilde{R}_j)$; if $i = j$, then $S_{ij} = 1$.

Step 3. Calculate the average similarity degree ASD_i of the i th expert in relation to the other experts.

$$ASD_i = \frac{1}{n-1} \sum_{\substack{j=1 \\ i \neq j}}^n S_{ij}, \quad i = 1, 2, \dots, n \quad (7)$$

Step 4. Calculate the relative similarity degree RSD_i of expert i .

$$RSD_i = \frac{ASD_i}{\sum_{i=1}^n ASD_i}, \quad i = 1, 2, \dots, n \quad (8)$$

Step 5. Compute the consensus degree coefficient CDC_i of expert i .

$$CDC_i = \beta \times w_i + (1 - \beta) \times RSD_i, i = 1, 2, \dots, n \quad (9)$$

where w_i is the weight of the i th expert and β ($0 \leq \beta \leq 1$) is a relaxation factor. When $\beta = 0$, no importance is assigned to the weight of an expert; when $\beta = 1$, the consensus degree of an expert is equivalent to its importance weight. Because the experts in this study exhibited heterogeneous characteristics, this value was set to 0.5.

Step 6. Compute the aggregation possibilities $\tilde{R}$.

$$\tilde{R} = \sum_{i=1}^n CDC_i \otimes \tilde{R}_i, i = 1, 2, \dots, n \quad (10)$$

where $\tilde{R}_i$ is the fuzzy opinion of the i th expert and CDC_i is the consensus degree coefficient of i th expert.

3.3.3. Defuzzifying the Aggregation Possibilities

To defuzzify the aggregation possibilities, the center of gravity method is employed, and the formula for calculating the defuzzification value is as follows:

$$DF = \frac{\int x \cdot \mu(x) dx}{\int \mu(x) dx} \quad (11)$$

where DF is the defuzzification value and $\mu(x)$ is the membership function. For a trapezoidal number $\tilde{M} = (n_1, n_2, n_3, n_4)$, the defuzzification value can be calculated as follows [43]:

$$\begin{aligned} DF &= \frac{\int_{n_1}^{n_2} \frac{x-n_1}{n_2-n_1} x dx + \int_{n_2}^{n_3} x dx + \int_{n_3}^{n_4} \frac{x-n_4}{n_3-n_4} x dx}{\int_{n_1}^{n_2} \frac{x-n_1}{n_2-n_1} dx + \int_{n_2}^{n_3} dx + \int_{n_3}^{n_4} \frac{x-n_4}{n_3-n_4} dx} \\ &= \frac{1}{3} \times \frac{(n_3+n_4)^2 - n_3n_4 - (n_1+n_2)^2 + n_1n_2}{n_4+n_3-n_2-n_1} \end{aligned} \quad (12)$$

3.3.4. Transforming the Defuzzified Possibilities into Failure Probabilities

FTA requires the probabilities of each basic event. To convert the defuzzified possibilities into failure probabilities, Equation (13) is used. This equation was proposed by Onisawa [44], and has been employed in numerous studies [39,45].

$$FP = \begin{cases} 1/10^k, & DF \neq 0 \\ 0, & DF = 0 \end{cases} \quad k = 2.301 \times \left[\frac{1-DF}{DF} \right]^{1/3} \quad (13)$$

where FP is the failure probability.

3.4. Identifying the MCSs

An MCS denotes the smallest combination of component failures that, when occurring, will result in the occurrence of the top event [46]. In other words, an MCS consists of various basic events; when all the basic events take place, the top event is assured to occur; on the other hand, if even one basic event fails to happen, the top event will not occur. Several methods have been proposed to obtain the MCS, with Boolean algebra being the

most commonly used method [47]. For a detailed description of the rules of Boolean algebra, refer to Vesely et al. [48]. A fault tree typically contains multiple MCSs, each unique to the top event. The mathematical expression for MCSs is provided as follows [35]:

$$TE = MCS_1 + MCS_2 + MCS_i + \dots + MCS_N = \bigcup_{i=1}^N MCS \quad (14)$$

where TE represents the top event, MCS_i denotes the minimal cut set, and N indicates the number of minimal cut sets.

