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Optimizing Railway Safety by Analyzing Human Reliability Techniques - A review

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Optimizing Railway Safety by Analyzing Human Reliability Techniques – A review

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Abstract. Human reliability analysis (HRA) is a critical component in ensuring the safety and efficiency of railway engineering. As railway systems grow more complex, the methodologies used to assess and improve human reliability must also advance. This review provides a comprehensive analysis of the evolution of HRA, from the first-generation techniques to the third-generation approaches currently in use. Through a broad survey of the literature, comparative analysis, and detailed case studies, this review traces the development of HRA methods, showing the evolution from traditional techniques to modern hybrid approaches. The review also emphasizes the significance of hybrid Human Error Assessment and Reduction Technique (HEART) methods, which integrate multiple HRA approaches to provide a more comprehensive and accurate assessment of human reliability. The hybrid technique offers a more accurate estimation than standard methods, as evidenced by the determined Pearson coefficient of 0.9990 between the simulation findings and the HEP values of HEART-related methodologies. It also explores the integration of human factors into railway safety systems, underscoring the importance of considering human-machine interactions and the cognitive and behavioural aspects of railway operations. Key findings indicate that while traditional HRA methods laid the groundwork, there is a growing need for continuous innovation to address the increasing complexity of railway systems. This includes the development of hybrid models that combine insights from various HRA techniques and the incorporation of advanced human-machine interaction paradigms to further minimize human error rates. The objective of this review is to offer recommendations for future research in the field of HRA for railway engineering. It advocates for the development of advanced hybrid models with the use of cutting-edge technology like machine learning and artificial intelligence. By combining historical insights with modern technological advancements, the goal is to create more robust and reliable HRA methods that can better support the safety and efficiency of railway operations.
***Keywords**: human error probability, fault tree analysis, error-producing conditions, human error assessment and reduction technique, assessed proportion of affect.*

1. Introduction

An essential mode of transportation is the railway system. Accidents and incidents involving trains continue to occur frequently despite decades of advancements in railway safety [1]. When operating a locomotive, railway drivers must deal with several situations that might lead to mistakes, such as tight deadlines, little feedback, small workspaces, difficult body postures, inadequate documented procedures, poor communication, etc [2]. These circumstances, along with fundamental human inclinations, lead to a variety of blunders. Most accidents and incidents in complicated systems, like the railway system, are caused by human error [3], [4].

The effects of human error have long been serious in the workplace. Research indicates that around 60% of worldwide accidental fatalities each year are the result of human error [5]. The rising frequency of human failure incidents in recent years has led to more effective investigation of human reliability analysis (HRA). Road transportation has an estimated 85% human mistake rate; nuclear power facilities have 50–70%; the chemical sector has 60–90%; aviation has 70–80%; and freighters have 80–85% human error rate [6].

The transportation system of railways is highly intricate, involving several technological features that require human labour, including design, building, operation, maintenance, and many more [7]. Therefore, much as in other industrial sectors (such as nuclear, chemical, or avionics), it is challenging to analyse the role played by human performance since each mishap is the result of a confluence of several mistakes and deficiencies[8]. The chance that an operator will complete a job requested by the system without error within a specific time frame is known as human reliability [9].

2. Section Snippets

2.1 Human Error

Numerous disastrous occurrences in recent years have been attributed to human mistakes or the combination of human error and system failure. Numerous incidents can be attributed to human mistakes; the most well-known ones include Chernobyl (1986), Bhopal (1984), and Three Mile Island (1979). Over 80% of accidents in the process industries, 75%–96% of deaths in marine operations, and over 90% of mishaps in nuclear power plants were caused mostly by human error, according to a study of significant industrial incidents [10], [11], [12].

Human error is a multidisciplinary problem that spans engineering, psychology, and medicine. Industry research in this area is essential to ensuring good performance, low management costs, and a high degree of safety [6]. Since the operator is a component of the system, errors and malfunctions might occur. This should constantly be remembered. As a result, its operating circumstances (ergonomics, time availability, microclimate, etc.) [8].

