16
Human Factors and Cognitive Engineering

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16.1
Introduction

In an early editorial in the *Journal of Loss Prevention in the Process Industries,* Michel Giot noted that the future of loss prevention engineering required a multidisciplinary approach integrating human and technical sciences (Giot, 1989). A review of incidents at Bhopal and Visakhapatnam in India suggested that they occurred not because of the unavailability of the loss prevention knowledge or lack of technical competence of the manpower, but due to carelessness and overconfidence (Abbasi and Abbasi, 2005). At Bhopal in 1984, ~40–45 tons of methyl isocyanate were released into the atmosphere from the carbaryl pesticide manufacturing unit of the Union Carbide Corporation in 1984. The gas, which is 50 times more toxic than phosgene gas, caused an estimated 3000–5000 deaths. The severity of the incident was aggravated by the fact that no emergency preparedness procedures were in place. At Visakhapatnam in 1997, one of eight Horton spheres filled with pressurized liquefied gas caught fire in the morning and created explosions that claimed 60 lives and destroyed property valued at US$60 million. Investigations after the incident found that the knowledge to prevent the incident was available but not implemented in the operating procedures.

The purpose of this chapter is to contribute to the multidisciplinary approach to loss prevention engineering by providing a human factors (HF) perspective. The HF approach seeks to change the things people use and the environment in which they use these things to match better the capabilities, limitations, and needs of people (Sanders and McCormick, 1993). Specifically, people's *cognitive* capabilities, limitations, and needs will be addressed. This chapter provides an overview of some HF methods applicable to loss prevention.

The chapter is composed of four sections. The first section presents conceptual models of human cognition to describe information processing and transitions between modes of processing. The second section covers task analysis techniques which characterize the interactions between humans and machines/equipment. The third section provides some sample applications in process engineering and surface transportation. The final section provides a summary of the chapter.

Handbook of Loss Prevention Engineering, First Edition. Edited by J. M. Haight.

16.2 Models of Human Cognition

We begin a discussion of HF in loss prevention engineering by presenting a standard model of information processing. The framework was developed by Wickens (1992) and is shown in Figure 16.1.

Stimuli and events are perceived by our sensory system and supplemented with meaningful interpretation based on memory of past experience. Our primary sense organs include our eyes and ears, but we may also perceive through other means. Once perceived, the events may be responded to directly by deciding on what action to take. Alternatively, it may be stored temporarily in working memory, an internal system that involves thinking about or transforming information that was either perceived or generated internally (e.g., mental images). Working memory places a heavy demand on our attentional resources and is of limited capacity. Working memory operates upon long-term memory, which provides a large-capacity store consisting of vast amounts of information about the world, including both facts and procedures.

Actions by an individual generally produce feedback, which is then sensed to complete the closed-loop cycle. In this framework, human attention, a limited resource, has two critical functions in information processing. As a selective agent, it chooses and constrains information that will be perceived. As a task management agent, it constrains what operations can be performed concurrently.

Although the standard model of information processing holds, the interaction between humans and their environment may vary depending on the features of

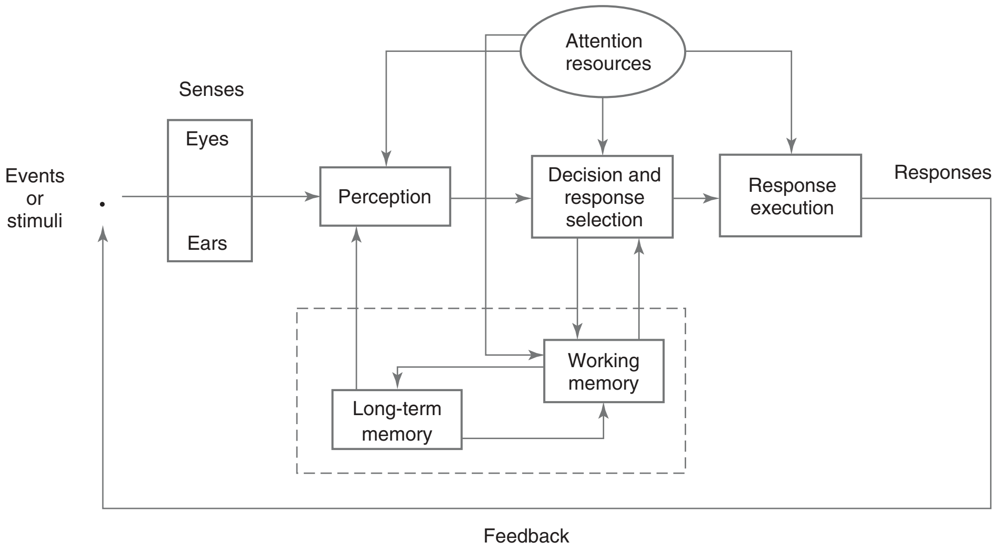


Figure 16.1 Model of human information processing (Wickens and Hollands, 2000).