3.5. Calculating the Failure Probability for the Top Event

The top event's probability is obtained from the basic events' probabilities and the logical relationships represented by the gates in the fault tree. Based on the MCSs, the probability of the top event is computed as follows [39]:

$$\begin{aligned} P(TE) &= P(MCS_1 \cup MCS_2 \cup \dots \cup MCS_N) \\ &= P(MCS_1) + P(MCS_2) + \dots + P(MCS_N) \\ &\quad - (P(MCS_1 \cap MCS_2) + P(MCS_1 \cap MCS_3) + \dots + P(MCS_i \cap MCS_j) \dots) \\ &\quad + (-1)^{N-1} P(MCS_1 \cap MCS_2 \cap \dots \cap MCS_N) \end{aligned} \quad (15)$$

where $P(MCS_i)$ is the probability of MCS_i and N is the number of MCSs.

3.6. Ranking the MCSs According to Their Values of Importance

The ranking of MCSs can help identify key path or weak links within the system, as well as the causes of a top event's occurrence. The value of importance for each MCS can be calculated as follows [38]:

$$I_i = \frac{P(MCS_i)}{P(TE)} \quad (16)$$

where I_i is the value of importance for the i th MCS, $P(MCS_i)$ denotes the failure probability of the i th MCS, and $P(TE)$ signifies the probability of the top event.

3.7. Evaluating the Results and Providing Advice

Based on the ranking of MCSs, we utilize the Pareto diagram to identify the cut sets that account for approximately 80% of the cumulative percentage. After identifying the significant MCSs, we can develop a comprehensive risk management plan to enhance the system effectively, in accordance with the design principles in HCI [49,50].

4. Case Study

In-vehicle information systems (IVISs) are characterized as representative interactive systems. About 90% of vehicle accidents are caused by human error [51], and the interaction design of IVISs plays a crucial role in driving safety; this topic has received significant research attention [52,53]. Heavy truck drivers must maintain a high level of attention during long hours of driving, and thus the risk assessment of human errors concerning IVISs in heavy trucks is crucial for improving safety. This case study used the IVIS in heavy trucks of the J7 model, manufactured by FAW Jiefang Automobile Co., Ltd., as an example to demonstrate the proposed methodology.

4.1. Analysing the IVIS

One of the user interfaces of the original IVIS is illustrated in Figure 3. This user interface features eight icons: My J7, Multimedia, Radio, Navigation, Telephone, Car Life, Internet, and Settings. Additionally, the top of the user interface displays the date, time, and volume level. According to the survey data, failing to complete the navigation task was identified as the top event that should be analyzed.

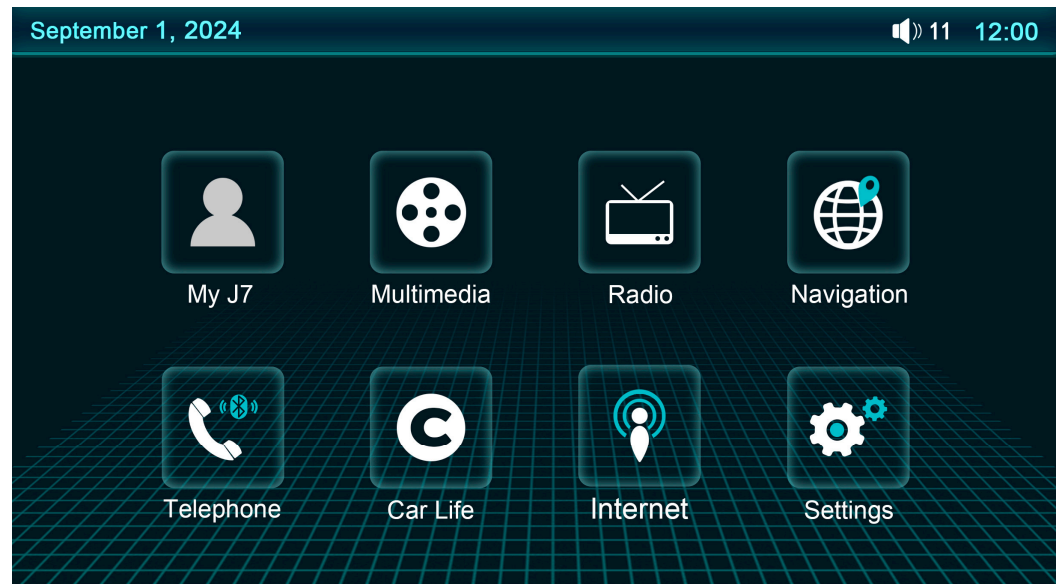


Figure 3. An interface of the original IVIS.

