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Operators are Only Human: Facilitating Situated Decision Support in Industrial Environments

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Summary

This thesis presents a review of the state of the art in Decision Making literature to elicit four current challenges in supporting Decision Making through system design, in situated industrial environments. A collaboration project with the Norwegian Aluminum industry identifies the need of continuous workplace-education for their operators. They lack knowledge of the processes they support.

A thorough literature review into human decision making, automation, and decision support systems provides a set of four current challenges for supporting human decisions: Decision Automation Systems, Feedback, Information Presentation, and Learning. These challenges are combined with human decision literature, indicating opportunities for solutions. A design of a screen-based Decision Support System using a theoretical case domain demonstrates an implementation of opportunities from the current challenges, into novel solutions.

The article recommends further research into the applications of the current challenges of Decision Support Systems in industrial environments, by implementing and evaluating a solution based on the opportunities of information systems in a situated environment.

Preface

This project was carried out as a Master's Thesis at the Department of Computer and Information Science at NTNU, spanning the period of August 2015 to June 2016. The project has been supervised by Sobah Abbas Pedersen.

Trondheim, June 1, 2016

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Chapter 1

Introduction

1.1 Background

This project set out on a path to address a problem identified in the Norwegian Aluminum industry. A challenge that is general for all modern industrial work; *reducing human errors*, specifically *decision errors*.

Automation has replaced most of the physical tasks of production work in western industries (Farrington-Darby and J. R. Wilson 2006)). While task-automation has continually become a defining part of organizations, the human operators work and responsibility has been extended, one operator is responsible for a multitude of complex processes. And the work characteristics are changing from a decidedly skill- and rule-based physical work to a challenging knowledge-based cognitive one.

The human operator is still performing routine tasks. The operators are now both supporting and governing the automation. Tasks include controlling machines, taking measurements and performing maintenance. But when automation fails, the human operator is responsible for both diagnosing that there is a failure, and to limit the failures impact on production. And the key to diagnostics is to both understand systems and the operating environment.

Operators currently learn by instruction from more experienced operators, and *by doing* (situated experience). They follow Standard Operating Procedures(SOP), and use these to guide their work. However, operators have a limited theoretical understanding of their workplace. This lack of knowledge sometimes lead to undesirable decisions.

The loss of expert and experienced workers is a great concern in some domains Farrington-Darby and J. R. Wilson (2006). As automated systems replace manual operations the situated process-understanding stays with the experienced operators, but these expert operators are rapidly transitioning to leader-positions and retirement.

This thesis aims to start a project for improving decision strength in the process industry by identifying opportunities for novel technological decision support systems. The main focus is on supporting the human operator's decision strength, by facilitating *expertise*.

An *expert* can be defined as "...has done the job for a considerable period of time, knows the rules and procedures and the range of routines required very well, but also knows where and when to sidestep these and to intervene on their own." (Farrington-Darby and J. R. Wilson 2006, p.17) Do we accelerate expertise?, or reduce the need for expertise through automated systems?

To identify opportunities for improving human decision we must first understand how humans make decisions, and how previous research has approached the problem. As the problem of improving human decision making is still unsolved and rarely approached in *situated* systems, a comprehensive review of the decision making literature is required.

Following the literature review, a set of *current challenges* will be identified. These challenges are based on the lacks of cognitive support in current identified industrial systems and from best practices in other environments.

A simple design suggestion will be demonstrated to highlight the importance of the literature review in designing novel systems to support what research shows as the most important aspects of human cognition affecting decision strength.

In the example above, we have used "author-year" references, which is the preferred format.

1.2 Objectives

The main objectives of this Master's project are to:

1. Review decision making as a cognitive process.
2. Identify means of supporting decision making at the workplace as a cognitive process.
3. Designing a technical solution to support learning at the workplace.

1.3 Structure of the Report

The rest of the report is organized as follows. Chapter 2 gives a thorough introduction to Human Decision making, highlighting approaches and research methodologies commonly used and culminating in a four sections of opportunities for improving Human DM. Chapter 3 Extends to the domain of Automation and the specific cognitive impact of automation design on the decision strength of humans. Chapter four reviews the state of the art in decision support systems, providing a comprehensive introduction to the various considerations required to create and facilitate human decisions.

Chapter 5 presents a set of four Current Challenges for industrial Decision System Design, defined based on the findings from previous chapters. A set of opportunities are also available, to facilitate solutions which can support the current challenges.

Chapter 6 reviews the current challenges by applying them in a simple design of a Decision Support System for a theoretical case domain. Finally chapter 7 concludes the project suggest further work.

Chapter 2

Human Decision Making

2.1 Job Satisfaction and Self-Efficacy

A much used definition of job satisfaction is by Locke , who defines it as "... a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences" (Locke, 1976 p. 1300, in Weiss 2002).

A central element in many of the theories of Job Satisfaction, is that for people to be satisfied with their job, they need to have increased self esteem and a belief in their own competence (See eg., Locke 1969; Ryan and Deci 2000; Weiss 2002) Understanding of work processes, and control over decisions are competence indicators, and can affect self-efficacy and self-esteem. If the individual does not receive enough feedback from the environment, this is likely to leave him dissatisfied (Weiss 2002).

(Seligman and Csikszentmihalyi 2000) argue that "normal" people need advice and guidance to create a more fulfilling life. One of their prescriptions for fulfilling activities in every culture is the development of wisdom. Understanding the world around us leads to an intrinsic wellbeing that cannot be compared to short time happiness.

Perceived Self-Efficacy is defined as 'people's beliefs about their capabilities to produce "designated levels of performance that exercise influence over events that affect their lives" (Bandura 1994, p. 71). Recently Schaubroeck, Kim, and Peng (2012) reviews the literature and show that this effect often correlates with an positive impact on happiness, job performance and job-turnover rates. Self-determination theory (Ryan and Deci 2000) is one of the approaches to show the relation of intrinsic and extrinsic motivations and how these affect tasks enjoyment and psychological wellbeing.

The leading causes of job burnout is exhaustion, cynicism and lack of accomplishment (Macnamara, Hambrick, and Oswald 2014). Exhaustion is caused by job stressors, such as time and workload. Cynicism is related to how the individual feels attached to his job and his own feeling towards aspects of his work. Finally, the feeling that the individual does not accomplish anything worthwhile, either through application of knowledge or productivity. The antithesis of burnout is speculated to be engagement (Macnamara, Hambrick, and Oswald 2014). Vigor, dedication and absorption are some of the leading causes, and these factors highly influence the leading causes of burnout.

To reduce the occurrence of burnout, an organizational approach seem to be the best (Macnamara, Hambrick, and Oswald 2014). Attempts to engage and reduce burnout in individual approaches often fail to consider work and task cynicism and accomplishments as considerable factors. Giving individuals vacations or temporary different tasks might alleviate the problem, but will not remove it. An organizational approach seem to have better efficiency in practical applications. Creating work-settings where the focus is to increase engagement, contrary to reducing burnout is recommended.

The most notable characteristic on job satisfaction is the nature of the work itself, the "intrinsic job characteristics" (Saari and Judge 2004) This includes job challenge, worker autonomy, variety and scope. These seem to be the best predictors of employee retention (Saari and Judge 2004). In a large metastudy Judge et al. (2001) measured an increase in worker performance by .30 the more satisfied he was with his job. Performance had greater impact in complex, professional work.

Zuboff (1988) is one of the earliest researchers analyzing employee job satisfaction when technology is introduced and modifies their workday. Their job satisfaction, attitude towards supervisors and the organization may be negatively affected if this reduce the self efficacy of employees, and reduce their previous expertise and competence to the same level as a novice.

These organizational requirements are considerations for the approach this thesis takes for assuming the human role in decisions as important. In order to retain and motivate employees a basic self efficacy is required. Humans need to build self efficacy deliberate decisions and individual responsibility to actually increase their enjoyment of work. Facilitating this process through the development of operator skill is a potent approach, and human decisions will be the focus of this thesis.

2.2 Introduction to Human Decision Making

Decision-Making is defined in Cambridge Dictionary as "The action or process of making important decisions" (*Decision-making* 2016) and a decision is often regarded as being based on a number of sub-decisions (Hoffman and Yates 2005). Decision skills are influenced by a number of cognitive processes, and when performed in complex environments human decisions are based on assumptions and intuition (Hoffman and Yates 2005; Klein, Ross, et al. 2003).

Hoffman and Yates (2005) argue that the decision making process as defined in the common language is insufficient, as it often is simplified to a three step model of identifying, deciding, and executing on a certain thing. These decisions are rare and artificial, compared to the decisions encountered in work outside of theory. Human decisions are influenced by such factors as inherited dispositions, abilities, training, culture. And research attention spans from option evaluation to heuristics and biases. Monitoring work processes to identify decisions is not enough, a theoretical understanding of human decision making and the approaches to our concepts of our environments and the goals and subtleties of decisions is important to create systems which are able to support decision making, and to improve the decision making abilities in non-computerized approaches.

I will analyze human decision making with a basis in the cognitive abilities and limitations of humans and its effects on human decision making. Decision making is in this thesis limited as the process of perceiving a problem, generating one or more hypothesis based on both internal and external cognition, and finally deciding on an approach to handle the problem. This process of decision making can be automated, or performed by humans. The main decision-making issues researched in this article are problems that have to be decided under 'uncertainty' (Tversky and Kahneman 1974). In situations where all data available cannot be compared to all information in a given period of time. Decision making is a subject to the cognitive sciences, the studies of how the brain works. To understand how to make industrial operators improve decisions, we need a basic understanding on the approaches humans take to make decisions outside of the laboratory.

Decisions are made every minute, but most are not consciously deliberated on over a period of time. The decisions made in this article is highly related to the individuality of operators, and their intrinsic motivation and autonomic decisions. The increased proficiency of an operator can affect both operational efficiency but also satisfaction. 80% of industrial accidents are said to be caused by human errors, in some reports even more (Rasmussen 1999; Salminen and Tallberg 1996). Accidents are often categorized into the Skills, Rules, Knowledge model (Rasmussen 1983) by lack of skill, knowledge, or the use and understanding of cognitive rules, and the understanding of how mistakes often are *partially* caused by wrong decisions is an important focus point of the following exploration of Human DM.

2.2.1 Applicability

Most if not all current frameworks for how Decision Making works in practice seem to be based on rigid research, but still there are tens to hundreds of models explaining both how simple and deliberate decisions should be approached. There will never become one generalizable model that solves human decision making, but the models developed can help understand how we make decisions, and guide humans on to a better path through *metacognition*.

There are several similarities between research on DM in avionics, medicine and industrial processing. Lindgaard (1995) argues that human problem solving characteristics are valid across domains such as clinical and process control, but that the systems developed will need to vary considerably between these domains . Systems design is not necessary generalizable, but much of the research on the theoretical basis for human decisions is applicable to a range of fields (Kaber and Endsley 1998; Lindgaard 1995).

The most compatible research to industrial decision-making is research exploring decisions based on data and observations which afford a reasonable amount of certainty and clarity. Kahneman and Klein (2009) argue that expertise is most applicable in these areas of high validity, fields where the same situation occurs multiple times and can be evaluated and learned. The reverse is expertise in stock markets, predictions on societal changes where uncontrollable external events have a high degree of impact on outcomes. A high validity environment is required for the development of routinely good decisions; thus for expert intuition. The high validity environment is defined by a sufficient regularity to make correct decisions based on previous experiences. Decisions made on equipment and in industrial process environments often comply with the concept of a high validity environment, but as we will see from this review, industrial systems awareness of the implications of high validity, and a continued commitment to implementing it into digital systems design.

2.2.2 Decision Support

P. J. Smith et al. (2012) argue that an understanding of the decision making literature is an important part of the knowledge engineering required to implement decision and automation systems. Familiarizing with the literature enables the designer to optimize decision making strategies, trying to avoid biases, and educating the decision maker.

The implementation of DSS has currently not been consequently proven as effective in all domains. Moja et al.'s 2014 review of support systems suggest that there is no statistical effect on morbidity in hospital in situations where DSS are applied as assistance to healthcare professionals. The low number of participants in these studies argue for a pessimistic view, where even positive results from scientific studies might be subject to publication bias. On the other hand, we know that people are capable of increasing their decision capabilities; the current systems might not approach the problem effectively.

Supporting decisions through learning is another approach, Billett (2001) states that: "How workplaces afford opportunities for learning, and how individuals elect to engage in activities and with the support and guidance provided by the workplace, is central to understanding workplaces as learning environments. " (Billett 2001, p2) (See also Bereiter and Scardamalia 1993, Ch. 8). This statement might be seen as commonsense, but the importance is in the context. The variety of opportunities provided for learners will be important for the quality of learning that transpires. Equally, how individuals engage in work practice will determine how and what they learn. Billet (2001) further state that "these factors might be overlooked if the links between engaging in thinking and acting at work and learning through those actions is not fully understood. And, establishing a workplace training system, without understanding the bases of participation, is likely to lead to disappointment for both workers and enterprises.“ (Billet 2001, p6). Decision System design with the goal of improving decision skill in operators will have to evaluate the learning opportunities, and the restraints this implies on the design of the learning approaches.

2.2.3 Human Cognition and Decicison Making

Decision making that involves humans is directly related to Human Cognition. The cognition of humans

2.3 System 1 and System 2

Cognition in decision making has in the last 30 years been greatly influenced by a dual-procession theory in which human cognition is divided in two distinct systems with greatly different attributes (eg. Kahneman 2003, 2011; Kahneman and Frederick 2002; Klein 1999). I begin the explanations of human decision making with these two "systems" because the underlaying principles should be prevalent in all models on real human, and operator decision making.

2.4 The dual-processing theory

A popular conception of cognition in decision making is represented by a dual-processing theory (eg: Evans and Stanovich 2013; Kahneman 2011; Kahneman and Frederick 2002; Klein 2009). Kahneman (2011, pp28-30) describe the two as the "automatic system" and "effortful system", but clarifies that we should not use the terms as more than nicknames for generalizations of a collection of processes in the brain. Kahneman's reasoning for using the names System 1 and System 2 is to have a concrete subject that humans can fit stories and opinions to. These systems represent different approaches in the brain to thinking. System 1 is fast, low effort, intuitive, optimistic and unaware. System 2 is largely characterized as a polar opposite, it is slow, analytical, critical and requires increased conscious effort. But System 2 is lazy, it resists work and works relatively slow. Because System 1 is quick, and always has an answer ready, but this answer is not necessarily the correct one, the relaxed monitoring state of System 2 is what makes us able to make reasonable but fast decisions using System 1.

System 1, the "intuitive" associative one, proves effective much of the time. It is very influenced by prior experiences, and associations with situations, people, shapes, colors, sound, smells and more. All processed sensory input is at first accessed by System 1, and it is instantly ready to provide an opinion. The system is characterized by heuristics and other mental shortcuts. Humans recognize patterns of sensory inputs, and decide on an opinion of the situation. System 1 is fast, and often provides the right answer. But it can fail, and it can fail catastrophically. When a situation is thought to be recognized, the normal response is to make new information fit the working hypothesis. If the working hypothesis is wrong, it can take a lot of conflicting cues to snap out of it. (Kahneman and Frederick 2002)

System 2, is the analytical system. It does not want to be set to work, because it requires a lot of attention, and it is often sequential. Every decision requires directed thought, and multiple hypotheses need to be generated and deducted before the "best" decision using the available information and best known weighting method. It is engaged when the cues does not fit any existing model. System 2 is required to solve complex problems that has not been experienced before, but can also be forcibly introduced to check System 1. When the cognitive systems are overloaded, system 2 often fails to monitor system 1 and obvious errors might occur (Kahneman and Frederick 2002).

The importance of introducing these terms is to familiarize with a prevalent view in psychology, that has an impact in all kinds of human decision making, where the "optimal" decision inevitably is influenced by aspects such as mental and physical mood, intelligence, knowledge, exposure to statistical thinking and time pressure (Kahneman and Frederick 2002).

2.5 Reasoning

The applicability of these as a model of human decision making models is widely accepted, but they are not rarely used on their own. Humans employ a variety of strategies, and the research for a good model of human decision making continues to this day. In the following I will present some models for human decisions, and two different

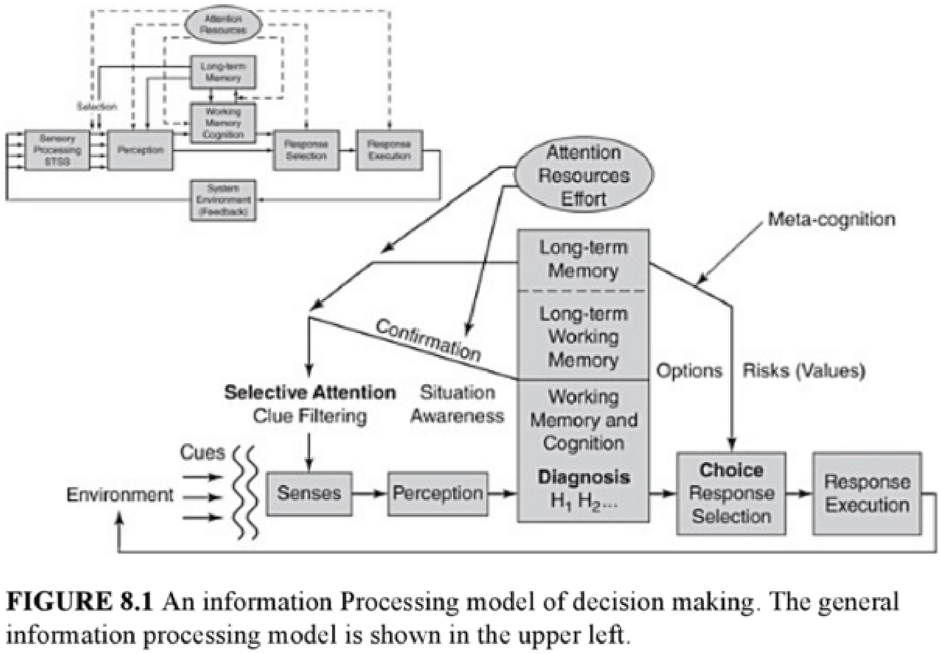

Figure 2.1: An information Processing model of decision making. Illustration from Wickens, Hollands, et al. (2012, Fig 8.1)

andsometimesperceivedasopposing research approaches to the human decision process is presented in short.

2.5.1 Reasoning Strategies

There are probably hundreds of reasoning strategies and various models for these, the models using cognition range from strictly analytical and objective to being based on intuition and heuristics. Some are based on simple features, such as lowest price of a product type. The ones that are more interesting in real-life decision making scenarios are those that are made under uncertainty. Where the situation does not fit into a previous model, and where the humans reasoning for coming up with an adequate solution is challenged.

Most models are based on a similar base of how humans make decisions, and the explanation from Wickens, Hollands, et al. (2012) is used below. The information processing model is an introduction to the basis for the following sections, and for the introduction of several strategies and approaches to decision making.

Wickens, Hollands, et al. (2012, Ch.8) describes a general approach to decision making in **Figure 2.1**. Simply explained; Any environment leaves an enormous amount of cues. Humans, machines, animals, plants, everything leaves cues to the observer as to their state; present and past. A cue is picked up by our senses, a person arrives late, a machine generates a new frequency of sound, a warning sign on a closed container. All cues require some degree of experience to be perceived, but might not necessarily be consciously interpreted. One or many hypothesis is generated based on one or multiple cues, and these are reviewed. The hypothesis cannot be created using long term memory, It is generated in working memory and later the long-term memory is accessed to retrieve confirming cues from previous situations. Using working memory, and long-term working memory the cues are compared to similar situations presenting the same cue, and hypotheses are created.

These hypothesis are compared to other cues in the environment, by constantly looking for confirming or contradicting evidence.The validation process is iterative, and when one hypothesis is discarded or modified, a new iteration of an evolved or adjusted hypothesis might be evaluated. A choice is made based on the best hypothesis, and the response is executed giving feedback to the environment.

By being aware of human and personal decision biases, often termed meta-cognition, we are able to better evaluate our choice and to make a conscious effort into avoiding traps and errors related to decision making (Wickens, Hollands, et al. 2012, ,Ch.8). The decision-process is limited by attention, resources, effort, situation awareness, experience, cognitive biases, abilities. To make decisions, humans employ a set of different strategies. While some are conscious, like making decisions based on a spreadsheet of weighted information, others are unconscious but elaborate. An example of this is expert decisions made in complex situations where the decision often is based on unconscious processing of cues and situated knowledge (Klein 1999)

To implement learning into the decision making process, we must retrieve feedback through a feedback loop (Wickens, Hollands, et al. 2012, Sect 8.4), (see eg., Black and Wiliam (1998) for a review producing convincing evidence for learning in all levels of expertise through correct feedback). Feedback of decision outcomes is sometimes used to assist in refining a diagnosis, when the action can be altered after receiving feedback. Meta-cognitive evaluation may trigger the search for more information. Lastly feedback may be transfered into learning and knowledge. Although often delayed this feedback may be processed in long-term memory in order for the decision maker to revise his internal rules of decision making or the estimates of risks.

2.6 A selection of DM Strategies

Wang and Ruhe (2007) presents an overview of decision strategies, and categorize them into four areas. While they do not present a deep review of any of them, awareness of these categories is a good basis for further reading.

2.6.1 Intuitive

Intuitive decisions are naturally based on intuition, unconscious thought and evaluation where a result of the decision process is picked. Examples are arbitrary, preference based, and commonsensical decisions. These examples often use simple familiarity, tendency, expectations, and cost measures to come up with an answer.

2.6.2 Empirical

Empirical decisions are based on a knowledgeable exhaustive research on the decision scenario. Common examples are trial and error, experiments, experience, consultants, estimation. These are all connected in that they use previous knowledge and experience to predict the future, the degree of certainty is varying but if performed correctly the outcome will be as rigorous as possible for humans. The problem is that these decisions require an amount of time, experience and level of reason which is not frequently available for most tasks.

2.6.3 Heuristic

Heuristic decisions are based on human estimation methods that work to make decisions easier and faster when making judgments under uncertainty. These decisions can be affected by principles and ethics, that the person has acquired over time. Other heuristic decision types are representative, availability and anchoring. Heuristics work by aggregating information acquired into a unconscious predisposition for choices. Picking a brand over another, guessing a time period of a picture based on clothes and image quality. All humans have biases in these heuristics, and they are hard to notice and to avoid. Some of these biases will be discussed in detail later, as they are significant for all kinds of decision making.

2.6.4 Rational

Rational decisions are ideal decisions based on all evidence and cues to an objective set of goals and requirements. But such decisions prove impossible for a human. Our best approach is to choose a *set* of variables to evaluate a decision, only then are we able to consistently make the “best” decision.The two main categories of rational decisions are based on the event’s rate of change; an event that is changing and uncertain should be handled with game theory, interactive events and decision grids. While static decisions, such as an investment of a new kind of equipment or choosing which machine to maintain first can be organized into strategies such as minimum cost, maximum benefit, maximum utility in a cost-benefit ratio. The cost/benefit can be based on an evaluation of certainty, risks, and uncertainty.

2.7 Decision Evaluation Approaches

2.7.1 Satisficing

The difference between singular and comparative strategies in decision making is related to the findings of Nobel Prize laureate Herbert Simon, which in 1957 introduced a theory of decision strategies called ’satisficing’; selecting the first option that works well enough. Satisficing is different from optimizing, which means trying to come up with the best strategy. Optimizing is comparatively hard, and takes a lot of time and the idea of Simon was that humans mostly satisfice, and that ’rational decisions’ are uncommon. Satisficing is by design more efficient. While satisficing was originally made as a decision strategy for use in business and economics, Klein (1999, p298) argues that it is even more applicable for events where time and outcome is highly related, in live and ongoing events with uncertainty to decisions. Klein lists examples such as in aviation, military, firefighting and medicine.

2.7.2 Expected value

By always choosing the most valuable outcome. The problem of this approach is that a general framework for defining the value of outcomes in a range of environments is impossible to create. A choice that would be optimal repeating over and over again, might not be optimal if you only have one chance. When time and pressure limits the available data to perform a decision, this problem of conceptualizing a value for every choice gets harder. (Wickens et al. 2012, §8)

2.7.3 Good decisions from good outcomes

One approach to decisions is to view a decision as a "good" decisions when the decision created a good outcome, and bad ones are the ones that create a "bad" outcome (Wickens, Hollands, et al. 2012, Ch 8). This view is an straightforward approach to evaluate a decision, although very susceptible to hindsight bias (eg., Croskerry 2003a). Klein (2009) disagrees, and counters with this definition: "a poor decision is one that if the knowledge gained would lead to a different decision if a similar situation arose." (Klein 2009, p.271) This view includes the feedback loop as an indicator for decision strength, and a good decision is a decision that would have been tried again if the same situation occurs twice, even if the outcome the first time was not "good".

One example of a bad decision that often appears in decision-making literature is the USS Vincennes case. A commercial airplane was mistaken for a fighter plane and shot down (Cooke 2008, pp. 78-80; Klein 1999, pp. 75-78). This is rightly and widely regarded as a bad decision, but as analyzed by Cooke the circumstances of the decision involved both errors in automatic systems, human performance and contextually driven expectations. Just one year earlier, on the USS Stark, the decision to hold fire was made and 27 soldiers lost their lives when attacked by a fighter plane mistaken for a commercial airliner. These two decisions could just as likely have been switched and would not have been the event to start the Natural Decision Making branch of cognitive research (Klein 2008), and a required mention in every article on the subject. Decisions are not black and white, and we must not succumb to the hindsight bias when analyzing and evaluating them.

2.7.4 Expertise

A third approach is using expertise as a measurement of probable decision quality. Experts in fields such as chess and physics make better decisions in their field, can we apply the same to all kinds of decision makers? One of the problems with this approach is that experts in several non-structured domains do not create decisions better than novices. (Wickens, Hollands, et al. 2012)

2.8 Two prevalent Approaches to analysis

2.8.1 The Analytical Approach

Rational or Normative decision making, and how people should make decisions according to some optimal framework. How can decisions be optimized to select the "best" outcome of a choice situation. The cognitive studies in this field is concentrated on the departures of the human choice from the optimal decision. Human Biases and heuristics are the prevalent themes. (Wickens et al 2015, §8.2).

2.8.2 The Intuitive Approach

The human short term memory operates with a small number of items (see eg: Brady, Konkle, and Alvarez 2011; G. A. Miller 1956), but there is evidence that humans can process more items better when not consciously deliberating them (Dijksterhuis, Bos, et al. 2006). Dijksterhuis and Nordgren (2006) suggest that small decisions should be made using deliberate thinking, but larger decisions benefit by using unconscious thinking. Contrary to the often established belief that choices are better when made with deliberation, a view that has been present for hundreds of years (Dijksterhuis, Bos, et al. mentions Descartes and Locke), it is according to the authors still presented as the most valid method in current literature. Using unconscious processing of decisions seem to lead to better satisfaction in the decision makers minds, and more often the objectively superior choice is made (Dijksterhuis and Nordgren 2006).

2.9 Cognitive Heuristics and Biases

There are several areas of decision making that are under current research, but the most prominent one is the Heuristics and Biases approach. Sprung out as an reaction to the "Rational Choice Model", and applying the Herbert Simon's idea of "Bounded Rationality" (Gilovich, Griffin, and Kahneman 2002). This approach assumes that human decisions are for the most part subject to a number of heuristic principles[1], employed to limit the cognitive work required to make decisions. This description can suggest they are a product of lazy and inattentive minds, but when experiments are performed with incentives for attention the effect of the biases is not sufficiently reduced(Gilovich, Griffin, and Kahneman 2002). Heuristics are piggybacking on basic calculations that the mind automatically associates with context and irrelevant data. The automatic processing seems to ignore sample size, prior odds, reliability of evidence and more similar effects, and the research on heuristics and biases has uncovered many more such 'biases'. This effect is present in everyday decisions, but the studies of heuristics and biases also try to find specific situations when these biases come into effect. To better be able to control and educate on these. (Gilovich, Griffin, and Kahneman 2002)

The Heuristics and Biases approach can be traced to the 1954 seminal book 'Clinical versus statistical prediction' by Meehl (Kahneman and Klein 2009). Meehl had reviewed

[1] "[Heuristic princpiples] ... reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations." (Tversky and Kahneman 1974, p. 1124)

20 cases where algorithms had been introduced and tested against human decision making, and in almost every case the algorithms performed better than human prediction. Meehl believed that systematic errors in the decision making process were the cause, such as ignoring a base rate and believing in intuition. Inconsistency is one of the major influences of the problems with human decision making, humans evaluating the same case will not be consistent in their decision (Kahneman and Klein 2009).

Tversky and Kahneman (1974) published their seminal article “Judgment under Uncertainty: Heuristics and Biases” in 1974 which examined three familiar heuristics that affect how people make decisions under uncertainty: (1) representativeness, when people automatically match patterns, (2) availability of instances of memories greatly affect how people look at situations, (3) adjustment from an anchor; how people anchor their estimates to numbers that is clearly unrelated to the current decision. This article has at the time of writing been cited over 30 000 times, and Kahneman and Tversky’s contributions in cognitive decision making ended up with Kahneman receiving a Nobel Price in Economics for this work. Tversky would after all accounts have been a part of the of prize if it was awarded posthumously (Kahneman 2003).