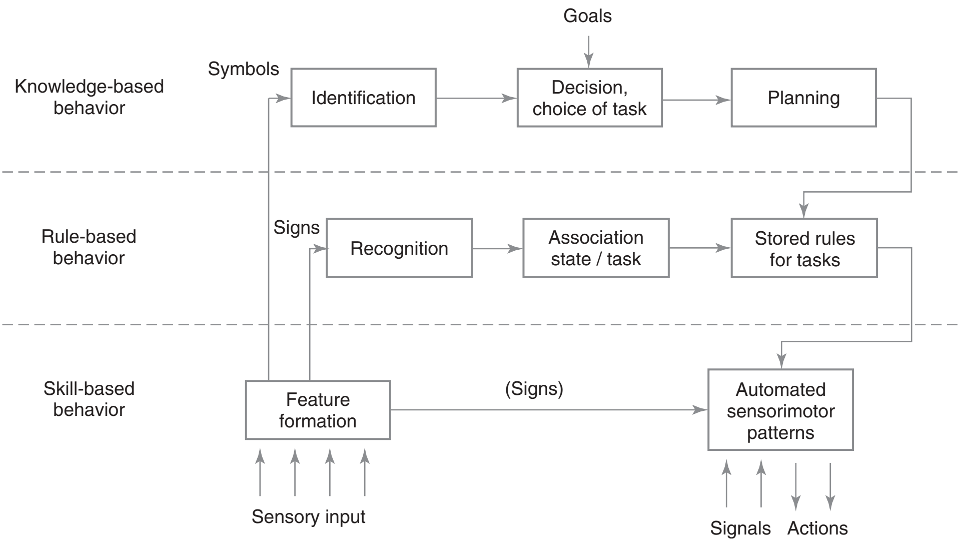


Figure 16.2 The skill-, rule-, and knowledge-based model (Rasmussen, 1986).

a work domain and the abilities of human controllers. A common hierarchical framework to represent the relationship between human abilities and the cognitive control of systems is the skill-, rule-, and knowledge- (SRK) based model (Rasmussen, 1986) shown in Figure 16.2.

Skill-based behavior is the lowest level of the hierarchy. At this level, human performance is governed by preprogrammed behaviors characteristic of routine situations. Skill-based behavior results from extensive practice whereby people develop a collection of cue–response patterns suited to specific situations without conscious analysis.

Rule-based behavior is the next highest level of human performance and is governed by conditional rules. Stored rules become specialized over time from interactions with the task environment. Rule-based behavior is slower and requires more cognitive resources than skill-based behavior. Rule-based behavior can be compared to the function of an expert system where situations are matched to a database of production rules and responses are produced by retrieving or combining different rules (Marmaras and Kontogiannis, 2002).

Knowledge-based behavior is the highest level of human performance and is governed by a thorough analysis of the situation and a deliberate comparison of alternative means for action. Knowledge-based behavior is driven by goals and a rational course of action and is bounded by an individual's mental model of the work domain. Knowledge-based behavior is the slowest and most demanding of the behaviors because it requires access to an internal representation of the system in addition to time-consuming comparisons of work methods (Rasmussen, Pejtersen, and Goodstein, 1994).

16.2.1
SRK Framework in Process Operations

An operator in a control room is exposed to several sources of information that contain data along varying dimensions and metrics. It is important for operators to be proactive and keep the plant from running into an abnormal or emergency situation. If there are deviations in the plant processes, a timely response to these situations is critical to maintaining safe operating conditions. How do operators function in such an environment that is dynamic and cognitively demanding? The SRK framework is a good method to explain the different levels of operator behavior within this context.

To become a console operator, there is a significant amount of training involved. Hence, by the time an operator is in full control of a console, they are an expert. An expert has been anecdotally described as ''someone who continually learns more and more about less and less'' (Salthouse, 1991). More importantly, an expert is capable of reproducing superior performance in a specific domain (Lewandowsky and Thomas, 2009). Therefore, by definition, experts are skilled performers, hence operators typically function within the skill mode of behavior. More specifically, their responses are mediated by cues that they pick up from their environment and there is minimal cognitive processing at this behavioral level. For example, when an operator starts off on a shift, and simultaneously relieves another operator from their shift, they will quickly scan through the main screens, alarm lists, and logbook, and create a mental picture of the current status of the plant and where it is heading. To execute these tasks, operators function within the skill mode of behavior. There is minimal cognitive processing involved, primarily because this is a daily routine. In addition, there is a structured, organized, and stepwise process for a shift handover process. They look for major cues, for example, broken equipment, falling or rising process values, and emergency alarms, if any. The number and criticality of such cues form the basis of response for the operators. In the refining world, there are also situations when the work environment demands operators to function in the rule-based mode. In this behavioral mode, the amount of cognitive processing is relatively higher than in the skill-based mode. For example, consider a situation in a refinery in which the maintenance team is working on a malfunctioning piece of equipment. To do so, they may have locked out a pipeline or diverted it, depending on the kind of process and type of pipeline. Because of this, at times, it is possible that there are one or more intermittent alarms that come up on the operator's console. When an alarm comes up, the operator typically looks at the alarm display, and applies certain rules to identify the right form of response. Consequently, they execute appropriate actions. This specific behavior falls within the rule-based mode of the SRK framework. For example, in the case mentioned here, the operator may apply rules of exclusion to ignore or silence a set of alarms that are initiated due to the equipment being worked on, or its effects on downstream or upstream processes. It is important for operators to maintain a good understanding of the situation to respond appropriately and effectively when functioning within the rule-based mode of behavior.

The knowledge-based mode of behavior is one in which there is the most load on the cognitive system. An indispensable aspect for functioning effectively within the knowledge mode of the SRK framework is for operators to have an extremely robust mental model of the situation. Operators function within this mode when there is a novel situation that confronts them, and an action in response to the situation requires a thorough analysis of the aspects involved. For example, a situation when operators almost always function within the knowledge-mode of behavior is when they have to trouble-shoot a process to understand the underlying root cause of an event and consequently select an appropriate decision and action strategy, During this phase, operators have to tap into their knowledge about the process, work environment, task constraints, and so on. As a result, the level of cognitive processing is immense.

