Experience-Performance Impact Curve (EPIC): A Conceptual Approach to Account for the Moderating Effect of Operator Experience on other Performance Shaping Factors in Human Reliability Modeling

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Abstract: Human reliability analysis (HRA) methods aim to account for the influence of performance shaping factors (PSFs), particularly those that heighten error probabilities. Decision-making, a critical aspect of human information processing, is influenced by PSFs and often relies on heuristics under constraints. Experience significantly moderates the impact of time pressure on decision-making, a factor often neglected in traditional HRA methods. This paper introduces the Experience-Performance Impact Curve (EPIC), a conceptual framework to integrate the moderating effect of experience on time availability in control room operator performance, thereby enhancing HRA methods by allowing joint PSF distributions. The discussion is structured into four sections: an overview of HRA and PSFs, decision-making models, the relationship between HRA and human information processing, and the integration of EPIC into dynamic HRA methods.
Keywords: Human Reliability Analysis, Performance Shaping Factors, Experience, Time Availability.

1. INTRODUCTION

Recent instantiations of human reliability analysis (HRA), which uses a systematic approach to assess and mitigate the risks associated with human performance fallibility in complex systems, has a strong theoretical foundation in cognitive science models such as human information processing (Boring and Blackman, 2007). HRA methods attempt to identify potential human errors called human failure events (HFEs) and quantify the probability of such events using human error probabilities (HEPs). Performance shaping factors (PSFs) are factors capable of increasing or decreasing the probability of error, such as time availability. More recently, dynamic HRA models seek to account for the effect of PSFs in HRA models, especially those with the potential of increasing error probabilities.

Decision-making is a crucial aspect of the human information processing model (Wickens et al., 2013) and is subject to PSFs. Experts have been shown to possess the ability to make good decisions under constraining conditions such as time pressure using mental shortcuts commonly referred to as heuristics. Evidence shows that improved decision-making skill is closely related to level of experience acquired through training, especially in complex operating environments. Experience is proposed to have a moderating effect on time pressure, and this moderating effect should be accounted for in computing the impact of time availability on HEPs. However, HRA methods compute HEPs by accounting for the impact of PSFs independently, neglecting the potential interactions between PSFs. Dynamic HRA modelling can be enhanced by exploring the moderating effect of one PSF on another in determining HEPs. This paper explores one such interaction by discussing the moderating relationship between experience and time availability using the Experience-Performance Impact Curve (EPIC). EPIC is a conceptual framework to account for the moderating effect of experience level on time availability in control room operator performance.

This discussion is captured in four major sections. The first section provides an overview of HRA and how PSFs are integrated into HRA modelling. Next, the essential elements of decision-making and different types of decision-making models are discussed. The third section focuses on HRA models in relation to human information processing, emphasizing heuristics as a viable strategy for expert decision-making under constraints. In the last section, we introduce the Experience-Performance Impact Curve (EPIC) and canvass its integration in dynamic HRA methods.

2. HUMAN FACTORS AND HUMAN RELIABILITY ANALYSIS

Human error is a complex and widespread issue that has significant implications across various domains, including aviation, healthcare, manufacturing, and nuclear plant operations. There are various definitions of human error – including failure to achieve intended outcomes, decisions or actions leading to unintended consequences, and an unintended deviation from following specified procedure (Reason, 1990; Sanders and McCormick, 1993; Hagen and Mays, 1981). Combining these multiple perspectives, human error may be described as an unintended deviation of human actions and/or task outcomes resulting from human fallibility. Understanding the causes and consequences of human error is crucial for improving safety, reliability, and performance in complex socio-technical systems like nuclear plant main control rooms operations.

HRA involves the examination of human actions, behaviors, and decisions within the context of socio-technical systems to identify potential HFEs. By understanding the factors that influence human performance, HRA aims to develop strategies and interventions to enhance reliability, safety, and efficiency through the application of probabilistic and qualitative methods, such as task analysis, human factors engineering, and error modelling.

Traditional methods of HRA typically involve the use of paper or software worksheets to capture critical elements of the operational context and the HEPs associated with different human failure events. However, recent developments have emphasized the need to model the dynamic aspects of human performance in the control room and elsewhere. Dynamic HRA methods employ automated Monte Carlo simulations to facilitate such error quantification, to give a better representation of operator performance. Dynamic approaches also afford the opportunity to break out of simplistic performance modelling and more completely consider compound effects and interactions. The dynamic HRA method uses a dynamic modelling system to replicate human decisions and actions, and to estimate human performance in a simulated virtual environment (Boring, 2007). The use of virtual humans to execute simulated scenarios in dynamic HRA enables the computation of PSF levels dynamically, which better reflect human behaviour and provide HEPs for any specific point in time, rather than a fixed HEP value.