The core idea of the heuristics and biases program is based on the observation that humans use simplifying procedures instead of extensive algorithmic processing to make decisions under uncertainty (Gilovich, Griffin, and Kahneman 2002). In many decisions, operators use mental shortcuts and rules of thumb to arrive at decisions. These are called heuristics, and are central in much if not all decisions we make. Kahneman (2011) uses this definition of heuristics: “[Heuristics] is a simple procedure that helps find adequate, though often imperfect, answers to difficult questions.” ((Kahneman 2011, p. 98)). The heuristics create a way for humans to make better decisions by replacing a gap of information with a qualified guess based on previous experiences and knowledge. While the gap is filled using informations that has been processed by the decision makers earlier experiences, this information might be misleading or wrong. Some heuristics decision models are initiated by System 1 and adopted by System 2, and other cases System 1 never involves System 2 (Kahneman and Frederick 2002). Awareness of these situations is important to be able to control the use of heuristics and monitor through metacognition (eg. Croskerry, Singhal, and Mamede 2013a).

Kahneman (2003) suggest that the use of heuristics is often giving a good answer to the wrong question. Before the actual question subject has been correctly identified system 1 fires an answer to what presents it self as an easy solution. When a discrepancy is detected people often discard their intuitive answer and utilize system 2 to analyze the situation and the discrepancy and to come up with a new solution.

As an example of biases in the real world Kahneman (2003) refers to his work with the recruitment of soldiers, where they went through an interview process and presented quantitative test results from performance and cognitive tests. The interview was the final obstacle in the admission process, and could keep or eliminate any applicant. What Kahneman found was that the interviewer feels certain that his choices are the best soldiers. When informed of the negligible correlation of soldiers with the expected results from the interviews, interviewers did not adjust their satisfaction with their choices. While the numbers clearly showed a correlation between test results and performance. The heuristics involved in the hiring process show how we often overestimate certain non-influencing characteristics as essential to the decision model. Both lack of feedback and the resistance to change led the decision makers to never revise their model of influencing aspects of a good soldier. This aspect of "superstition" is one of the many aspects of heuristics that are wrongfully applied.

> "The best we can do is to compromise: learn to recognize situations in which mistakes are likely and try harder to avoid significant mistakes when the stakes are high. … it is easier to recognize other peoples mistakes than our own." (Kahneman 2011, p. 28)

Kahneman and Klein presents Goldbergs evidence (In Kahneman and Klein 2009, y1970) of the *bootstrapping effect*, in which Goldman observed the decision making of 31 practitioners over a 900 cases and created an individual profile for each of their predictions. The he applied this profile to review the net 900 cases, and found the profile to make better decisions than the humans. This effect illustrates the point of inconsistency in human judgment, in some cases to an extent that severely impacts the validity and repeatability of human judgment.

2.10 Intuitive Reasoning

Dane, Rockmann, and Pratt (2012) and Goldstein and Gigerenzer (2002) argue that the research on heuristics has switched the definition of heuristics from "…heuristics are strategies that guide information search and modify problem representations to facilitate solutions." (Goldstein and Gigerenzer 2002, p. 75) to "Poor surrogates for optimal procedures rather than indispensable psychological tools". Their argument is that much of the research performed has a major focus on the shortcoming og heuristics and the positive and inevitable performance impact on real-life tasks is overlooked.

Neys, Cromheeke, and Osman (2011) show how research in intuitive responses and in correlation with the effects of earlier H&B research shows how the study design and nuances of experiments often produce contradictory results. They argue that the image of cognitive heuristics as misleading seems to be withering.

2.10.1 Naturalistic Decision Making vs Heuristics and Biases: Intuition vs Analytic?

Naturalistic Decision making (NDM) and Heuristics and Biases (H&B) are two approaches to unwrapping the decisions of humans. The different approaches they use can be seen as a top down, and bottom up approach, where NDM looks at experts in real situations to figure out how they work, while HB looks at laboratory studies with control groups and controlled studies (Kahneman and Klein 2009).

NDMs primary goal is to 'demystify intuition in decision making' (Kahneman and Klein 2009). Klein (2008) argues that the NDM is a continuation to the work from Heuristics and Biases field. The argument for branching off and approaching DM in a new way is that while HB has recognized how people fail to make decisions, they will never find how people actually make decisions by continuing with laboratory experiments. NDM argues for observing *experts* in the field, the goal is to better understand how experts think and apply their knowledge. Knowledge elicitation methods such as Cognitive Task Analysis (CTA) is often used, because the experts rarely know what they actually are doing. They seldom strictly adhere to procedural instruction, but utilize tacit knowledge to adjust their performance according to the situation (Kahneman and Klein 2009). The approach from the initial NDM researchers was to look away from HB and how people make suboptimal decisions. They wanted to approach the actual decision makers in their own domain, and study how they actually made good decisions and what factors impacted this real life decision making (Klein 2008).

"A person will consider a decision to be poor if the knowledge gained would lead to a different decision if a similar decision arose." (Klein 1999, p. 271) People make decisions all the time, why are some of them better than others? The main ideological difference towards this question between HB and NDM, according to Klein (2009, p. 272), is that the heuristic view sees poor decisions as caused by biases in the way we think. Klein argues that this often is seen as an indicator of the poor performance of heuristics, and in many cases it seems that the negative sides of heuristics is demonstrated. The naturalistic view tend to reject the idea of faulty reasoning because of biases and take the position that poor decisions are caused by factors such as lack of experience, lack of information, and due to mental stimulation. These 'de minimis' errors in which signs of an environmental problem are explained away as unimportant to a future or past error or mistake (Klein 2009, p. 247).

In contrast Heuristics and Biases (HB) has a skeptical attitude towards expertise and expert judgment. It is leaning more towards clinical trials and using decision support systems and procedures to limit errors in human decision making. They focus on the biases and processes that reflect limitations in human attention, working memory or strategy choice. As well as focus on common decision routines, known as heuristics, that work well most of the time, but occasionally lead to undesirable outcomes.H&B does not focus on the deviations from the optimal choice, but how people process information and the structure and limits of humans as an information processing system. Although these fields might seem different, the goal is the same; What makes the best decisions and how can experts improve their own and the non-experts knowledge (Kahneman and Klein 2009).

2.10.2 The Intuitive Approach

The intuitive approach is investigating what they deem a more naturalistic approach to human decisions, as we can not (and should not) eliminate "System 1" thinking, so analyzing the positive and negative effects of this outside and inside laboratory studies the research of unconscious information processing often provides results that differ from the analysis of the H&B and NDM approach.

The intuitive approach to decision-making is based on the assumption of expert knowledge can be applied into correct decisions without explicit awareness of the steps taken to make the decision. Experts often make correct decisions based on limited or no obvious explicit evidence, unconsciously absorbing cues into the decision process. The decision making process is characterized by a 'satisficing' approach and is often fast-paced. By satisficing, the decision maker tries to generate a hypothesis using the readily available cues. The hypothesis can be modeled as a story, containing the available cues, and using prior experience to both notice cues and recalling the best approach when certain cues and combinations are appropriate. By using patterns from similar situations, the expert is often combining these patterns to generate a new decision, without awareness of this. This requires expertise, and prior experience is key.

Because this process is fast, and not based on a complete weighted analysis of all possible outcomes, intuition and human decision is has bounded-rationality. It is based on a hard-wired response to the cues, and often little or no “slow” thinking occurs. The heuristics and mental-shortcuts necessary to perform quick decisions rely on instinctive first impressions, and can lead to mistakes if these heuristics are caught in biases that are unfounded. (Kahneman and Klein 2009) Croskerry (2009) argues that because of the uncertainty of intuitive decision making, and the non numerical representation of it, the research into improving this form of decision-making has been limited in fields such as clinical decision making. The argument in other domains is that research on experts requires domain expertise, something which most academic researchers understandably lack. It seems like most of the relevant research to industrial applications in NDM is in avionics, medicine, military, and process control.

Experience seems to be the most influential factor in a decision makers intuitive judgment validity. (eg. Dane, Rockmann, and Pratt 2012). Farrington-Darby and J. R. Wilson (2006) argue that an effective way of eliciting knowledge of how experts differ from novices can not be achieved by comparing experts and novices in laboratories, they need to be compared in naturalistic environments to have a higher skill ceiling so that real expertise can be elicited.

C. A. Miller and Parasuraman (2007) state that knowledge about human reasoning is largely based on the studies of constrained problem spaces eg. chess and physics. Experts recognize patterns of activity within a domain at an integrated higher level, ”chunking”, than novices do. This abstraction method is important to limit the amount of chunks the mind has to process, as is already mentioned as a limitation and issue of optimal human cognition.

Recognition Primed Decisions

To evaluate a single course of action, fire-ground commanders use the power of mental stimulation, running the action of a certain process trough their minds (Klein 1999, p298). If they spot a potential problem, they adjust the course of action mentally and try to come up with a satisfactory solution. This is not a foolproof solution, but it seems to work better than the option of comparative analysis of options in a time-sensitive decision process.

One of the findings Klein (1999) wants to emphasize is the fact that it seems that its not the novices that impulsively jump to conclusions and the experts comparatively analyzing situations. It might just be the opposite, novices try to analyze the situation and find multiple opportunities before settling for one of them, while the experts find one opportunity and try to work within the constraints of that opportunity - creating a satisfactory solution more efficiently than the novice. This fits the model of skill development by Dreyfus and Dreyfus (1980), which remarks this trait in experts and not in experienced non-experts.

The *Recognition Primed Decision Theory*(RPD) modeled in **Figure 2.2** is an abstraction of this expert decision process (Klein 1993, 1999, pp. 15-30). According to RPD, there are three different types of decisions; (1) simple matches where the situation is recognized as fitting; (2) diagnostics of the situation is needed; (3) Evaluation of the course of

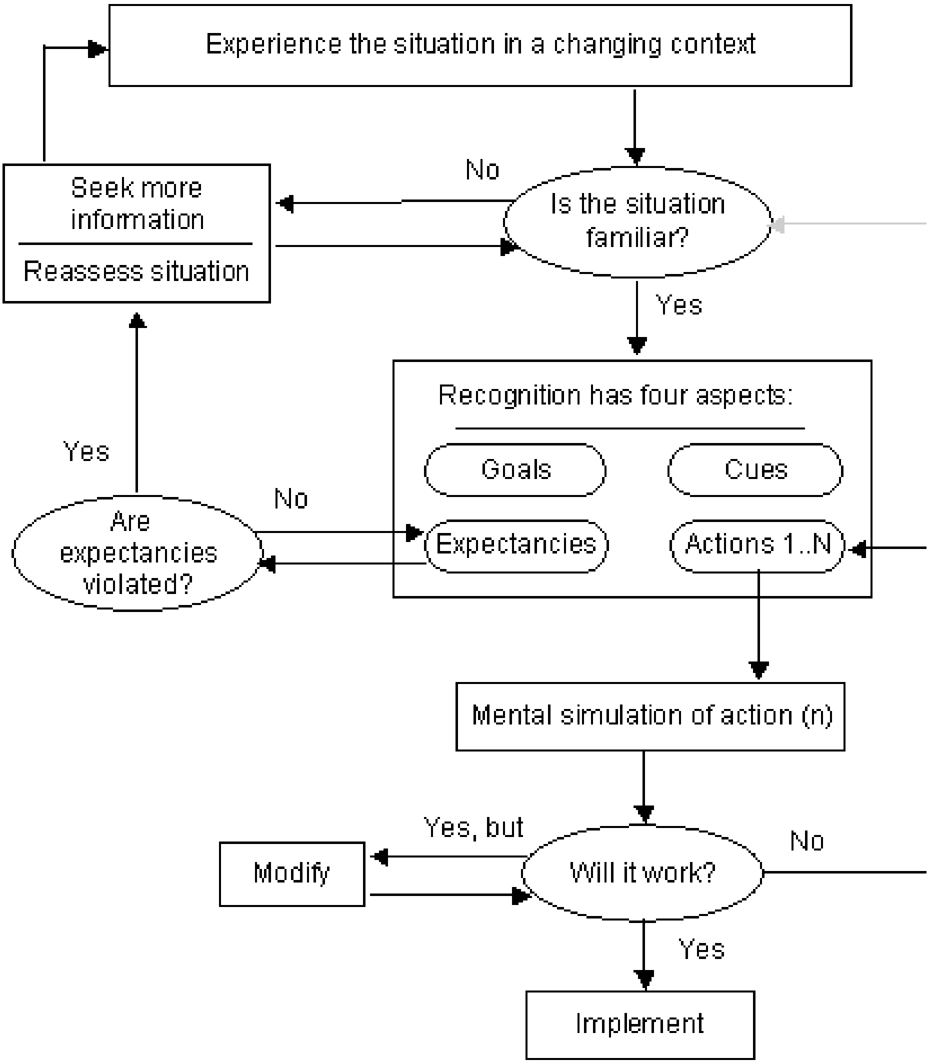

Figure 2.2: Recognition Primed Decision Model. From (Klein 1993)

action is needed. The basic implications are that a situation can be recognized as a similar or equal situation to a former instance that the decision maker has knowledge of, from tacit experience or literature. If the situation is recognized, we get four attributes. Expectancies, Goals, Relevant Cues, Actions. If the expectancies do not match, we need to find another experience to adjust the current working model. But if the model is adequate we have a number of actions available that might fit the current situation. The first action that comes to mind is evaluated based on a mental simulation, and if it will work it is implemented.

Models like the RPD model suggest that humans rarely perform sequential wide searches for solutions, but rather employ memory and previous experience. The knowledge and experience is combined to what seems like prototypical response plans (P. J. Smith et al. 2012).

2.10.3 Macrocognition - A natural extension

Klein states that the core of the RPD model is based on the same heuristics described by Tversky and Kahneman (1974), the simulation heuristic used for diagnostics and evaluation, and the availability and representativeness heuristics , for recognizing situations as typical(Klein 1993, 1999, p. 298). This continues the view that both NDM and HB are interconnected and possibly should cooperate more than they have done. A combination of views from these researchers might be the most fitting for a "realistic" model of the average human decision maker. Klein, Ross, et al. (2003) works to unify a broad approach to natural cogntion outside of DM with defining macrocognition, a top down approach to cognition in which expert performance in real workplaces and environments are analyzed to generate hypotheses for laboratory testing. The macrocognitive approach encompass sensemaking, problem detection, adapting, re-planning, coordination and decisionmaking. Each of these rely in various degree on a number of supporting processes; maintaining common ground, developing mental models, managing risk, and managing uncertainty (Patterson and Hoffman 2012) The phenomena examined by a macrocognitve approach is related to microcognitive heuristics and biases research. Klein, Ross, et al. (2003) argue for macrocognition as a better approach for the discovery of methods; decades of research on heuristics had not lead to the discovery of models such as RPD. According to them a top down, situated, macro-perspective have a significant role in the endeavor to discover and conceptualize human cognition.

Some argue that this notion of Macrocognition encompass and is a natural extension to the Naturalistic Decision Making term, and that the science and study of NDM will have to address issues besides DM to get a more complete impression of the complex environment of decision making (Klein 2008; Patterson and Hoffman 2012).

2.10.4 Intuition and Expertise

In relatively recognizable environments, expert operators implement a great del of implcit knowledge of constraints, equipment, opportunities, environment, other participants, and previous experience to create a working strategy and will combine these into a prototypical response plan for sitautions that are unfamiliar (Klein 2008; Klein, Moon, and Hoffman 2006; P. J. Smith et al. 2012). The expert will often look for opportunities and satisfice for the first and best solution that fits the constraints identified.

While the intuitive approach is used by experts in their own domain of expertise, they use patterns and mental models and does not consciously process cues. Experts do rely on causal reasoning and scientific knowledge when applying to areas outside their expertise (R. A. Miller and Geissbuhler 2007). Experienced readers see words, not letters when they read. The same situated knowledge is applicable in many fields of expertise, and the development of proficiency should be supported through system interface design and learning programmes. Working to enhance chunking enabling operators to “see the matrix” is an important job of the information system.

The mental models of experts are often contrasting the teaching material and the mental model of beginners/non-experts (Klein 2009, p. 24). Experts know what signs to look for when both acknowledging that there might be a situation, and will in many cases spot the signs of errors earlier than procedures and similar models. Knowledge elicitation methods such as Cognitive Task Analysis (eg., Militello and Hutton 1998; Zachary, Ryder, and Hicinbothom 1998) can be applied to better understand and to possibly generate teaching content more in line with the experts models. .

2.10.5 Grounded Cognition

Grounded Cognition is a research approach to the cognitive research on humans that explicitly incorporates our senses into cognition. Barsalou (2008) has reviewed the current state of the research, and argues that scientific rigor in methods is oppressing progress into a field of cognition which has indications to be a better model of human cognition. Including vision, tactile, movement and similar senses and a connected distributed cognition in representation of things and concepts. And the differences caused by the ways people have experiences with these concepts, by feeling, smelling or reading about them. The argument is that the brain recollects concepts by simulating an experience and the implicit memory to create a perceptual inference.

2.11 The Analytical Approach

The analytical approach is the rigid way of performing a decision. It is the approach to a decision using analysis and weighting and Bayesian calculations for finding a ’best option’. If we want to make the perfect decisions, with all cues available and quantifiable, this is the approach to use. When in a laboratory setting, performing a selection of the rational choice, human biases often clutter our minds. The analytical approach attempts to reduce the bias effect using decision-frameworks, but these are mostly applied as decision models in economic and . Where all possible hypothesis are deduced and critically analyzed. It is based on acquired critical, logical thought and analytical skill. The analytical approach often characterize novices which attempt to make a decision the “correct” way. But it can be used as a tool by experienced practitioners when the diagnoses are rare and esoteric, as well as fatigue and sleep deprivation. In these situations the brain does more mistakes, and relies more on automated systems. A conscious attempt to analyze the situation can improve decision making efficiency. SourceS? Wickens?

2.12 Human Reasoning Errors

To better understand how people can make better decisions, we need to understand the process behind their current decision errors. (P. J. Smith et al. 2012) This section presents a categorization of cognitive errors and biases to highlight situations and types of problems that humans have a problem making the optimal decision.

Human errors can be classified into two categories; slips, and mistakes (P. J. Smith et al. 2012). Slips are decisions in which the human has the knowledge and the correct goal of operation but his actions does not match the intentions, due to conflicting motor or cognitive activities. Contrary, mistakes result from the correct appliance of a persons current knowledge to achieve a goal, but the 'knowledge' is inadequate or incorrect.

D. A. Norman (1981) define these slips, and explains how they are further classified into; (1) slips that result from errors in the formation of intention, (2) result from faulty activation of schemas, and (3) result of faulty triggering of active schemas. These categories are further detailed. (1) Intention slips; Intent: "Put lid on sugar bowl", Result: "Put sugar lid on coffee cup". (2a) Capture slips; where frequently performed tasks are executed in place of the intended one. (2b) Activation slips: Heading to the bathroom but realizing that you have no idea of why you were going there. Only minutes later recalling that you wanted to put in contact-lenses. (3) Errors caused by thinking too far ahead while performing an automated skill; Such as switching up words while presenting a speech. These slips can occur in a number of situations, and can cause incidents in industrial settings. Norman argues that the reduction method for slips is to implement feedback mechanisms, making people aware of their slips.

2.12.1 Human Error and Blame

Klein (2009, p. 129) presents Jim Reasons work on the basis of human error. Reasons "Swiss Cheese" model of errors has had a major impact in deflecting the blame on the person working at the sharp end, the operator, pilot or nurse. Spreading the investigation throughout the organizational influences. Reason argues that there are two approaches normally applied: "Human as a hero" and "Human as a hazard". According to Reason we overemphasize the "human as a hazard" model and should reduce the focus on 'human' errors.

Reason (in Klein 1999) coined the term latent pathogens, the term describes all the factors, such as poor training, design, procedures, that might be undetected until the operator falls into the "trap". If we try to understand the information available to a person, the goals the person is pursuing and the level of experience, we will stop blaming people for making decision errors. No one is arguing that we should not look at poor outcomes. The real work is it find out the range of factors that resulted in the undesirable outcome.

Woods, Johannesen, et al. (1994, Ch.2) discuss errors and incidents in Human-Computer systems. One of their main statements in this chapter is that *systems fail*(p52). Errors are a part of a bigger system where all the constraints and the context of the error is important, see **Figure 2.3**. A problem is by Woods et al. described as the culmination of a multitude of environmental issues leading to the sharp end of the error: the direct entity causing it. If this entity is a human, we will according to Woods et al. regularly see that they ignored routines, were stressed, tired or inattentive, and similar explanations. When the analysis

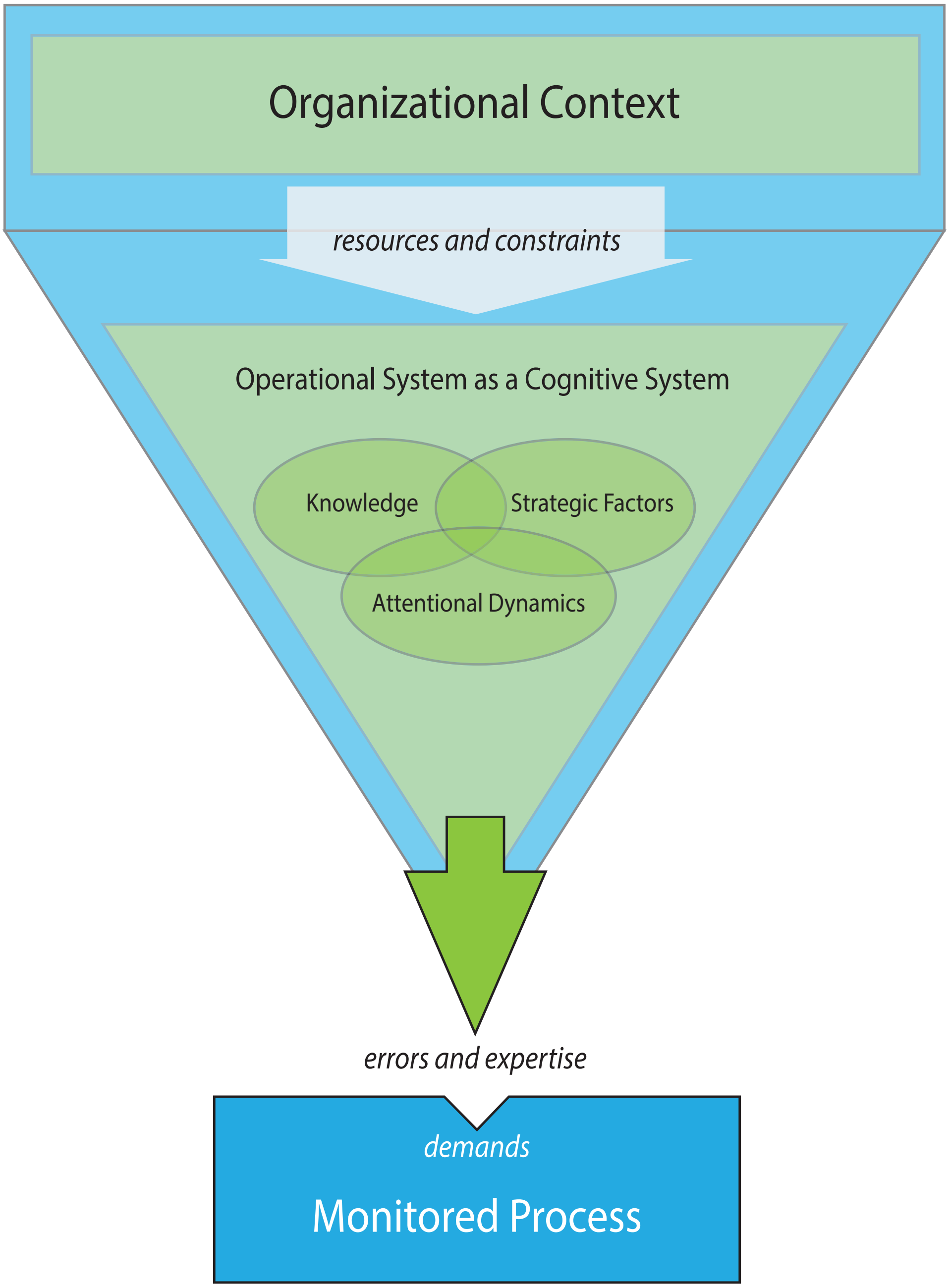

Figure 2.3: Operators work within the boundaries of knowledge, attentional dynamics and strategic factors. errors and expertise are developed at the connecting point between operations and process demands. Figure adapted from Woods, Johannesen, et al. (1994, p. 21)

of the fault can single out one thing, its easy to focus on the improvements/punishments directed to the single instance. But when examining such errors, we need to redirect attention to the environmental causes that culminated into an error.

> "The design of artifacts affects the potential for erroneous actions and paths towards disaster." (Woods, Johannesen, et al. 1994, p. 27)

Woods, Johannesen, et al. (1994) have identified a seemingly obvious statement with the above, but the importance is that it *affects it*. Systems may *increase* the potential for mistakes and errors. In some instances the new systems are so good at automatically adjusting for problems without indicating the state, that when it no longer can compensate it will fail catastrophically. Systems design has to take into account the environment, the opportunities and limitations of human operators, and they have to expect and embrace failure.

Klein (2009) further argue that we have a tendency to overlook those that perform well, and try to "fix" those that make errors more than we follow up those that achieve consistently.

> "…In contrast, when we watch people who work in well-ordered and stable domains, who carry out rules, and who remember facts, we don't find much to admire. **We evaluate their performance by counting how often they make mistakes.**" (Klein 2009, p. 111)

2.12.2 Mental Simulation

Klein defines mental simulation as "The ability to imagine people and objects consciously and to transform those people and objects through several transitions, finally picturing them in a different way than at the start." (Klein 1999, p. 45) They are effective methods for adjusting a model of a similar situation to fit a new context. Kleins earlierly mentioned Recognition Primed Decision model assumes this as the most commonly used methods for expert decision makers.

But what causes failures in mental simulations? We tend to hang on to our mental models, and adjust out world view to fit the model. While Klein (1999, p. 68) argues that its not a failure of mental simulation that they are sometimes wrong, as the point is to generate a valid explanation – not a proof. But when we use a simulation to predict a future event, we have a *overconfidence* in the simulation we created. Additionally mental simulation requires effort and time, but seems to be the better option than eg. a deductive reasoning of the situation. Which will take even more time and effort in situations where time is critical.

Simulations also have limitations when the number of "parts", elements or variables are involved. According to Klein (1999, p. 52) (Chase and Simon 1973, and eg.) a mental simulation rarely apply to more than three factors, and seems to last for around six transition states. An expert might merge factors based on previous experience, increasing the ability to simulate a complex task. In the cases where just abstracting will not help, a simulation of specific events might contribute to abstraction of a sequence or factor. If there are too many simulations, externalizing and fusing some of the knowledge into a chunk, by writing notes or drawing diagrams is a supporting task for the cognitive workload.

2.12.3 WYSIATI

According to Kahneman (2011, p. 85) an essential design-feature of the associative machine that is the human mind, is that it only represents the *activated ideas*. Kahneman coins the term “What you see is all there is” (WYSAITI) to describe the effect. This effect is a major influence in intuitive thinking, and is a way for human cognition to fill in gaps and . Information which is not recognized is not (and cannot) be taken into account when making a decision. System 1 excels at creating a story fitting the available information, but cannot take into account what it does not have access to. It works just as fast using little and much information, and largely ignores the volume in deciding on the quality of a decision. System 1 is radically insensitive to the quality and quantity of information. The first impression of a situation, a machine or a person can be determined by a few factors. An introduction, a strange noise, an annoying feature. All these effect how people make decisions using relatively few data points.

2.12.4 Superstition

Klein (2009, pp. 280-282) describes *superstition* and how it affects decision making. Learning from experience is hard, because the relationship between cause and effect is hard to grasp and to learn from, and time delays confuse this process even more. Every time we compile a story from an experience we can be understanding the effects of our decision wrong. Following this superstition problem, Shanteau (1992) argues that fields where expertise is possible are those which involve things, regularity, possibilities for errors, good feedback routines, where problems can be decomposed, and where decision aids are common. He lists fields of work like chess masters, physicists, accountants, grain inspectors. Expertise is not necessarily linked with good performance in fields such as: psychiatrists, personnel selectors, stock brokers. In these lines of work the listed traits are not as common, and unclear feedback based on irregular and unique events lead to ’superstition’ and misleading mental models.

2.12.5 Omission and Isolation, System Design Influencing Operator Decisions

Woods, Johannesen, et al. (1994, pp. 30-33) contextualize one error caused by omission of a step in a setup-procedure. A routine task to set up some equipment had a step that was not embedded in the structure of the equipment. This step then require more knowledge, and has memory demands. This error is more often committed when operators are under stress, time pressure, or are new to the system. By isolating this step it increases the chances of omission errors, one error that is majorly impacted by the cognitive state and skill of the operator. By designing procedures that reduce possibilities for omissions by isolation, by requiring, highlighting, triaing, reminders, feedback, forcing functions we have opportunities to revise the system design to reduce these errors.

Errors caused by a discrepance in the state of the system and the state the operator believes the system is in, a *mode error*. Only when the operator or the system can identify that the other has interpreted the wrong state are we able to fix this problem. Cognitive forcing strategies can often easily address this problem, and it is one of the simple "obvious" problems that occur daily with no effect, but can have a great impact on decisions if larger systems and humans operate with different views of reality.

2.13 Dynamics for Human Operating Error

Woods, Dekker, et al. (2010) divide the factors influencing operator error in a system into three categories (Seen in figure 1 above). Knowledge factors, Attentional dynamics, and strategic factors. These groups cannot be evaluated alone, they overlap and influence each other and are also affected by elements such as demands, and organizational context. The demands are on the sharp end of the problem. Demands are in a constant balancing game with resources, such as expertise and knowledge. When the demands are large, available resources are essential to avoiding errors.