In summary, depending on the environmental and task constraints, operators controlling consoles in a refinery function across the three behavioral modes of the SRK framework. Importantly, these three modes differ in the level of cognitive processing. To prevent loss in production, it is most ideal to help operators to maintain their functioning within the skill-based mode. Apart from providing appropriate training to operators, from a human–technology interaction perspective, it would be beneficial to develop systems and tools that can help the operators overcome limitations associated with functioning within the three behavioral modes. More specifically, the likelihood of operator error is much higher when functioning outside the skill-based mode. Therefore, to reduce losses due to operator error, loss prevention engineering teams should focus on at least two aspects. First, refineries should have competent training programs that are designed to maintain operators' skills and expertise at a high level. Second, the process engineering tools and related decision support systems that operators use to monitor and manage a plant should be engineered to represent the apt semantics of the domain, address the tasks, constraints, goals, and mental representations of the operator, and be easy to use (e.g., Tharanathan *et al.*, 2012). Such well-engineered systems focused on loss prevention will be instrumental for operators to function at the skill-based level.

16.2.2
Cognitive Task Analysis

An understanding of the human processing model must be accomplished by the constraints of the task at hand. Cognitive task analysis (CTA) provides a method for such understanding. CTA involves a consideration of user goals, means, and work constraints in order to identify the what, how, and why of operators' work (Rasmussen, 1986; Klein and Militello, 2001). CTA differs from traditional task analysis, which describes the performance demands imposed upon human operators in a neutral fashion (Kirwan and Ainsworth, 1992) regardless of how operators perceive the problem and how they choose their strategies. CTA analyzes how operators respond to tasks that have been delegated to them either by automation or by other humans. Here, tasks are operations undertaken to achieve certain system goals. CTA is used to examine mental activities or operator processes to enable practitioners to assess the current situation, make decisions, and formulate plans of action.

A common technique for task analysis is called the hierarchical task analysis (HTA). HTA is best regarded not so much as a strict procedure but as a generic approach to the investigation of problems of human performance within complex, goal-directed, control systems, including those involving computers (Annett, 2004).

HTA is based on functional rather than behavioral or psychometric constructs and uses a fundamental unit called an operation. A functional task analysis begins by defining goals before considering actions by which those goals may be accomplished. Complex tasks are defined in terms of a hierarchy of goals and sub-goals. Goals are elaborated with the means of achieving it, called operations.

An operation consists of conditions under which the goal is activated and the actions which may be employed to attain the goal. These actions may themselves be defined in terms of sub-goals. For example, thirst may be the condition which activates the goal of having a cup of coffee and sub-goals are likely to include obtaining boiling water, a coffee maker with filter, and so on. In practice, Asimakopoulos, Dix, and Fildes (2004) used HTA as a grammar to map actions in supply chain industries. An extension of their work to loss prevention engineering in process industries is highly conceivable. In summary, HTA is seen not so much as a describing of actions or even cognitive processes as such but as a systematic method of investigating problems of human performance.

16.2.3
Situation Awareness

The information processing and the SRK models provide a basis for understanding the information processing behaviors of humans and CTA gives an appreciation of the task at hand. To access the understanding of human operators in a loss prevention environment, however, requires access to the situation awareness (SA) of the operator.

The standard model for SA was developed by Endsley (1995a,b, 2006) to represent dynamic human decision-making in a variety of domains. *SA* is defined as ‘‘the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future’’ (Endsley, 1995). In her model (shown as Figure 16.3), a person’s perception of relevant elements in the environment forms the basis of their SA and leads to action selection and performance.

The first step in achieving SA is to perceive the attributes and dynamics of relevant elements in the environment. A plant operator would perceive elements such as the current value of a process variable, presence or absence of abnormal variations in the process, and so on. Comprehension of the situation is based on a synthesis of disjointed Level 1 elements. Level 2 SA goes beyond simply being aware of the elements that are present to include an understanding of the significance of those elements in the light of pertinent operator goals. For example, to avoid losses

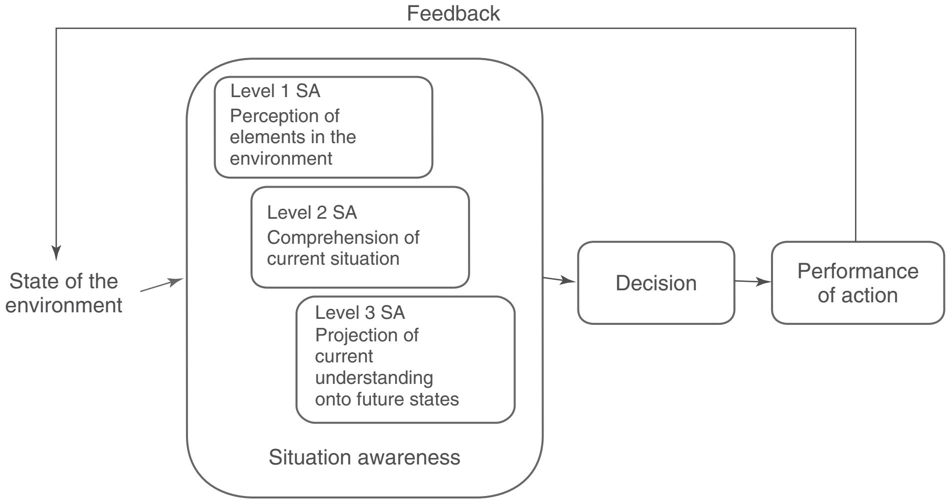


Figure 16.3 Situation awareness model. (Adapted from Endsley, 1995.)