4.2. Constructing the Fault Tree Diagram for the IVIS

The fault tree can decompose the top event into intermediate events such as IE1 (Unable to locate the navigation system channel), IE2 (Difficulty in setting up the starting and ending positions), and IE3 (Poorly designed icons). Each of these intermediate events was then further broken down into base events, including BE1 (Insufficient visualization of the elements), BE2 (Incongruous color scheme), and BE3 (Mismatch between the name and the graphics). The constructed fault tree diagram is presented in Figure 4. Event information for the fault tree of the IVIS is provided in Table 3.

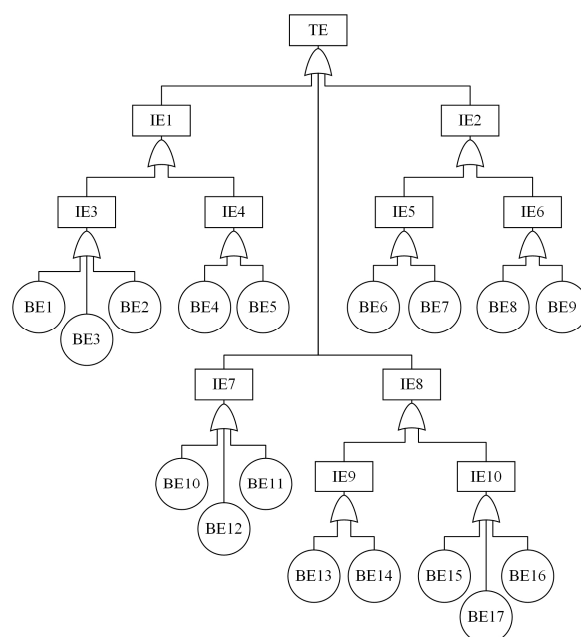


Figure 4. Fault tree diagram for the selected human error.

Table 3. Event information regarding the selected human error related to IVIS.

Event Type	Symbol	Description
Top event	TE	The navigation system is not working.
Intermediate event	IE1	Unable to locate the navigation system channel.
Intermediate event	IE2	Difficulty in setting up the starting and ending positions.
Intermediate event	IE3	Poorly designed icons.
Intermediate event	IE4	Hierarchies are not well structured.
Intermediate event	IE5	Entered the wrong location.
Intermediate event	IE6	Can't find a common location.
Intermediate event	IE7	Return to the main screen without finishing the navigation.
Intermediate event	IE8	Failure to understand the functional interfaces.
Intermediate event	IE9	Driver cognitive factors.
Intermediate event	IE10	Improper use of text.
Basic event	BE1	Insufficient visualization of the elements.
Basic event	BE2	Incongruous color scheme.
Basic event	BE3	Mismatch between the name and the graphics.
Basic event	BE4	Excessive framework layers.
Basic event	BE5	Confusing content categorization.
Basic event	BE6	Unreasonable layout.
Basic event	BE7	Invisible indicator icons.
Basic event	BE8	Categorization of locations is confusing.
Basic event	BE9	Difficulty in finding history.
Basic event	BE10	Lack of orientation information.
Basic event	BE11	Lack of feedback.
Basic event	BE12	Lack of information alerts.
Basic event	BE13	Low level of education.
Basic event	BE14	Fear of improper operation.
Basic event	BE15	Poor choice of language.
Basic event	BE16	The font doesn't fit.
Basic event	BE17	Font size too small.

4.3. Deriving the Probabilities for Each Basic Event Related to the IVIS

Seven experts were invited to participate in the study. The traits of the experts are presented in Table 4. Based on the weighting scores (see Table 1), the weights for the seven experts can be calculated using Equation (4), as shown in Table 5.

Table 4. Traits of the experts in the study.