2.13.1 Knowledge Factors

Mental Models and Buggy Knowledge

Mental models is defined as a "... a mental representation of the way that the (relevant part of the) world works ..." (Woods, Dekker, et al. 2010, p. 104). This world-view is used in simulations to make inferences about how the world interacts and to predict future events. The mental models are the basis for human knowledge, and are a result of practitioners experiences and builds upon prior models. Most of the time mental models of things and concepts are suitable approximations to the environment, but when oversimplifications or 'buggy' mental models are used as a basis for decisions we see errors and accidents happen (Woods, Dekker, et al. 2010, pp. 104-105). Woods et al. discuss that buggy mental models of automation systems often create a dysfunctional relationship between system and operator, where the operators trust or distrust in machine performance is the cause of accidents, an *automation* bias.

Knowledge Calibration

Knowledge and mental models requires *knowledge calibration*, an awareness of the "accuracy, completeness, limits and boundaries of their knowledge" (Woods, Dekker, et al. 2010, p. 106). Woods et al. Argue that miscalibration of mental models is caused by lack of feedback and lack of experience with applying the knowledge. This knowledge calibration cannot occur before a cue is intercepted to indicate that the model is wrong. Explicit feedback, on job education and alert performance is some of the approaches to calibrate these models. The avoidance of miscalibration, from faulty feedback or knowledge is possible, and cognitive checks has to be set in place, the biases of the mind can fool our own models of the world.

Combined Knowledge

Operators have knowledge and models which they have no knowlege of how to combine; models in a similar domain can often be combined from inert knowledge to explicit knowledge (Woods, Dekker, et al. 2010, pp. 107-108). Combining knowledge of individual models into a concept of relation and connecting prior knowledge to this connection creates an improved understanding of the environment. The problem is that environmental cues often direct what knowledge we possess and are able to recall. Knowledge is often not summoned during an incident, but readily available when probed. Wick et al. Complicate how this measure of understanding when not probed is important, but it is complicated to measure objectively.

Oversimplification

(Schwenk 1984) argues that simplification processes are unavoidable in human decision making, the models and heuristics we apply to fit our observations correct for complexity. Woods, Dekker, et al. (2010, pp. 108-110)agree that simplifications are necessary, but that there is a pitfall in oversimplifying. Oversimplification occurs when the mental model does not inherit enough complexity to correctly define the workings of the system it models. As with Recognition Primed Decision making we often try to find matching models, and look for cues and opportunities for adjusting the model to the current situation. If the original model is insufficiently advanced, we are in danger of performing a decision on the wrong basis. Cognitive biases can often be represented as oversimplifications, where prior events and experiences bias our decision skill in novel situations. But required simplifications are often regarded as oversimplifications when seen in retrospect, while the situation often require these simplifications to make any decision in the required timeframe. This aspect of simplification is hard to manage and to give guidance in which situations they are required.

2.13.2 Attentional Dynamics

Situation Awareness, and commonly the lack of situational awareness, has a major impact on decision strength Woods, Dekker, et al. (2010, pp. 116-117). Operators in changing environments with hazards, opportunities, misinformation and novel situations require great cognitive strength to process and calculate the impact of these impressions. An internal coherent model of the state of the world is an indicator of awareness, so when this model breaks down in to fragments with no clear connection we cannot perceive and comprehend the current state or predict the future. This can lead to a situation where the operator is unable to connect and complete the situational picture without rebuilding it from the start, an opportunity not commonly available when the situation is ongoing. Individual mental capacity is important in some situations, but even team awareness is an approach to reduce the cognitive workload of the individual. Systems design might impact SA, because of data presentation and cues that are different and colliding with the mental model of operators, and alarms that rip operators out of their "attentional" bubble.

2.13.3 Strategic Factors

Goal Conflicts

Human decisions are affected by the goals we operate with. Both personal goals, and internal and external organizational goals and the expectations from colleagues affect how and why we emphasize certain choices and ignore others Woods, Dekker, et al. (2010, pp. 118–123). Choices in prioritizing attention, ordering evacuations, modifying and following routines and personal safety are greatly affected by the involvement and the actual goals of the organization and the individual. In the Norwegian industry, there is a great focus on safety as a goal for operations.

For instance, I (the author) practitioned as an industrial mechanic at a Norwegian nickel refinery. We had the saying “Think Safety First” indoctrinated from the first day at work. The official stance, and the real stance of the management was that personnel safety was more important than production. Meanwhile, the operators at times sacrificed safety for efficiency, our personal intrinsically motivated goals were to keep the process going, even when there was some personal risk. Some of the more seasoned employees which had worked there for 30-40 years, their entire working career, were accustomed to the “get things done” principle. They would perform tasks efficient but at the cost of personal safety. There were no rewards for risky behavior, and injuries were scrutinized by management. This goal of safety had greatly reduced injuries and incidents, but had reached a point that seemed incompatible with operation demands to operators in my division. The incentives for high safety operations were directly affiliated with the bonus program for the division of the company, and in my impression currently led to the underreporting of minor injuries and failures to ‘dress up’ safety-statistics, which . Weick, Sutcliffe, and Obstfeld (1999) argue that humans in non-open cooperative-environments like these perform worse than teams open to admitting accidents and mistakes.

Organizational goal conflicts and incentives might cause unintended consequences even for programs that have only the best intentions in mind. The cost of different decision paths are highly related to the individual operators goals Woods, Dekker, et al. (2010, pp. 123-125). The consequences of possible failure is weighed, opportunities for instant gratification is tempting.

Woods, Dekker, et al. (2010, pp. 129-131)describe the problem of by authority-responsibility double bindings. These double bindings occur when procedures are developed that should and must be followed, limiting the operators opportunities to modify and produce new paths to solutions. In situations where the operator believes that following procedures is inadequate, but departing from procedures is disallowed. In a case of a review, the operator following the inaccurate procedure (or system ‘advice’) will have his fault be attributed to system error, reducing the “demands”, but not the responsibility of the sharp end operator. This will inhibit the growth and opportunities resorting from operator expertise.

2.13.4 Data Overload

Most accident reports show how data was available, but not used correctly or never examined (Klein 2009, pp. 129-146) Klein argues that ’less is more’. Human information processing has an upper boundary, and providing operators with infinite information often leads to worse performance compared to a limit of the number of cues. Data and information overload will lead to cognitive biases such as anchoring, as humans work with a few numbers and look for confirming evidence. When there is no awareness of a problem, this issue is increased. When information is presented context insensitive, operators will overlook and ignore issues that in review are obvious. Woods, Patterson, and Roth (2002) argue for the *data availability paradox*. In every field of practice the consensus is that more data is important for better decisions, but at the same time the flood of available data is problematic and hampers performance. The data availability paradox is result from the data avaliabilitys ""...simultaneous juxtaposition of our success and our vulnerability." (Woods, Patterson, and Roth 2002, p. 23).

2.14 Decision Biases

Researchers over the last 40 years have delineated a number of cognitive errors and biases, and more will still be found. The universality of these heuristics and biases applied by humans seem to be valid Tversky and Kahneman (1974). But the most promising cure for these errors is *awareness*, and the ability to collect and investigate sources of errors in decisions and outcomes of decisions that could be affected by debiasing. A majority of errors in clinical diagnostics performed by professional seems likely to be caused by cognitive errors (Croskerry 2003a).

2.14.1 Three Mile Island Incident

An prominent example of a real life, industrial incident influenced by two prominent biases, *anchoring* and *confirmation* biases was the Three Mile Island Accident (*Three Mile Island accident* 2016). This incident led to much of the research on Human Computer Interaction, because of its publicity and danger, and public investigation of the causes. In review, the problems were initiated due to a wrongly operating valve, and following system error. A valve controlling coolant for the nuclear operator was remotely closed by an operator, and the status lights indicated that it was shut. This valve was still open, although all system indicators on this valve told operators it was closed. Only when the next shift arrived, diagnosing the problem with fresh minds, they diagnosed that this indicator was incorrect and that the valve was still open. Metacognitive debiasing strategies are important to avoid ignoring "obvious" errors. Operators have the skills and knowledge to find the problem, but they are not looking for the obvious and simple errors Woods, Dekker, et al. (2010, pp. 117-118). On a general decision proficiency note, Weick, Sutcliffe, and Obstfeld (1999) argue that the tight coupling between systems to increase operational efficiency and time-dependent processes may have influenced this accident because of the disconnection of the human element in normal operations.

2.14.2 A collection of simple Biases

There are a number of identified biases in human thinking, that seem to be applicable to the majority of humans. Expertise in a domain will as stated earlier alleviate some of these, but a great deal of them will remain as unconscious adjustments to our decisions. In 2.1 are some of the most interesting for the current analysis of industrial decision making, but they are not exhaustive (See Croskerry 2003b, or Wikipedia for a more exhaustive list)

Table 2.1: A Selection of Biases (Adapted from Croskerry 2003a)

Bias	**Description**
Availability	Knowledge effect when experience would have led to a better outcome, and this was not evident to the decision maker. ie., The problem has not been seen for a long time, or alternately a reverse diagnosis.
Base-rate neglect	Tendency to neglect the true base rate of an occurrence. Events that rarely happen, but are available in recent memory, are often overvalued in the hypothesis generation.
Commission Bias	Obligation to do something for the problem, right now. The practitioner feels obligated to do something/anything for the patient. Tendency to not await, but execute any idea.
Confirmation Bias	The human tendency to look for cues that support the current hypothesis.
Framing Effect	Framing due to information presentation. The procedure has 90% chance of working, or 10% chance of failing. The presentation of data with identical meaning significantly influence peoples decisions.
Feedback sanction	The bias that happens when a procedure is performed, and the performer is happy about the result and will use the same approach again. The real consequence of the error is learned later, or never.
Hindsight Bias	Under or over-evaluation of the abilities of the person or system that caused the error.
Multiple alternative Bias	Reducing the number of alternatives might cause the process to be simpler to manage, but might impact the ability to see new alternatives later. Hard to reactivate discarded alternatives.
Omission Bias	A bias towards ignoring errors made by the practitioner, when something that was already breaking down is not salvaged.
Order Effects	Information pick-up can be represented by an 'U' diagram. We remember the first and last things people tell us. It is important to be aware of this tendency when receiving and giving information.
Outcome Bias	If a bad decision turned out good, it will be remembered as good. And the reverse is true for a good decision that turned out bad.
Overconfidence Bias	A universal tendency to believe we know more than we do. Using intuition, incomplete information, ignoring cues and creating them to fit our world/view. Very related to the anchoring and commission biases, in that our own ideas and actions are more valued.

Table 2.1: A Selection of Biases (Continued)

Bias	Description
Playing the odds	When two problems can be recognized by the same cues, there is a tendency to try to fix the most common one first. Instead of further examining to verify or disprove the hypothesis of a less common problem.
Posterior Probability error	Dismissing symptoms because of equipment/patient/other history. "The pump has always made that noise." – rejecting it as a potential symptom or cue for a bigger problem.
Premature Closure	Coming to an conclusion before it has been verified, and stopping the search for a better solution while waiting for the verification.
Search Satisficing	The tendency to call off a search when a fitting hypothesis for the problem has been found.
Vertical Line Failure	Silo thinking and performing tasks economically, efficient and utility. Carries the inherent penalty of inflexibility. Lateral thinking is necessary to find the best solutions.
Visceral Bias	Your feelings towards the patient can affect decision-making capabilities.

2.14.3 Biases and Debiasing Strategies

Tversky and Kahneman's 1974 article, "Judgment Under Uncertainty: Heuristics and Biases" is the seminal articles on biases and how they affect human decision making. The three main categories of biases discovered by Tversky and Kahneman set the stage for a plethora of research on how people make decisions based on Herbert Simon's idea of Limited Rationality. The effect on human reasoning errors are massive, although some (eg: Klein, Ross, et al. 2003) argue that the effect on experts is limited. Others (eg. Croskerry 2003b; Croskerry, Singhal, and Mamede 2013a) argue that a metacognitive awareness of biases is critical for optimal diagnostic performance.

The three categories of biases Tversky and Kahneman found are related to how people make decisions when not all the information is available or processable, or when the technique in the trick is unfamiliar or novel to the problem solver. While the issue they found is that common problems; situations in personal economics and everyday decisions, show the same biased effect.

Availability Bias

The *availability bias* shows how recent and extreme events are easier to remember and have a greater impact on decisions. Events which happened in previous accidents on similar equipment might impact the diagnostic approach. The operator might ignore warnings because of recent instances of misleading error messages. Heuristics are a way to limit cognitive work, and ignoring such a common error might be one strategy. But even when machines are crying wolf, the expert operator must be able and curious to check the cause of false alarms.

Representational Bias

The representativeness bias represents the human tendency to have a limited cognitive understanding of how events are related, basic statistical reasoning and how correlation does not imply causation. This bias is important in how operators decide based on events that come to mind, and how the mind wants to create patterns, even in random data. We will also ignore base rates, such as 1 in every 100 ovens have overheat errors. If operators are presented with a hypothesis related to overheating, they are likely to ignore the base rate of the error when diagnosing the oven. We do not respond optimally to sample size or A coin flipped to Heads 5 times in a row is not that uncommon. It will happen about every $2^5 = 32th$ time. If we flip a coin 100 times this sequence occurs at least once, but humans observing will often believe that the coin is non-random.

Further people tend to predict and project outcomes that are favorable, discarding the odds. People are susceptible to an illusion of validity. In which the operators base their decisions on the similarity of the values of the problem, and what the proposed solution is supposed to fix. Largely ignoring the prevalence of more common problems a uncommon fix is applied. *Regression towards the mean* is another issue, Tversky and Kahneman apply it to feedback. A common belief is that commendation often leads to worse performance, and a critical evaluation leads to better. The real cause of this effect is that the mean performance is more common. So when an operator is critiqued for bad performance he statistically will perform better on the following task, as that is his normal operating level.

Prior Hypothesis Bias

Decision makers have a prior hypothesis bias, in which they look for confirming evidence of their current hypothesis, existing information and beliefs (Schwenk 1984). People have a tendency to find the bad sides of non-preferred alternatives. If an idea has been chosen, implicitly or explicitly, the decision maker will often resist changing the decision. An open mind to switching and reverting decisions is important for making critical decisions.

Strategy Locking

A bias towards picking the same strategy for choosing alternatives is also problematic, if operators get stuck in always making the same assumptions and applying the same strategy we might miss solutions that are use different resources and opportunities. (Schwenk 1984)

Unfounded Optimism

Schwenk (1984) further describes a bias towards making strategic decisions in which decision makers often have a tendency to decide on something thinking that if any problems come up they will be able to amend and work around them. This tendency seems to be alleviated with experience, but is important to be aware of when performing decisions under uncertainty.

Fixation and Cognitive Lockup

Often called Fixation Bias, humans have a tendency to not revise and account for the evolving situation often occurring in large dynamic event-driven environments (Woods, Dekker, et al. 2010, pp. 117-121). In retrospective reviews there are often a number of available cues that with observation should have forced a review of the situation. This fixation can be through elimination, selection or ignoring a change in the environment. Because of the wide definition, only mental forcing strategies can alleviate the general problem. Fixation often occurs due to attempts to adjust a common strategy to a problem where the strategy cannot account for the environmental differences. The best approaches to amend this fixation is to invite new people to see the situation, create new models of the situation and forcing a situational review using forcing strategies and routines. Several major accidents, such as Chernobyl and Three Mile Island, was in part caused by a fixation to a problem which could be solved by revising and revitalizing the assessment based on new evidence.

Incorrect Revision of Probabilities

Failure to revise probabilities when sequential or parallel tasks are performed that can affect probability of earlier simulated tasks.

2.15 Improving Reasoning

Human decisions have a tendency to extremity (Koehler, Brenner, and Griffin 2002) . We use subjective probability to generate decision models, but as humans are affected by frequency, availability and other biases the subjective models cannot compete with a statistical model. Experts have a tendency to attribute much of their judgments to these subjective models of event frequency. If these events are monitored and a correct statistical model is computed and learned, experts will have less biased view of the situation. They also suggest that some of the biases often attributed towards subjective probabilities are affected by self-investment. People with a stake in the outcome have a tendency to be more optimistic, (eg., the Unfounded Optimism Bias).

2.15.1 Metacognition and Cognitive Forcing Strategies

Croskerry (2003a) argue that procedural errors are easy to notice, we miss a step in a recipe and later figure out that we miss something required. Cognitive errors in comparison are tough to notice, they are internal errors that the operator has no awareness of . Cognitive errors often occur even with expert domain/skills and knowledge. People are generally not familiar with cognitive biases and errors, and by education and familiarization with biases and cognitive errors can facilitate metacognition. Klein (1999) defines metacognition as "...the awareness of the inherent limitations in human cognition." (Klein 1999, p. 158). Croskerry (2003a) has a broader description of the impact and opportunities of metacognition. For effective metacognition an understanding and appreciation for the learning process is required; the importance of the information has to be evaluated, specific items has to be remembered and forgotten. A broader view of the situation is required, beyond immediate perception. Actively pursuing information with the awareness of cognitive traps, and the issues presented. Finally, the ability of experts to use all this in the selection of decision processes and how experts often have automated the selection of approaches, using a deliberate intervention in the thinking process to identify the real deciding factors and internalizing these into the decision model.

Croskerry (2003a) describes an overview of cognitive forcing strategies for clinical decision making, but the model is generalizable to every structured environment. A prerequisite to minimizing cognitive errors is to understand the theory of cognitive errors. There are three sequential levels of cognitive forcing strategies. (1) Universal, at this level knowledge about cognitive errors must be learned to understand and be aware of biases. (2) Generic, knowledge on generic situations where heuristics might be involved in the searching for cues. An example is the 'Satisficing' heuristic where searching vigilance is reduced when the first possible cause of error is found, thereby overlooking other possible causes. (3) Specific, understanding of how cognitive errors often play a role in specific scenarios and knowing how to debias accordingly.

The levels mirror the cognition theory of humans, and by creating a depth tree of categories we highlight areas of cognition that can often be overlooked. To improve reasoning, the steps are cumulative but separate. Increasing knowledge and appreciation of the underlaying principles of improvement stands out as a key to improving general DM skills.

Croskerry (2003a) propose that a five step model can be applied, a *cognitive forcing strategy*. His approach tries to encompass an approach to awareness of common biases and their impact on a number of situations where intuition needs to be validated or scrutinized: Learning techniques for de-biasing, increasing knowledge of specific heuristics and biases, scenario recognition through case knowledge, and finally the goal of avoiding and minimizing specific errors at the *sharp end*. Stepping back and de-anchoring, broadening the horizon and simulating the decision one more time before executing irreversible processes. These cognitively 'simple' strategies force the best mentally processable decision model, and is intended to avoid pitfalls in common situations by familiar biases.

Expert Metacognition

There are indications that experience and age seems to reduce the effect of bias in human DM (eg. Neys, Cromheeke, and Osman 2011). Klein (1999, pp. 158-160) state that experts unaware of the term metacognition often apply a practical version of metacognition. Characteristics of expert implicit metacognition is awareness of own limitations. They are more often utilizing cognitive aids that reduce the use of working memory. Experts apply a perspective view of most tasks, and stepping back from the initial solution. Self critique and an ability to reflect on decisions both while they are happening and retrospective, seems to be more prevalent in experts. Finally experts are better to generate strategies based on the information gathered, for better performance on the current task. This strategy will often include cognitive debiasing strategies that they have applied due to previous experiences.

Rasmussen's 1983 Skills-Rules-Knowledge (SRK) framework is intended to categorize human proficiency into three categories. Level 1 proficiency is *Skill*, it is accomplished when a task is simple to perform and automated by the operator, the task is not necessarily simple, it can be to play a piano or driving a car. Level 2 is *Rules*, require more cognitive input but often follows a procedural pattern whereby a mix of skills and knowledge is applied to reach the goal state of a procedural instruction. And finally Level 3 is *Knowledge*, this behavior requires people to apply knowledge in any form to create or practice novel (to them) solutions. Farrington-Darby and J. R. Wilson (2006) argue that its not unreasonable to expect that experts might move more easily between the skill levels in the SRK framework. Experts adapt more easily and have a greater repertoire of rules and knowledge, while the tacit skills are often more elaborate. The reasoning for mentioning SRK in the metacognition part is to highlight how experts seem to have an easier time of incorporating knowledge based performance into a skill, or that they are able to transform a skill into knowledge. As we will see later, the SRK can be applied to learning and possibly shortening the long path to expertise.

External and Internal Cognition

R. A. Wilson and Clark (2009) compiles research showing two different approaches to cognition. The internal and external views of cognition are separated in how they perceive environments effect the decisions and cognitive work. Internal Cognition can be described as the part of our thinking in-between perception (input) and action (output). While External Cognition suggests that the internal view of cognition only sees a part of how humans perceive and process information, and suggest that a model of cognition has to address this problem. They argue that we need to see cognition in a perspective of extensions and modifiability. Extended computationalism the process of offloading cognitive resources onto external objects, such as pen and paper. This use of external resources is extremely important when modeling how people make cognitive decisions and trying to increase their decision making skills through systems design .

These new cognitive extensions are often identified from internal cognitive processes, but where the mind has identified that external extensions can help with reliability, speed and memory(R. A. Wilson and Clark 2009). Humans often use Task Specific Devices, such as hammers and screwdrivers. (Wilson and Clark argue that analysis of these TSD is essential to identifying opportunities for creating new TSD and improving cognitive support for a process, not just the individual task.

2.15.2 Deliberate Practice

> "...experience is not the mere passage of time or longevity; it is the refinement of preconceived notions and theory by encountering many actual practical situations that add nuances or shades of differences to theory" (Benner 1982, p. 407)

Kahneman (2011) quotes Herbert Simon's definition of intuition, from 'What is an Explanation of Behavior': "The situation has provided a cue; this cue has given the expert access to information stored in memory, and the information provides the answer. Intuition is nothing more and nothing less than recognition." (Simon 1992, in Kahneman 2011, p. 239)

Kahneman (2011) describes the implications of this definition as ""...reducing the apparent magic of intuition to the everyday experience of memory" (Kahneman 2011,

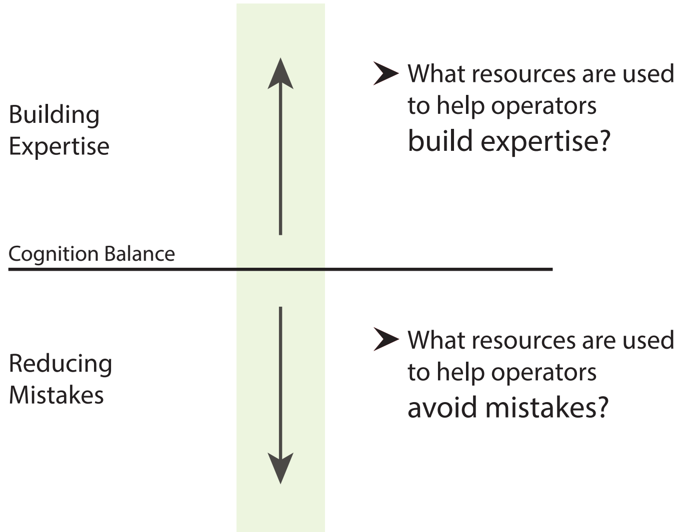

Figure 2.4: Developing Tacit Knowledge, figure adapted from Klein (2009, p. 112)

p. 239). We gain experience and expertise by recognizing known situations and predicting outcomes based on the previous cues we either consciously or unconsciously perceive.

A mind that follows what was earlier referred to as WYSIATI (What you see is all there is) will achieve high confidence in his abilities and knowledge, by ignoring what he does not know. This might be why humans have high confidence in unfounded intuitions. System 1 is System 2, the operator needs to be aware of this framing effect and its impact on decision-making. WYSIATI is the way that we can function as humans, we infer a situation through some observed cues and fit this to a model. All performed in system 1. Unless the operator is made aware of more cues, and system 2 might be set in motion. Kahneman is aware and highlights the differences between NDM and H&B approaches to decision making, relating to WYSATI and expertise, he recognize that they are applicable in different domains and at different times.

Klein (2009, Ch.7) argues that the current emphasis on reducing mistakes in organizations severely limits the development of expertise. He argues for the view of *Positive Psychology* to be applied into workplace environments. Seligman and Csikszentmihalyi (2000) started the modern movement towards Positive Psychology, their argument for the movement the focus in psychological science to develop remedies. They argue that this approach will never give fulfillment and happiness, only reduce pain and sadness and possibly just remove the identity of a person. Klein argue that this is true for operators too. And one of the areas of fulfillment is developing expertise. **Figure 2.4**. Klein (2009, Ch.7) argues that this is applicable to cognitive sciences. Klein's argument is that "...a fear of mistakes should be balanced with a pursuit of expertise" (Klein 2009, p. 112).

Tacit Knowledge

According to Klein (2009, Ch.2) tacit knowledge plays a prominent part in our ability to cope with complex conditions. Tacit knowledge is the knowledge that we cannot express, but that is unconsciously learned trough practice of a profession or task. Normal explicit knowledge such as declarative information and routines & procedures are usually known to the operator, but they are supported by a stack of tacit knowledge that cannot be easily expressed. Klein remarks that it is easy to ignore tacit knowledge when analyzing humans and organizations, because it is hard to articulate or even notice. (This issue has been approached using Cognitive Task Analysis (eg., Militello and Hutton 1998; Papautsky et al. 2015; Parasuraman and Manzey 2010))

Procedures might be applicable in simple environments and to support tasks that have a finite list of possible states, but knowing how to violate the procedures is a type of tacit knowledge (Klein 2009, p. 39). Noticing changes is a tacit knowledge, when the procedure closely match the current scenario - the expert is often the one to recognize that the procedure is not applicable to this scenario, as the cues do not fit the procedural assumptions (Klein 2009,p39).

> It is hard to give people feedback about tacit knowledge. As a result, when settings or tasks are complex we give feedback about departures from procedures instead of helping people to notice subtle cues and patterns. Except when having a conversation about procedures, we don't know how to learn from one another about tacit knowledge. (Klein 2009, p. 42)

2.15.3 Supporting Intuition

Supporting intuition is important for improving reasoning. One definition of intuition is: "Intuition depends on the use of experience to recognize key pattens that indicate the dynamics of the situation" (Klein 1999, p. 31). Subtle signs that conflict with or fit a model, that can often not be articulated by the decision maker in regards to why they observed the situation. Skilled decision makers know that they can trust their intuition, but at the same time may feel uncomfortable trusting a source of power that seems so accidental. Klein (1999, p. 33) argues that intuition is a byproduct of expertise, an expert processes clues for situations without direct awareness. He further argues that the idea of *Extra Sensory Perception*(ESP) is actually intuition, and influenced by expertise and familiarity. The sensory inputs from the situation is compared with available models of similar situations. When the situation fails to present the cues that are expected, the expert will recognize the need to step back and reconsider. This is the main difference in NDM from H&B research,

Kahneman and Klein (2009) argue that experts in structured fields have a better understanding of their own limitations, possibly because of the personal risks associated with the tasks. If an engineer has to make a decision in a field he is not an expert, he will more likely ask another expert in that domain. Clear feedback, standard methods and consequences for error appear to be factors implicating how much outside of their expertise people are willing to go, and how far they are confident in going.

An approach to teaching intuition is to develop a training program (Klein 2009, pp. 42-44). Using exercises and realistic scenarios, so the person has the opportunity to size up numerous interactions quickly. A good simulation lets you stop the action, step back and see the cues, and you can use multiple scenarios together - to better illustrate the similarities. An other approach is to compile stories using important cues. The core element is that we teach pattern matching, that has the relevance to be applied into working situations.

Kahneman (2011, pp. 240-241) argues that regularities of the environment might be easier to observe in certain domains. Immediate and unambiguous feedback are signs of a task that is easier to use intuition and "System 1" control, these are kind environments. Good and quick feedback and opportunities for practice is what Kahneman argues as the predictors of developing intuitive expertise. Whereas a system with a delayed or ambiguous feedback, a *wicked learning environment*, might trick your intuition to thinking that the process had a positive result, while the real results are negative and never addressed or acknowledged (Hogarth 2001 in Hogarth, Lejarraga, and Soyer 2015). Hogarth, Lejarraga, and Soyer (2015) suggest that we try to create kind environments in the learning resources, avoiding confused learning and emphasizing correct feedback. They suggest that simulation technology is one of the best methods for reliably featuring instant feedback on temporal-"real life" tasks.

The characteristics of expertise vary according to the cognitive demands that must be met (Mosier 2008). Expertise in hybrid ecologies entails the ability to recognize not only patterns of cues and information, but also potential pitfalls that are artifacts of technology. Mode errors, hidden data, or non-coupled systems and indicators. Expertise includes knowledge of how a system works, and the ability to describe the functional relations among the variables in a system. (Mosier 2008). Experts must be able to combine information to create a better picture, and when digital systems are applied we have a better opportunity, but also a possibility of bias towards automation that must be avoided, and taken into account in system design. Both digital and real information is examined by experienced practitioners, validating their model from system input to the cues provided by the physical object or situationn. "The physician may interpret the digital data on a set of monitors, and then examine the patient to see if the visual appearance corresponds to his or her interpretation" (Mosier 2008, p. 49) Understanding all the states of the technological systems and the clues presented, while continually auditing and relating data to compare validity is one of the challenges and advantages of using automated systems. Expertise necessitate knowledge of which strategy is appropriate at a given time in a given situation.