in production, plant operators must comprehend the status of the alarm summary, the quality of product feed, abnormality in trend displays, and so on. The ability to project the future actions of the elements in the environment – at least in the near term – forms the third and highest level of SA. This is achieved through knowledge of the status and dynamics of the elements and comprehension of the situation (both Level 1 and Level 2 SA). For example, to prevent the plant from running into an emergency situation, it is important for operators consistently to project the status of the plant to the future based on the current state of events and process values. Consequently, operators have to take the appropriate decisions and actions to maximize efficiency. Importantly, to project the status of the plant to the future, it is critical for operators to maintain a good mental model of the processes, the underlying dynamics of the plant, the situation as a whole with the appropriate task, and environmental constraints. In addition, loss prevention engineering teams can help operators maintain a high level of SA by designing support systems (e.g., effective displays) that can better guide their monitoring, decision-making, and action execution tasks.

16.3 Applications to Process Engineering and Surface Transportation

16.3.1 Process Engineering

In the refining industry, operators in control rooms have to monitor the processes continuously and execute appropriate actions to reduce alarms and avoid accidents. While executing such tasks, they also have to maintain the daily production targets set by their management. Therefore, it is essential for operators to maintain an accurate mental picture of the whole plant, understand the underlying dynamics of the processes including the level of dynamic coupling between the different components, control moves, and procedures associated with different events. In short, the task of *operating* a plant is cognitively and sometimes emotionally demanding.

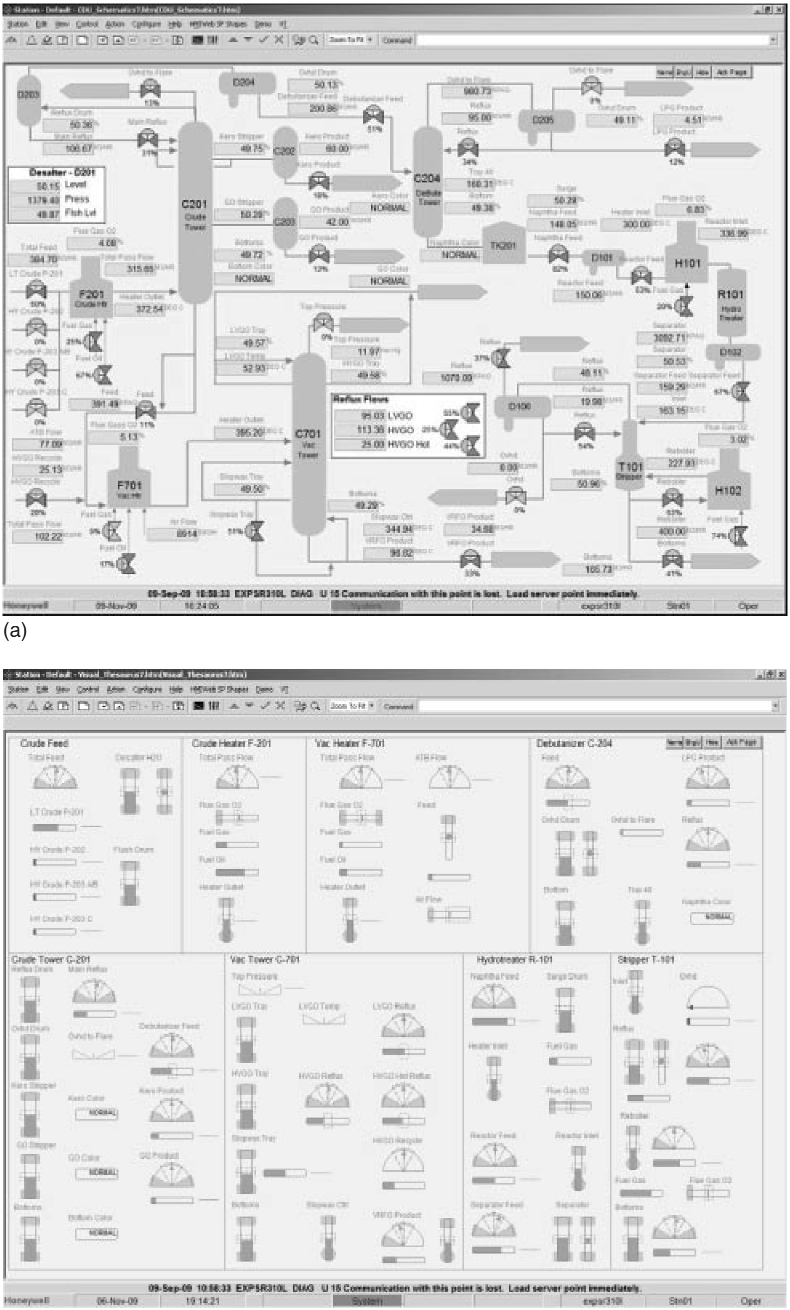
To help operators execute their tasks effectively and safely, while simultaneously trying to avoid any loss in production, it is essential to design and develop technological systems that can support human information processing, decision-making, and action execution. In this section, we describe two research studies that looked at improved interventions to support operators' SA and overall performance in control rooms.