2.1. Performance Shaping Factors and Cognitive Modeling

Recent HRA methods have sought to integrate knowledge about human performance derived from established cognitive science models especially various human information processing models (Boring and Blackman, 2007). The contextual nature of human error makes it susceptible to a broad range of factors. Any factor – whether individual, environmental, organizational, or task-specific characteristic – that is capable of improving or degrading human performance is referred to as a PSF. HRA methods like Standard Plant Analysis Risk-Human Reliability Analysis (SPAR-H; Gertman et al., 2005) account for PSFs by making adjustments to nominal HEPs using corresponding multipliers of PSFs' severity. For example, time availability is a common PSF and is categorized into five levels of severity in the SPAR-H method with corresponding multiplier factor assignments for adjusting the HEP: inadequate time, barely adequate time, nominal time, extra time, and expansive time (with multipliers ∞, 10, 1, 0.1, 0.01, respectively). The assumption is that the higher the PSF's severity multiplier, the higher the HEP, and by extension the more the potential for error due to operator performance decline. Additionally, multipliers lower than 1 serve to credit the PSF or decrease the overall HEP.

Although HFEs are observable behavioral outcomes of the human operator, PSFs exert their influence on the HFE at the decision-making level of human information processing. Therefore, there is a need to understand the decision-making process and the impact of PSFs on decision-making.

3. DECISION-MAKING

3.1. Essentials of Decision-Making

Across all domains of decision-making, three essential elements are brought to focus: judgment, preference, and choice (Fischhoff and Broomell, 2020). The interplay between these elements is central to how people perceive options, how they weigh options, and what options they eventually choose.

Judgment is essentially the act of making a subjective prediction about the potential outcome of different options, whether positive or negative. At the beginning of the decision-making process, decision-makers consider all available options (or some of them) and try to predict what could happen if they chose each. The accuracy of these predictions depends on the amount of information decision-makers have about each option and their ability to use this information to make accurate predictions. Consider the decision to shut down or continue running a nuclear power plant (NPP) during an emergency. The crew in the control room would need to rely on the information available to them via control room displays and their ability to interpret that information to make an informed decision. Ultimately, the accuracy of their judgment would depend on the quality of the information available and their level of expertise in interpreting the information.

Individuals tend to assign different levels of importance to various possible outcomes. Preference refers to the relative importance given to the expected outcome of a particular option. For instance, the shift manager in the above-mentioned scenario would typically place a higher value on safety over revenue loss. Unlike judgment, which can be assessed for correctness, preference is unique to each individual – people simply prefer what they prefer. Choice is the end result of the decision-making process, which involves both judgment and preference. The decision-maker assesses the available options, subjectively predicting the outcomes of each based on factors such as their knowledge and the information available to them. They then assign relative values to the projected outcomes, which may vary among individuals and are not subject to evaluation for accuracy. Ultimately, the decision-maker selects one or more options from the available alternatives, leading to a final choice.

The interplay between judgment and preference significantly influences choices made in the decision-making process. For instance, a shift manager's preference for safety may lead to choosing conservatively to shut down operations during a plant upset, despite information suggesting a tremendous cost of the shutdown. Therefore, judgement and preference may be said to shape the choices that people make.

3.2. Decision-Making Theories

The above example suggests a rigorous review of outcomes by the decision-maker, but not all decision-making is enshrined with formal and conscious weighing of options. There are three main categories of decision-making theories: classical decision theory, behavioral economics theory, and naturalistic decision-making theory. Each of these categories can be illustrated by using an archetypical theory – Expected Utility Theory, Prospect Theory, and the Theory of Bounded Rationality for classical decision, behavioral economics, and naturalistic decision-making theories, respectively.

3.2.1. Expected Utility Theory

Expected Utility Theory is a classical decision-making model that explains how people make choices when faced with uncertainty (Friedman and Savage, 1948). According to this theory, individuals make decisions based on the expected utility of different outcomes that are associated with various options (A, B, C...). Utility (u) represents the subjective value or satisfaction that individuals expect to derive from different outcomes. Decision-makers consider the uncertainties of outcomes and assign probabilities (p) to different possible outcomes based on their subjective assessments. The expected utility (EU) of an option is calculated by multiplying the utility of an outcome by its probability ($EU_A = u_A * p_A$). Expected Utility Theory assumes humans to be rational beings, and the rational decision-maker is always expected to choose options with the highest expected utility (Neuman and Morgenstern, 1944).