Expert – Novice differences

In a study of the difference cognitive work in expert vs novice emergency department physicians Schubert et al. (2013) found significant differences in how expert practitioners (10,000+ hours) and novices, handle situations in the Emergency Department. Among significant differences is: (1) novices often use the checklist approach or create a timeline of objective data acquisition (for instance lab results or radiographs). The novice looks primarily for objective information. Experts are better at telling the patients story by focusing on the extraction and interaction of essential information.

Secondly the novices had greater problems when there were no "textbook" signs of any specific diagnosis. Further novices tend to discard data that does not fit with their textbook description of a case, and will try to frame the case into previously diagnosed cases. Experts, on the other hand maintain a broader view over the situation, and because of their experience with similar non-textbook cases, are more vary of cues that should discard the working hypothesis, and are more willing to adapt to these new cues.

Error Diagnostics

To diagnose errors and to find solutions we have to compare a model with reality, or compare reality with the model (de Kleer and Williams 1987). To work effectively and efficient with mental models we have to revise and create new models based on experience, and be able to alter realtiy to fit good and working models. What separates the study of de Kleer and Williams is that they approached how models could be used to diagnose *multiple fault errors*. Their data suggest that good model based diagnostics need to use a-priori designed models to find Bayesian best approach diagnostic guides.

2.15.4 Improving Understanding - Workplace Learning

> "How workplaces afford opportunities force learning, and how individuals elect to engage in activities and with the support and guidance provided by the workplace, is central to understanding workplaces as learning environments."
> (Billett 2001, p. 4)

Both how individuals engage in activities and how the workplace offers support and guidance are central aspects as to how knowledge is acquired. In industry appliances such as aluminum industry a big portion of the work is performed on appliances the operator never understand the principles behind his work. By understanding how people learn on the workplace, we can better support the learning process and the affordance of workplace learning.

As mentioned in section 2.15.3, intuition and expertise has a decisive impact on decision strength. To facilitate acquisition of expertise some background knowledge is required, and professional learning is one way to build this understanding.

As Billett (2001) states, the findings that *if and how* the workplace affords learning impacts actual learning in the workplace, are commonsense. The kinds of opportunities provided for learners will be important for the quality of learning that transpires. Equally, how individuals engage in work practice will determine how and what they learn. Billet (2001) further suggest that "These factors might be overlooked if the links between engaging in thinking and acting at work and learning through those actions is not fully understood. *And, establishing a workplace training system, without understanding the bases of participation, is likely to lead to disappointment for both workers and enterprises.*[emphasis added]" (Billett 2001, p. 6)

Hoffman, Feltovich, et al. (2009) and Kahneman (2011, p. 240) indicate that there are a number of requirements for supporting skill and expertise in workplaces.

- working on the edge of proficiency, a stretching of skill using increasing challenges.
- intrinsic motivation to put in work at the required level
- feedback that is meaningful
- an expert mentors support and encouragement
- opportunities for practice in a regular environment

Kahneman (2011, p240) describes two basic conditions for acquiring intuitive expertise:

- An environment that is sufficiently regular to be predictable
- An opportunity to learn these regularities through prolonged practice

Kahneman argues that when both these conditions are satisfied, intuitions are likely to be skilled. Physicians, nurses, athletes, and firefighters are said to face “complex but fundamentally orderly situations” . “While decisions for stock prices and political scientists who make long-term forecasts operate in a zero-validity environment. Their failures reflect the basic unpredictability of the events that they try to forecast.punct” (Kahneman 2011, p. 240)

Instruction

Eiriksdottir and Catrambone (2011) argue for three main types of instruction: Procedural Instruction, Principles or system-oriented instructions, and examples or instances of the task. These have widely different characteristics and are used among each other in instruction. Procedures explain the steps of an operation, principles explain why the steps are chosen and the theory behind them, and examples are instances of the task where the operator gets to try or see how the problem is supposed to be handled. The goal of instruction is vital to the shape of the learning material; one time instructions can be simple and produce correct results without much understanding. In other scenarios the instructions have to take into account that the operator is expected to adjust the instructed information into new cases. Initial performance of a task might not indicate long term proficiency.

Eiriksdottir and Catrambone (2011) suggest that design of instructions to support learning and transfer of information requires a different set of factors opposed to initial performance. People often choose the cognitively easier path to solve problems, and instructional design has to take this into account. Eiriksdottir and Catrambone have through a literature review identified that fading information; reducing information available during each iteration of a procedure. Improving understanding and mental models through presenting principles of the procedural instructions will improve the mental model of operators. People can learn from examples, but only when analogical reasoning and one-to-one mapping with procedures is avoided. Incomplete information seems to be the most proficient way of inciting learning, as the cognitive work is forcibly increased and this leads to improved understanding and especially performance when going outside of standard operating procedures.

In contrast Feltovich, Spiro, and Coulson (1989) argue that initial simplified models can limit the depth students embark into the material. The initial model is often more satisfying and has glanced over some of the non-intuitive aspects of the more accurate description of the modeled concept. The first model is then often the one memorized, because the story has more relations to peoples other models and experiences. They suggest *advanced knowledge acquisition* as a method where the primary goals of the education is to get the concepts right, sacrificing the speed of which learners gain adequate knowledge but accessing the maximum potential of learners. Learning that shows comparatively low initial proficiency increase, can lead to greater flexibility and transfer when these advanced principles are practiced over time. The learners are evaluated by their understanding and applied knowledge, combining concepts to engage novel situations. Klein (2009, pp. 269-282), argues that unlearning is hard. People hold on to simplified mental models because they are relatable to experiences from other domains. To become an expert you will need to be open and able to change and dismiss mental models for models that do not fit your current world view. Klein suggest that identifying and disconnecting some "unintuitive" models early is a good approach for alleviating this issue, and experienced practitioners must be aware of this when instructing novices.

Feedback

"Experts learn more from their mistakes than from what they get right." (Hoffman, Feltovich, et al. 2009, p. 20). Mistakes happen, and they might happen frequently. But mistakes can be elusive and hidden. A practitioner that get little feedback about the result of his decisions will never have any indication of his choices impact on the environment. Humans have a tendency to believe our practice is the correct one, so debiasing this through feedback, and presenting feedback in a way that encourages learning can separate good from bad decision making development.

2.15.5 Information Needs

Zhang and D. A. Norman (1994) argue that research on cognitive decision making often ignore that physical items can support the cognitive task. They work with the term *Distributed Cognitive Tasks*, in which they argue that the external representations of cognition, such as in writing down a number, or creating physical models are not emphasized enough in the current research. They found evidence for a recommendation to further investigate the physical representation of the data and information in the external world that supports cognitive decisions. They use the term representational effect, to describe "a phenomenon where different isomorphic representations of a common formal structure can cause dramatically different cognitive behaviors" (Zhang and D. A. Norman 1994, p. 88).

Zhang and D. A. Norman (1994) continue by explaining the distributed representational space. A task can be viewed as an internal and an external representation. These two representations both combine to and extend an abstract task space, the distributed representation. The main argument of the article is that the external space and its representation might be seen as identical to a theorist, but three different representations of the same external knowledge can for a normal human occur to have no relation with each other, and task performance is greatly impacted by both instructions and artifact shapes. The design of a decision aid and the external representation of the decision system is highly important for an improved understanding of systems of all kinds.

2.16 Situation Awareness

A large portion of the tasks operators are performing in todays world are increasingly dynamic and in changing environments. Changing environments cause challenges for decision making, and one of the critical precursors to a good decision is that of maintaining *situational awareness* (SA). One commonly used definition of SA is ""…the perception

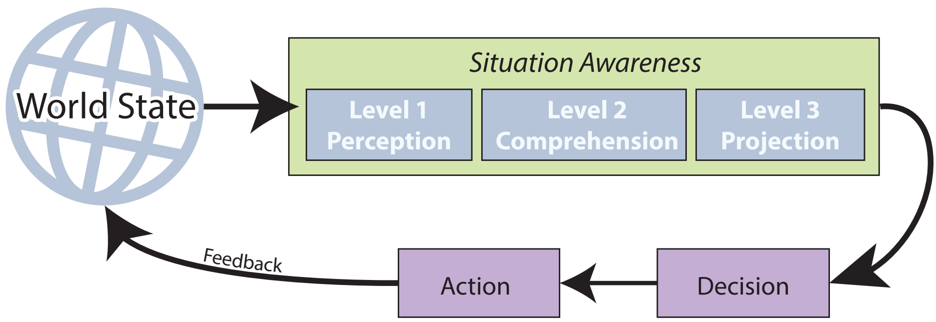

Figure 2.5: Model of situation awareness, simplified from Endsley (1995, p35)

of the elements in the environment within a volume of space and time, the comprehension of their meaning, and the projection of their status in the near future." (Endsley 1988, cited in Sneddon, Mearns, and Flin 2006) Task performance is dependent on an up to date understanding of the environment, and a temporary loss of SA can be enough to cause both injuries and economic damage. It is not enough for the operator to perceive the environment trough observing values and cues, he must be able to both understand the connection between the cues, and to project a future state based on these cues. (Endsley 1995) "Recognizing the situation provided the challenge to the decision maker, " (Kaempf, Wolf, and Miller (1993, p1110) in Endsley 1995).

In Sneddon, Mearns, and Flin's 2006 study of accidents in offshore crews, they define characteristics of the operating environments where they state that situational awareness is an important factor:

1. Multiple goals to be pursued by operators simultaneously;
2. Multiple tasks having different relevance to goals competing for the operators attention;
3. Operator performance under time stress and negative consequences associated with poor performance.

2.16.1 Levels of Situation Awareness

Endsley (1995) suggests that there are three levels of situation awareness, and that errors can occur on any of these levels. Figure 2.5 visualize her model of Situation Awareness. The three levels are Perception, Comprehension and Projection and are sequential and level based. The levels are described below to show

Level 1 SA: Perception of the elements in the environment

This is the lowest level of situational awareness and is associated with the perception of data in its raw form. This can be that a operator notices other people, status of equipment values and various labels for these data. Worker environment should be continually monitored to encode sensory information and to detect changes in significant stimuli. Attention is limited and is intrinsically limited to include the boundaries of the working memory system (Sneddon, Mearns, and Flin 2006). Consequently attention is selective and critical elements may be missed or ignored in the perception stage.

Level 2 SA: Comprehension

This involves the combination, interpretation , storage and retention of information to paint a holistic picture of the current situation (Endsley 1995). This level is shown to be a deviation of meaning from the perceived elements. This is partially supported by the mental models already stored in long-term memory. The degree of situational comprehension will vary from person to person , and expertise and skill has major effect on the level of comprehension, especially in high activity situations (Endsley 1995).

Level 3 SA: Projection

This final level occurs as a result of the combination of levels 1 and 2. The stage is responsible for extrapolating the information gathered into a projection of future events. Having the ability to correctly forecast possible future circumstances is vital, as it enables the formulation of suitable action courses to meet goals (Sneddon, Mearns, and Flin 2006) .

2.17 Expertise

A recurring theme in the previous section has been that experts perform decisions better than novices. In this part the expert will be presented, and methods for facilitating expertise are presented. The concept of an 'expert', "Experts are operationally defined as those who have been recognized within their profession as having the necessary skills and abilities to perform at the highest level." (Shanteau 1992, p. 255) This implies that an expert is anyone that performs better than most practitioners in the field. Expertise is not necessarily related to *experience*. An oft stated figure is that 10,000 hours of *deliberate practice* is the baseline to become an expert in any advanced profession, from chess to music to medical doctors. Although some evidence show that the effect of *deliberate practice* is overstated (Macnamara, Hambrick, and Oswald 2014). Experts approach problems in a different way experienced-nonexperts (Woods 1995, p. 2374). They are able to devote resources into specific tasks, or managing parallel attention and to keep track of tasks. They are able to identify which tasks are critical and suspend even important tasks to cope with developing vulnerabilities. They assign and distribute tasks to subordinates. And they know what sacrifice is required, and where to invest resources.

An example of the difference between experts and novices is presented by Serfaty et al. (1997). They studied expertise in battlefield commanders. Their findings indicate that expert commanders create a more elaborate and extensive mental model, where the steps were more detailed, and they understood and articulated the risks involved. The non-experts often came up with the same approach, but without the understanding of why and how the plan could fail. It seems that experts use prior experiences, and *war-stories* where they have personal experience, or have heard about similar events to better generate their mental model, and simulating the event. This is highly related to the feedback-loop

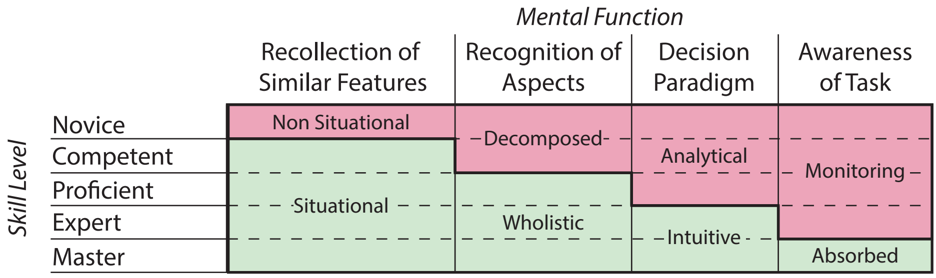

Figure 2.6: Dreyfus's judgment and decsions process model. Based on Sage (1981, Fig. 8)

discussed Wickens, Hollands, et al. (eg., 2012), where knowing both the why and what happened, will adjust future approaches to similar situations.

Bereiter and Scardamalia (1993) present one of the defining works on the elicitation and specification of expertise. There is a significant difference in performance from people with identical amounts of experience, as measured in *time*. Experience does not imply expertise. "The difference between experts and experienced practitioners is not that one does things well and the other does things badly. Rather, the expert addresses problems whereas the experienced nonexpert carries out practiced routines." (Bereiter and Scardamalia 1993, p. 11). An experienced-nonexpert and an expert might operate at the same level when practicing routine procedures, but when incidents and innovations are required the true experts use their low level domain knowledge and associative mental models to understand how the problem can be solved. Bereiter and Scardamalia suggest that the differences between experts and experienced non-experts is how they pursue their career: The expert wants to be challenged, to understand more, and apply the knowledge into novel situations. In contrast, the experienced nonexpert tries to align their work to routines and procedures. An expert practitioner that is supposed to fix a lever, will not only fix or replace the lever with an identical one, but figure out why the lever broke and create a new solution.

The expert is not born with 'intellectual brilliance', the skill and extraordinarity is based on a knowledge base of both intrinsic and extrinsic knowledge. Understanding is often based on understanding the *systems* on a deep level, experts understand the engineering and processes of the domain of expertise, rather than recognizing the process from a symptomatic level.

Figure 2.6 is designed to to visualize S. E. Dreyfus and H. L. Dreyfus's 1980 general specification of the sequential levels of skill development. As skill develops different mental functions are used based on level of understanding. Their idea is to show that expertise often replaces and extends basic operating procedures. At the same time they show that these operating procedures must be introduced to get the practitioner faster from novice to proficient. Recognizing aspects and cues in an holistic sense is one of the signs of a proficient practitioner. Relating to decision making they too see an expert as someone that makes decisions based on intuition and not an analytical approach. (For a further explanation of the levels of proficiency see: (Benner 1982))

Formal Knowledge in Expertise

Bereiter and Scardamalia (1993, pp. 61-74) discuss *formal knowledge* and its applicability to expertise. Their definition of formal knowledge is loosely based on 'it can be represented in textbooks' but they argue that the traditional view of knowledge has always been using this a kind of physically reproducible knowledge. Formal knowledge is more tangible, and ready for discussing, criticism, comparison and to teach without reconceptualizing or modifying. However, the connection between expertise and formal knowledge is not a 1-1 relationship, and experts utilize formal knowledge in various applications. Bereiter and Scardamalia argue for three main functions of importance to experts: (1) formal knowledge is essential for dealing with issues of truth and justification. According to them there is reduced use of formal knowledge to make decisions with experience (See eg: Schubert et al. 2013). But the formal knowledge is often used in justifying choices and connecting performance to understanding. Non-experts use more formal knowledge while performing tasks, but experts utilize their *informal knowledge* and experience, before justifying their choices referring to formal knowledge later. (2) Formal knowledge is important for communication, teaching, and learning. An ontology of knowledge is required for communication with other practitioners in the same profession, and to formalize knowledge using the terminologies applicable to the field. (3) Formal knowledge provides starting points for the construction of informal knowledge and skills.

A scenario illustrating the conversion of formal knowledge into skill is given by (Bereiter and Scardamalia 1993). The task of driving to your friend Amy's cottage is a skill you do not possess. Amy gives you a series of instructions of how to get there. 'Drive left at the intersection, follow for x km, under the bridge and take a sharp left'. These instructions break the main goal into subgoals that are obtainable, but you might have to use other formal knowledge and skills such as map reading and inferencing based on implicit information. After a few times following these procedures the task of driving to Amy's cottage is proceduralized and automated. This same approach is used in textbooks, with incremental learning to attain bigger goals. This 'textbook approach' can only get you partway to expertise, applied knowledge and an attentive situated experience is required to bring most practitioner to a level of expertise.

Developing Expertise

Bereiter and Scardamalia (1993, p. 222) argue that to better support expertise, the organization has to develop societies and culture where the process of expertise is normal rather than exceptional. The inherit curiosity of humans must be supported and "exploited" to give those operators that want to understand, a better chance at developing expertise. They further suggest that individual goals (In traditional education) can be replaced with goals of *classroom understanding* of a topic. If a group of operators are tasked to understand a problem, not everyone needs to completely understand it. But if a shared society within the group is encouraging learning together both individuals and the society winds up with more knowledge and experience.

Bereiter and Scardamalia (1993, pp. 77-120) uses a metaphor of driving, which show their view of how expertise require a different mindset and environmental support. Normal learning by experience tapers of when the level of performance is adequate. When learning to drive a car, most of us stop learning and are satisfied when able to handle driving on roads. This is how we satisfice, the tasks is performed adequately. They argue for an approach called *Learning Reinvestment*, learning to drive a racing car with the intention of winning races. To win races, a requirement is incremental challenging tasks building upon knowledge and skill. The difference between normal learning and the learning that fosters expertise is what we do with the capacity we gain by automating and proceduralizing knowledge. Normal learning leads to satisficing. If the environment is the same, the skill of the operator will remain sufficient, but no more. A change in environment or tasks will lead to learning, but will stop when sufficient. An expert has an intrinsic motivation to utilize the capacity gained by experience to further experience and knowledge of the task and environment.

Three common forms of reinvestment to build expertise are: (1) reinvestment in learning, (2) Seeking out novel and difficult problems, and (3) Tackling more complex representations of recurrent problems. By working towards the edge of competence the expert *create themselves*, we cannot force expertise through workplace-learning programs and systems design. But we can support the elicitation and curiosity of those whom strive to understand and challenge their knowledge.

> The real world mostly provides opportunities to do the routine. Expertise involving the nonroutine is harder to get from everyday work experience because the right situations occur rarely and often are handled by established experts when they do occur, not by students. (Lesgold (1992), in Hoffman, Feltovich, et al. 2009, p. 18)

Hoffman, Feltovich, et al. (2009) argue for the introduction of the term *Accelerated Learning* into the world of intelligent systems. Accelerated learning is an idea that we can develop proficiency in tasks faster than by a traditional situated teacher-student approach. They argue that the current learning systems often attempt to help people become proficient in as short time as possible, but what is really needed is an approach that helps with the journey from competent to expert. An adaption of the criteria has been presented in Section 2.15.4.

Chapter 3

Automation

3.1 Introduction

> In the fullest contemporary sense, the term automation refers to a. the mechanization and integration of the sensing of environmental variables (by artificial sensors), b. data processing and decision making (by computers), c. mechanical action (by motors or devices that apply forces on the environment), and/or d. "information action" by communication of processed information to people. (Sheridan and Parasuraman 2005, p. 90)

Sheridan and Parasuraman (2005) base this definition as an opposition to the dictionary definition which is outdated and mostly referring to the physical labor that is replaced by automation. Current automation focus in the industry is just as focused on the *cognitive labor*. Automated computers perform analysis, makes decisions, displays information, and record and compile data. Humans work with and are considered essential to automation systems. In comparison to the technical capabilities, human capabilities – human performance and cognition in automated systems – are much less frequently written about (Parasuraman and Riley 1997; Parasuraman, Sheridan, and Wickens 2000). Automation does not supplant human activity, but the nature of work is changed.

When discussing the use of automation in regards to decision making, the category of cognitive supporting automation systems are the most applicable. The average human brain has for a long time not been able to compete with systems on simple arithmetic tasks such as mathematics and simple procedural calculations. Recently, systems have been able to utilize better developed models, big-data and more processing power to replace an ever-increasing number of human tasks.

But automation is applied to reduce human workload and increase efficiency (Parasuraman and Riley 1997). What this implies for the human role in the industrial environment in the future is still uncertain, but in the following it is presented some of the current research on the effect of automated systems and their influence on humans, and vice versa.

The most common task for a human when interacting with an automated system is to take the role of supervisor. This supervisory control, has five main cognitive functions (Sheridan and Parasuraman 2005). Planning, teaching the automation, monitoring the automations execution, intervening or assuming control if needed, and learn from experience.

A central theme in later years is *Human-Centered Automation* popularized by Billings (in Sheridan and Parasuraman 2005, p. 94). The focus on this is the aspect of human interaction with automation systems and how we can best create automation systems that support the operational flexibility a human supervisor or operator provides. There is no consensus to this quest for excellence, but the notion that automation must be designed to work in conjunction, and adapt it to a human operator is generally agreed upon (Sheridan and Parasuraman 2005)

3.2 Levels of Automation

Automation can be usefully characterized by a continuum off levels rather than as an all-or-none concept (Parasuraman and Riley 1997). Under full manual control the particular function (or decision) is controlled by the human, with no automated system influence. At the other extreme of full automation, the machine controls all aspects of the function, including its monitoring, and only its products (not internal operations) are visible to the human operator.

Parasuraman, Sheridan, and Wickens (2000) present a model for the types and levels of human interaction with automation. Human interactions with automated systems is a critical part of decision support, and the degree of automation greatly affect both use, misuse, disuse and abuse of automation, both by the operators and the designers. The question they set out to solve is: given technical capabilities, which system functions should be automated and to what extent? Automating tasks is traditionally viewed as a technical problem, and the research on the human parameters is limited. By approaching four stages of automation, and separating each stage into a grade of automation, the framework proposed should impact automation designers.

Table 3.1 is referenced and used by Parasuraman, Sheridan, and Wickens (2000) and I will use their explanation of the model. The table shows a ten point scale where higher levels representing increased autonomy of computer over human action in decision making systems. For example at level 2 the system propose several options to the human and the system has no say in which option is chosen, while in level 4 the system presents one decision alternative, but the human retains authority. At level 6 the computer gives the human a limited time to interact.

Figure 3.1 describes four stages of human information processing as described by Parasuraman, Sheridan, and Wickens (2000). Sensory processing is the acquisition and registration of multiple sources of information. The second stage is where conscious perception and manipulation of processed and retrieved information in working memory. The third is where decisions are reached based on such cognitive processing. And the fourth stage involves the implementation of a response or action consistent with the decision choice. These four stages have an equivalent in automatic systems; (1) information acquisition, (2) information analysis, (3) decision and action selection, and (4) action implementation. Each of these functions can be automated to different degrees. One system

Table 3.1: Levels of Automation - Scale of Levels of Automation of Decision and Control (From Wickens, Mavor, et al. 1998, p. 14)

High Automation	10.	The computer decides everything and acts autonomously, ignoring the human.
	9.	informs the human only if it, the computer, decides to
	8.	informs the human only if asked, or
	7.	executes automatically, then necessarily informs the human, and
	6.	allows the human a restricted time to veto before automatic execution, or
	5.	executes that suggestion if the human approves, or
	4.	suggests one alternative, and
	3.	narrows the selection down to a few, or
	2.	The computer offers a complete set of decision/action alternatives, or
Low Automation	1.	The computer offers no assistance: the human must take all decisions and actions.

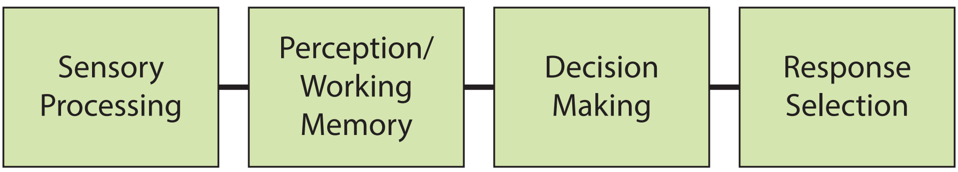

Figure 3.1: This illustration extends Table 3.1 to the four stages of information processing by Parasuraman, Sheridan, and Wickens (2000)

might have a high automation in the information acquisition phase, but not on the subsequent phases. Another system might be close to completely automatic, only requiring human interaction only when it needs to.

This scale is used for describing *Levels of Automation* (LOA) in several consequent articles. Parasuraman, Sheridan, and Wickens (2008) argue for a further simplification. (Stage 1 and 2), and (Stage 3 and 4). The first two stages (1 and 2) are responsible for information acquisition and analysis, physical and mechanical tasks . While the last two (3 and 4) are responsible for decision making and action; cognitive information processing. They contextualize the LOA with some examples: A medium LOA in information acquisition and analysis, the data acquisition phase, can highlight relevant data to indicate a potential problem. In a higher LOA this is not necessarily the case, here filtering is used to hide "irrelevant" data and highlight "relevant" data. The reliability of filtering can be important, and a potential performance cost may occur if the priority of information is suboptimal. Stage 2, automation of information analysis, supports working memory, situation assessment, diagnosis, and inference. Parasurman and Wickens use an example at a low LOA where an automated analysis is performed and extrapolation over time, or prediction is performed (eg., Fleming and Pritchett 2016; Wickens, Gempler, and Morphew 2000). At higher LOA at Stage 2 involves integration, in which several input variables are combined into a single output value (ie Cooke 2008, p60).

Parasuraman, Sheridan, and Wickens continues by explaining stage 3 and 4. These automated decision aids are responsible for choices, and can be seen as if-then systems. The system must take assumptions of the cost, risk, and values of different choices. When reliable these decision automation systems increase performance, but when not reliable they perform worse than an information analysis system (stage 2 system), likely because of the recommendation approach (Sarter and Schroeder 2001). Sarter and Schroeder's findings suggest that unless the reliability of a decision aid is perfect, status displays may be preferred. Thus avoiding automation biases while increasing performance benefits over a non-automated baseline, this is also the conclusion of Rovira, McGarry, and Parasuraman (2007) who performed a study on imperfect decision making in high risk, low timeframe situations where they found unreliable decision automation inferior to unreliable information automation in all three measured tests. Parasuraman, Sheridan, and Wickens (2008) Speculates that information automation may be the superior approach because the user must continue to generate the decisions for the courses of action. As a result, users might be more aware of the consequences of the choice, and of the impact of a faulty dataset.

If we are to increase the level of automation to the highest, both level 3 *and* 4 automation must be performed by the system. This can be implemented in time critical decisions, such as automatic breaking in cars. This introduces a trust issue, in virtually all implementations where the operator has no understanding of the 'opaque' system and when and what it makes decisions (Lee and See 2004).

3.2.1 Procedural Instructions

Procedural instructions are an approach to decision-automation, where the material for how to diagnose and solve a problem is standardized into a stepwise instruction guiding operators. Procedures are used for everyday tasks, an example is baking: Most of us use procedures for baking bread, in which all ingredients and tools are listed, and the exact flow of the process is detailed. This will produce the same result, using the same amount of time, and the same resources every time. If we learn this recipe by heart, we will be able to make a good bread. But the issues arise when there are other issues complicating the problem. An expert baker might see the same recipe but identify opportunities that fit the current situation better. We might need the bread earlier, or we lack some of the ingredients. The expert connects prior experience and modifies the procedure to create a good result.

Klein (2009, pp. 22-30) propose that following procedures can limit understanding. In many areas the understanding of the process and especially what happens when something goes wrong beyond procedures is a decaying skill. Klein is critical of the statement "Teaching people procedures helps them perform tasks more skillfully", this claim is supported by some scenarios such as the implementation of procedures for Surgeons and Operating Rooms. In other fields, where the decision making process often has to take into account many different variables and a changing scenario. The operators are led into mindlessness and complacency by following instructions instead of understanding the process. "By understanding the process, experts are usually working around or loosely following the procedure." (Klein 2009, p. 23). Klein refers to scenarios where accurate procedures are made, but they are presented in ways that are not appropriate. Examples of this are procedure documents with hundreds of pages made to handle time sensitive and rare situations. Procedures and mind-automation should according to Klein be approached as guidelines and best-practices, but understanding is the key to handling non-routine exceptions.