16.3.1.1 **Overview Displays Study**

As a part of their daily task routine, console operators are exposed to an enormous amount of information. Importantly, operators have to be able to process the most pertinent information to make the most effective decisions. Previous research studies on advanced visualizations and cognitive engineering methods have shown that there are effective ways of representing process information to console operators (Vicente and Rasmussen, 1990; Jamieson and Vicente, 2001; Burns and Hajdukiewicz, 2004). However, most operator consoles in oil and gas refineries still use traditional piping and instrumentation diagram (P&ID)-based schematic displays to present data and information (Tharanathan *et al.*, 2010). A representational example of such a traditional schematic display is shown in Figure 16.4a.

As one may observe, it can be cognitively demanding to monitor and infer the most pertinent information from such displays to make appropriate decisions. In other words, it is challenging for operators to understand the "big picture" with a quick glance at such traditional displays. Hence, from an HFs perspective, it is critical to develop advanced visualizations that can support the cognitive functioning of operators, especially for them to gain a quick overview of the "big picture" (see, e.g., Tharanathan *et al.*, 2010). Hence a study was undertaken to meet this objective. The study involved multiple stages. First, the team worked with an expert operator to understand the most pertinent information that operators would need to monitor plant status effectively. It is important to note that although there is an enormous amount of data that can be made available, it is important to filter out the most critical information that operators need in order to execute specific tasks. Second, based on the input from the expert operator, the team developed an overview display, hereafter denoted the functional overview. This display was expected to help operators detect qualitative changes in the process much faster. A representational example of the functional overview display is shown in Figure 16.4b. It is important to note that in both displays, the amount of information is exactly the same. However, the way in which information is represented is different.

Second, the research team designed an experiment to test the effectiveness of both the displays in supporting operators' SA while monitoring the processes. The



(a)

(b)

Figure 16.4 (a) Schematic overview display (Tharanathan *et al*., 2010) and (b) functional overview display (Tharanathan *et al*., 2010).

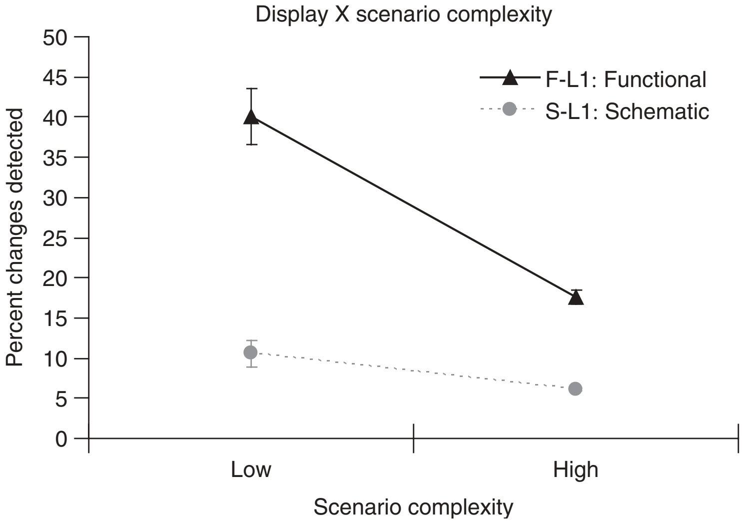


Figure 16.5 A general representation of the results indicating benefits of the functional overview display compared with the schematic overview display (Tharanathan *et al*., 2010).

study was done with actual operators at a site. As represented in Figure 16.5, the results from the study indicated that the functional overview display was much more effective in supporting operators' SA while monitoring compared with the traditional schematic overview display. Such findings are more critical because the operators who participated in the study were familiar with the traditional layout. Even then, they showed a higher preference for the functional overview displays, and their SA was significantly higher.

In summary, the results from this study indicate that if systems designed to support operator performance are developed using a human-centered approach, it can result in technologies that can enhance overall operator performance, which will subsequently reduce injuries, accidents, and losses in production.

16.3.1.2 **Interface Study**

In a similar study, Errington *et al*. (2005) investigated the effectiveness of two different interfaces, namely a traditional interface and a human-centered interface, in supporting operators with detection, diagnosis, and response to an abnormal situation. The human-centered interface design was intended to provide a continuous broad overview of process conditions, while simultaneously giving access to the needed detailed information. This advanced design was expected to reduce the potential for tunnel vision while operators were cognitively engaged in solving complex process-related problems (Errington *et al*., 2005). Importantly, the human-centered interface included features such as multi-level simultaneous views of the increasing plant details, tabbed navigation within a display level, integrated alarm management into graphics, and navigation tabs and yoked navigation between display levels.

(a)

(b)

Figure 16.6 (a) Human-centered interface design (Errington *et al.*, 2005) and (b) traditional schematic drill-down interface design (Errington *et al.*, 2005).

In contrast, the traditional interface was developed before the concept of multi-windowing. In addition, the process graphics closely emulated the representation of the P&ID. Furthermore, the navigation and operator input was supported through a specialized and dedicated keyboard (Errington *et al.*, 2005). In summary, the human-centered interface included multiple design components that were incorporated to reduce the cognitive and physical load on operators while executing their tasks. Schematic representations of the two interfaces are shown in Figure 16.6a,b.

An experiment was conducted in a high-fidelity training simulator to investigate the effectiveness of the two displays. Twenty-one petrochemical plant operators participated in the study. The operators were exposed to multiple upset scenarios in which they had to orient themselves to the situation and execute appropriate actions to address the abnormal events. The results provided strong support for the human-centered interface. More specifically, the operators who used the human-centered interface completed scenarios significantly faster than the operators who used the traditional distributed control system interface, with a

41% improvement. In addition, operators who used the human-centered interface showed a 26% improvement in dealing with failures compared with the other group. Finally, the operators who used the human-centered interface showed a 38% improvement in recognizing the presence of a failure before the first process alarm (Errington *et al.*, 2005).