Literature and technical data indicate that human error is the primary cause of most railway accidents [7], [13]. Thus, an essential consideration in the design stage of any railway system is the evaluation of human reliability. Railway engineering design, installation, and verification stages are mostly responsible for human mistakes that result in a loss of safety and potentially catastrophic incidents [8].

EN50126 "Railway applications – The specification and demonstration of Reliability, Availability, Maintainability and Safety (RAMS)" is the standard that addresses human error in the railway industry [14]. The most widely used standard for RAMS (Reliability, Availability, Maintainability, and Safety) assessment in the railway industry emphasises the significance of accurately assessing the impact of human error on the system's total RAMS parameters [14].

2.2 Human Reliability Analysis Techniques

There are several methods for calculating the likelihood of human mistakes. Based on its characteristics, each approach is categorised into one of three generations. The first generation of approaches are historical; they see humans as nothing more than components that may either succeed or fail [8]. The second generation is an extension of the first, emphasising the relevance of context and the involvement of cognitive action in an accident scenario [8]. Lastly, the third generation concentrates on the dynamic interplay and interdependence of the variables influencing human performance [8].

2.2.1 First Generation

Human Error Probability (HEP) is based on employment effects and variables including available time, stress, and working time. It was initially presented by the first-generation Human Reliability Analysis (HRA) approaches, which were created between 1970 and 1990. According to these methods, mistakes are categorised as commissions (doing something needless or poorly completing a task) or omissions (not completing a task) [8]. They also identify Performance Shaping Factors (PSFs) [15], [16], [17], [18], which variables may have an impact on operator performance; a basic cognitive model is then used to classify operator performance as knowledge-based, rule-based, or skill-based [19]. On the other hand, these methods are criticised for their narrow focus on behaviour on the outside, disregard for psychology and cognitive processes, and frequent omission of pertinent PSFs, all of which might exacerbate health-related problems and increase ambiguity. Several companies continue to employ them despite these drawbacks because of their simplicity [8].

Table 1. First Generation HRA.

	Author and year	Origin	Main Tool	Strength	Weakness
THERP (Technique for Human Error Rate Prediction)	(Catelani et al., 2021)[8], (Yang et al., 2014)[34], (Swain et al., 1983)[35]	Developed at Sandia Laboratories for the US Nuclear Regulatory Commission	Event tree analysis	Widely used, historically significant	May not consider all relevant Performance Shaping Factors (PSFs)
HEART (Human Error Assessment and Reduction Technique)	(Catelani et al., 2021) [8], (Castiglia et al., 2015)[36], (Kirwan, 1996)[37]	Derived from ergonomics literature	Error Producing Conditions (EPCs)	Flexible, accommodates several task options and different EPCs	May oversimplify the relationships between different tasks and errors.

2.2.1.1 THERP & HEART

2.2.2 Second Generation

The goal of the second-generation approach (1990–2005) is to use cognitive models and human performance factors to address the shortcomings of the first generation. This generation's focus is on estimating the likelihood of human mistakes while taking cognition into account. The mental processes involved in learning and understanding such as reasoning, recalling details, and solving problems are called cognitive processes [20].

2.2.2.1 CREAM vs SPAR-H vs ATHEANA

Table 2. Second Generation HRA.

	Author and year	Origin	Main Tool	Strength	Weakness
CREAM (Cognitive Reliability and Error Analysis Method)	(Hannaman et al., 1984)[21], (Zhang et al., 2023)[22], (Fan et al., 2022)[23], (Joey Deeter B et al., 2008)[24]	Developed by Erik Hollnagel	Contextual Control Model (COCOM)	Clear, structured, systematic	Too complex, requires more resources
SPAR-H (Standardized Plant Analysis of Risk-Human Reliability Analysis)	(Gertman et al., 2004)[25], Ahn et al., 2022[26], Merwe et al., 2014[27]	Developed by the US Nuclear Regulatory Commission (NRC)	Uses eight different Performance Shaping Factors (PSFs)	Considers context appropriately with eight PSFs	May not be detailed enough for very specific or complex tasks
ATHEANA (A Technique for Human Error Analysis)	(Cooper et al., 1996)[28], (Dougherty, 1998)[29], (Forester et al., 2004)[30]	Developed by the US Nuclear Regulatory Commission (NRC)	Error Forcing Contexts (EFCs)	Improves system safety by reducing error occurrence	Not quantitative, limited to post-accident analysis

2.2.3 Third Generation

The purpose of the third generation of HRA is to create new HRA techniques or alter current techniques to take into account how human behaviour changes over time and how human error results from those changes[8]. This last-generation uses simulation and modelling in three different ways to generate data for the analysis.