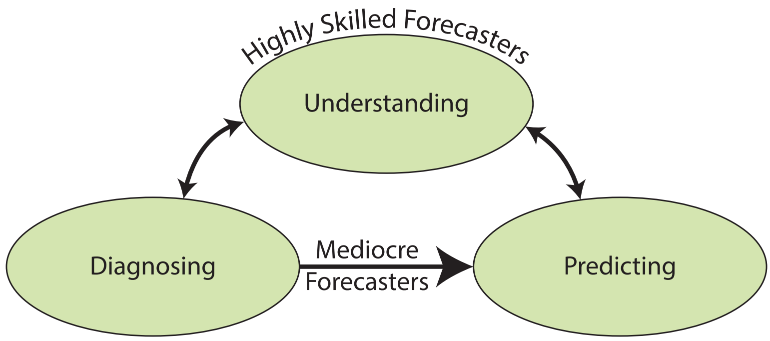

Figure 3.2: "Forecasting Processes used by mediocre and skilled weather forecasters." (Recreated based on Klein 2009, p. 23)

Klein (2009, p. 23) illustrates the issue using weather forecasters in **Figure 3.2**. In forecasting procedures mandate which data to collect and the analysis to perform. But expert forecasters seem to follow their intuition and more often detects unusual weather conditions.

Operators which do not understand the process they are supporting: operators supporting tasks performed only by following step-by-step procedures, will never be able to learn or operate at an expert level. Procedures seem to equalize the levels of operators, both unskilled and experts now operate on the same level and expertise can be dwindling from the organization because of the absence of challenge and learning opportunities in mindlessly performing routine tasks.

3.3 Automation Cost

> ”With computerization I am further away from the job than I have ever been before. I used to listen to the sounds the boiler makes and know just how it was running. I could look at the fire in the furnace and tell by its color how it was burning. I knew what kinds of adjustments were needed by the shades of color I saw. . . . I feel uncomfortable being away from these sights and smells. Now I only have numbers to go by. I am scared of that boiler, and I feel that I should be closer to it in order to control it." (Zuboff 1988, p. 63)

Mosier et al. (1998) describe a China Airlines flight, where power in one of the four engines was lost. The flight was running on autopilot, controlling both speed and pitch. When one of the four engines started having troubles the system responded with compensating for the problem by holding the wing down and increasing power to the other engines. Even though all the individual information pieces were available the crew did not realize that they had lost an engine. When they disabled the autopilot to land, they suddenly lost altitude and yaw of the airplane. Automation can mask errors, and when compensations in effect are not reliably addressed to the operators this is a major cause of accidents.

Mosier (2008) presents a view that *highly technological* environments are significantly different from purely *naturalistic* environments and that this difference impacts all macrocognitive functions and thus decision making. She states that technological aids in decision environments reduce the ambiguity inherent in naturalistic cues. They process data from the outside environment and display them as highly reliable and accurate information rather than probabilistic cues. While some of the data is retrieved from sensors, experts often need to validate with a real situation. This leads to a *hybrid ecology*: It is deterministic in that much of the uncertainty has been engineered out through technical reliability, but it is naturalistic in that conditions of the physical and social world — including ill-structured problems, ambiguous cues, time pressure and rapid changes interact with and complement conditions in the electronic world. In a hybrid ecology, cues and information may originate in either the naturalistic environment (external, physical) or the deterministic systems (internal, electronic). Inputs from both sides of the ecology must be used by effective practitioners to make the optimal decision. Technologically 'invisible' cues such as smoke and sounds, can often provide critical input to the diagnosis of high-tech system anomalies.

This hybrid ecology leads to implications in expert decision making. Models like the Recognition-primed decision model (RPD) (Klein 1993), is claimed by Mosier (2008) to not apply when data is presented on a monitor. Data can be hidden below surface displays or mean different things in different display modes. A critical component of expertise in hybrid environments is knowing whether and when the situation is amenable to being intuitively recognized. Mosier makes the proposal that successful decision making in hybrid environments is supported by analysis, more than intuition. The analysis is here defined less rigidly than in other decision sciences. We do not need to create a diagram and model of alternatives and mathematically weigh them. We define analysis as "conscious, logically defensible, step-by-step process" (Hammond 1996,p60, in Mosier 2008). This definition presents analysis as an opposite to intuition, but not necessarily using empirical decision strategies.

(Onnasch et al. 2014) found in a meta-study of automation systems that the skills of operators are greatly decayed when not in use, as can be the case with automated systems. Task automation greatly reduced operator ability when returning to manual execution of the task, and situation awareness was reduced when automated. Task efficiency was positively affected by almost any kind of automation, so there seems to be a settlement in current systems by reducing operator understanding and increasing operational efficiency. According to Ornash et al.s findings, there are indications that if the goal is operator understanding and supporting operator knowledge, task automation should be limited.

3.3.1 Mental Workload

Parasuraman and Riley (1997) states that one of the fundamental reasons for introducing automation into complex systems is to lessen the chance of human error by reducing the operators high mental load. However, this is not necessarily applicable to reality. Humans seem to distrust automation and often prefers performing the task manually. Bainbridge (1983) exemplifies the need for a challenge, any cognitive or physical endeavor, by from a processing plant: The operators would switch equipment to manual during the graveyard shift when no managers were on site. If the operator cannot manually perform the task he is made to oversee the job is classified as: "...one of the worst types [of job], it is very boring but very responsible, yet there is no opportunity to acquire or maintain the qualities required to handle the responsibility." (Bainbridge 1983, p. 776) If the job is *deskilled* by being reduced to a monitoring task, it is hard for the individual to come to terms with and will often require compensation in pay or other benefits (Bainbridge 1983).

Mosier (2008) present some common issues with 'intuitive' displays. According to her system designers often concentrate on 'enhancing' judgment environments by providing decision aids that are designed to increase the accuracy of judgment, but this is often based on assumptions for information the individual needs, and how it should be presented. In aircraft instrumentation, the trend has been to present data in pictorial, intuitive formats whenever possible, an approach that seems fitting based on the research on mental models and situated understanding. But this focus on highlighting and simplifying automated information has inadvertently led the decision-maker down a dangerous path, operators start assuming that the systems represented on the screen can be managed in an intuitive fashion. This is according to Mosier a false assumption. Within seemingly intuitive displays are often layers of complex data. These system couplings may produce unanticipated, quickly propagating effects if not analyzed and taken into account.

3.3.2 Cognitive Skills

"We are locked into a spiral in which poor human performance begets automation, which worsens human performance, which begets increasing automation." (William Langewiesche Langewiesche 2014)

The quote above is one of the ending statements in a critical analysis of the 2009 Air France Flight 447 crash, which seems to have occurred in part because of pilots with "experience" from hundreds of hours in the air having limited practice flying without advanced automation assistance (Langewiesche 2014). When suddenly the automation fails, because of a sequence of "bad luck", the pilots fail their job as knowledgeable and responsible operators.

An operator will only be able to create successful new strategies for unusual situations if he has an adequate knowledge of the process (Bainbridge 1983). There are two problems with this for 'machine-minding' operators: Efficient retrieval from long-term memory requires frequent usage. And this type of knowledge develops only through use and feedback about its effectiveness. Bainbridge (1983) argues that people given this knowledge in theoretical classroom instruction without appropriate practical exercises will lack understanding as it will not be within a framework which makes it meaningful. They will not remember much of it as the knowledge will not be associated with retrieval strategies which are integrated with the rest of the task. There is some concern that the present generation of automated systems, which are operated by former manual operators, are using their experience for understanding, which later generations of operators cannot be expected to have.

Cooke (2008, p. 60) describes the implementation of a monitoring system for anesthesia, where a simple automated unit displays the projections of the blood content of the various drugs enabling a full body anesthesia. The task is quite simple, but it is cognitively demanding to track three different drugs each with unique half-life and absorption rates. The system described by Cooke both monitored and displayed a prediction of future developments. This unit replaced monitoring of “proxy variables” such as heart rate, breathing, and twitching with a standardized display for blood content and an estimate for total anesthesia. The initial results were positive, and *even a novice* was able to perform the role. This is argued to have sparked resistance because the system was not well received by the anesthesia community – possibly fearing for their profession to erode.

> Technology in hybrid environments should support human cognition, but often does not do so effectively. The way in which data and information are presented may have a powerful impact on judgment strategy that will be induced, and thus whether or not the appropriate cognitive strategy will be elicited or facilitated. (Mosier 2008, p. 48)

Decision-aiding systems should recognize and support this requirement. Many technological systems are designed on the basis of incomplete or inaccurate suppositions about the nature of human judgment and the requirements for metacognitive awareness and sound judgment processes. (Mosier 2008, p. 48). In their efforts to provide an easy-to-use intuitive interface display format, designers have often buried that data needed to retrace or follow system actions. These calculations and resultant actions often occur without the awareness of the human operator. System opaqueness, another facet of many technological systems, also interferes with the capability to track processes analytically. Mosier argues that the elaborate electronic screen systems with hidden complexity might impair rather than support macrocognitive processing and decision making, as it does not facilitate appropriate cognitive responses and awareness.

3.3.3 Situation Awareness

Automation of decision making systems may reduce situation awareness (eg., Onnasch et al. 2014; Parasuraman, Sheridan, and Wickens 2000). Humans adjust their awareness when other agents perform changes, opposed to performing the changes themselves. Also if a decision support system reliably suggest the best alternative, operators might become complacent and discard their own view of the situation.

The cognitive process required in hybrid systems, may be apparently intuitive but they are really analytical (Mosier 2008). Only when all systems represent the same information and present redundancy the data can be trusted. Failure to control data can lead to inadequate or incorrect situation assessment, with subsequent injuries and incidents.

3.3.4 Automation Bias

Parasuraman and Manzey (2010) state that it is important for the designer to be aware of the biases involved when designing automation systems. Designers and operators must recognize the unpredictability of how people will use automation in specific circumstances, because people are different. They suggest that if automation is to be used appropriately, potential biases and influences on decisions must be recognized by training personell, developers and managers. Individual operators needs to be made aware of operational biases that might lead to lower decision quality.

Experts must be aware of the problems on over-relying on technology for problem detection. A byproduct of this tendency is *automation bias*, "a flawed decision process characterized by the use of automated information as a heuristic replacement for vigilant information seeking and processing," (Mosier 2008, p. 50) as a factors in professional pilots' decision errors. Mosier (2008) presents two classes of technology related errors that commonly emerge in hybrid decision environments: (1) omission errors, failure to find and understand information that is not presented by the system or procedure and (2) commission errors, where operators follow procedures and directions without verifying against available information, or in spite of contradictory information. Wickens, Gempler, and Morphew (2000) findings indicate increased commission bias frequency when in making decisions using difficult to process data, but that conclude that the complacency to automation provide enough benefits to outweigh the reduced Situation Awareness and manual-review.

Mosier et al. (1998) argue that automated systems are often introduced as superior to human performance. The automated cues they produce have a more accurate mathematical background, and can visualize and combine a thousands of calculations that the average operator could never fathom. The risk involved is when some automated cues require resources to interpret and operator knowledge is required to find the underlaying problems.

Humans go for the path of least resistance, often named the *garden path*, and when one approach is supported by automation this path if often chosen. Automation is often beneficial, it helps offload information seeking and compiling, it highlights warning signs and gives the operator more cognitive resources to focus on other tasks. The main problem of automation is that it makes it less likely for operators to seek information supporting or contradicting the automated statement (eg., Mosier et al. 1998).

Automation biases occur when there is an over-reliance on automation, causing suboptimal decisions. Humans are bad at monitoring, and will often lose track of system states when automated.

Another effect of the automation bias can happen if the user is not aware of the limitations of the system (C. A. Miller and Parasuraman 2007). When the user is unaware of system capabilities, he might suppose that nothing is wrong when diagnosing a problem using system guidance. But if the system is incapable of detecting this error, it can have catastrophic consequences when the operator trusts systems to guide his diagnostics and decision.

3.3.5 Complacency

As mentioned above, operators can become complacent when expected to overlook automated processes that are almost reliable (eg. Klein 2009, pp. 23-30). Operators do not learn why the procedures are performed as they are led into mindlessness and complacency by following instructions instead of understanding the process. Yeh, Wickens, and Seagull (1999) describes the results of an automated air to ground targeting system, where performance of a slightly faulty system was worse than the control-group lacking any automated support. The automated target would not always be the highest priority, but because of the the systems highlighted target pilots were inattentive and showed complacency to the surrounding environment. This supports what Parasuraman and Manzey (2010) indicate as a correlation between the effects of automation complacency and -bias. Complacency seems correlated with the frequency of *observed failures* in the decision making system. Trust is built up over time, and failures detected is inversely related ot the time since last detected decision system failure.

Bainbridge (1983) states that operators that are expected to solely monitor that an automatic process is acting correctly, but which has the responsibility if anything goes wrong, can not acquire this skill through his work. This raises complexities as: can an operator that is unskilled with lack of real understanding really monitor a process or evaluate a decision proposition? Bainbridge states that 'Vigilance' studies indicate that it is impossible for even motivated humans to maintain an effective awareness of a system where nothing happens for most of the time. This leads to a reliance on automated alarm systems, thereby reducing the role and skill of the human operator to a alarm-processor. A classic method of forcing data monitoring is to require the operator to make a log, but according to Bainbridge people frequently write down numbers without processing what they represent.

Operators do not learn why the procedures are performed as they are led into mindlessness and complacency by following instructions instead of understanding the process (Klein 2009, pp. 23-30).

3.4 Summary

In this chapter, a quick review of some terms related to the use of automation by human operators. Current Automated systems seem to conflict with goals of human understanding. Automation is no longer merely automation of a physical task, but can facilitate and automate decision making and information retrieval. The appliances of automation systems seem to ignore features of human cognition, and more than ever, operators require knowledge to understand opaque automation features and limitations.

Chapter 4

Decision Support Systems

"Our design problem is less – can we build a visualization or an autonomous machine, and more – what would be useful to visualise and how to make automated and intelligent systems team players." (Woods, Patterson, and Roth 2002, p. 34)

4.1 Introduction

This chapters focus is on the interaction between Decision Support Systems (DSS) and the operators decision capabilities. The study shows how many problems have been approached, and the most glaring errors and opportunities for the design of Decision Support Systems have been selected. This part continues in the style of the previous parts by presenting selected authors views on a challenge in human decision when using automated systems, and often the opportunities for alleviating such problems are included.

P. J. Smith et al. (2012) defines an *Active* Decision Support system as "[Systems that] use algorithms to actively monitor situations and to generate inferences in order to assist with tasks such as planning diagnosis and process control." (P. J. Smith et al. 2012, p. 590). Other types of *computer-assisted* decision systems are those that improve: User access to information, presentation of information, or which helps improve communication. The definition of the Decision Support Systems(DSS) in this chapter are not necessarily systems that automate the decision process and requires user input; it is a broad term that encompasses all types of systems and environments designed for improving operator decision strength during a situation in a certain environment.

Zuboff (1988, pp. 7-12) clarifies what distinguishes current information technology from earlier generations of automated *machine* technology. While IT can be used to extend, reproduce, and improve upon machine technology, it also is able to convert the current state of sensors, equipment, products into data and information. Modern automation is not mute, can via sharing data produce a rendering of events, objects, and processes so that they become visible, knowable and shareable for operators. Current automation systems should be designed to inform as well as automate. Systems are no longer limited to performing their actions in a 'black box', we can utilize them to translate the current process and making it understandable. But this requires intent and leadership to implement correctly.

Zuboff (1988) argue that the introduction technological support systems cannot in itself 'enslave' or 'liberate' people, the managements decisions for introducing either empowering them by education through systems or subjugating them by using automation to eliminate cognitive tasks.

P. J. Smith et al. (2012) argue that improving process efficiency through procedure redesign, improving communication and better memory aids might prove as, or more effective than an Active DSS would. The process goal has to be the most important part of the design process. The goal is rarely to develop a DSS but to improve operator and process efficiency and safety. If complete automation is better, it should be implemented. Contrary monitoring decisions and alerting when they are objectively wrong can be another approach. Weick, Sutcliffe, and Obstfeld (1999) argue that a defining part of High-Reliability Organizations are how they avoid oversimplifying process instructions to facilitate better understanding of routines and to find opportunities hidden in the shadows. Operators should possess the knowledge, and have the responsibility of decisions, but a direct access to his leaders for input, collaboration and coordination.

Yoon and Hammer (1988) referencing Wickens arguments in 'Engineering Psycology and Human Performance', the hardest cognitive task is the diagnosis, a precursor of any decision. Wickens based this on two factors; the number of cues available vs the number that can be held in memory, *and* the number of mental operations to be performed. Supporting this diagnosis process seems to be one of the hardest tasks to implement, especially when diagnosing novel problems. The system needs to be able to support the humans discovery of cues, and the mental model of the operator should be able to adjust to problems not modeled in the system.

"The challenge for applied cognitive psychology is to provide models, data, and techniques to help designers build an effective configuration of human and machine elements within a joint cognitive system. " (Woods 1985, p. 89)

Building decision support systems is not a technical problem, and it is not a human problem. If the goal of the system is to improve decision quality, the dilemma of automation, and conditions for expertise is central to the process. The degree of automation, level of guidance, design of the interface all needs to support the goal of improving the decisions made in the industrial processes.

Woods (1985) suggest that a problem based approach to developing systems is always more appropriate than an technology driven approach. The technology utilized has to suit the problem, and is only a tool and possibly a limitation. A problem in a dangerous environment might imply automation as the tool, while a problem of inconsistency and memory lapses might require redundant support and validation. Should the system be designed for specialists or generalists, or even specialists in diverging fields requiring use of identical systems? The requirements for discoverable interfaces and usability change according to the users training and frequency of use.

One of the main issues of designing DSS are that the routine decisions they often support are the same ones that operators already performed well, but when the DSS requires an operator to act as a safety net when the designers have failed to anticipate a situation, situated knowledge from routine operations should have been applied, but it might have eroded (P. J. Smith et al. 2012).

Rogers (2004) argue that design and research has to work together. Designers should use research as their basis for innovative designs. And designers can contribute to science by doing rigorous research and publishing their novel findings. A common problem according to Rogers is that academics are unfamiliar with designers work and methods, and designers have reserved appreciation for academic rigorous methods. Throughout this chapter I have compiled a number of methods generated both by design and research to support the design of decision support systems. Research and generalizing method from other domains as a base for designing specific domain resources can be a valuable input to the creative process, and has been the basis for the designs presented in this thesis.

The automation systems that support operator decisions are not necessarily there for minimizing the loss from operational mistakes (Hoc, Amalberti, and Boreham 1995; Woods and Hollnagel 2006, Ch.6). Decision Systems should help prevent malfunction, support maintenance tasks, limit operation mistakes, and monitor specific indicators of malfunction. A system that detects a malfunction can help predict the course and cause, and provide procedures with automated responses to contain the issue. Finally when a malfunction is at a late stage, the system should support the repair and minimize loss. Every observed issue should be reported, for a statistical preventative effect and a objective source of failure information to be utilized in the design of later system iterations, or in modifications of the current one.

As seen in Chapter 2, one sensible approach if we want to improve human decision making. To reduce the effect of human decision biases, and to avoid theoretical mistakes, we have to help operators build expertise. Improving mental models, to help people adjust their own assessments of situations and thereby improving their own decision making heuristics to better fit with the correct anchors.

4.1.1 DSS Requirement Elicitation

Eliciting the real mental models of operators and to find the actual operational difficulties of users require a number of methods and approaches. Below a best practice review by P. J. Smith et al. and D. Norman's requirement principles are selected as an introduction to the specific needs when designing novel decision support systems are selected. These methods require a deep understanding of the target domain and human cognition to be effective. When incorrect assumptions are applied in the design of decision support systems, the subsequent changes often require organizational changes (Woods, Dekker, et al. 2010, pp. xv-xx). Researching prior examples and methods to prevent and identify these possible causes for incidents is one of the main keys to implement and enhance capabilities of decision support systems.

Woods, Dekker, et al. (2010, pp. xv-xx) argue that researching errors in HCI is an issue in which many stakeholders are impacted when issues are discovered. Systems that are composed with design-flaws are hard to modify, both latent organizational issues and direct operational procedures has to change and the impact on the orgnization from these errors might be unsurmountable when the system is already in use. Researching prior examples and methods to prevent and identify these possible causes for incidents is one of the main keys to implement and enhance capabilities and capacity of mental and computer systems, thereby reducing errors.

D. Norman (1983) suggest that there are four different concepts we have to consider when researching the mental models of operators: the target system, the conceptual model of the target system, the user's mental model of the target system, and the scientist's conceptualization of that mental model. The target system is the system the user is learning about. The conceptual model is the model the teacher, designer, scientists and engineers have created for the target system. Mental models seem to be *functional models*, not necessarily technically accurate. These mental models are influenced by the users interaction with the system and the users theoretical and practical familiarity with similar systems. The Scientists representation of a mental model is how the scientist analyze the mental model of a learner or operator to find discrepancies between this and the established model of the system.

There are a number of elicitation methods for uncovering the actual domain-requirements for a DSS, P. J. Smith et al. (2012) list a number of methods, but a short summary of their approaches is presented below.

Needs analysis

Needs analysis, we need to establish if the system is required, and how humans should be a part of the system. We need to establish the underlaying goals of the operators and executives, and analyze how a system could satisfy the actual needs of the company. Further operations of actual operators is required to see the larger context of the DSS, often the problem caused by inadequate decision making is caused by contextual issues. Smith et al states that system designs can be tested using use case scenarios, but the best test is performed by real users. Multiple iterations are required to produce the best kind of system.

Cognitive Task Analysis and Walkthroughs

Cognitive Task Analysis (CTA) and Cognitive Walkthroughs are methods for understanding how tasks are performed, and how they would be performed using the DSS developed. CTA observes operators performing their day to day job, and compares this with what believe they do and the official procedures. Cognitive Walkthroughs are used to predict task performance for the new system by asking operators to follow the steps proposed in the design of the new DSS, and having them evaluate how and why this would/would not work by acting out the process.

Work Domain Analysis

Work Domain Analyses, is a supplement to CTA. CTA is often looking at the processes of an identified objective or goal. However DSS in complex environments will never be able to find all the scenarios that can arise. WDA will attempt to approach the problem from the other side, evaluating and modeling the environment and analyzing the possibilities for situations in the environment. P. J. Smith et al. (2012) use the common analogy of describing a route to a location by words or by using points on a map. The route is easier to accomplish using 'language'-based sequential instructions, but when an issue occurs we have more problems adjusting. Using the map we have to use more cognitive processing, but it is more resilient to unexpected occurrences, like blocked roads and traffic.

Ecological Interface Design

Ecological interface design is a paradigm in the design of automated systems that try to reduce the time operators spend on skills and rules in interface interaction (see Rasmussen's 1983 SRK framework, section 2.15.1), and to optimize the application of human knowledge in cooperation with the system (See eg., Jamieson et al. 2007; Rasmussen 1999). The ecological analysis can be done using task-based or work-domain analysis but should optimally use a combinations of various knowledge elicitation approaches. Ecological interfaces often highlight goals, current tasks and other features that operators are interested in automatically and available.

4.1.2 Importance of Analysis and Knowledge

Woods, Dekker, et al. (2010, pp. xv-xx) argue in their search of explaining "human errors" suggest that there is an tendency to "declare war" on errors. We track and count them, and analyze them using flawed frameworks. Their argument is that organizations work by the cognitive glue of operators and management working towards a common goal, with constraints such as time, workload, motivation and more. They make flawed systems work together, often so well that external and internal investigators will not discover their adaptations and effort. What often is left to discover during routine safety audits and error counts is errors, incidents where a practitioner or system created an "obvious" incident. Woods, Dekker, et al. argue that most of the potential, and often dangerous errors lie behind the label of "human error", where an error is attributed to a human cognitive failure leading to an incident. The authors argue that the new world of highly coupled and connected systems

4.1.3 Automation Cooperation

Automation Systems are often designed with automation in mind, suppressing the human element of the system design. Christoffersen and Woods (2002) argue that the human is seen as a risk and a cause of errors, and the common design ideology is to automate the operators tasks without managing the surrounding working environment. An automated task might reduce a humans manual labor, but will inevitably place an increased workload into the *cognitive tasks*. This change of workload has a great impact on the operating capacity of the human. As mentioned in Chapter 3, humans have issues managing and supervising automated tasks. When the automation system is reliable, the human focus attention to his other tasks. When a sudden inconsistency in the automation occurs, this can cause a wave of workload changes both down and up from the new automated system. Systems need to be able to indicate its current and projected state to the operator, and the operator has to be able to understand what tasks the system performs.

Christoffersen and Woods argue that more advanced automations systems result in an increase of system autonomy and authority, but with this increase in sophistication the requirements for effective human-computer *cooperation* increase. Systems have to be able to make the operator aware of its goals and current process just as any human would be able to as another human operator. If this cooperation is faulty we will see more automation surprises , where the state of the system conflicts with the state the human supervisor expects.

When humans collaborate they create a common ground for understanding, in order to support coordination of their problem solving efforts. Christoffersen and Woods suggest that this notion of a shared representation is important when designing HCI. They break shared representations down into two parts; shared representation of the problem, and representation of the activities of other agents. A common understanding of the problem at hand is required, and several questions are proposed as evaluation metrics: What type of problem is it? Is it a difficult problem or routine? High or low priority? What types of solution strategies are appropriate? How is the problem state evolving? . If both parts are able to communicate this, the collaboration is complete. Additionally the other part is the information of what hte other part is working on and the related information to that process.

Modelling systems after human interactions might have an positive impact on the strength of human decisions. Automation etiquette is an example, where the interruptions of automation systems are modeled to fit what humans etiquette would indicate is the best approach. Sheridan and Parasuraman (2005) show how systems with high reliability (80%) which interrupt, hurry and bother the human operator can result in inferior results to a lower reliability (60%) system that works better together with humans. Automation etiquette improves automation cooperation. Quantity, quality, relation and the manner in which you present it all has an impact on the user experience, and has a direct connection with task performance.

4.1.4 Reliability

Weick, Sutcliffe, and Obstfeld (1999) discuss High-Reliability Organizations and how the discussions of reliability of organizations and the effect of human-computer interactions and design of operations to allow for errors, or to automated to the degree of elimination of the error. How far should an automated system go to alleviate errors before the reduction is considered better than to not have automated it?

The traditional definitions of reliability argues that a repeatable and reproducible actions or patterns of activity is a fundamental principle of "…the notion of repeatability or reproducibility of actions or patterns of activity is fundamental to traditional definitions of reliability." (Weick, Sutcliffe, and Obstfeld 1999, p. 35). Weick, Sutcliffe, and Obstfeld agree that this definition is accurate on a macroperspective, but not when studying reliability in *individual* system and operator performance. Situated operations require constant adjustment for regular performance at optimal capacity. This adjustment process is rarely supported by routines and programs alone, and cognitive processes and decision skill has a major influence on reliability. The argument is that an overreaching concept in the production of systems and evaluation reliability is that routines and procedures have to *guide* cognitive tasks instead of attempting to replace them.

Rasmussen (1999) argues for three central design issues controlling that the Human-Machine System facilitates the ability for reliable operator control.

- ”Are objectives, intentions, and performance criteria known and communicated effectively among controllers (decision makers)?”
- ”Are controllers supplied with reliable information on the actual state of affairs, and is that information directly comparable to the formulation of objectives?”
- ”Are controllers capable of control, that is, do they know the effective control points and system responses?”
- (Questions from Rasmussen 1999, pp. 208-209)

The relevance of these questions to the design of DSS is that they emphasize the structure that is required for learning and operator understanding. Design of systems with a human component must implement methods for communicating its intentions and take input from the operator in an understandable fashion. Rasmussen explain that the traditional display of only factual information and data is insufficient for effective system understanding, systems should also display *intentional information* explaining how and why the system is proposing a decisions.

4.2 DSS Examples

Below I have included a number of reports on current systems present in the research literature. A number of categories of decision support systems are available, and this list is intended as an indicator for the wide range of possibilities to facilitate operator decisions and understanding.

Diagnostic (Medicine) Decision Support

DSS have been attempted employed in Medical systems since the inception of the idea, R. A. Miller and Geissbuhler (2007) describe how earlier Diagnostic Decision Support Systems (DDSS) attempted to solve the “global” problem of diagnosing all diseases, the development focus has shifted to creating DSS for the individual procedures in a clinical diagnosis. The current systems assume that the user will interact in an iterative fashion, where the DSS and the user cooperate in finding the solution.

Decision Trees

Martignon, Katsikopoulos, and Woike (2008) describe a model for decision-support using *Fast Frugal Trees*, simple yes now questions that the operator must answer for a step by step diagnostic sequence. The process is “fast and frugal”, only if the operator has at least one exit at each level. Every level has to be able to provide an answer to the problem, or dig deeper. While quick, this model is hard to design and has severe limitations when the diagnostic model is incomplete.

Communication Support

P. J. Smith et al. (2012) present some design decisions made for a communication system incorporating a Decision Management component to reduce interruptions for in field military communications. By incorporating sensors such as heart-rate, motion monitoring, EEG (Brain-activity scanning), they were able to both make communicators aware of the ongoing situation, and converted non-important messages to a text display to limit the cognitive workload of the field-operator. The equipment required to support this is by Smith et al. regarded as a possible source of reduced situation awareness, and this is a blocking limitation for adoption in field-operation. The reduced SA from equipment is not enough to warrant the opportunities of the communications system, but with some sensor development we might have such systems in the future.

Multi-Level Automation

Multi-Level automation is an decision automation approach using computer meditated mode switching to collaborate with the humans perceived information needs.

Fleming and Pritchett (2016) describe the levels of automation in a common Traffic Alert and Collision Avoidance system. (TCAS) This system normally acts as a low level information automation ((Using the scale from Parasuraman, Sheridan, and Wickens 2000)) by displaying nearby traffic on a radar for pilots. When an anomaly or discrepancy occurs, the system alarms and warns the pilot and might suggest precautionary 'traffic announcements' and more imminent 'resolution advisory' (RA) warnings. When the system identifies a time-critical RA and both aircraft have TCAS, it will coordinate the RA to suggest opposite paths for the fastest avoidance agreement. Additionally some newer aircraft have RA connected to the autopilot, and automated avoidance can happen unless the pilot overrides the system advice.