In short, the human-centered interface supported the operator tasks much more effectively compared with the traditional interface. An additional objective of the research team was to identify the economic benefit associated with the human-centered interface and the enhanced support it provided to operators in performing their tasks. Hence the results from the study were input to a Monte Carlo simulation. The study yielded a benefit of Can$1 090 000 per year for a plant of comparable size (Errington *et al.*, 1995).

16.3.2 Surface Transportation

Motor vehicle crashes lead to thousands of deaths every year. For example, Marchau *et al.* (2001) reported that 42 500 people are killed and 3 500 000 are injured every year in Europe due to traffic accidents. Similarly, according to a report from the National Highway and Traffic Safety Administration (2006), 42 000 people are killed per year in the United States due to motor vehicle crashes. In addition, the economic impact associated with such crashes is extremely high. For example, it was estimated that the lifetime cost of crash-related deaths and injuries among drivers and passengers was US$70 billion in 2005 (Naumann *et al.*, 2010). In short, traffic accidents lead to significant losses of lives and have an enormous financial impact globally. Therefore, it is important to understand the root causes of different traffic accidents, and to develop systems and technologies that can reduce such accidents and save more lives (e.g., Tharanathan, 2012).

Importantly, the human factor is a significant root cause of traffic accidents (Rumar, 1985). In addition, Brookhuis *et al.* (2001) suggested that ~90% of all traffic accidents can be attributed to human error. Therefore, it is essential to develop systems that can help drivers circumvent their limitations (e.g., Tharanathan, 2012). Several studies in the past have investigated the role of perceptual and cognitive limitations in driving performance and related judgments. In this section, we describe two research studies that investigated the capability of humans to make judgments that are critical to a driving task. We also elaborate on a recent conceptual model that was developed to help in the design of collision avoidance warning systems (CAWSs) to support drivers during overtaking maneuvers.

16.3.2.1 Study on Judgments of Time-to-Contact

About 25% of traffic accidents are rear-end collisions (Shinar, Rotenberg, and Cohen, 1997), and such collisions lead to a significant number of injuries and deaths every year. To reduce injuries and loss of lives due to rear-end collisions, it is important to understand the underlying reasons for such collisions. From an HF perspective, it has been suggested that to avoid rear-end collisions, it is important

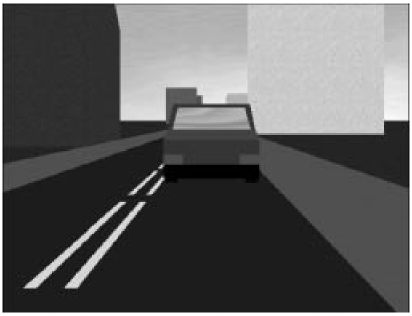


Figure 16.7 A schematic representation of the scene (Tharanathan and DeLucia, 2006).

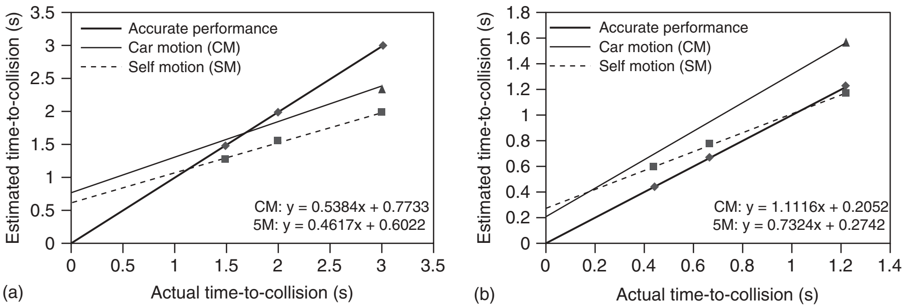


Figure 16.8 (a) general representation of the mean TTC as a function of actual TTC during constant velocity motion and (b) general representation of the mean TTC as a function of actual TTC during accelerated motion (Tharanathan and DeLucia, 2006).

for drivers to judge accurately the time remaining until collision with an on-coming lead car (e.g., Lee, 1976; Gray and Regan, 2000, 2005; Hesketh and Godley, 2002; DeLucia & Tharanathan, 2009). Interestingly, studies have shown that humans are not always accurate in making such judgments. For example, using simulated traffic environments, Tharanathan and DeLucia (2006) investigated the capability of participants to make accurate time-to-contact (TTC) judgments with an oncoming car. A schematic representation of the scene is shown in Figure 16.7.

Participants viewed scenarios in which a lead car moved towards the virtual self or the virtual self moved towards a lead car either at a constant velocity or at an accelerated rate. At some point during the approach motion, the scene disappeared, and participants were instructed to judge when they would collide with the oncoming car.

A general representation of the results is shown in Figure 16.8. The results indicated that participants were generally inaccurate in their judgments of TTC. More importantly, the results indicated that participants overestimated the time it would take for the lead car to collide with the virtual self when motion was at an accelerated rate. In other words, participants judged the lead car to collide with the virtual self at an instant later than when the collision would have actually occurred. Such findings have important implications for traffic safety. More specifically, cars typically accelerate and decelerate. If judgments of TTC are overestimated during such motion conditions, it is possible that one underlying reason for rear-end collisions is the incapability of drivers to judge TTC accurately during car following.