Table 3. Third Generation HRA.

	Author and year	Origin	Main Tool	Strength	Weakness
Probabilistic Cognitive Simulator (PROCOS)	(Paolo Trucco, 2006)[38], (Trucco et al., 2007)[39].	Developed in 20[illegible]6	Combines HAZOP and event tree with cognitive human error analysis	Incorporates cognitive factors, comprehensive risk assessment	Semi-static approach, complex to develop and apply
Man Machine Integration Design and Analysis System (MIDAS)	(Corker et al., 1993)[40], (Gore et al., 2002)[41], (Smith et al., 1997)[42], (Tyler et al., 1998)[43], (Gore, 2011)[44]	NASA Ames Research Center	3D rapid prototyping, human performance modeling, and simulation	Dynamic and integrated, supports quantitative predictions, facilitate design optimization	Complex to develop and use, requires expertise, model limitations
Simulator for Human Error Probability Analysis (SHERPA)	(Catelani et al. 2021)[8], (Pasquale et al. 2015)[45], (Embrey 1986)[46]	Developed in 20[illegible]6	Weibull function with time-dependent HEP	Dynamic model for flexible evaluation, considers performance shaping factors	Reliance on Weibull function, potential limitations in complex scenarios

3. Research Methodology

The process begins with task selection, where the specific activity within the locomotive driving process to be analyzed for human error is identified. Next, the situation is determined, defining the context and conditions under which the task is performed, including factors such as workload, time pressure, environmental conditions, and the state of equipment. Once the situation is understood, the task is analyzed by breaking it down into smaller subtasks or steps to identify potential error-producing conditions (EPCs), which are circumstances that could lead to human errors. For each subtask, a Generic Task Type (GTT) is selected, representing predefined categories of tasks with associated generic error probabilities. Multiple experts then conduct a multi-rater identification of relevant EPCs, ensuring diverse perspectives in identifying conditions most likely to induce errors. These experts assign an Assessed Proportion of Affect (APOA) to each EPC, quantifying the likelihood of an error occurring in its presence.

The analysis proceeds with two approaches. In the traditional HEART method, the Human Error Probability (HEP) for each subtask is calculated by multiplying the generic error probability (GEP) of the GTT by the APOA of the identified EPCs. Alternatively, in the hybrid HEART approach,

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evidence theory is employed to fuse APOA values from multiple raters, integrating various viewpoints and uncertainties. The fused APOA values are then used to calculate the HEP for each subtask. To further enhance the analysis, a fault tree is constructed, visually mapping potential failure paths that could lead to human error, thus identifying critical areas for targeted interventions.

Finally, the estimated HEPs are validated using Monte Carlo simulation, which assesses the robustness of the results by conducting multiple simulations under varying parameter uncertainties. The process concludes with the presentation of the final HEPs for each subtask, accompanied by recommendations to improve human reliability and mitigate the risk of errors in the locomotive driving process. This comprehensive approach ensures a systematic and robust analysis of human error within the context of locomotive operation.