The system described has a 'multi-level automation' which is context sensitive. The functions provided to the operator changes with context, and in critical situations the operator might even be eliminated from the decision sequence. Fleming and Pritchett argues that operator compliance is an important part of using the TCAS system correctly. Simultaneously, the Federal Aviation Administration (FAA) shifts the responsibility to the flight crew; they are required to check and validate the RA. In some situations the flight crew might resolve to ignore the TCAS, but this requires a simultaneous cognitive process to scrutinize and actualize on the situation . This use of the system requires education systems based on actual expert performances and how they utilize systems in a variety of situations. (Fleming and Pritchett 2016) argues for the appliance of the SRK framework (discussed earlier) as an application for learning goals and material.

Virtual Reality

As Virtual Reality (VR) quickly is becoming a reality in a number home-techonlogy applications, they are still rare in industrial systems. Re, Oliver, and Bordegoni (2016) looks at the results of a number of studies on VR in Industrial tasks, they indicate improved performance, but at the cost of ergonomics, situational awareness and monetary expense. These factors currently prevent adoption. Technology limitations are a major hurdle even today, systems are either large and high-fidelity or small and relatively low information display capacity. Hand-held displays such as Mobile phones and tablet require a operator to hold them reducing manual ability. The current generation of Virtual Reality applications are "currently unacceptable in industry because they are unstable, not scalable and they have ergonomic and economic issues that negatively affect working conditions in long-term usage" (Re, Oliver, and Bordegoni 2016, p. 382). The potential is clearly there, and laboratory tests show reduced cognitive workload with increased performance, but the impact of these types of devices is still low in the current day possibilities for developing Decision Support Systems.

4.3 Learning Requirements

To implement effective automation systems we need to implement learning into the system design. Zuboff (1988) argue that 'informating' technology cannot be useful without a supporting learning structure. Understanding is a requirement for comprehension of information, and the environment around any system must support learning to optimally utilize such systems. "...a *learning environment* [emphasis added] would encourage questions and dialogue. It would assume shared knowledge and collegial relationships. It would support play and experimentation, as it recognized the intimate linkages between the abstraction of work and the requirements for social interchange, intellectual exploration, and heightened responsibility." (Zuboff 1988, p. 308).

Davenport and Short (1990) argue that IT Systems can be designed to *monitor* or *empower* employees. When implementing automation to redesigning business processes the learning-potential of information systems is often neglected. This potential must be evaluated when contemplating new systems.

Not everyone is motivated to be an expert learner, but creating an environment where learning resources is available and supported will enhance the possibilities for those who want to develop expertise. (Bereiter and Scardamalia 1993, pp. 152-181)

C. M. Karuppan and M. Karuppan (2008) reviews research showing that the timing of training emerges as an important factor of performance, in accordance with *learning/forgetting theory*. They found that a solid mental model and understanding of the system had a great effect on both operational efficiency and adaptability. This effect is especially large on far-transfer tasks, where information has to be combined and understood. In training they found that *Active* experimenters performed better, and generated more accurate mental models, hands on experience seems to be one of the major sources of learning to use IT systems, and should be emphasized in instructional design.

IS trainers should emphasize the acquisition of highly capable users to first learn the system, and utilize these to help during education of "Normal" users (C. M. Karuppan and M. Karuppan 2008) .

Cognitive Overload in Learning

Mayer and Moreno (2003) suggest that *Multimedia Learning*, learning using written- and spoken words and illustrations, can be used to improve *meaningful learning*. Meaningful learning is defined by them as a "...deep understanding of the material, which includes attending to important aspects of the presented material, mentally organizing it into a coherent cognitive structure, and integrating it with relevant existing knowledge." (Mayer and Moreno 2003, p. 43). In short their model of multimedia learning suggest that a problem of cognitive learning system is *cognitive overload*. The brain can only process so much information at once, and information-presentation greatly affects the learning process. These overloads can be managed, by general principles such as eliminating redundancy, aligning, synchronizing, and individualizing content. While this is not directly related to decision making processes, the learning output of the system design is greatly influenced bu design principles such as these and must be taken into account as in any other system that involves user interfaces directly exposed to users.

Recognizing Training Requirements

Cues are identified as an important part of human decision making, but might be as important in learning and understanding how systems work (Clark et al. 2008). By observing experts use of cues, these should be incorporated into the learning program. Using identical cues in the learning and sitauted experience is important to understand which goals and procedures are appropriate for the individual cues when observed in the production environment

One such applications is to use the Skills Rules Knowledge model by Rasmussen (1983, See **Section 2.15.1**), it is recommended as a a foundation for developing operator training programs. Evaluating actual situated performance of expert operators show us which situations an operator has to be skilled, where he can use rules and the situations in which (and what) knowledge is applied to resolve the condition.

Fleming and Pritchett (2016) use the SRK framework and argue that Skill Based and Rule based behavior is overemphasized in the learning program for the Traffic Control Automation System (TCAS) (see **Section 4.2**. Knowledge Based limitations are hard to learn from experience, behavior is often misunderstood and operators seem to have incorrect or lacking models of the functionality of the systems black-box calculations. However, responsibility is given to the operator because of their presumed elaborate knowledge-based competence. Knowing when to ignore the systems advice is dependent on modal and abstract knowledge of the system limitations. And when most TCAS in the future are connected to the autopilot, the operators Knowledge Based Behavior is the most important role in the Human-Computer cooperation. By using frameworks such as SRK to eveluate the learning process, there is an opportunity to find areas of competence where the learning program and actual operational operator-requirements diverge.

4.4 Cognitive Requirements

> If we engineer complex cognitive systems on the basis of mistaken or inappropriate views of cognition, we can wind up designing systems that degrade performance rather than improve it. The results stemming from the application of any cognitive systems engineering methodology will be incomplete unless they include a description of the cognition that is needed to accomplish the work. (Klein, Ross, et al. 2003, p. 1)

Identifying the cognitive limitations of humans is a requirement for designing effective decision support systems. Humans use heuristics, intuition, analysis to comprehend the environment and arguments for decisions.

4.4.1 Cognitive Elicitation

By identifying the cognitive biases and decision-limitations of operational problems, the basis of both system- and learning design is argued as more appropriate. Real problems outside the laboratory are usually presented with incomplete information, and humans will subconsciously try to fill gaps in their understanding. (Simon 1983). The data inferred by humans is based on assumptions of the problem domain, heuristics. By assuming that the operator is able to infer and use heuristics to help automated systems, can facilitate inherently better decisions. An analysis of operators work and repeated errors require an observer which has an deep understanding of both human cognition and the work-process, to be able to uncover these internal biases (Croskerry 2003a).

Zuboff (1988, Ch. 2) show that operators which possess mainly *action-centered* skills often have difficulties mastering the transition computerized systems, but those that are able to convert their situated knowledge into their understanding of the decision support system seem to understand and make better decisions than those familiar with only one environment. In this instance the systems are not designed with the mental models of the operators in mind, so the abstract thinking employed seem to be easier for those with intricate knowledge of the background workings of the systems.

4.4.2 Knowledge Requirements

Both Morris and Rouse (1985) and Zuboff (1988, Ch.2) argue that theoretical knowledge is not a requirement for improved performance in operating industrial process systems. Operators understanding of the theoretical aspects of the process does not impact ability to support a automation system. Operators with a form of *process feel* has an improved performance, but this experience cannot be obtained through textual instruction. Morris and Rouse argue that educating operators in technical knowledge is disproportionate to the level of system understanding gained, and that the traditional approach with instruction through theory should be challenged. Meanwhile findings from other researchers (Yoon and Hammer 1988), argue that theoretical understanding might be important for accurate diagnostics in novel situations.

4.4.3 Cognitive Models

One problem of decision support systems are that they often operate in a *black box*. The system can often propose a solution, but the reasoning is either hidden or unavailable to the human operator. This limits the possibilities for learning and intuitive understanding. The decisions of a system might be based on a faulty approach, and the process must be repeatable. Some systems have presented textual step-by step reasoning explanations (eg., Musen, Middleton, and Greenes 2014), but these are not universally acclaimed (eg., Jonassen and Ionas 2006; Mosier 2008).

Mapping the users mental models and the designers and engineers conceptual models of the system is highly important to support the development of a correct understanding of the instantiated system (D. Norman 1983). The operators use their System 1 (See Chapter 1) explaining and connecting causality by heuristics. Cognitive Decisions require definite explanations of limitations to the reasoning strategy of the decision support system to avoid automation complacency. This will cause faulty mental models, satisficing to meet operating demands, not trusting systems and not revising based on experience.

Causal relationships are one of the defining features of mental models, but is an aspect often denied in automation systems. Decision support systems should present explanation of the causal reasoning applied, and that the user understands the basic implications of each sequential node in a decision path (Jonassen and Ionas 2006). Jonassen and Ionas (2006) use Influence Diagrams as one approach that helps understanding, which can be adapted to screen based reasoning systems.

4.4.4 Monitoring Automation

As seen in Chapter 3, humans are bad at monitoring screen based displays of automated systems. They become complacent. Even when motivated, humans are unable to effectively review mostly static data in an efficient manner.

O'Hara et al. (2000) state that two factors influence fault detection through monitoring: The characteristics of the environment and the operators knowledge and expectations. The first one is generalized as data driven, and the second model driven. Data-Driven is data that works by itself eg., temperature, color, smoke, sound. Alarm systems usually support the data driven approach, highlighting data that is outside operating values. The model driven is how humans and computers use a model to combine data into a bigger picture, either by standard procedures to monitor data at intervals and combining them according to a procedure. Or by knowledge and expertise and reading values to create a picture of a situation.

4.4.5 Automation Bias

The automation Bias is presented in Chapter 2, and is a bias influenced by humans overtrust, complacency, and of omission and commission errors by automation of both cognitive and physical tasks and procedures. The bias is common in automation systems, because systems often employed and designed to reduce human workload, often eliminating the human to a responsible entity. As a result, humans re-prioritize their cognitive resources on other tasks, and trust automation more than reasonable.

Mosier et al. (1998) and Skitka, Mosier, and Burdick (2000) studied the effect of *accountability* on automation bias, and found that subjects with more responsibility and accountability improved performance on monitoring automated decisions. They were more alert of system errors, and also able to support their own choices when their opinion differed from the machines. The subjects in both articles were instructed that the machines inferences could be flawed, but that the digital measurements were reliable. Accountable operators were more attentive, as was evidenced by more information seeking and use of verification procedures. One effect that is described as interesting by Skitka, Mosier, and Burdick is that the operators that put in more time on verifying and validating information did not spend more time overall on the laboratory test scenarios. The accountancy effect led to vigilance only when accountable for monitoring *system behavior and accuracy*, when accountable for other types of tasks not requiring increased information acquisition and vigilance there was no reduced automation bias.

Bereiter and Scardamalia (1993, pp. 58-61) describes how *self-regulatory knowledge* is important and one of the most learnable and generalizable expert skills. The ability to use metacognition and meta-knowledge to adjust and correct the current model of a situation can be performed by taking a step back and comparing to literature and previous experiences (eg. Croskerry, Singhal, and Mamede 2013b). By comparing ongoing problems to experience, the current mental-model and the model of the domain is connected and there is an increased possibility for learning and knowledge.

4.4.6 Distributed Cognition

Hollan, Hutchins, and Kirsh (2000) presents an approach called *distributed cognition*. They argue that system design has to account for how both people and systems interact, when designing systems supporting cognitive work.

A further observation from is that people offload cognition to their environment (R. A. Wilson and Clark 2009; Hollan, Hutchins, and Kirsh 2000), by taking notes, looking up information and using automation systems we reduce the cognitive requirements for processing advanced decisions.

4.4.7 Summary

To create better DSS we have to become proficient in the domain. We can never understand experts decision processes without understanding some of the principles behind their decisions. When building new systems, a requirement is awareness of the genuine usage-patterns of the precursor system. The system we replace might have tacit features that were unintended in design, but widely used and that are difficult to uncover and represent using the intended hardware for the novel systems.

4.4.8 Reasoning Strategies for automation systems

Pople (1982) suggest that using a *differential diagnosis* approach, where decision support is aggregated into groups that can be eliminated using few variables. This is the approach of expert practitioners, whom often utilize the approach of finding conflicting cues to eliminate frequent problems first. By selecting and eliminating the most common diagnosis, the practitioner keeps alternatives in the back of his head. The problem of creating good algorithmic computer aided decision making systems is greatly impacted by the level of understanding required for most expert practitioner tasks. The approach suggested by Pople is to create diagnostic systems that have the ability to finalize decision paths when a finite number of problems are possible. Human Diagnostic reasoning can be supported by these processes, by using computerized automation in finalizing a diagnosis. It might simply be to generate an exhaustive list of all possible diagnosis, where the system can assuring that the correct diagnosis is on the list. A simple approach like this can affords the practitioner to redirect his cognitive abilities, and to debias from eg., an anchoring effect or confirmation bias.

Abductive reasoning is a retrospective diagnostic strategy, looking at the current symptoms to infer the problem component (P. J. Smith et al. 2012). It is a common occurrence in current decision support systems. The issues for human decisions in such environments are that there can be a multitude of problems co-occurring, maybe even masking the true problem. Noisy data is hard to interpret. To utilize such data the human processing it has to search, but he has to know when to stop.

4.5 Environmental Considerations

The environmental considerations in DSS design are related to the impacts of the operators surroundings to his understanding of the working domain. The entire workplace and the operational requirements affect operators decision strength (Rasmussen 1999).

In domains where data and impressions are overwhelming in amounts, and where understanding of the current status is complicated, decision support systems are often correctly applied to help humans. But as P. J. Smith et al. (2012) indicate, the role of the human has to be evaluated to the accuracy of the DSS. If the automated decisions are accurate and reliable, the humans role might be a supervisory one. Contrary if the automated domain is incapable of reliable decision support, it might be better to implement the automation as a critic to the operator.

4.5.1 System Design Considerations

When creating systems a requirement should be to support expert operations. To facilitate expertise in using computer systems we have to avoid creating *wicked environments* (Kahneman and Klein 2009). To support intuitive learning and understanding of data interfaces, the data has to be represented in the same way at any two times where identical data is the basis of the presented visual model. Blauner's 1964 study *Alienation and Freedom* (Related in in Zuboff 1988, pp. 51-57) highlights that automation of production is increasing the requirements for breadth of knowledge and awareness over a wider part of the factory, but the deep knowledge of the technical and scientific process is reduced. In industries involving chemical processes a knowledge gap is created, where the operator has less understanding of the physical processes than what is apparent in automotive and production industries. Zuboff states that this not inherently is a problem, the new skills required is to manage the system interfaces – understanding the context of numbers and figures is the new skill. The understanding of the actual operating systems could just as well be simulations, and Zuboff argues that controlling tasks have become similar to craftsman skills. But for craftsman skills to develop, a number of design features and helping systems should be applied.

As mentioned earlier, "Experts often make opportunistic use of environmental structure to simplify tasks." (Hollan, Hutchins, and Kirsh 2000, p. 182) Taking into account how current systems are utilized by experts is one of the great opportunities for designing effective new systems. Good decision system design cannot be based on procedures, interviews and operator accounts alone — we need to observe through task analysis. This Cognitive Ethnography approach is by Hollan, Hutchins, and Kirsh addressed as especially good for observing behavior in situated experiences and then validating the cause of this through experiments. When the theory for an interaction behavior is defined we are able to base new designs on this, where we create a loop for new observations.

4.6 Presentation Requirements

When designing Decision Support Systems a focus on Presentation is a requirement to represent understanding. Systems have to facilitate transparency and discoverability, and relate the functional relationships between models and systems. To facilitate understanding of information, an explanation of the computers reasoning has to be available. The *situated* experiences with devices and interfaces are major influences of understanding systems and how they work (Woods, Dekker, et al. 2010, p. 106).

Currently automation systems are designed to avoid errors, but rarely to facilitate expertise. One problem caused by this is that humans rarely get to apply their knowledge on real problems, reducing the feedback and learning potential for when a real problem occurs.

Rasmussen (1999) argue for a method improving system and operator safety by "accepting all errors as inevitable". Systems has to be designed by this principle. Automated systems will never be able to correct for all errors. If an error passes through all safeguards in the "safest" system, it will be much harder for operators to diagnose and prevent the error because they have no experience with the rare event. Systems should accept malfunctions and errors, display and highlight these, and require operators to support the decisions adjusting for the error. Operators familiar with the system are able to diagnose and intervene when a major malfunction happens. The responsibility and trust is again in the hands of operators, and to some degree removed from the system and system-designers.

Users base their understanding of 'normal' on prior experiences, and major system changes might collide with mental models and demands in a way that is incompatible with the decision flow prior to the system was added. This aspect has to be taken into consideration, and model mapping in learning environments is one possible approach.

4.6.1 Information Channels

Preserving information channels was earlier presented as an important part of the cognitive affordances of a new system. Operators use approaches uninteded by the initial designers to accomplish their goals, and their mental and extra-cognitive usages of systems to store data and remember operations are just as important as the intended usage of the systems.

Data requires context in representation (Woods, Dekker, et al. 2010, pp. 162-169). Most data has baselines, expected values and off scale values indicating error or stoppage. Monitoring this data is a cognitive task that is hard for humans to follow by just using numbers, such as reading a digital pressure gauge. Analog pressure gauges often have operator marks using a pen to indicate an optimal value. Any operator will be able to see that a value outside of the indication is an incident, and no knowledge is needed to report to a supervisor. This aspect is often lost when converting to digital values, even in "analog" - speedometer representations you are often unable to indicate operational and optimal values. Systems have to be able to represent context to facilitate recognitional diagnosis and decision making. Each value should be monitored, and their status over time should be available to discover when the value started diverging, and how it has changed over time.

Hollan, Hutchins, and Kirsh (2000) highlight the roles of representation of cognitive models in interfaces of computational systems. They argue that systems have to map the important physical features onto the interface, to facilitate adjusting the cognitive work of converting the digital data to the physical problem and vice versa. (See: Re, Oliver, and Bordegoni 2016, for a direct mapping using Virtual Reality).

This coupling with environmental and situated learning is highly important to system design, and discovering and sharing methods and models for designs is a highly important task to create the best possible systems for improving decision skill via screen systems.

Operators often utilize their workspace to remember and prioritize work. On a PC the operator opens windows, resize them based on current importance, checks back on completed windows to verify information. Hollan, Hutchins, and Kirsh (2000) argue that studies of planning and activity often observe the temporal activities, but they should in addition analyze how " . . . agents lay down instruments, ingredients, work-in-progress and the like" (Hollan, Hutchins, and Kirsh 2000, p. 190). Humans are constantly organizing their workspace, some times consciously other times not. Workspace organization has individual patterns, but supporting information storage and possibilities for navigating in seemingly arbitrary ways to debug selected problems seems to be important for optimal cognitive offloading.

History Enriched Digital Objects

Physical objects are components to wear, movement, ordering, stacking and more. This perceivable usage history is an important factor in distinguishing how equipment is used, and has been used recently. Hollan, Hutchins, and Kirsh (2000) argue that is an often overlooked component of expert perception that rarely is transfered into digital systems. The opportunities by digitalizing systems is that we can record all these interactions and create better systems based on them. A button that is worn down on a physical system is the most used one, it implies functionality and safe operations to use the patterns others have utilized before.

Various approaches to *history enriched digital objects* are possible. Through data collection we can generate heatmaps and inspect usage patterns related to various situations and procedures. Using this systems can provide improved decision support to the operator by eg., highlighting commons steps and removing information sources based on context. The opportunity is that digital systems can contextually guide operators more than the physical interfaces they replace.

4.6.2 Information Convenience

Convenience and ease of access are one of the main factors for human information seeking. People expect fast access to information. Users seem to be transitioning quickly from getting information in books and libraries, to more accessible digital information sources (Connaway, Dickey, and Radford 2011).

R. Smith (1996) explains how the traditional sources of information doctors are provided does not suit their needs for information seeking. Books are outdated and slow, journals have a low signal to noise ratio. Clinical operators information needs is often more for feedback, guidance, affirmation and support. Smith argues that the existing ICT solutions are insufficient, but as we now are 20 (!) years later it seems like there has been a shift in knowledge retrieval towards using ICT and Internet based information sources (Clarke et al. 2013).

Fiol et al. (2008) present an example of a system where a low barrier to information retrieval both increase efficiency and decision-making capabilities. They found an average 17% decrease in time spent, and in 60% of the cases the practitioner reported that their decision-making had been supported by the increased availability of information.

Automation etiquette seems to have an impact in the efficiency of human operators consulting with automated decision support systems. Sheridan and Parasuraman (2005) show how systems with high reliability (80%) which interrupt, hurry and bother the human operator can result in inferior results to a lower reliability (60%) system that works better together with humans. Automation etiquette is an approach to implement human cooperative etiquette into automation systems, to improve automation cooperation. Quantity, quality, relation and the manner in which you present it all has an impact on the user experience, and has a direct connection with task performance.

Makary and Daniel (2016) indicate that to reduce harm from individual and system errors, we have among other principles to ”facilitate a culture of speaking up”. Organizations which recognize that diagnostic- and decision-errors are frequent should design systems that embrace human errors, and which facilitate reporting incidents to better understand and prevent recurring errors.

4.6.3 Data Overload

A common issue in humans decision awareness is overlooking and discarding information because of the sheer amount of information. (Woods, Patterson, and Roth 2002) describe some methods to reduce the problem of data overload in computer systems. (1) organization of information should follow recognizable patterns and mappings to related data, and the system must provide different perspectives to the data. (2) information systems need to positively highlight data, not negatively eliminate other data. (3) context sensitivity, improving information validity requires a context sensitive approach, both by visualizing data departures from normals and highlighting events and patterns. Additionally highlighting related data to the current interest of the operator. (4) Observability, designing with the objective of fast recognition even when not given explicit attention. (5) conceptual spaces in the design, using mental models of systems to map and coordinate data while visualizing this relation to the operator so that the connection is explicit.

An example of the studies of “simple” subsystems that will affect how HCI and DSS are designed is how Woods (1995) show how alarms impact human decisions through directed attention. Automated alarm systems are often disconnected from each other, so when one component fail alarms sound for every dependent component. The *alarm problem* is that alarms mostly occur in situations with the highest cognitive workload, time sensitive and unsafe situations. The idea of alarms is to highlight sudden changes in the monitored data, and to support human cognitive abilities, and avoid biases. Attempts to use automation finesse has according to Woods (1995) often failed, the automated diagnostics of issues are often surpassed by improved information handling and visualization capabilities. New systems has to take into account emphpreattentive reference; the idea that information from alarms should be displayed without breaking operators attention their current task.

Systems have to be designed with the principle of discoverability and a peripheral vision of alarm states. Alarms are an informational task, and should not force information processing over the current task. Focus on establishing the correct operational and HCI types in areas like spatial dedication, auditory displays, analogue alarm displays, and alarm intelligence are components of system design that have great impact on the cognitive workload and abilities.

4.6.4 Procedural Instructions

O'Hara et al. (2000, CH.5) presents guidelines for nuclear power plant *response plans*. The objective of the operator when following procedures in Nuclear Power Plants is to compensate for inadequates, fill in gaps and resolve conflicts between control objectives. Operators must be able to work around and use procedures as a basis, as the overreaching goals are more important than following individual steps. Both the coming and past steps of the procedure is important for operators understanding and awareness. And the goal of the procedure is important to highlight. Further systems must support navigating within and across procedures, to better support human operations in high impact situations. An approach for improved instructions is applied by Eiriksdottir and Catrambone (2011), as it is rarely enough to just provide proceduralized instructions. We need to digitalize the principles behind procedures. Principles explain the reasoning for procedures, and are able to fill in and support the human searching for knowledge.

4.7 Summary

In this chapter a number of results and indications for the design of decision support systems were presented to highlight the opportunities for creating DSS in industrial environments.

Chapter 5

Current Challenges in Facilitating Industrial Human Decision Making

5.1 Introduction

An understanding of Human Cognition is important to improve decision making in organizations (P. J. Smith et al. 2012). The state of the art and the research communities current understanding of human cognition and decision strategies are presented in the preceding chapters. There are a number of approaches to human decision making. Human decisions are greatly influenced by *biases*, cognitive shortcuts that make us able to infer from incomplete data and make quick choices. Humans use these shortcuts to make fast decisions, and the ones that work appropriately are called *heuristics*. Natural Decision Making argues that applying heuristics through *intuitive* thinking makes good decisions. *Effective* intuition requires an extensive situated knowledge of the domain. Humans can adapt strategies to minimize reasoning errors. These strategies involve cognitive forcing, learning, and deliberate practice.

Automation seems to increase efficiency while reducing expertise, but this is not a requirement. By reducing the opacity of automation systems, there seems to be potential for human learning and understanding.

The third chapter presents current 'state of the art' of considerations for Decision Support Systems (DSS), highlighting important concepts recognized in literature specific for the development of DSS and *situated* learning elicitation.

In this chapter presents four current challenges and opportunities for industrial DSS based on the literature study. These indications from literature and current systems designs and are a combination of current 'state of the art' of DSS and lack of presence from concepts with the cognitive decision literature.

5.2 Automated Decision Support

Humans are likely to make mistakes, our decisions are based on a number of biases and heuristics. The most commonly applied solution is automation, automated tasks eliminate the human inconsistencies and replace routine tasks. But when a task requires a mix of knowledge and skill in an environment not suitable for complete automation, an automated decision support system comes out as one possible design solution.

Any type of automation is employed to reduce human workload, and by reducing work we also reduce opportunities for learning and understanding. 'Machine-minding' operators are thought to be slowly deskilled, because frequent retrieval of knowledge is required to maintain long-term memory. Operating systems often lead to a 'black-box' of inaccessible information, and understanding of the workings of such a system is impossible without assistance.

Automated systems also affect humans through the Automation Bias, and automation Complacency. Humans operating with systems where no errors are discovered trust the system to perform the task correctly. Operators using decision support systems with undiscovered errors are observed to perform worse, than the control group without any assistance.

The literature study also indicate that the efficiency of Decision Support Systems in Medicine currently is uncertain, and laboratory effectiveness has not yet been observed in actual performance results (See eg., Moja et al. 2014).

The decision systems need to balance between task specificity and generalizabley. Developing decision support software requires an intricate understanding of the domain, and the operators in the domains requirements.

Opportunities

While the current systems have a number of problems, several opportunities have been discovered through the literature study presented in 3.

Decision Automation Systems are in better at interpreting data and have access to an infinite number of sensors and procedures. The limiting factor for the employment of automation in decision is that creating the software and, machine collaboration is hard.

To alleviate the problem of automation system a human operator is often applied as a responsible decision maker and as a validation entity. To facilitate this symbiosis, the opportunitiy is to design systems for *human computer collaboration*. These systems ar designed with the collaboration of user and system in mind. All automated decisions and steps are available for review by the user. The automation system can request data from the operator, and opposite. The system has to be able to collaborate in human terms, expressing certainty and doubt when needed. The goals of the system, and the user has to match, when goals are discrepant mode errors can undermine the progress on the diagnostic task.

As with the levels of automation discussed in Chapter 3, a system helping with a high automation data analysis and presentation, but low level of automation of decision and execution is a system more reliant on humans for a full picture evaluation and systems for simple model based checks of the environment. Systems need to encourage procedures on the side of the “happy path”. To better de-bias humans in how they follow automation, we need to make them aware and remind them of the limitations of the system, and the opportunities of alternatives. If the system is uncertain, suggesting or doubting decisions it must be visible to the human. The human part of the system is the one that can combine cues across procedures and find what could be a common cause.

Operations require constant adjustment for regular performance at optimal capacity. And systems design must allow for the human to adjust and control system choices. Experienced decision makers rarely follow procedures, because procedures never facilitate the correct response for specific cases. Allowing for adjustments and recording adjustments to create better procedures using expert feedback is one opportunity available.

The hardest cognitive task is the diagnosis, and automated DSS might have problems identifying errors caused by the components without sensors. To follow up on the data collection approach that is undervalued in research is to identify failure patterns by applying a retrospective analysis of the diagnosis systems. Similar patterns might require the same procedures for diagnosis.

Decision support systems have the opportunity to display more of the *causal reasoning* of the decision it creates in a visual or textual way. Causal models are highly important to human cognitive performance and memory, and by makeing these available through automated decision support systems they facilitate an understanding of the principles behind the reasoning.

5.3 Encouraging Learning

A big part of increasing decision strength is as highlighted in the literature study to build expertise. Experts make better and quicker decisions because of their greater knowledge base and understanding of both automation and environment, and they are capable of combining this knowledge into a novel discoveries and solutions. Current system design seems to discourage learning, as automated ’black-box’ systems and simplified proceduresare employed to avoid human error. Even systems which provide the operator with adequate information does not by itself provide learning opportunities Zuboff (1988).

Current industrial systems discourage mistakes and errors to a point where humans lack opportunities to make errors. Errors are in the first section shown as the way people learn most efficiently. Organizations are usually right in attempting to lower errors, but they rarely compensate by building opportunities for expertise.

Understanding is a requirement for comprehension of information, and to make decisions. The entire environment around systems must be designed to facilitate such understanding to help the responsible operator diagnose and scrutinize automated support systems (Zuboff 1988).