3.2.2. Prospect Theory

Prospect Theory identified three systematic violations of the Expected Utility Theory in human decision-making when presented with the prospects involving losses and gains (Kahneman and Tversky, 1979). These violations are certainty effect, reflection effect, and isolation effect. Certainty effect states that when confronted with the prospect of sure gains, people exhibit a risk-averse behavior by underweighting probable outcomes relative to certain ones. In contrast, reflection effect involves decision-makers showing a risk-seeking behavior when faced with sure losses. In isolation effect, individuals tend to downplay attributes that are common to a set of choice options and decide based on unique attributes. In other words, preference is less dependent on the amount of information presented about the attributes of choice options when such attributes are common to all (or most) of the options. In such circumstances, decision-makers combine and minimize the preference of common attributes while amplifying their preference for unique attributes. The decision-maker perceives difference more than commonality, a phenomenon similar to the Naturalistic Decision-Making theory (Klein, 1998).

3.2.3. Naturalistic Decision-Making Theory

Humans make decisions differently in real-world scenarios compared to controlled experimental settings (Klein, 1998). Naturalistic Decision-Making refers to the process of how humans make decisions in their natural environment, which has been found to be inconsistent with the analytical approach described by classical decision theory and behavioral economics theory (Beach, 1993; Hammond, 1993). In fact, it has been argued that the real world rarely provides all the necessary information required to make the right decision. Even when the required information is present, there is often not enough time to use all the information for lengthy analytical processes. So, how do people make decisions with either limited information or limited resources for a detailed analysis of unlimited information? The theory of bounded rationality helps to shed some light on this question.

Simon (1955) proposed that human rationality is constrained by limited information, cognitive capacity, and time. Due to the limitations imposed by these constraints, individuals cannot use complex principles like Bayes' probability rules to make inferences in their day-to-day lives as suggested by the expected utility theory and prospect theories. To compensate for their limitations, individuals often rely on simple heuristics or decision rules that are tailored to specific environments. Heuristics are mental shortcuts or rules of thumb used to simplify the decision-making process in the absence of sufficient information, cognitive capacity, and time.

As an NPP control room is a real-world environment, it is likely that operators use heuristic strategies to make dynamic decisions under normal, abnormal, and emergency conditions. Therefore, heuristic decision-making has a place in control room operator performance and should be accounted for in HRA. It must be noted that reactor operators are heavily trained on how to approach changes in plant conditions – they must follow written operating procedures closely. At the same time, the complexity of the control room and the need for swift response requires a high degree of experience and expertise. Such experience and expertise help build heuristics in responding to plant upsets. However, overreliance on primary indications may be a potential operational shortcoming, and ongoing training helps ensure that reactor operators do not fall too much into incorrect heuristics instead of mindful decision-making. The next section explains how experts can make decisions quickly and accurately.

3.3. Recognition-Primed Decision-Making

The application of heuristic strategies may lead to effective or ineffective decisions depending on the level of expertise of the decision-maker. When faced with complex choice problems, experts have been shown to make accurate decisions under time pressure and limited information using intuitive heuristics (Simon, 1977). The ability of experienced firefighters to make the right decision at the scene of a fire incident under intense time pressure and the accuracy with which expert chess players make the right decisions with limited information are typical examples of the applications of expert intuitive heuristics. The Recognition-Primed Decision-Making theory (Klein, 1993) is a plausible explanation of the mechanism underlying expert intuitive heuristic decision-making.

The recognition-primed decision-making theory outlines a step-by-step process that experts use to make decisions when they are faced with limited information. This process can be broken down into three stages:

1. Situation Recognition: First, the individual evaluates the circumstances and decides whether they have experienced something similar in the past.
2. Option Evaluation: Next, they generate multiple alternative solutions and compare them to find the best solution.
3. Mental Simulation: Finally, they imagine what might happen if they implement the chosen solution. If the outcome seems satisfactory, they create a series of action plans for carrying out the solution.

Experts can make effective decisions quickly because they have a robust mental model built by extensive experience. They can match a current situation with a similar one in memory which is readily available due to extensive experience. Simulator training can help provide suitable experience to form expert mental models. Non-experts may not have this ability to draw on prior experience and may make systematic errors known as heuristic biases (Tversky and Kahneman, 1974) when applying heuristics.