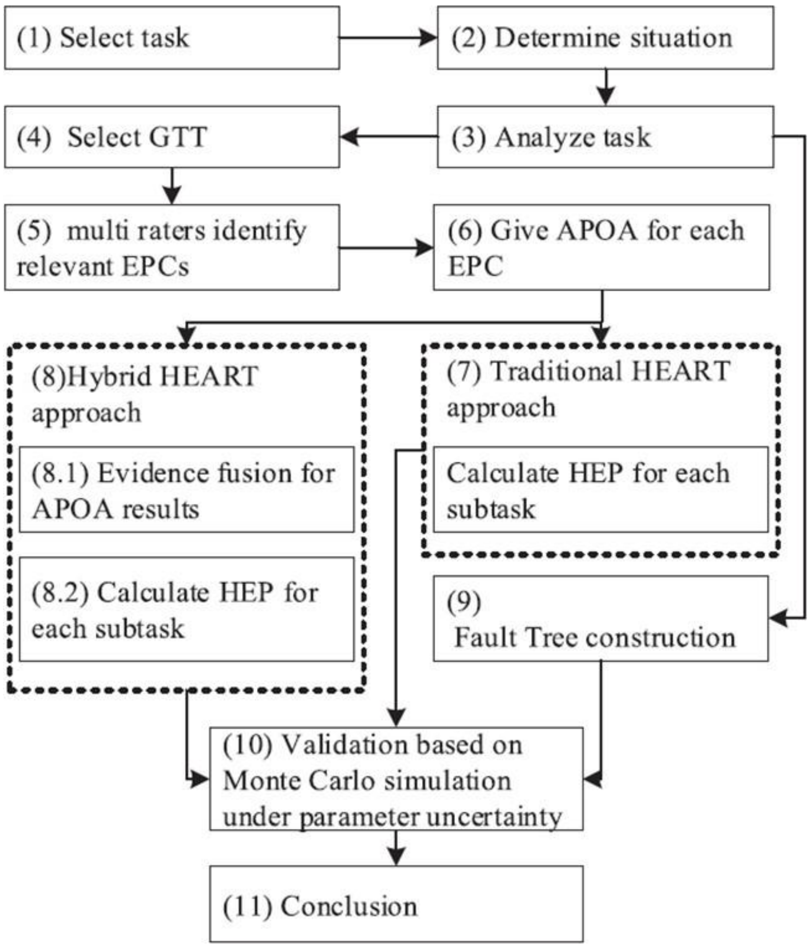

Figure 1. Flow diagram of the methodology [2].

Table 4 lists the three railway accident raters that the author chose from the Wuhan Railway Bureau. The selection of raters is based mostly on appropriate academic qualifications and sufficient job experience; gender and age are not given much importance.

Table 4. Basic information of raters [2].

Rater ID	Gender	Working seniority	Profession	Education
1	Male	22	Safety Engineer	Master
2	Male	14	Train Examiner	Bachelor
3	Female	15	Driver	Bachelor

3.1 Task Analysis

Task analysis is carried out for a full locomotive driving procedure with the help of the three raters. The three raters' brainstorming session enables researchers to pinpoint human behaviors that might result in a system failure.

Table 5. HTA of a complete locomotive driving process in railway [2].

A Complete Locomotive Driving Process
1. Attendance
1.1 Make sure that all crews should be on duty on time without drinking and have a good rest in advance.
1.2 Proper dress with certificate, ic card and driving material.
1.3 Copy command, read notes, get notebook and hold pre-shift meeting.
1.4 Listen the dispatcher's instructions and orders carefully.
1.5 accept the alcohol test, hand the notebook to the dispatcher for confirmation, get the driver's declaration form and information card
1.6 Contact with the dispatcher to obtain the train notices.
2. Succession
2.1 After attendance, all crew take a fixed route and ensure personal safety
2.2 Ensure a smooth transition, check shift handover and takeover records, and confirm the technical quality of locomotive.
2.3 Input related data of monitoring device correctly and confirm the speed limited data input of ic card
2.4 Conduct oil supply
2.5 Check locomotive driving safety equipment and perform functional experiments
3. Preparing outbound trains for departure and trailering
3.1 Confirm wheel set maintenance, handbrake lever and parking device in relief position
3.2 Lock anti-electric shock door, and launch the locomotive according to the signal
3.3 Strictly control the speed and carefully implement the call response system when the locomotive gets outbound trains or shunts.
3.4 Stop and sign in the intermediate train distancing point, and understand the path
3.5 Properly sprinkle sand according to actual demand and strictly control the speed when the locomotive enters the trailer line.
3.6 Check and confirm the hook status of the locomotive before trailering
3.7 Perform a steady connection and make a good pull experiment after confirming the removal of derailer and no-hanging sign

3.8 Implement overall braking with single valve and open the train line angle cock after trailering
3.9 Input the data of monitoring device correctly, recheck the locomotive, and conduct the train braking experiment

4. Discussions

4.1 HEP Determination

The HEP values are determined for each subtask by Eq. (1), and the matching GEP value may be found as previously indicated and displayed in Table 4.