Operators with situated knowledge from before a decision support system is implemented, and whom convert this knowledge into their model of the automated system seem to make better decisions. But this situated knowledge seeps from industries where operators only are familiar with the automation. These operators perform their tasks just as well as those with theoretical knowledge (Morris and Rouse 1985). The argument is that a combination of operational proficiency and environment knowledge creates the best operator for diagnosing and non-routine decisions.

“Thus, confronted with complex, real-world process disturbances, operators must monitor the performance of the procedure to verify its correspondence to the higher-level goals that it was designed to achieve." (O'Hara et al. 2000, p5–46) O'Hara et al. are recommending usage of procedures in Nuclear Power Plants, describing the tasks of operators and the limitations of procedures when applied to real world problems. The operators task is to achieve the *goals* of the procedure, not to follow procedural tasks. The procedure is a cognitive tool to guide operators on the correct path, and the response of the operator has to be adjusted to fit the limitations of the real world. This principle has to be emphasized in the current systems design, by guiding and instruction operators with procedures operators can develop complacency and reduced knowledge.

Current learning practices at industrial environments seem to be based on an instructional and procedural approach. The problem of situation awareness and safety leads to little instruction performed in the operational field. Guidance is given and in some communities shared by discussions. But theory is rarely readily available. Often simplified models of the main operating systems are presented before entering the workplace for the first time, but there is rarely any theoretical follow up unless the operator specifically requests it.

Opportunities

Systems design can facilitate expertise. Bereiter and Scardamalia (1993) show us how facilitation of expertise is to provide new challenges and opportunities for learning. Those operators who are interested must be provided with a low-effort, encouraged system for furthering their understanding. A supporting learning structure following any decision support software will help interested operators understand the reasonings behind a situated experience and theory.

a solid mental model and understanding of the system had a great effect on both operational efficiency and adaptability (related to training before use of industrial systems) C. M. Karuppan and M. Karuppan (2008)

Shortening the path to operator expertise seems to be possible through other areas than situated practice. We may apply the SRK framework as seen in Section 4.3, to facilitate instructions on the actual cues and tasks of experts operators. Supporting understanding has effectiveness on operational efficiency and adaptability C. M. Karuppan and M. Karuppan (eg., 2008)

Mental Models are rarely available on their own, they are systems connected to other mental models to complete a big model of the domain and the entire human cognition. Learning theory is easier when connected to experience.

Webster-Wright's 2009 idea of Continued Professional Learning (CPL) requires a holistic approach to learning, where learning continues before and after a "course" or "event" (Webster-Wright 2009). Billett (2001) argue that the workplace can support or dismiss learning through the activities they apply. Instructional Scaffolding, mentoring, dedicated learning time, and more are applied to provide opportunities.

Effective learning assumes active experience, observation, reflection, formulation of concepts and applying and testing these in practice (Webster-Wright 2009).

Instructional Systems design is an opportunity that, as far as I have been able to understand is a novel concept in *industrial* systems. Learning is regarded as a supporting process, separate from the production programs. While this separation from the working environment is reasonable, because of safety constraints, an under-appreciated opportunity is to connect individual operators situated experience with learning resources.

“Domains in which expertise can flourish are domains in which there is no inherent limit on progress. There is always a larger context within which the present problem-solving effort is partial and oversimplified.” (Bereiter and Scardamalia 1993, p. 98)

The ability to look up interesting procedures, chemical elements, and the specifications, connection and roles of automated equipment is a possibility. Systems that accompany instructions together with a concept that is able to catch the users interest in the working environment should have the ability to connect to an system outside of the production area.

One such supporting system could be an simulation software, using an identical interface to the situated automation software. Providing an identical state to the situated environment. The ability to explore and inform could be supported by instructional learning (C. M. Karuppan and M. Karuppan 2008), ie., by a guidance ”teacher” – an operator proficient in the inner workings of systems that have a pristine opportunity to learn away the principles in a safe environment to subjects that are there because of their expressed interest in a certain situated experience.

5.4 Feedback

Decisions in any environment offer ambiguous feedback, the choices and modifications done to systems can have repercussions that only become apparent hours, days, or weeks after the modification is performed. Mistakes are not a problem if they are only made once, and thereafter are avoided. But environments with lacking feedback may base influence of human decisions nn the wrong assumptions. These environments are regarded *wicked*, because inherently ambiguous feedback is unconsciously inferred by human cognition and heuristics.

Feedback of such delayed processes are currently hard to accomplish. The individual operator making the decision might not be available, and discovering the reasonable tasks.

Feedback is also a requirement in the information seeking of professionals, they want to validate their strategy before making a decision (R. Smith 1996),

Opportunities

Bereiter and Scardamalia (1993, pp. 58-61) and Croskerry, Singhal, and Mamede (2013b) describes how *self-regulatory knowledge* and *cognitive forcing strategies* can be applied to make experienced operators more aware of the inherent difficulties of industrial systems.

Digital systems inherit possibilities for logging events, decision and feedback for each interaction. Using personalized user accounts to create environments intending to provide feedback for delayed operations and for example discovering insufficient awareness of operators, that can be informed of their limitations. A system designed through this approach limits the issue of wicked feedback from delayed process results. The interactions are logged so that both human and automation decisions will be able to find the source of error and to correct the misunderstanding.

Working with situated systems are one of the most important features of learning to perform task efficiently in many industries (Woods, Dekker, et al. 2010, p. 106)).

Situated feedback is possible by implementing monitoring systems instead of Automated Decision Support Systems.

5.5 Information Presentation

A current challenge in any information system, and even more so in automated ones is the challenge of supporting expertise through the presentation of data.

Systems often break down their representations to oversimplified representations. These representations often seem to afford expert intuition when using them. But such systems are dangerous and can mislead decision makers, especially in situations of errors and incidents.

Mental Models and Cues from the prior systems are often eliminated. Physical wear on buttons indicate a history of use, but this if often overlooked in system design. Many systems mask the data behind aggregated models and inferred understanding. Sytems that seem simple to the operator might combine a large number of data sets. Users often are unaware of the complexities and base their intuitive decisions on misguided assumptions.

Alarm Systems are one example of systems that work best in the situation where they are the least important. System design require a central focus on their effectiveness for supporting human decisions in high workload situations.

Opportunities

Experts use mental models and cues for their environmental understanding. By providing bites of theoretical models directly into the situated environment, there is an opportunity to facilitate the applications of theory. This is a central part in maintaining theoretical knowledge instead of making a task merely routine.

Users should have the opportunity of modifying the displays of information to their needs. Using contextual displays seem to be an opportunity that is promising if the context can be inferred correctly.

Systems should relate data in a way that connects the current system to the other system in the production line. A ”process” feel is an indication for operational performance and can be improved by .

Using the same information displays in training and in the real system helps connecting the mental model from the theoretically approached training with the situated experience gained from the workplace.

Chapter 6

Design

6.1 Case

The introduction to decision strategy and cognitive science has focused on adult cognition, especially in industries where the working environment is stable and regular. In 2006 the Norwegian industry was composed of 33% process and machine operators, transport workers and similar(Bore and Skoglund 2008, p. 10). These lines of work mostly require a low amount of education, and most process specific knowledge is (as in many other professions, learned at work). 23% are craftsmen with prior education on their craft, such as carpenters, welders, mechanics. It can be hypothesized that many of these professionals also have a limited understanding of the intricacies of their workplace systems. Automation has become a reality in most of the industrial work, in the Norwegian metal industry the number of workers have gone from 24 000 to 8 000 employees in the period of 1974-2006 (Skoglund 2008, pp. 114-115), and the reason for this is the introduction of IT and automation systems for both supporting and production tasks. The requirements for knowledge and profession has increased, and in many industries the prior roles of unskilled workers are replaced with automation and increasingly advanced machines (Berg 2015, Ch.4) .

Indications like those mentioned above, and personal experiences from work at two industrial companies is that operational tasks are often performed by operators with limited theoretical education, their professional experience is often from profession training, such as mechanical and process-industrial skilled workers, and situated learning. This combination of prior experience and skill makes workers proficient at most tasks, but they lack expertise gained from understanding.

6.1.1 Example Industry - Aluminum Refinement

Through a cooperation project with the Norwegian aluminum industry an identified problem is that operators make mistakes due to a lack of understanding or knowledge. Currently operators in the aluminum industry mainly learn on the job, they are guided by

Figure 6.1: A potroom at a Norwegian Aluminum Plant (©2002 Norsk Hydro ASA, *approved for royalty-free reproduction in all media by any person or organization.*)

operators with situated experience and are taught the tools and tasks they are to perform until proficient.

This has lead to operators with limited ability to make their own inferences and judgments, and both operators and the management indicate that responsibility knowledge is a need for work satisfaction and performance.

6.1.2 Case Problem

Aluminum (Al) is refined from Alumina(Al_2O_3,), using the Hall-Héroult electrolysis process to reduce the Alumina down to Carbon-dioxide (CO_2) and Aluminum (Al) . The simplified equation is $(\mathrm{Al_2O_3} + 3\mathrm{C} = 2\mathrm{Al} + 1.5\mathrm{CO_2})$,in practice producing around 1kg Aluminum and 1.5 kg CO_2, requiring 13-15kWh energy per kg ((Kvande and Drabløs 2014).

The work environment at an aluminum smelting plant is seen in Figure 6.1. Huge halls, called potrooms, can be more than 1km long, at 50 meters wide and 20meters high (Kvande and Drabløs 2014). Each potroom usually contains between 100 and 400 electrolysis cells, often called *pots*. Each pot is connected, where the cathode of one cell is connected to the anode of the next one, creating a cell-line (potline). Each pot require electric power to run, and this is the major cost in producing aluminum. Figure 6.2 illustrate the structure of an individual cell and the requirements for converting Alumina to Aluminum

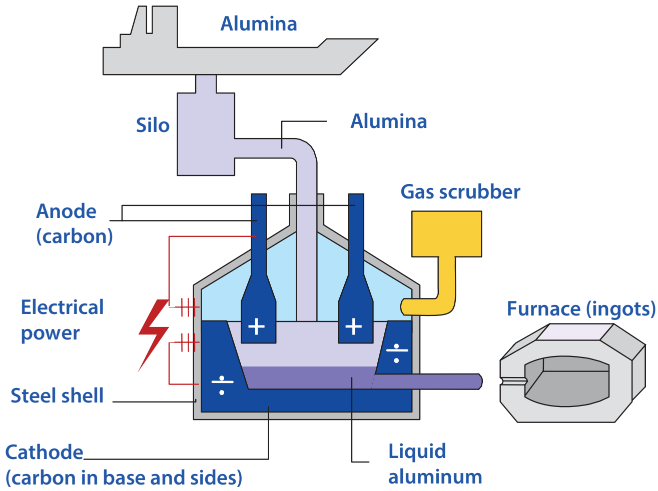

Figure 6.2: "Flow sheet of the aluminum production process." (From Kvande and Drabløs 2014, 25, CC BY-NC-ND 3.0)

6.1.3 Operations

An example problem often identified is related to operating at high efficiencies. As seen in figure 6.2 feeding of Alumina happens from a silo to the electrolyte solution. A quick summary of the problem is that modifications of the electrolyte contents are required for optimal cell efficiency. Modern pots operate at between 88-96% efficiency. A pot operating at 100% efficiency @ 200kiloAmpere will produce 1610kg aluminum in 24 hours. The difference between operating at 88% and 94% at this pot is $(1513kg - 1417kg = 105kg)$ a day. With a market value of USD 1.54 per KG (as of 2016-02-18) this will over the course of a year amount to an revenue difference of USD 59 000.00, with negligible extra costs (Grjotheim and Kvande 1986, pp. 137-138)

Operating at high efficiencies require accuracy in operational methods. The most important factor is reducing heat. A $10\,^{\circ}\mathrm{C}$ reduction in electrolyte temperature will result in a 1-2% efficiency increase (Thonstad and Rolseth 2005). Most plants operate using 10-13 wt% excess Aluminum Fluoride content. This is a compromise between increasing current efficiency and maintaining stability. The ratio of Aluminum Fluoride (AlF_3) can go up to 40% in theory, reducing temperature even more, but it is limited by the accuracy of system and the manual labor still involved in operations (Thonstad and Rolseth 2005). The increase of (AlF_3) lead to a reduced absorption of Alumina (Al_2O_3) into the electrolyte. Alumina levels under 2 wt% can cause an depletion of Alumnia at the anode; an *anode effect*, releasing extremely potent greenhouse gases (perfluorocarbons). Overfeeding Alumina will cause slug to drop to the bottom of the pool, requiring maintenance and reduced cell operating time. This leads to a current operating efficiency at around 2-4 wt%, maintained by point feeders which feed the electrolyte every minute (Kvande and Drabløs 2014).

One of the major problems they have is that Aluminum Fluoride has a delayed effect, it will take hours before the melting temperature of the electrolyte lowers. If the cell has high levels of Aluminum Fluoride and is unmonitored high*overheat* can occur. Overheat is the delta between heat and melting point, is optimally at $5 - 10\,^{\circ}\mathrm{C}$. This range cause the electrolyte to harden at the sidewalls, reducing wear on the outer wall linings.

The cost of operational errors in an aluminum cell can be extensive. Relining of the cathode in a modern pot costs more than USD 100 000.00 (Thonstad, Fellner, et al. 2001, p. 5). A normal cathode lifetime is between 1 800 and 2 800 days, but some cells have operated for more than 4 000 days. There is considerable variation among cells, even with the same design and construction, indicating that cell operation may have a significant impact on cathode lives (Thonstad, Fellner, et al. 2001, p. 5).

The human operator is largely as a supervisory controller and a data provider for the automated routine systems. The cooperation process between the human and automation seems like an likely influence to cell lifetime.

6.1.4 Scenario Description

In the following I have created an usecase of the idea for a systems design based on the knowledge from the State of the Art literature study.

Simon Persona

Simon has worked at the aluminum plant for three weeks, and this is his first job of its kind. He is quite athletic, wants to work hard when he can. He got the job when referred from a friend, and they work together on the day to day job. He intends to work over the summer, and possibly return the next summers. He wants to spend the next three years at university studying economics. Simon is inexperienced and non-skilled, and started the job a few weeks ago. Until now he has had a personal support when performing routine tasks, but from now on he is on his own. He is reasonably scared of the big and dangerous machinery. Performing a mistake is his largest fear, and he is extra aware of his performance because of this.

Scenario - Last pot of the day

Simon is on his way to a routine measurement check. The last pot of the day, but it is the cell that everyone says is problematic. This is Simon's first time checking this one alone. Simon starts by performing the temperature check on the electrolyte. He has learned that a measurement by only a few centimeters wrong can invalidate the assessment, so he performs the procedure as advised by his instructor. The temperature is $1002,2\,^{\circ}\mathrm{C}$. Simon is aware that this was a high number, but nothing out of the ordinary. All other measurements are on point for the optimal values. When entering the data onto the fixed touch screen, he received a warning that the temperature was deviating from the projected value. The projected value was almost $50\,^{\circ}\mathrm{C}$ lower, and the system suggested performing another measurement. The second measurement measured $1001,8\,^{\circ}\mathrm{C}$, and was entered into the system again. The system does a calculation and displays a number of approaches to explain the correlation between electrolyte temperature and AlF_3 contents. An explanation was given to Simon for each step of the calculations, and the confidence was displayed.

Figure 6.3: Operator working on an Electrolysis Cell (©2004 Norsk Hydro ASA, *approved for royalty-free reproduction in all media by any person or organization.*)

While Simon's familiarity with chemistry is inadequate to make inferences to the cause, he is able to understand the effect because of the graphical relation display, as it is similar to one used in training. When AlF_3 percentage rises, electrolyte temperature should decrease. The current measured difference indicates an *overheat* effect of $50\,°C$, which if untreated at this level will severely impact cell lifetime. The system explains all this, and requests Simon to validate with an observation. The observation is instructed by a procedure automatically retrieved. Simon observes a shade of yellow on the oven being significantly brighter at the edges than in the middle, validating procedure expectations.

Because Simon's validating tasks support the working hypothesis, he is suggested (by the system) to check voltage levels, as there has not been any recorded validations of the automated measurement since Operator 'Vibeke' checked it 57 days ago. The automated measurement system might have malfunctioned, and is supplying excess electricity, elevating temperature.

Simon is not certified to work with electricity, and is instructed to request assistance. He contacts the control-room using the built in microphone and camera in the display-unit. The information currently on Simons display is available to the operator in the control room. Because the situation as explained by Simon could be wasting both power and cell longevity, Control sends, Åsmund, an experienced operator over at once. An incident is quickly recorded referring to automation and human choices in the Decision Support, to better find causes and improving procedural support. As Simon is disconnecting from his session, he interested in understanding more about one of the terms in the explanation. He uses the display to mark his session as 'Interesting', causing the recorded data and situation to be available for review in a simulator setting. Åsmund overtake computer system control to continue the operator-guidance. And Simon ends his shift for the day, as Åsmunds task is a specialized task where safety trumps further learning for Simon.

Scenario - Incident Review

The next day Simon refers to the incident at the morning review meeting. His manager is interested in the error, as it is uncommon. Simon is encouraged to review the situation in the simulator to better understand the significance of his experience. He is also able to follow the steps of the more experienced operator to finish the maintenance procedure and the real data source is used as a basis for the model. Using a computer with bot the same interface as used in production, and a supporting visual simulation and learning system Simon is able to review and create a situated learning experience outside of the operating environment. He is guided by an expert, showing and explaining the chemical reactions and challenges. Simon is able to ”play” with the values and a timeline to see exactly when and how the voltage measurements are thought to separate from the real values. The instant overview of the effects of interactions is important for Simons understanding of the delayed effect, as it was hard to see how a normal operating temperature could cause such damage to the equipment.

6.2 Design Considerations

THe design is identified to visualize a possible solution to the Current Challenges in Decision Making.

6.2.1 Limitations

Environment

The design process is using the domain of the aluminum industry as an example for a well structured domain, where a repeatable process is performed using chemical and physical reactions to create aluminum. The supporting tasks performed by operators are in large part proceduralized, making decision support systems viable. Complete process automation is not possible with the current technology, so the human operators are a vital part to efficient production.

Functionality

The design proposed is based on the supposition that supporting systems can be implemented. The novelty of the findings in this section is to apply the general user experience of a system supporting decision strength, and to follow this goal there will be no actual support structure implemented. Some of the required supporting systems for the proposed solution includes the back-end of a competent Decision Support System, a communications platform, and a visual process simulation.

Hardware Technology

A simple technology survey was performed using a search into established methods for evaluating hardware interfaces. The basis was Maike et al.'s 2015 framework for evaluating natural user interfaces, but arguments were also adapted from Anhalt et al. (2001), Hinckley and Wigdor (2012), Siewiorek, Smailagic, and Starner (2012), and Thomas and Richards (2012) and domain requirements. The completed framework used six main categories: technology, interaction, support requirements, safety and awareness, learning, ergonomics, and communication. The final document is supplied in Appendix 1.

A total of 19 technology categories were analyzed. From Virtual Reality, cognitive-state-sensors, to stationary consoles. The analysis of possible systems were more extensive than those eliminated by insurmountable complications, and was based on a Internet Search and from '*The human-computer interaction handbook*' (Jacko 2012).

The main challenges for adapting novel technologies are environmental safety challenges such as: the operators safety equipment (such as gloves, glasses, helmet, and hearing-protection, see **Figure 6.3**), reduction of situation awareness, operating in conjunction with tools, a issues caused by the electromagnetic interference from potlines, and more.

Solutions for a system capable of demonstrating the current challenges in decision making are limited. To best support the current high importance tasks, a combination of a touch screen (either capacitive or resistive) and utilizing a personal *Near Field Communications*(NFC)-enabled stylus as a part of the mandatory operator equipment was chosen..

The touch screen is supposed to be placed as a terminal on each cell, replacing the current input systems based on a keypad and a one-line display. The screen size is assumed to be small, between 12-20 inches, depending on the selection of a monitor that can withstand the demanding environments (Two modern examples are Hope Industrial Systems NEMA 4X[1], and Beckhoff CP22xx[2]).

The use of a personal stylus for industrial interactions is a novel concept, and no similar combination of products have been found by the author. Only one commercial touch stylus is found with NFC implemented, the vWand[3] – but an implementation of an NFC chip in any mass-produced stylus will be possible as the technology is highly compact and resilient. The stylus can be attached to the belt or chest pocket using a retractable reel, as commonly seen with access cards and key-chains. Using NFC the system will be able to recognize the operator based on the pen, while the NFC technology provides low cost, replaceable pen styluses.

6.2.2 Approach

Designing software is a complicated task. To create systems for a specific environment a number of studies and elicitation methods should be employed. Decision Support Systems should be created using a Human-Centered Design, where a number of methods are applied to facilitate adequate consideration of user needs ((P. J. Smith et al. 2012)), methods such as Cognitive Task Analysis, Needs Requirements, and Work Domain Analysis should be performed in cooperation with the specific industrial entity.

In this report a theoretical aluminum plant has been used in place of a real environment. The importance of best-practice methods in developing a real design cannot be overemphasized, but because such methods are well researched this design has no real re-

[1] http://www.hopeindustrial.com/
[2] http://www.beckhoff.no
[3] http://www.vwand.com/

quirements analysis performed except for the theoretical domain and environment review presented in Section 6.1.

The five Current Challenges were all attempted implemented in the system. As the requirements are cognitive and not physical, the creative process has few limitations. The prototyping process went over several weeks where approaches were created and dismissed, using pen and paper for element design.

The prototype was developed using Pen and Paper before porting over to Mockplus[4], a rapid prototyping software.

6.3 Design

The design is created to inspire a further development process using the current challenges to implement a system in a real industrial environment. The system is low-fidelity and has severe limitations in readability, usability, and accessibility, and should not be programmed in the current form. In the following a description of the thoughts behind each of the subsystems are reviewed, before some screens are presented.

6.3.1 Automated Decision Support System

The automated decision support in my system is based on already existing routines and procedures. What separates this from existing systems is that it is more open for human interpretation with system guidance. The system highlights its own preferences, how it got there and where it will continue after. By following each step of the systems decisions, skilled operators can review and validate the decision guide. The decision support system is high on the automation scale in information retrieval and presentation automation. It should will automatically choose straightforward decisions, but when there is an opportunity for sidestepping the procedure, and requirements for progress choices that system only guides the human which has the final call. The idea of presenting the full procedures and showing them to the operator, instead of displaying instructions for the current step only is to make the operator aware of the systems limitations. If the operator has though of a different path, he can investigate if the system has checked that step. The systems goals have to be clear "," (O'Hara et al. 2000, p5–46) the operator has to be able to understand the overlaying plan of the system to be able to collaborate with it. The current goals of the collaboration has to be established in a way that both operators and the system are explicit in their understanding of the problem. We have to think of the system as a collaborator, in which humans are able to communicate with the system, and the system communicates and adapts to the humans wishes. Offloading decisions that are easier for a machine than a human is encouraged for the best decision performance, but when the system fails we need to have humans that are capable of A) recognizing that the system has failed, and B) diagnosing what needs to be adjusted to keep the system running, C) diagnosing the system malfunction or error.

Separating large unstructured problems into smaller structured ones, can be a method for implementing better problem solving in machines (Simon 1983)

[4]Mockplus v2.1.8.2 (http://www.mockplus.com/)

6.3.2 Feedback

The system proposal supports feedback by providing each operator with a personalized interaction device that register the interactions made with a cell panel. When an operator has been involved in a step of a procedure, a measurement, or any other interaction with the cell it is logged on a personal basis. The intention of this logging is not to monitor employee efficiency, but to be able to correct mislearned behavior. By following up on these interactions, especially when an error occurs in a cell. This can help operators adjust their performance, but also highlight patterns in decisions that require modification of procedures and learning resources.

Current operators retrieve too little feedback on their changes, so a system could help management and operators connect to fix these performance issues The organizational culture will have to be very open for failures and to encourage learning from mistakes. Implementing this kind of surveillance can lead to employee dissatisfaction.

Essential Part of Decision Experience Learning Decisions

6.3.3 Learning

Imagine reading an article on Wikipedia, but not having links to the highlighted words in the text. Most of us would not be able to generate a deep understanding of a subject if we could not understand certain core elements and how they collaborate. The cognitive models and stories that we create from a situated interaction and event that we maintained has an increased ability to store theoretical information if it is connected to the tacit experience.

The idea is to implement a learning element as a core feature of the system. Every key word, procedure, step, and more can be saved in a "curious" list. Because the operator is in the dangerous working area, there is safety and awareness reasons for not presenting learning in the situation. But if we are able to spark curiosity while performing situated work, and later connecting with the same situation, simulated on "on screen" in a safe environment, while supporting this learning through any kind of E-learning material, books, peers or instructors. I hypothesize that one of the largest blockades to developing expertise in highly difficult, technical and tacit environments is eliminated. The problem is how to connect learning to situated material. This is the eternal problem of developmental learning in organizations. People forget what they learn because they can not relate to it.

Learning programs for new employees can be based on the information that is most commonly tagged as "curious", and individual profiles can be made to support operators in shaping their learning. Operators might want to overlook certain procedures when they are performed, and could possibly connect with the performing operator if notified of this interest. Growing knowledge workers in situation and outside of education.

If we implement possibilities for learning into the systems we create, we might be able to engage some of the willing operators to deeper understand the chemical and technological interactions of the process that the operator is supporting. Encourage usage of this functionality Experts use procedures as guidelines, while novices follow them. Experience combined with theory has the potential to create an expert that can combine these two into new knowledge and methods.

6.3.4 Live Support

Decisions can be hard to make on your own, especially when you are unexperienced or unfamiliar with the procedures you are performing. A low effort system to connect with more experienced control-room operators where they see the same screen as you and are able to guide using both knowledge and tacit skills to explain why and how the problem should be handled is an approach to supporting learning.

6.3.5 Avoiding Biases

Procedural Checklist

Increasing awareness trough a simple procedural checklist approach to verify system status. This step is to avoid automation complacency and biases. By requiring that the operator signs of on each cell, we force him to take responsibility for the status of the cell and we get instant feedback if something is not as good as it could be. Cell state is an important factor of cell health, and if there is any visual cues and hunches that operators can easily report we can get a better overview of the long time effects of inspections. This cell inspection can be used to trigger operating procedures if needed.

Operational Feedback

Feedback can also be provided by the operator in regards to the automated system. For a good cooperation with automated systems and procedures, an operator can provide feedback on how he used the procedures and if there was any other steps that were necessary or unneeded for this particular procedure. Simple feedback strategies like this one will enhance the possibilities of operator engagement in the happy path of a system.

Happy Path

Encouraging and showing procedures on the outside of the “happy path”. To better debias humans in how they follow automation, we need to make them aware and remind them of the limitations of the system. System design that takes into account automation bias will have to cooperate with the human operator in a human way. If the system is uncertain, suggesting or doubting decisions it must be visible to the human. The human part of the system is the one that can combine cues across procedures and find what could be a common cause.

6.3.6 Design Description

Figure 6.4 shows the design of the automated decision management system. A procedure initiated because of a discrepancy between the measured and projected value of the electrolyte temperature. The goals of the procedures are highly visible at all times, to inform the operator of the systems intentions. A timeline is displayed with a red ’dashed’ line in the middle of the screen, illustrating the current time of procedure. It has the affordance of going back in time to review decisions and alternate decision paths. Every decision node has indications if the task performed for the node is manual, automated or requires a deliberate override of the systems model of the cell state. The system provides estimates for the decision strength, for each alternative of the current decision section. Each of the decision nodes are available to click on for more information of the decision systems choices.

Automated Decision Node

Figure 6.5 further explain what happens when pressing a node in Figure 6.4. This node displays the decision systems inferred reasoning for starting the automated procedure, and who was responsible for executing the next step. Logging is important for understanding the flow of procedures, but limited operator input is requested while in the working environment.

Human Intervention Decision Node

Figure 6.6 is what is displayed to a decision maker to the current recommended step in the automation overview. As always the reasoning and projection of the automation is the main content. At the right side the *theoretical explanation* is provided, the *principles* behind the automated choice. These are simple elicitation and mental model recollection cues to facilitate connection theoretical knowledge with the current situation, and should be created by experts for each step of procedures.

Certain words are marked with a red underscored highlight, and entire parts are marked with 'hearts'. These highlights represent the explicit connections to the learning program described above. Clicking each one provides a heart and a list of situation-connected terms, that can be accessed outside of the production environment. The screen space required is very limited, and by developing systems with this in mind implementing the feature should be uncomplicated. The actions provided show the operator that alternatives can be explored, attempting to reduce automation bias.

Status Report Screen

The status report screen (**Figure 6.7**) is intended to facilitate operator awareness and safe operations of pots. A central element discovered in the automation requirements are that

It is a simple, fast-and-frugal checklist approach to easily report discrepancies of the state of the cell, intended to use after every manual job performed. With only five clicks an operating cell is verified as correctly operational. If an discrepancy is detected a simple checklist continues the process, avoiding manual text-input. The process should take seconds to perform for experienced operators. Every status report is linked to the individual operator, and each cell interaction can be verified by other operators with the event log.