Expert No.	Professional Position (F1)	Job Experience (F2)	Education (F3)	Years of Using System (F4)
1	Senior academic	21	PhD	17
2	Junior academic	18	Master	10
3	Senior academic	36	Bachelor	23
4	Senior academic	21	Master	16
5	Engineer	3	Master	3
6	Advanced user	28	College diploma	21
7	Ordinary user	6	High school	4

Table 5. Expert weight based on traits.

Expert No.	Weighting Factors				Total Score	Weight
	F1	F2	F3	F4		
1	5	4	5	3	17	0.191
2	4	3	4	2	13	0.146
3	5	5	3	4	17	0.191
4	5	4	4	3	16	0.180
5	3	1	4	1	9	0.101
6	2	4	2	4	12	0.135
7	1	2	1	1	5	0.056

Fuzzy evaluations from the seven experts for all the basic events are presented in Table 6.

Table 6. Fuzzy evaluations and aggregation of opinions.

Basic Event	Linguistic Evaluations of Experts						
	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7
BE1	L	VL	L	ML	L	M	L
BE2	L	L	VL	L	L	L	VL
BE3	ML	M	L	M	ML	ML	L
BE4	MH	M	M	H	H	MH	MH
BE5	M	M	ML	ML	MH	MH	M
BE6	ML	ML	ML	L	M	M	L
BE7	M	MH	MH	ML	MH	M	ML
BE8	ML	L	L	ML	L	M	L
BE9	ML	M	M	L	L	ML	ML
BE10	H	H	VH	VH	H	MH	MH
BE11	L	L	ML	ML	M	L	L
BE12	ML	ML	M	M	M	L	L
BE13	L	VL	VL	L	ML	ML	L
BE14	L	L	VL	VL	ML	ML	VL
BE15	ML	M	L	ML	L	M	ML
BE16	ML	ML	M	M	L	L	L
BE17	M	MH	H	M	M	ML	ML

For the aggregation of fuzzy opinions in risk assessment, SAM was employed. Based on Equations (5) and (6), the similarity matrix for basic Event No. 1 (BE1) can be derived as follows:

$$SM = \begin{bmatrix} 1.000 & 0.111 & 1.000 & 0.091 & 1.000 & 0 & 1.000 \\ 0.111 & 1.000 & 0.111 & 0 & 0.111 & 0 & 0.111 \\ 1.000 & 0.111 & 1.000 & 0.091 & 1.000 & 0 & 1.000 \\ 0.091 & 0 & 0.091 & 1.000 & 0.091 & 0.091 & 0.091 \\ 1.000 & 0.111 & 1.000 & 0.091 & 1.000 & 0 & 1.000 \\ 0 & 0 & 0 & 0.091 & 0 & 1.000 & 0 \\ 1.000 & 0.111 & 1.000 & 0.091 & 1.000 & 0 & 1.000 \end{bmatrix}$$

Following the application of Equation (7), the average similarity degree *ASD* was computed. Thereafter, the relative similarity degree *RSD* was obtained utilizing Equation (8). Then, according to Equation (9), the consensus degree coefficient *CDC* can be computed. The calculated values of *ASD*, *RSD*, and *CDC* for BE1 are presented in Table 7.

After that, using Equation (10), the aggregated expert evaluations can be obtained as follows: $\tilde{R} = (0.123, 0.214, 0.234, 0.334)$. Finally, employing Equation (12), the defuzzification possibility for the aggregated fuzzy opinions was determined to be 0.227.

Table 7. The computed ASD, RSD, and CDC for BE1.

Expert No.	Average Similarity Degree (ASD)	Relative Similarity Degree (RSD)	Consensus Degree Coefficient (CDC)
1	0.534	0.232	0.212
2	0.074	0.032	0.089
3	0.534	0.232	0.212
4	0.076	0.033	0.106
5	0.534	0.232	0.167
6	0.015	0.007	0.071
7	0.534	0.232	0.144

In a similar manner, the aggregated fuzzy numbers, along with the corresponding defuzzification results for all basic events, were obtained and are summarized in Table 8.

Table 8. Aggregated expert evaluations, possibility, and probability.