4. EXPERIENCE-PERFORMANCE IMPACT CURVE (EPIC)

The response selection phase of the human information processing model (Wickens et al., 2013) can be viewed as a decision-making process. Simon's (1955, 1982) Theory of Bounded Rationality describes the factors that limit required rationality, which can be considered PSFs in HRA parlance. To overcome these limitations, humans often adopt heuristic strategies when making decisions. Therefore, any effective HRA model should account for the effect of heuristic strategies on human failure events, and by extension, HEPs. It is on this basis that we propose the Experience-Performance Impact Curve (EPIC) as a conceptual approach to account for the moderating effect of operator experience on performance due to time availability.

Experts have been shown to make accurate decisions under time pressure and limited information (which are examples of PSFs) using intuitive heuristics in real-world environments (Simon, 1977). Strong evidence shows that training can enhance decision-making skills (Pliske et al., 2001; Pliske and Klein, 2003). More importantly, cognitive simulation has been proven to improve decision-making significantly in complex medical environments (Satish and Streufert, 2002), where information about a patient's condition is ambiguous, uncertain, and subject to dynamic changes, akin to what is experienced in an NPP control room. The U.S. Nuclear Regulatory Commission requires control room operators to record a specific amount of simulator training before licensing certification, plus ongoing simulator training to maintain their licenses (Elliott and Wanner, 1985). In an empirical control room study using naïve operators, task completion time and error rates decreased drastically with higher levels of training (Kim et al., 2023).

We propose cumulative amount of training results in a robust repository of multiple scenarios in the operator's memory that enhances recognition-primed decision-making when exposed to negative PSFs like time pressure. Therefore, experienced operators are capable of speedily performing situation recognition under time pressure, leading to accurate option evaluation and effective choice selection.

As noted, HRA methods like SPAR-H account for PSFs by performing adjustments to nominal HEPs using multipliers for different levels of PSFs. This approach to computing HEPs – although helpful – accounts for the impact of PSFs like experience and time availability independently, neglecting the effective performance at higher experience levels despite time pressure using heuristic decision-making. For example, barely adequate time will have the same impact (PSF multiplier of 10) on the HEP of an operator with high level of experience and one with a low experience. EPIC proposes determining the PSF multiplier for time availability based on the moderating impact of experience.

A similar approach was adopted in the original HRA method, the Technique for Human Error Rate Prediction (THERP; Swain and Guttman, 1983). THERP formally considered a very limited number of PSFs. Table 20-16 provides the modifications on the HEP for stress level based on skilled vs. novice operators. While in THERP, stress and experience are inseparable considerations, subsequent treatments of PSFs such as in SPAR-H have actively sought to ensure PSFs are treated orthogonally (Boring and Blackman, 2007). This is a byproduct of the need to capture more PSFs than in THERP, but there is value in revisiting the interconnections between PSFs.

EPIC conceptually describes the moderating effect of experience level on time availability in control room operator performance using notional curves. There are three curves in EPIC corresponding to the different levels of experience as defined by SPAR-H. The curves are a plot of time availability (horizontal axis) using SPAR-H's five levels against performance decline due to time availability (vertical axis). Three distinct regions are identified on the curves based on the moderating impact of experience on time availability: regions of high moderating effect, nominal moderating effect, and minimal moderating effect.