HEP is calculated by Eq. (1) [31]:

$$HEP=GEP \times \{IIi, [(EPCi - 1)APOApi + 1]\} \tag{1}$$

Table 6. Railway HTA of a whole locomotive driving process [2].

Subtask	GTT	Hybrid HEART HEP	rater1 HEP	rater2 HEP	rater3 HEP
1.					
1.1	G	6.940E-04	6.756E-04	8.909E-04	7.083E-04
1.2	G	1.386E-03	1.901E-03	1.464E-03	2.496E-03
1.3	E	1.304E-02	1.626E-02	1.019E-02	1.144E-02
1.4	G	5.000E-03	5.824E-03	6.300E-03	5.192E-03
1.5	G	9.269E-04	1.637E-03	2.246E-03	1.198E-03
1.6	G	2.375E-03	4.400E-03	3.794E-03	4.752E-03
2.					
2.1	H	5.848E-05	6.084E-05	5.375E-05	6.998E-05
2.2	G	3.823E-03	3.910E-03	3.261E-03	3.730E-03
2.3	F	1.589E-04	1.915E-04	1.814E-04	1.997E-04
2.4	G	2.634E-03	2.851E-03	2.419E-03	2.430E-03
2.5	F	8.268E-03	7.326E-03	7.033E-03	7.174E-03
3.					
3.1	F	9.414E-04	1.198E-03	1.217E-03	1.004E-03
3.2	G	1.203E-04	1.198E-04	1.348E-04	1.555E-04
3.3	F	2.622E-03	4.248E-03	3.861E-03	3.744E-03
3.4	H	3.420E-05	5.018E-05	5.803E-05	4.608E-05
3.5	F	1.010E-02	9.222E-03	1.225E-02	9.188E-03
3.6	G	1.292E-03	1.702E-03	1.246E-03	1.452E-03
3.7	F	2.772E-04	2.294E-04	3.557E-04	3.125E-04
3.8	G	1.013E-05	1.478E-05	1.498E-05	1.584E-05
3.9	F	5.624E-04	7.956E-04	6.006E-04	8.892E-04
4.					

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4.1	E	9.623E-04	1.254E-03	1.075E-03	1.080E-03
4.2	E	4.051E-03	5.158E-03	5.616E-03	3.696E-03
4.3	G	1.265E-03	1.597E-03	1.758E-03	1.936E-03
4.4	F	1.179E-03	1.373E-03	1.174E-03	9.105E-04
4.5	D	4.720E-03	5.514E-03	4.885E-03	5.661E-03
4.6	E	3.437E-02	4.004E-02	3.744E-02	3.584E-02
5.					
5.1	G	1.510E-03	2.341E-03	1.997E-03	1.936E-03
5.2	F	1.852E-04	2.016E-04	1.958E-04	1.915E-04
5.3	F	1.551E-02	2.016E-02	1.756E-02	1.014E-02
5.4	G	1.214E-03	1.290E-03	1.059E-03	1.344E-03
5.5	F	2.027E-02	3.672E-02	3.060E-02	2.625E-02
5.6	H	3.240E-05	4.659E-05	3.947E-05	3.968E-05
5.7	E	4.599E-04	4.493E-04	7.142E-04	3.681E-04
5.8	F	8.758E-04	9.408E-04	8.501E-04	9.734E-04
5.9	F	9.553E-03	1.555E-02	9.547E-03	1.188E-02
5.10	G	2.283E-03	2.789E-03	2.417E-03	2.867E-03

4.2 Model Validation

4.2.1 Fault Tree Analysis
A graphical quantitative approach called fault tree analysis (FTA) is used to assess and analyse big complex systems' risk, safety, and dependability. FTA looks at an unfavourable system state using a top-down, logical approach to failure analysis [32].