Basic Event	Aggregated Fuzzy Number	Defuzzified Possibility	Probability
BE1	(0.123, 0.214, 0.234, 0.334)	0.227	3.435×10^{-4}
BE2	(0.081, 0.162, 0.181, 0.281)	0.178	1.468×10^{-4}
BE3	(0.231, 0.331, 0.381, 0.481)	0.356	1.570×10^{-3}
BE4	(0.522, 0.622, 0.670, 0.770)	0.646	1.308×10^{-2}
BE5	(0.364, 0.464, 0.516, 0.616)	0.490	4.653×10^{-3}
BE6	(0.222, 0.322, 0.378, 0.478)	0.350	1.485×10^{-3}
BE7	(0.406, 0.506, 0.577, 0.677)	0.542	6.664×10^{-3}
BE8	(0.150, 0.250, 0.277, 0.377)	0.264	5.741×10^{-4}
BE9	(0.230, 0.330, 0.378, 0.478)	0.354	1.545×10^{-3}
BE10	(0.690, 0.790, 0.839, 0.909)	0.805	3.687×10^{-2}
BE11	(0.145, 0.245, 0.272, 0.372)	0.258	5.377×10^{-4}
BE12	(0.283, 0.383, 0.412, 0.512)	0.398	2.276×10^{-3}
BE13	(0.094, 0.167, 0.217, 0.317)	0.200	2.227×10^{-4}
BE14	(0.073, 0.124, 0.194, 0.294)	0.173	1.338×10^{-4}
BE15	(0.224, 0.324, 0.374, 0.474)	0.349	1.473×10^{-3}
BE16	(0.215, 0.315, 0.344, 0.444)	0.329	1.212×10^{-3}
BE17	(0.394, 0.494, 0.526, 0.626)	0.510	5.364×10^{-3}

To convert the defuzzified possibilities into failure probabilities, Equation (13) was employed, and the results are presented in the last column of Table 8.

4.4. Identifying the MCSs Related to the IVIS

MCSs are the combinations of basic events that are sufficient to trigger the top event. By applying Boolean algebra rules, the MCSs can be identified, and the results are presented in the first column of Table 9.

Table 9. Importance value and ranking of each MCS.

MCS	Probability	Importance Value	Ranking
BE10	3.687×10^{-2}	4.855×10^{-1}	1
BE4	1.308×10^{-2}	1.722×10^{-1}	2

BE7	6.664×10^{-3}	8.775×10^{-2}	3
BE17	5.364×10^{-3}	7.063×10^{-2}	4
BE5	4.653×10^{-3}	6.127×10^{-2}	5
BE12	2.276×10^{-3}	2.997×10^{-2}	6
BE3	1.570×10^{-3}	2.067×10^{-2}	7
BE9	1.545×10^{-3}	2.035×10^{-2}	8
BE6	1.485×10^{-3}	1.955×10^{-2}	9
BE15	1.473×10^{-3}	1.939×10^{-2}	10
BE16	1.212×10^{-3}	1.596×10^{-2}	11
BE8	5.741×10^{-4}	7.560×10^{-3}	12
BE11	5.377×10^{-4}	7.080×10^{-3}	13
BE1	3.435×10^{-4}	4.522×10^{-3}	14
BE13	2.227×10^{-4}	2.932×10^{-3}	15
BE2	1.468×10^{-4}	1.933×10^{-3}	16
BE14	1.338×10^{-4}	1.761×10^{-3}	17

4.5. Calculating the Failure Probability for the Top Event Related to the IVIS

Based on the identified MCSs, the failure probability of the top event was derived by using Equation (15), resulting in a value of 7.595×10^{-2} .

4.6. Ranking the MCSs Related to the IVIS According to Their Values of Importance

According to Equation (16), the value of importance for each MCS was determined. Based on these values of importance, the MCSs were ranked. The MCS with the highest importance value was assigned a rank of 1. The importance values and rankings of each MCS are presented in Table 9.

4.7. Evaluating the Results and Providing Advice Related to the IVIS

The Pareto diagram illustrating the significance values of the MCSs is shown in Figure 5. As a result, five cut sets (BE10, BE4, BE7, BE17, BE5) were selected, yielding a total cumulative percentage of 85.26%. Among these cut sets, BE10 ranked first and received the highest priority, followed by BE4, BE7, and BE17. Additionally, BE5 was the last to provide corrective action.