Such results also have implications for the design of intelligent CAWSs. For example, drivers may find collision avoidance warnings to be more useful during conditions when their judgments of TTC are significantly poor. Information theory suggests that events that are expected convey less information than unexpected events (Sanders and McCormick, 1993). Hence collision avoidance warnings may be more informative to drivers under those traffic conditions in which their judgments of TTC are poor. In contrast, warnings might be perceived as redundant or uninformative when a driver's TTC judgment is accurate (Tharanathan and DeLucia, 2006).

16.3.2.2 **Study on Judgments of Collision Avoidance Action Gap**

Another potential contributing factor to rear-end collisions, and one that has been glaringly overlooked, is the ability of drivers to judge the collision avoidance action gap (CAAG) with oncoming vehicles (Tharanathan, 2009). The CAAG is the time remaining until collision with an oncoming car (e.g., a lead car), at the instant the driver of the following car decides to initiate a collision avoidance maneuver, for example, steering to the side lane. The CAAG can also be seen as the temporal gap available for a driver to complete a collision avoidance maneuver. Driving conditions which lead to a short CAAG could increase the likelihood of a rear-end collision. In other words, if a driver is too late in deciding when to initiate a collision avoidance maneuver, there may be very little time to complete such a maneuver. In short, longer CAAGs may decrease the likelihood of rear-end collisions (Tharanathan, 2009).

To investigate judgments of CAAGs, Tharanathan (2009) conducted a simulator-based study. The scenarios represented a lead car in front of the virtual self. One half of the scenes depicted constant-velocity motion and the other half depicted accelerated motion. In addition, the starting headway, or the distance between the virtual self and the lead car, was manipulated. Further, in one half of the scenes the lead car moved towards the virtual self, and in the other half the virtual self-moved towards the lead car. Finally, the gap closure rate was manipulated to be either slow or fast. Participants were instructed to click a button at the last possible instant when the virtual self should move towards another lane so as to avoid a collision with the lead car (Tharanathan, 2009).

The findings are represented in Figure 16.9. The results indicated that the CAAG was significantly smaller during accelerated motion conditions compared with constant-velocity motion conditions. In addition, the CAAG was significantly smaller when the gap closure rate between the lead car and the virtual self was fast compared with slow. It is important to note that such findings have important practical implications for the design of CAWS, which can help drivers avoid rear-end collisions, eventually reducing injuries and loss of lives. Specifically, CAWS have to be designed to help drivers under those conditions in which their judgments of CAAG are poor (Tharanathan, 2009).

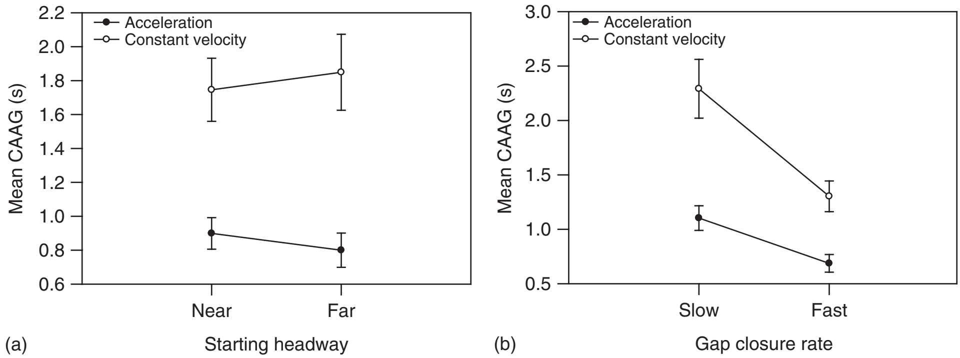


Figure 16.9 (a) Mean CAAG as a function of starting headway and motion condition and (b) mean CAAG as a function of gap closure rate and motion condition (Tharanathan, 2009).

16.3.2.3 **Overtaking Maneuvers**

Traffic accidents that occur during an overtaking maneuver are a worldwide problem leading to numerous injuries and fatalities every year (Tharanathan, 2012). For example, between 1995 and 2000, ~30 people died each year in The Netherlands due to overtaking failures (Hegeman 2004). In addition, Clarke, Ward, and Jones (1998) reported that overtaking maneuvers led to a considerable proportion of accidents causing injuries in Nottinghamshire, England. Furthermore, in the United States, in 2000 there were 138 000 accidents due to overtaking, and these accidents accounted for 2.1% of all fatal crashes and 1.1% of injury crashes (NHTSA, 2001). Therefore, it is important to understand the underlying reasons for traffic collisions that happen during an overtaking maneuver.

Very few studies have focused on drivers' judgments during overtaking maneuvers (e.g., Gray, 2004; Gray and Regan, 2005). This is even more critical because an overtaking maneuver is a complex task, hence it has a high probability for human error, primarily from a perceptual standpoint (Tharanathan, 2012). Importantly, there is a need for CAWS that are designed specifically to help drivers during overtaking maneuvers. Tharanathan (2012) highlighted some of the primary task constraints during an overtaking maneuver, arguing for the design of CAWS specifically for overtaking maneuvers. In other words, CAWS designed to help drivers avoid rear-end collisions may not be helpful during overtaking maneuvers (see Tharanathan, 2012, for a detailed review). Figure 16.10 is a schematic representation of a conceptual model that describes the need for specific CAWS to support drivers during overtaking maneuvers.