A system's flaws are classified as human and mechanical defects, climatic factors, and any other associated events that may cause an undesirable outcome. Operator absence and mistakes are examples of human error. Mechanical problems include damage to the brake system, electric circuit, and signal device. Climate factors are atmospheric variables that might interfere with the operation [33].

To demonstrate the hybrid HEART technique's efficacy, calculate the subtask's reliability and carry out the simulation. Three raters create a fault tree by applying the fault tree analysis's top-down methodology. Table 7 provides the component failure rates, whereas Fig. 2 displays the tree structure.

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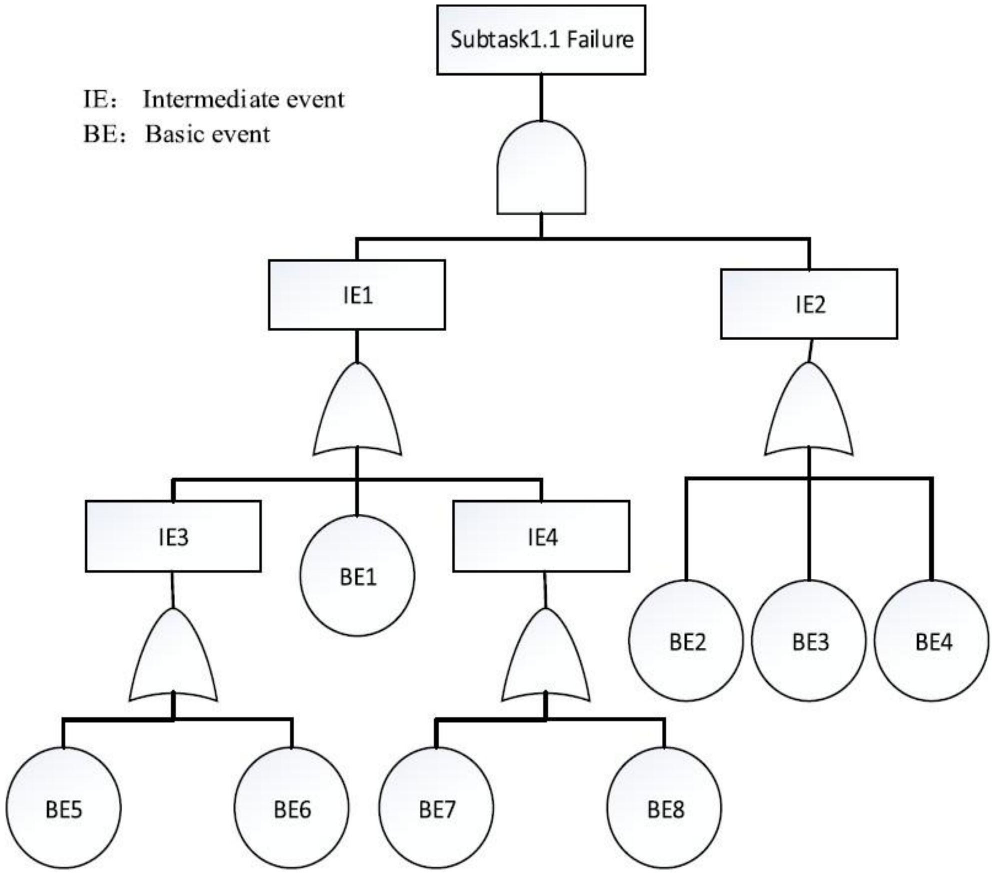

Figure 2. Subtask's Fault Tree Structure [2].

Table 7. Description of the event and the failure rates [2].