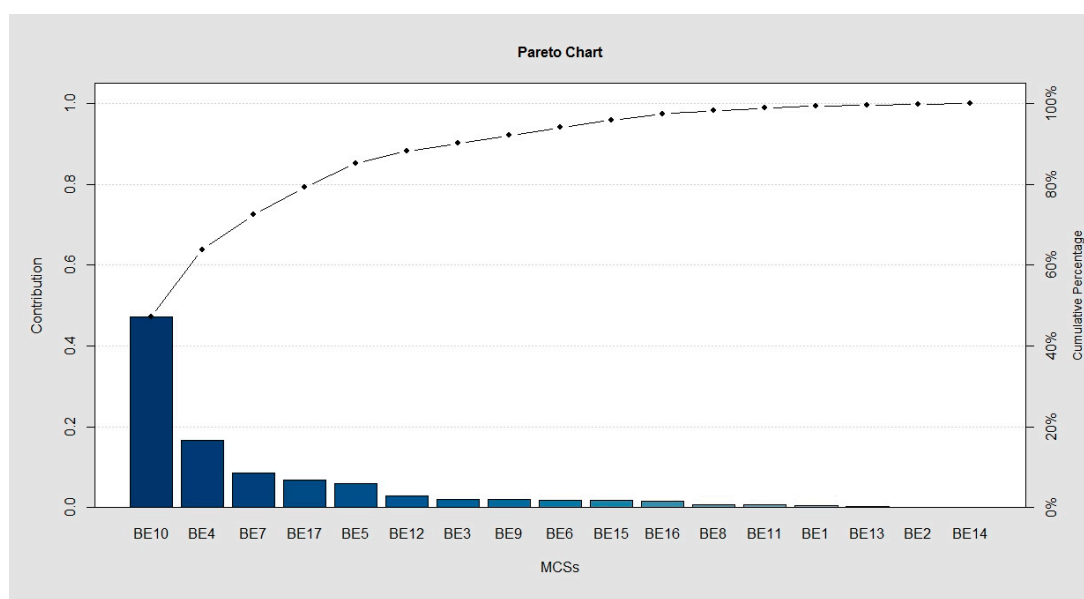


Figure 5. Pareto diagram for MCSs.

To address BE10 (lack of orientation information), it is recommended to integrate guidance prompts to facilitate users during their initial interaction with the system. Furthermore, the deployment of lane guidance animations and the provision of real-time feedback are essential to optimize the user interaction process. To address BE4 (excessive framework layers), it is essential to streamline the system by eliminating redundant layers. The hierarchical design of the IVIS should minimize users' visual engagement with the interface. Additionally, frequently used functions—such as telephone, multimedia, and navigation—should be placed in a scrollable function bar located at the bottom of the interface, thereby minimizing page switches during user interactions. To address BE7 (invisible indicator icons), the vehicle's position and route information should be prominently centered within the interface. Furthermore, the lane guidance icon should be aligned to the left side of the screen, while speed information and alerts regarding speed camera detection should be displayed on the right side. To address BE17 (font size too small), it is recommended that the default font size in the interface be set to 12 points. Additionally, users should be granted the ability to customize the font size according to their individual visual preferences and usage needs. To address BE5 (confusing content categorization), we adopted a card sorting technique to restructure the interface elements of the IVIS in a user-intuitive manner.

5. Discussion

In this research, a fuzzy FTA approach was developed to improve user experience in interaction design, with a heavy truck IVIS as the case study. Within the proposed framework, the IVIS was analyzed, and failing to complete the navigation task was selected as the undesired event. The corresponding fault tree diagram was constructed. Clearly, FTA provides a structured and logical approach to identifying and analyzing potential human errors, ensuring a comprehensive assessment of human errors in interaction design. The graphical representation of fault trees facilitates a clearer understanding and communication of the mechanisms behind the causes of human errors.

Due to the inadequate failure probabilities associated with each basic event, we integrated fuzzy set theory with FTA. First, the possibilities were obtained through the assessments of seven experts, and these possibilities were subsequently aggregated using SAM. After that, the aggregated values were defuzzified, and the results were converted into failure probabilities. Based on these probabilities, the failure probability for the top event was calculated, and the MSCs were ranked according to their values of importance. A total of five cut sets were selected to provide recommendations for corrective actions. It can be observed that by quantifying the probability of occurrence for the top event and its contributing factors, fuzzy FTA can assist interaction designers in prioritizing their mitigation efforts for human errors and effectively allocating resources.