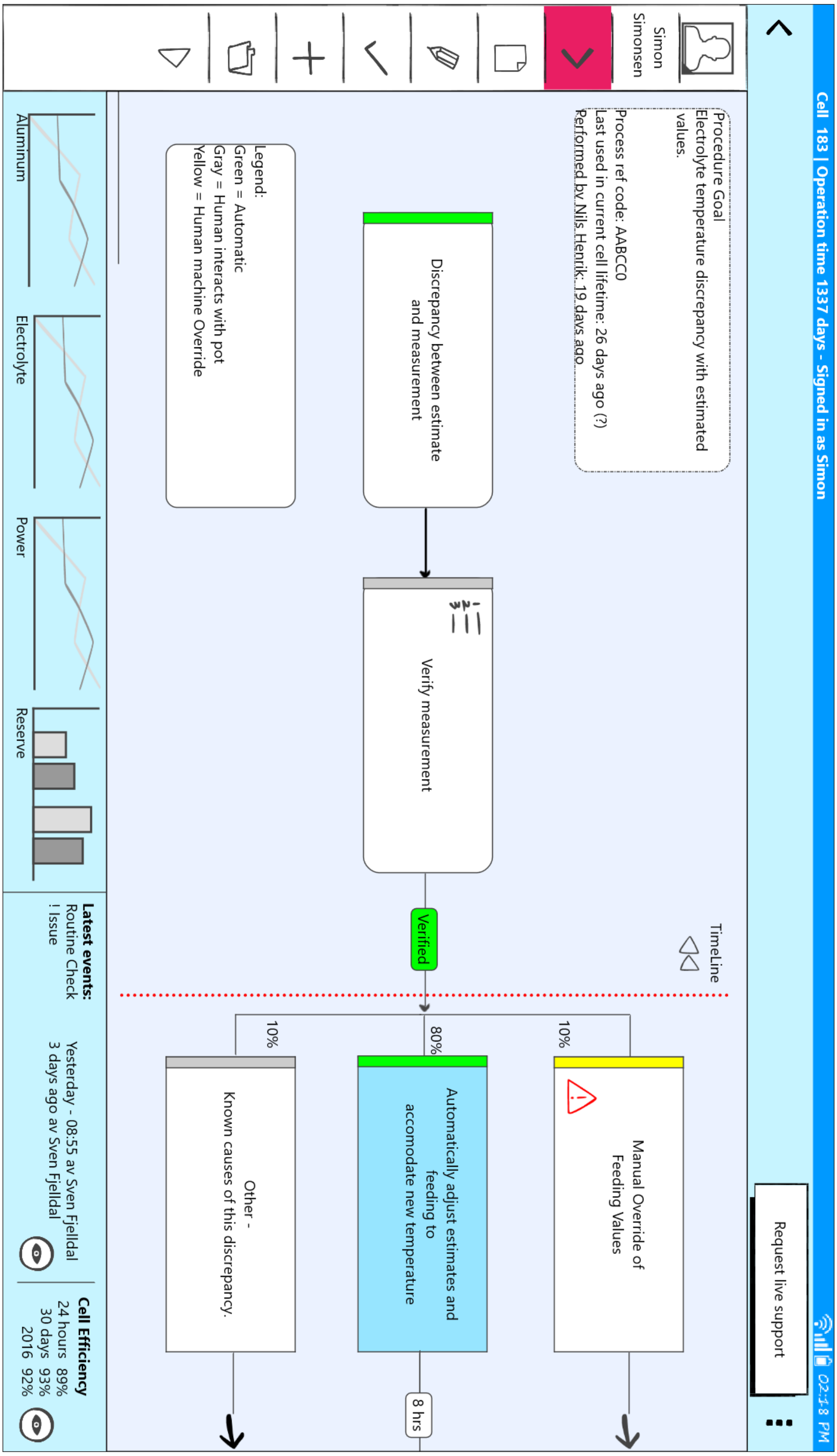

Figure 6.4: Alluminate, a theoretical tool for supporting human operator decisions and understanding in a situated industrial environment

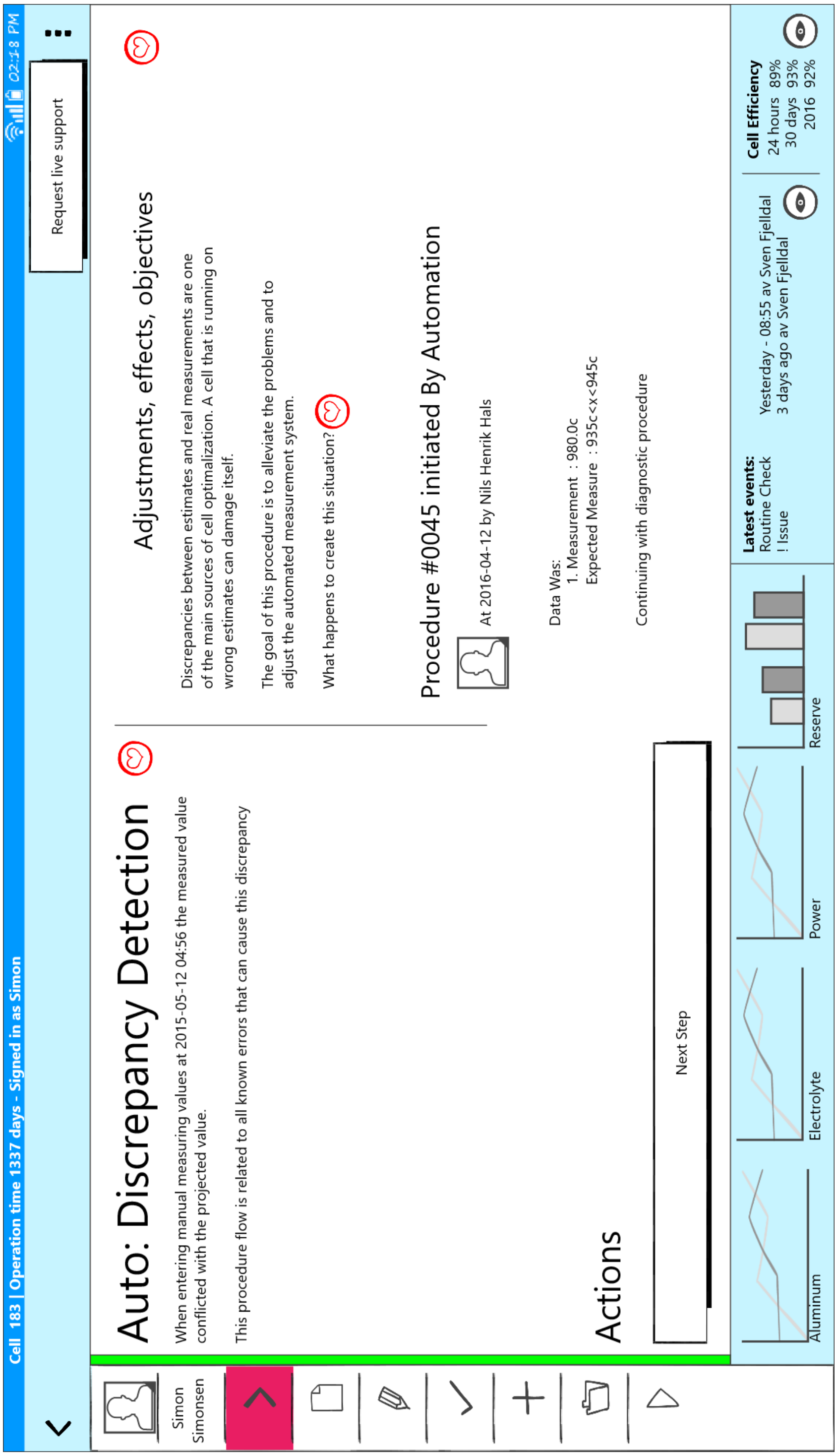

Figure 6.5: Automated Decision Node

Feeding1.png

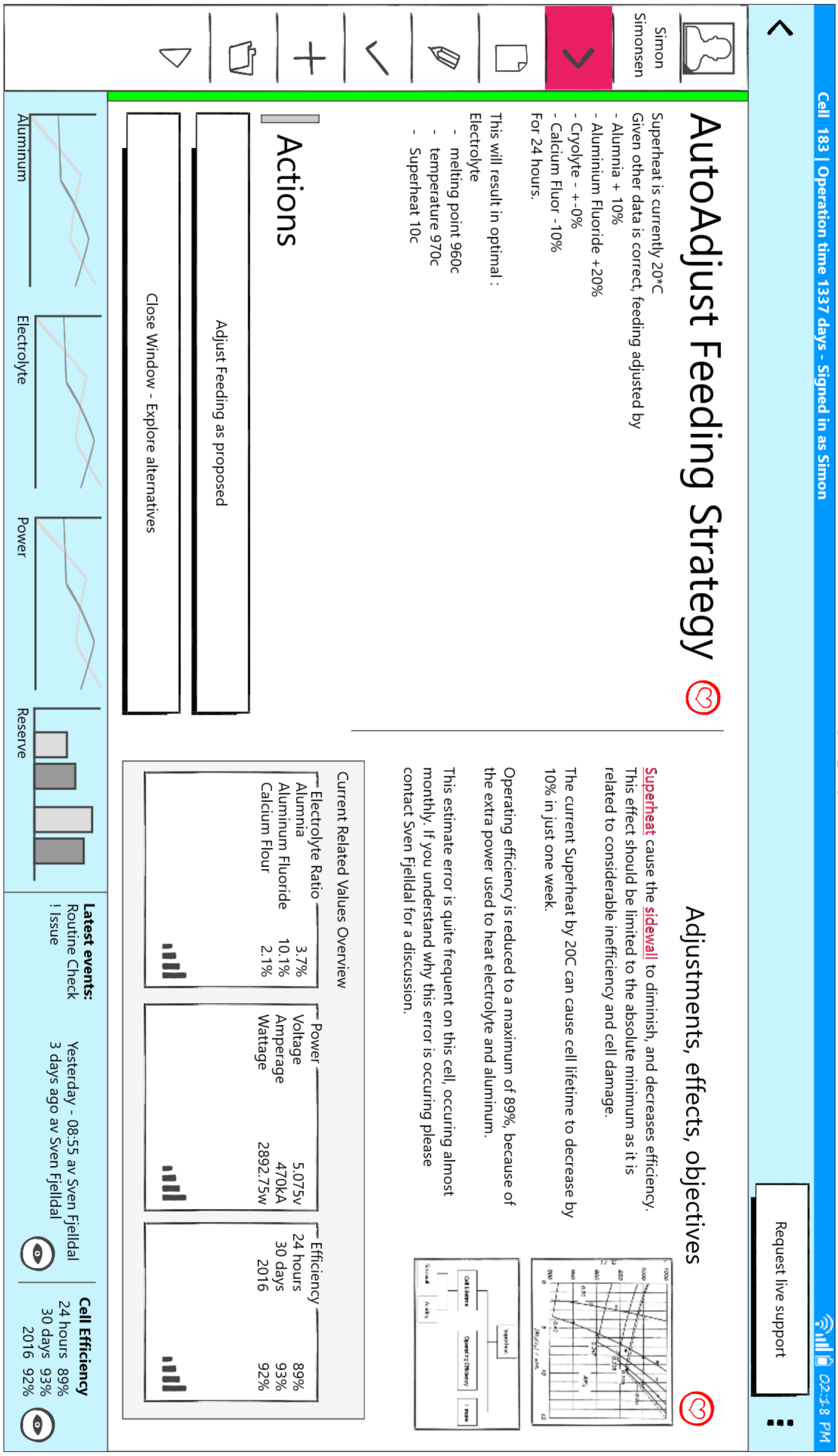

Figure 6.6: Human Intervention Node

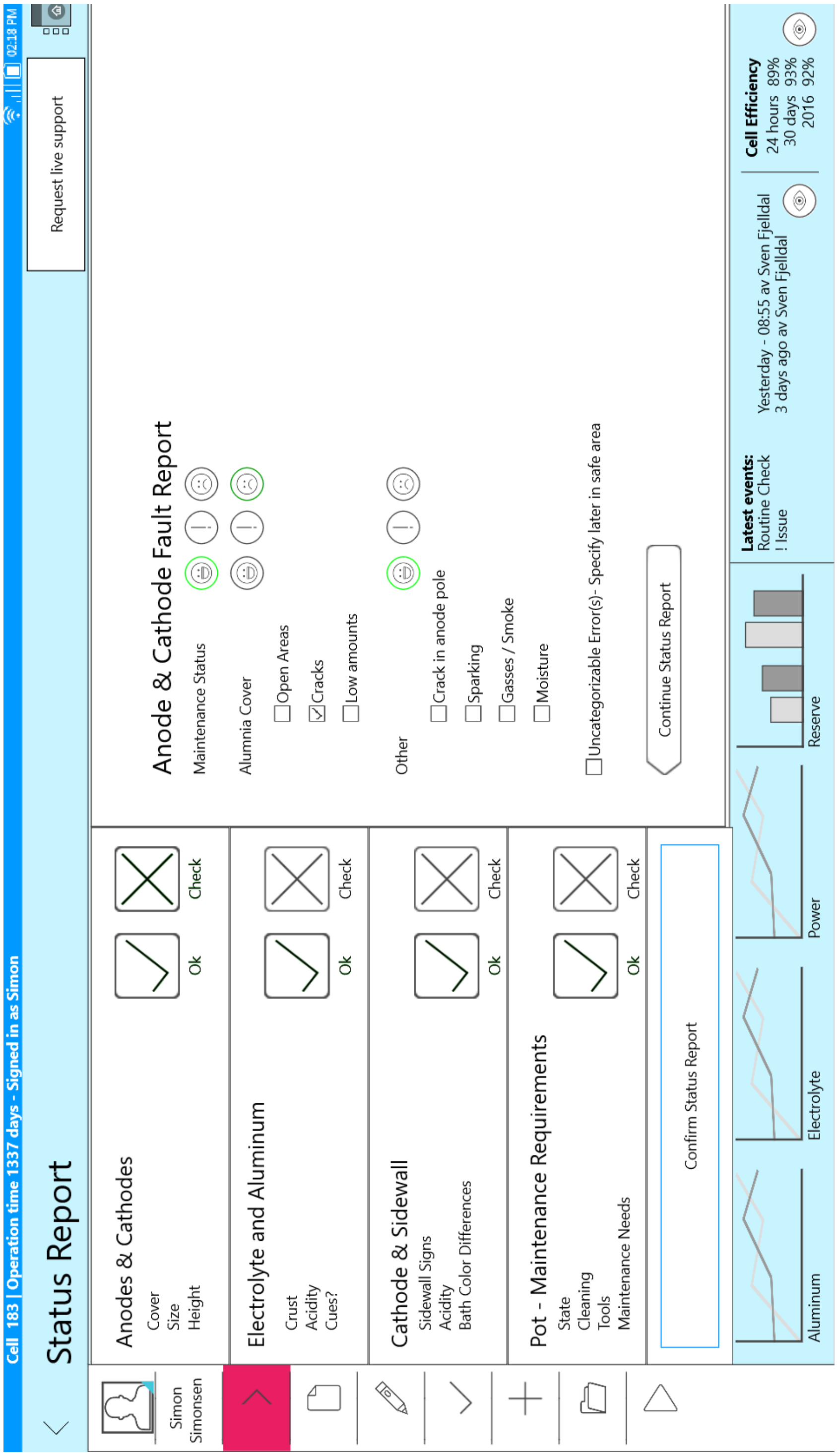

Figure 6.7: Status Report Screen - After pressing "Check" on Anodes and Cathodes a sidepanel for explaining the report slides out.

Chapter 7

Summary and Recommendations for Further Work

7.1 Summary and Conclusions

The objective of this thesis was to review the current state of the art in Human decision making and decision support systems, to elicit current challenges and opportunities for implementing effective decision making in industrial environments. Human decision making (DM) is a complicated process, often debated in research. Two different research approaches, Natural Decision Making (NDM), and Heuristics and Biases (H&B)] approach the problem of human DM from a different perspective. NDM approaches situated decisions in the working environments, while H&B use rigorous methods and experiments to understand the microperspective. A wide range of theories of human errors when making decisions under uncertainty are approached as a foundation for a review of opportunities for improving human DM. Metacognitive Forcing strategies can be a solution for decision makers, MF requires an understanding of the domain and of human cognition, and employing general and problem-specific strategies to reduce the impact of human limitations. Deliberate Practice is required to understand and operate at a high level, and understanding the limits and that understanding is only an approximation of the actual effects. To build knowledge, a requirement is the opportunity to practice the acquired knowledge. Expertise cannot be developed in environments controlled by procedures and error prevention, this common industrial environment seems to result in ”average” operators.

The environment can be designed and modified to support *intuition*, *learning* and information availability. These three categories are important in facilitating the decision proficiency of human operators.

Further, we have identified that humans are often replaced with automation. And while the automation of physical routine tasks is approaching complete, the automation of non-routine cognitive decisions have a long way to go. Current Automation in industrial applications seem to help understanding the automation system, but not the underlying principles. The lack of observability and transparency of automated systems mean that in safety critical applications humans are not able to intervene when an issue arise. The impact of automation on human cognition is still uncertain. Some argue that a deskilling process occurs, while others argue that the understanding of systems is more important than the actual physical and chemical process and that operations require system understanding more than environmental knowledge.

The third chapter presented a state of the art and common guiding principles for the design of Decision Support Systems (DSS). DSS are categorized into *active*, using automation to support the actual decision task. And *passive* systems helping the operator decide by using presentation and learning methods to improve the operators cognitive decision strength through *situated learning* and user experience guidelines.

The research from the first part of the report culminate in a summary of the prominent areas requiring further research as applied elements in industrial environments. Current challenges in the design of systems supporting human decision making are: (1) the design of cooperative, informative Automated Decision Support Systems. (2) increasing the Feedback operators receive from the production envrionment. (3) Improving the inherent Learning provided by the system and supporting systems; operators need to have accessible learning resources (4) Supporting operators through expert operators and requests for personal assistance.

As an evaluation of the process, a design was proposed from a theoretical Norwegian Aluminum Plant environment. The design shows how the current challenges in decision making can be approached with both basic and more demanding information systems solutions.

7.2 Recommendations for Further Work

As the practical result of this work is in identifying and creating a hypothetical solution, further work has to apply the current challenges to a design for a real industrial partner, where effectiveness of one or more solutions is evaluated. The solution should be developed using best practice strategies as highlighted throughout this paper and in Section 4.1.1.

The effectiveness of a solution is dependent on the problem area approached. Both long and short term decision strength evaluation has to be performed, and a number of approaches for this are available in the current literature (See eg., Crandall 2006; McGeorge et al. 2015; Papautsky et al. 2015; P. J. Smith et al. 2012).

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Appendix

1. Product Matrix

		Technology				Interaction				Support			
Category	Type	Example	Usecase	Why	Comms Type	Operation Modes	Interactability		Metaphor Adequacy ^Applicable when real task is known-	Learnability	Guidance Balance	Wayfinding	Safety Equipment Issues
							Type	Issues/Advantages					
	Augmented Reality HoloLens	Microsoft Holo Lens	A lens based overlay that can enhance reality by showing daata and similar stuff on surfaces and can recognize the environment.	Will help understanding of teh environemnt and equipment. Could visualize future problems and solutions?	Wifi?	Visual, Tactile, gestures, sound, vocal	camera, microphone, accelerometer, gestures	Very disconnecting from real life.		No idea. No applicable software developed.	No current way to implement depth	-	Eye Protection and Helmet
	Augmented reality Phone	Cellphone + Camera	Use the devices camera and other sensors to display a enhanced reality visualization of the process in front of the camera. Might avoid physical pinut?	Visualizing the process in the correct context might help understanding	Wifi.	Visual, Tactile	touch, accelerometer, camera	Requires vision and total attention to the screen for understanidng. Removes from dangerous situation at hand		Easy to learn.	No current way to implement depth	-	Gloves
	Augmented reality Simple	Google Glass/Similar	Using camera and HUD to visualize and or update the operator one the current state of the process	Might be a low intrusive tech	WIFI, Bluetooth	Visual, Vocal(?)	camera, microphone,	Requires vision and can limit safety equipment	-	Low discoverability, requires voice input	Hard to guid, but might implement help function	No in depth navigation	Eye Protection
	Enahancing learnign using - Near Field Communications / RFID	RFID Reader/Skanner/Tag	Using rfid tags. Either useit to enhance a learning system, or to promote a structured approach to performing routine work.	RFID is a low cost tech with possible usecases and probably a tiny safety and security impact.	RFID, NFC	Tactile	none? Moving the device, no direct need for input.			easy	Might be "boring" and have low adaptation.	-	None.?
	Gesture based interaciton	Kinect and otehrs	Navigating without touching.	The problem with gloves.			body-movement	Works with gloves!		Possibly hard. Accurate navigation is still an unsolved problem.	Depends on the system design.		Must have free hands?
	Heart-Rate/Bodysensors	Bluetooth Heart Rate Monitor, step counter, "BioHarnessTM"	Using biodata to discover injuries and awareness during tasks?	- ? ...	Bluetooth, WIFI, Other (sim card?)	-	-	No interaction while working.		Use as instructed+	Migt be seen as less important. Low number of injuries and often people overlooking.		Can Electromagnetic Radiation become a problem?
	Improved Communications	QUIETPRO QP100Ex and similar digitally enhanced hearing protection	Use communication devices to improve the amount of communication in a noisy workplace.	Improving auditory communications between workers lowers the barrier of speech in a loud environment. Will improve information exchange and situated learning.	Bluettoot, Radio?	Voice, Some tactical, and some visual	tatical, Nfc	Low interaction while working.		Use as instructed, sync with others using NFC or channels. Easy peasy.			People are talking to someone that might not see the situation they are in. Eg. drivers and talking in phone
	Learner centered content creation	Input/Output device (Camera/smartphone/other)	Using the operators documentation of irregularities and issues creating opportunities for learning for both current and new employees.	Supporting operator awareness t better inspect and document errors by them selves and other operators. Might be low impact when in operations, but will need debriefing and followup when not.	USB, Wifi, Bluetooooth	tactile, visual	camera, microphone,	Can be made to work with safety equipment		Intuitive for anyone with a camera	Requires a lot of support systems and procedures. But not that hard.	No navigation while in the field.	Very little. Taking photos can offset situation awareness, but this is not your facebook-selfie.
	Mobile Screen Learning	Smartphone/Tablet	Present data using information from the process using a portable mid-sized monitor. Inlcude instructions as in a physical instructional manual + Procedure instructions	Using existing "cheap" tech to make information more avaliable for the operators.	WiFI/some tranfer capability needed. Not a lot of "live" fresh data.	visual	touch	gloves.		Interaction is familiar. Application can be made using common fatures.	Low guidance for new users, will help with information retrieval and supporting the process	Not complicated enouth for this to be a problem.	removes gloves. Requires a lot of attention
	Personal Stylus	Stylus for touchscreens, with rfid and personal identification.	Using a Pen like stylus to interact with stationary monitors. Personalized history and connection with simulator events.	A simple interaction device that works OK with gloves and is low effort to use and reltively cheap? Can be used in and out of production env.	RFID, NFC	tactile	tactile-	Works with gloves!		Everybody knows touch and pens.	The pen should be low guidance, the systems its used with might not,		-

Proxemic Interactions	Kinect ++	Using proximity to monitors to change screen content. Overview when not near, and more detailed when present.	To better adjust monitor content for a quick overview of the status without looking too near.		proximity	body-movement		Easy	Easy		none
Smart Watch / Similar	Smart Watch/Similar body worn device	Using smart watches to display data can be an approach to having data more "at hand" while not obscuring view.	Low impact, could be used together with RFID and a tracking system.	NFC, Bluetooth	Visual, Vocal, Tactile, Audio	touch, voice, accelerometer, nfc	touch and gloves... voice in loud environments, accelerometer and EM.	Easy. Low depth device.	Low guidance needed.	No in depth navigation.	Touch and gloves. Worn on wrist?
SmartCap	SmartCap.au.com	Using sensors on the brain to sense operator awareness and cogntive abilities. Like drowsyness and alerntess.	Avoiding fatigue.	unknown	-	-					
Speech Recognition	Microphone, Voice-Recognition	Using it like Siri or CortanaTM to control a system.						Problems with norwegian dialects will occur. Not possible to use accurately.			
Standardize Procedures	http://wi.co app and similar. Standardizing procedures and tracking progess.	If possible, standardize procedures. Record progress of the procedure directly in the app.	If one of the problems are taht operators do not follow standard procedure, try to focus on this through an app taht records the values in the same space. COULD ALSO BE PERFORMED ON PAPER...	Wifi	Visual, Tactile	touch	gloves.	Familiar interaction	The app guides the rocess, should be simple and require little learning.	Not complicatd-	removes gloves. Requires a lot of attention
Stationary Consoles	Monitor with touch,	High fidelity data display with a backend taht is placed in arelatively safe location. Possibility for predicitons and measurement input.	Avoiding the situation-awareness issues with most of the portable display options. Possibility for high-fidelity accurate data. No need forwireless comms?	Cable? . Wifi, NFC, Bluetooth	visual, tactile	touch/pen		Can support learning. Must be instructed on use, but should be more usable thatn traditional Decision support systems.	Guiadnce should be balanced for beginners anddexperts alike.	Low navigation depth.	gloves...
Vocal Instructions	mp3Player, SmartPhone, Heardset	Using auditory feedback and information. Either manually or contextual.	No visual impact.	Bluetooth, WIFI, Cable..	audio	audio, tactile, voice	Should work with safety equipment				audio
Voice-Based Notes	Microphone, Voice-Recognition	Using a low impact feature to log events, to not when there was something the operator did not understand or would like to remember.	Approaching low or no effort to take notes of the issues you experience in the field can improve learning.	-	Voice, some tactical, audio feedback	tactile, voice	Very low impact interactions.	Speaking into a mic. Not that hard?	Few functionalities, simple x button interface?	not compex	none? (Shortlasting interactions using a hip placed recording device)

Safety	Learning Hypothesis		Ergonomy					Communication			Notes.
Solutions?		Known learning approaches and experiences fr	Comfort	Space	Engagement	Battery/Power	Device-Task Compability	Social Acceptance	Awareness of others	Two-way communication	
Not currently avaliable.											
Remove gloves when using. Use other input mechanism than touch.			Requires removal of gloves.	Not good. Requires a lot of attention in a dangerous situation	Allows for immersion, and information retrieval	No problem		-	LOW	-	
Alternative eye protection. Implement into special eye protection when deployed irl?	Using glasses to monitor process values might give better opportunity to validate results from measurements and to minotor trajectories and predictions.		Comfortable. Easy to use, no weight	Might obstruct situational awareness in some cases.	Easy information retrieval and use.	Might be a problem for 8+hours shift.			Medium- Should not be that impacful.	Can be implemented, video call ish.	
	Use to store events and state of equipment to later review in a safer location. Networked equipment status remembers when tagged and by who. The tagger should remember the situation and what he wanted to do?		Low impact device. Can be worn as a smart-card/can be a smart card...	Very low impact	Very little engagement. Can be an issue.	-	Good		No loss.		
	No/Little obvious learning output.		Optimally low omfort issues.	no impact	No engagement, unless there is an accident.	No problem	Bad.		No loss.		
Range/visual contact limitations. Much like in RL.	No learning through tech, but greatly enhances the opportunities for situated learning using an instrcutor and/or a sparring partner.	“CDC - Mining - An Evaluation of Sound Restoration Hearing Protection Device!! - NIOSH.” Accessed September 22, 2015. http://www.cdc.gov/niosh/mining/works/coversheet1598.html.	Improved comfort? Low impact haring protection is nice.	no	High engagement when people want to talk	Should not be problematic	Define the task				Some use this at my old workplace using telephones and calling up their partner, and using radio comms on another channel.
SECURITY issues can be a problem, but not more than before. Same contracts and same possiblities for existing operators...	This seems like one of the most promising methods for learning. Especially due to utilizing mLearning for creation while learning.	Pimmer and Pachler (2014) "Instead, we suggest that, from a pedagogical perspective, the learner-centred creation and sharing of content such as multimedia materials in the form of text, audio, images and video is much more promising. "Inquiry activities can lead learners to con-front the boundaries of their knowledge or recognize gaps in that knowledge" - (Edelson, Daniel C., Douglas N. Gordin, and Roy D. Pea. 1999)	Low comfort impact.	Works in most contexts. Not neccessary .	Can be made engaing using programs to support.	Not an issue during 8 h shifts,			Not taht impired		
Major problem.	Well established learning, especially through quizes and digitally enhanced learning programs.										
Using gloves and physical interactions system.	No learning directly. But the personalized input opportunities can be used together with other systems.										

	Better overview of equipment, might improve awareness of status but not understanding.		Very good	Uses space and no problems	Makes people check status when errors are more visible.	-	.++
Worn outisde of clothes. Touch is an issue.	Allways avaliable data. Can be ueed to sync with NFC.		No prob	Low impact verifying infrmation.	Information retrieval	No problem	No loss.
The glove issue might be avoided using a stylus.	As in (Mahajan 2011) the effect of standardizing procedures and introducing cheklists close to eliminate basic operting errors. But following decsion-making litterature these procedures might stop expertise from developing.						
Used in combination with specialized input like a pen? Not likely a proble min a loud environment. The heaing should be blocked by Hearing Protection.	Established by some publications as a valid method for learning. Mostly using podcasts supporting teaching curriculum.	*Evans, C. (2008). The effectiveness of m-learning in the form of podcast revision lectures in higher education. Computers & Education, 50, 491–498.					
	Situated learning is improved by hopefully enhancing curiosity and awareness. Operators should be taught to be curious and the organizational structure should value feedback.	"Inquiry activities can lead learners to con-front the boundaries of their knowledge or recognize gaps in that knowledge" - (Edelson, Daniel C., Douglas N. Gordin, and Roy D. Pea. 1999)					