In summary, it is important to note that HFs play a significant role in traffic collisions. There is a lot that can be done to help drivers avoid such collisions and reduce injuries and loss of lives. Most importantly, when designing support systems to help drivers avoid collisions, it is essential to contextualize the problem from the perspective of human capabilities and limitations, be it from a physical, cognitive, or perceptual standpoint.

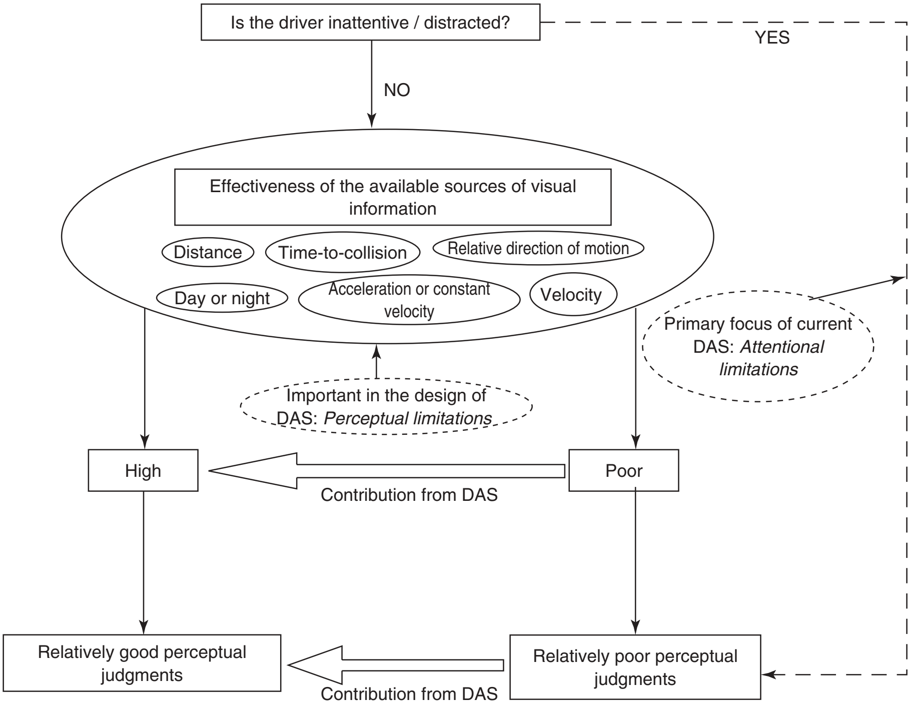


Figure 16.10 Conceptual model for designing driver assistance systems (DASs) to overcome perceptual limitations in drivers (Tharanathan, 2012).

16.4 Conclusions

The human factor is an extremely important component that should not be overlooked when designing for safe and risk-free systems. It is important to note that human error cannot be completely negated from a socio-technical system. However, such systems can be designed to handle better the abnormalities in human behavior, which primarily arise due to the limitations that exist within humans' cognitive and physical systems. Applying valid HF principles in the design and development of systems and technology to support human performance can greatly reduce potential losses that may otherwise be incurred. Depending on the domain, the savings that result from such well-designed systems can be in the form of human lives, injuries, production targets, and so on.

It is important to recognize a problem early enough before it leads to significant losses. For example, if operators in a control room are complaining about refresh rates of their screens, it is important to investigate the problem before a major accident occurs. In short, being proactive about improving systems is important. Second, one should clearly understand the task of the human. In addition, it is extremely critical *not* to separate the task of the human from their environment.

The environment creates several constraints and capabilities. Hence it is essential to understand the task of the human within the context of the work environment (Vicente, 2003). There are several task analysis methods available that can be used during this stage (e.g., Kirwan and Ainsworth, 1992; Vicente, 1999). Third, identify the root cause of the problem within the problem space. The root cause could vary from limitations of the human to equipment to environment. From an HFs perspective, it is essential *not* to ignore the human-related root causes. Fourth, investigate and identify effective measures to address such problems and limitations. These could be in the form of initial conceptual designs and rapid prototypes. When developing these potential solutions, it is important to involve the actual end-users or workers in the process. This will improve the buy-in from the end-users and will also help designers and engineers to fit the functions to the needs of the user better. Fifth, it is often a beneficial exercise to validate the prototypes with actual end-users. This can be done through behavioral experiments or simulations. During this stage, some of the problems that were unidentified in the earlier stages may start to come out. It would be more cost-effective to make design and engineering changes at this stage than after the solution has been implemented. Finally, based on the outcome of the validation exercises and experiments, the engineering team can decide on mechanisms to integrate the solution within the work environment. An important step to consider during this phase is change management. More specifically, when there is a change in the work environment, humans may initially reject the concept, even though it may help to enhance overall performance. By involving the users from the initial stages of design, some of this problem can be addressed. However, proper change management techniques are important to help the end-users fully accept and adopt new interventions in their work space. Effective change management can be done through training sessions, group discussions, and seminars.

In conclusion, designing for the *human factor* plays a significant role in loss prevention. Wherever there is a human component involved, there is a possibility for error. Therefore, it is essential to design systems to overcome limitations in humans' cognitive and physical abilities, while capitalizing on their strengths. Unlike several other components in an engineered system, the criticality of the human component is hard to measure and evaluate until an accident occurs. However, by then it is too late. Therefore, the key to successful HF design and implementation is in being proactive, giving due importance to the human role in the work process, integrating actual users in the design and development phases, and effective change management.

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