IE1: Poor self-discipline	IE2: Inadequate supervisory
IE3: Inadequate rest	IE4: Incorrect work attitude
BE1: Drinking	λ_{BE1}: [5.5E − 04, 6.8E − 04]
BE2: Insufficient training	λ_{BE2}: [5.2E − 03, 6.1E − 03]
BE3: Inappropriate operation schedule	λ_{BE3}: [8.4E − 04, 9.3E − 04]
BE4: Poor cooperation, coordination, and teamwork issues	λ_{BE4}: [5.7E − 04, 6.4E − 04]
BE5: Fatigue due to overlong working hours	λ_{BE5}: [1.5E − 03, 2.3E − 03]
BE6: Physiological reasons such as illness	λ_{BE6}: [7.4E − 04, 8.1E − 04]
BE7: Misjudgements and inattention	λ_{BE7}: [1.3E − 04, 2.2E − 04]
BE8: Carelessness	λ_{BE8}: [7.2E − 04, 8.1E − 04]

As seen in Fig. 3, there is a noticeable difference in the HEP values across the various subtasks. This author compared the ratios of simulated HEP with the HEP values derived from the hybrid and traditional methods to improve the clarity of the results. Most hybrid HEART HEP outcomes, it is noteworthy, fall somewhere between the simulation results and the classic HEART HEPs. The hybrid technique offers a more accurate estimation than standard methods, as evidenced by the determined Pearson coefficient of 0.9990 between the simulation findings and the HEP values of

HEART-related methodologies. By contrast, the standard HEART introduces biases in HEP estimation as it selects and weights EPCs based on the judgement of a single expert [2].

The analysis revealed that some EPCs, such as time constraints and inadequate communication, had a major impact on HEP values. This emphasises the necessity of incorporating these elements into operating processes and training to enhance safety. Monte Carlo simulations were used for validation, and the results showed that the hybrid HEART technique closely matches real-world safety management experiences while successfully resolving the complexity of human error in dynamic railway systems [2].

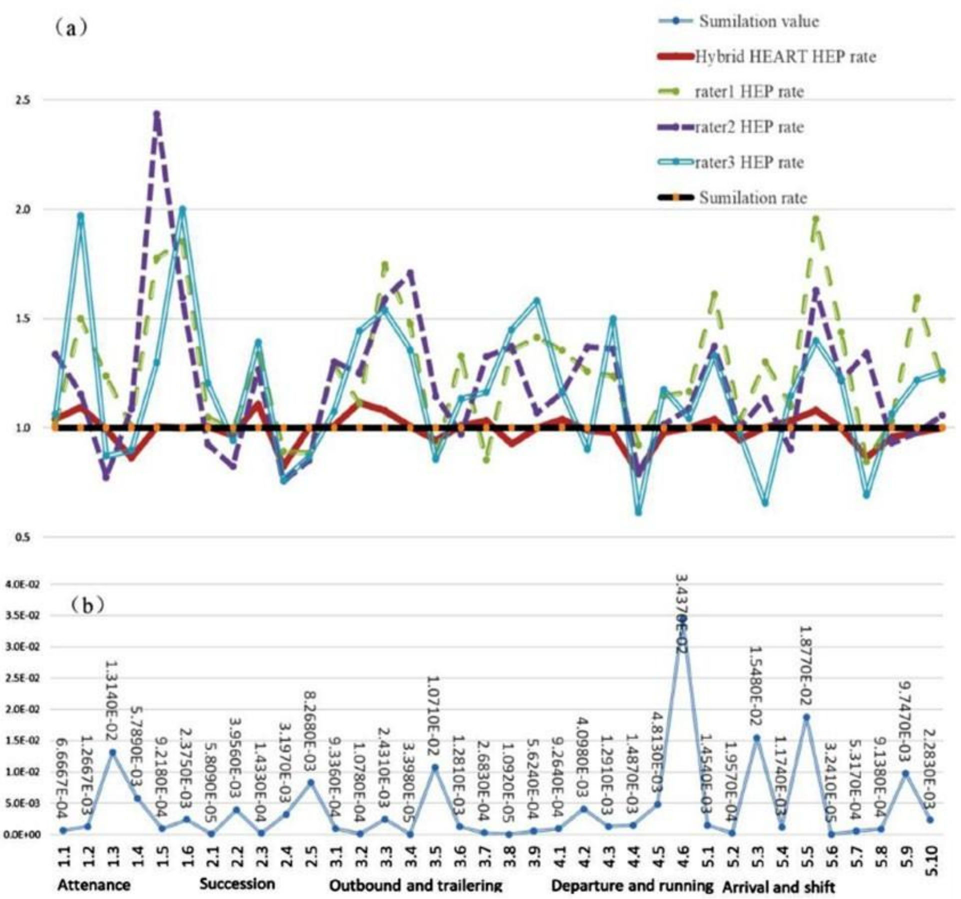

Figure 3. A HEP distribution graph showing the locomotive driving process in the railway sector [2].