Following the recommendations for corrective actions, the IVIS was revised. One of the user interfaces of the revised IVIS is illustrated in Figure 6. The A/B testing technique was employed to compare the original system with the revised version [54]. Thirty participants (15 females and 15 males, aged between 25 and 50, all with a minimum of 2 years of experience using IVIS in heavy trucks) were invited to participate in the experiment. A repeated-measures experimental design was employed; that is to say, the same participants took part in both tests. The tests were carried out in a stationary heavy truck. Each participant was asked to complete the navigation task using both systems. To control for learning effects during the tests, fifteen participants completed the task in the order of the original system followed by the revised system, while the other fifteen participants completed the task in the order of the revised system followed by the original system. After completing the navigation task, the participants were asked to evaluate both systems using the system usability scale. The score of the system usability scale for the revised system

was 86.27, significantly higher than the original system score of 62.48 ($p < 0.001$). This indicates that the optimization measures have significantly reduced the risk of human errors. Consequently, the insights gained from fuzzy FTA can guide the development of interaction design strategies aimed at preventing or detecting potential human errors. From these results, we can conclude that fuzzy FTA can be effectively utilized in interaction design to identify potential weaknesses and enhance user experience.



Figure 6. An interface of the revised IVIS.

In this study, a heavy truck IVIS was used as a case study. The IVIS in early heavy trucks used mechanical buttons for interaction, similar to process control, allowing Equation (13) to be applied. With the development of intelligent heavy trucks, icons have replaced mechanical buttons, and the operation process retains some similarities. Therefore, Equation (13) is used to calculate the failure probability. However, certain differences still exist between icons and mechanical buttons. Future research could focus on developing an equation to calculate the probability of failure in user interfaces.

In the field of interaction design, the mechanisms of human errors associated with risk assessment are often analyzed based on the subjective judgments of interaction designers. When these mechanisms are complex, it becomes challenging to depend on subjective judgments. Additionally, the importance value for each basic event cannot be systematically determined. In contrast, the proposed approach utilizes fuzzy fault tree analysis to examine systems and comprehend the mechanisms behind error causation. The importance value for each basic event can be determined, allowing for the identification of significant basic events. As a result, a comprehensive risk management plan can be formulated to enhance the user experience of the system. In this study, although fuzzy FTA has proven to be an effective tool for enhancing the user experience of HCI systems, it does have certain limitations. FTA is based on binary events, which may not adequately capture the nuances of systems or events with multiple states [55]. Future research could focus on combining Bayesian Networks to achieve a more flexible and intuitive approach to modeling complex systems [56]. Furthermore, in this study, the failure probabilities for the basic events were obtained from expert assessments, which are inherently subjective and uncertain. Subsequent studies could incorporate big data and machine learning to further improve the efficiency and precision of FTA.

6. Conclusions

In this paper, we propose a fuzzy FTA approach to assess the risk of human errors in interaction design. An IVIS in heavy trucks was used as a case study. The results indicate that this approach effectively addresses the subjective and even subconscious aspects of risk assessment related to human errors in interaction design, providing accurate evaluations. Additionally, the proposed approach can effectively handle situations where the probabilities associated with human errors are imprecise, inadequate, and ambiguous. The academic contribution of this paper lies in integrating diverse methods from various disciplines into a cohesive framework and applying it to the emerging field of interaction design. The practical contribution is that the proposed approach can be universally applied to enhance the user experience of HCI systems.

The limitations of this research are as follows: HCI systems encompass various factors, including users, systems, and technologies; however, this study primarily focused on system design. Future research could model this complex system from multiple perspectives, thereby enhancing its reliability and user experience. Additionally, future studies could emphasize integrating human needs, expectations, and behaviors with computer systems to achieve greater efficiency and intuitiveness.

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Abbreviations

MCS	Minimal cut set
HCI	Human–computer interaction
HTA	Hierarchical task analysis
SHERPA	Systematic human error reduction and prediction approach
FTA	Fault tree analysis
SAM	Similarity aggregation method
IVIS	In-vehicle information system
ASD	Average similarity degree
RSD	Relative similarity degree
CDC	Consensus degree coefficient

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