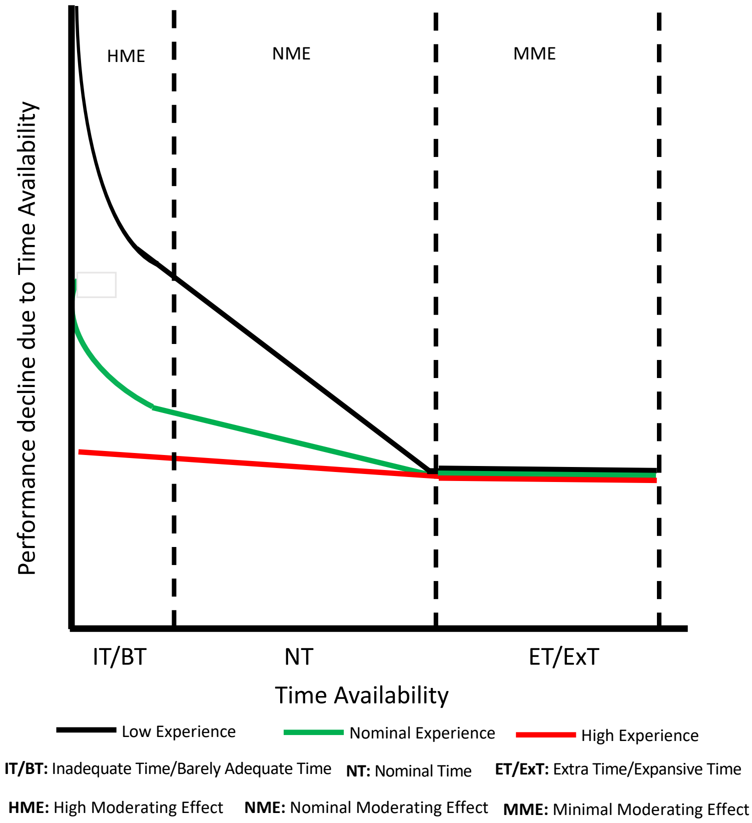

Figure 1. Experience-Performance Impact Curves (EPIC)

The region of high moderating effect (HME) represents the most significant performance decline stage due to time pressure (i.e., inadequate time and barely adequate time). This part of the curve has a characteristic exponential nature, indicating a disproportionately high impact of time pressure on performance decline. Second is the region of the nominal moderating effect (NME). This region shows a decline in performance proportional to time availability and includes the nominal level of time availability. The region of minimal moderating effect (MME) shows almost no significant performance decline with increasing time availability. The curves in the region of minimal moderating effect appear stable, suggesting an upper limit beyond which a higher level of experience does not impact performance meaningfully. Although time availability impacts the three regions of EPIC, the corresponding curves reflect the variability of these impacts on performance decline. Low and nominal experience levels are the most impacted by time pressure. The high experience curve is not significantly impacted by time pressure in the first two regions due to the application of effective heuristics. Put differently, a high level of experience strongly moderates and nominally moderates performance decline due to time pressure in the HME and NME regions, respectively, due to operators' ability to adopt heuristic strategies for effective decision-making. Across all three levels of experience, performance is largely unaffected under the extra and expansive time availability conditions.

Considering a hypothetical scenario of 3 operators identified as operators A, B, and C with high, nominal, and low experience levels, respectively. Suppose these operators were required to complete a control room operational task under five different conditions of time availability as described by SPAR-H (i.e., inadequate time, barely adequate time, nominal time, extra time, and expansive time). In such a scenario, EPIC proposes a characteristic pattern of performance decline in three distinct ways (as depicted by the three regions of EPIC) based on operators' experience level. On the one hand, there will be a remarkable decline in performance for operators B and C under inadequate time and barely adequate time and a proportional performance decline for both operators under nominal time conditions. On the other hand, operator A's experience will moderate the impact of time pressure on performance decline under these time availability conditions due to adopting heuristic decision-making strategies. Operators A, B, and C's performance will be unaffected when performing control room operational tasks under extra time or expansive time conditions. Generally, EPIC proposes that performance declines significantly for less experienced operators under time pressure. In contrast, highly experienced operators maintain stable performance due to their ability to apply heuristic decision-making strategies.

We propose an integration of EPIC into dynamic HRA modelling by determining multipliers corresponding to the moderating effect of various levels of experience on time availability based on empirical investigation and HRA subject matter expertise. Furthermore, the moderating relationships between other PSFs should be explored using EPIC as a guide. The expectation is integrating EPIC into HRA models will further enhance real-world representation of operator decision-making in the control room.

The worksheet approach common in static HRA methods may be challenged to treat interrelated PSFs and moderating effects. The permutations necessary to account for different effect distributions for PSFs based on moderating PSFs can quickly overcome the simplicity afforded by these methods. Dynamic HRA approaches may be able to better handle such joint probability distributions in terms of creating usable HEP outputs.

5. CONCLUSION

This paper explores a conceptual approach to account for the moderating effect of PSFs on one another using operator experience and time availability to illustrate the idea. The moderating effect of experience level on time availability in control room operator performance was described using the Experience-Performance Impact Curve (EPIC). EPIC reveals the varying impact of time availability on operator performance decline based on different levels of experience, especially the minimal performance degradation of experienced operators due to their ability to use heuristics to make effective decisions under time pressure. To enhance dynamic HRA modelling, we proposed an integration of EPIC into dynamic HRA modelling by determining distributions corresponding to the moderating effect of various levels of experience on time availability, and further exploration of the moderating relationships between other PSFs using EPIC as a guide. Additional empirical data collection of PSF distributions and joint distributions is necessary to facilitate accurate HRA models of complex performance.

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