Individual biases were effectively reduced by using multiple raters to assess error-producing conditions (EPCs) and determine the assessed proportion of affect (APOA). The integration of diverse expert opinions for a more comprehensive understanding of factors influencing human error was made possible by the D-S evidence theory. Nonetheless, the research recognised several constraints, such as possible partialities in rater evaluations and the fluctuations brought about by depending on professional opinion. The results underscore the need to integrate human reliability analysis into railway safety management protocols. They imply that railway operators may enhance safety in locomotive operations by employing the hybrid HEART technique to more effectively detect and eliminate human error hazards. Subsequent studies should investigate automated techniques for gathering data, increase the number of raters to obtain a wider range of experience, and apply the hybrid HEART approach to other intricate systems. All things considered, the hybrid HEART approach seems to be a useful tool for calculating the likelihood of human mistakes when operating a locomotive, enhancing safety and dependability in the railway sector [2].

4.3 Suggestion improvement

To improve the paper, several suggestions can be considered. First, it is essential to clarify the study's objectives in the introduction, emphasizing the unique contributions of the hybrid HEART method compared to traditional approaches and highlighting its practical implications for railway safety and human reliability assessment. Additionally, enhancing the literature review by including a broader range of studies on human error assessment methods, particularly in the railway sector, will provide a more comprehensive context.

Strengthening the validation section by providing more details on the Monte Carlo simulation and fault tree analysis used to validate the hybrid HEART method will improve the reliability of the results. A more in-depth discussion of the results, comparing the hybrid HEART method's outcomes with traditional methods, will allow for a better analysis of the implications for practitioners in the railway industry, including recommendations for implementation. Acknowledging the study's limitations, such as reliance on expert judgment and potential biases, and suggesting ways to mitigate these in future research will add to the paper's credibility.

Furthermore, expanding the section on future research directions to include specific areas for further development or testing of the hybrid HEART method, as well as discussing the potential for integrating it with emerging technologies like real-time monitoring systems or predictive analytics, will provide valuable insights.

In the railway sector, human-machine interaction paradigms are crucial for ensuring safety, efficiency, and effective communication between operators and the systems they manage. Automatic Train Operation (ATO) systems automate certain aspects of train operation, such as acceleration, braking, and stopping at stations. Human-machine interaction paradigms are applied to ensure that operators can easily monitor and intervene when necessary. The interface provides feedback on the system's status and performance, allowing operators to maintain situational awareness and take control if needed.

5.0 Conclusion

This paper proposes a novel approach that combines standard HEART with a D-S theory, which it calls hybrid HEART. The multi-rate data is fused to incorporate the full APOAs using the former method, a simple and popular tool for decision-making. The work system in the railway industry is highly dynamic and varied. According to the study's findings, it is critical to measure human uncertainties throughout the locomotive operating process to reduce the likelihood of failure, including attendance, arrival, and shift phases. Parts of the evidence from several raters have been modelled and fused into an integrated complete APOA using modified D-S evidence theory, as the standard HEART does not give the practitioner a tangible way to determine the APOA. With information coming from several sources and interactions between subtasks, this hybrid HEART can offer meaningful content to evaluate and reduce the HEP for various sectors. The proposed hybrid HEART approach has several limitations. Its accuracy relies heavily on the expertise of the raters, and subjective EPC selection may introduce variability in results. The complexity of integrating HEART with Dempster-Shafer theory can complicate implementation, requiring additional training and resources. The whole process of running a locomotive involves multitasking, consisting of five primary jobs, each of which has several, sequential, non-overlapping subtasks. Some requirements must be fulfilled for each subtask to function. A subject for further research is the HEP calculation of the multi-phase job for the main tasks.

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