Preface

The "complex task" of writing this thesis has been an interesting and challenging journey. While the work on this thesis mostly has been an independent process, I have recieved good help from, and had excellent discussions with several people. First I'd like to thank my supervisor Karin Laumann for a great introduction to the field of HRA as well as sharing her knowledge and nudging me in the right direction whenever I was a bit lost. I'd also like to thank all the people involved in the Petro-HRA project, with whom I've had interesting discussions. Especially PhD candidate Martin Rasmussen has been a great help. In addition, the HOK class of 2013 has created a wonderful working atmosphere, both socially and academically, and should receive a collective thanks from me.

I would also like to thank my wonderful friends and family for supporting me during all my years at the university, and I'm sure they will continue to support me in whatever I choose in the future. A special thanks to my girlfriend, Hanne, who is always there for me, with a cup of coffee to get me out of bed in the morning or a loving remark when I'm tired.

To all those who have helped me or supported me in the work on this thesis, simply thanks.

Martin Inge Standal

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Abstract

This master's thesis in psychology examines task complexity in an attempt to meet industry needs of creating a stronger theoretical foundation for the complexity performance shaping factor (PSF) in Petro-HRA and better guidelines for HRA methods. Petro-HRA is a Human Reliability Analysis (HRA) method being developed for the petroleum industry based on SPAR-H. In this thesis, a literature review is performed to identify factors contributing to task complexity. Based on this review a conceptual framework of 13 complexity factors is created and described. Seven of these 13 factors; goal complexity, size, complexity, step complexity, connection complexity, dynamic complexity, variation complexity, and structure complexity, are found to be usable in a description of the PSF complexity in Petro-HRA. These seven factors' effect on operator performance is discussed and the factors are integrated into an easy-to-use guideline for users of Petro-HRA. This guideline offers a description of the seven complexity factors and a recommendation for assigning the PSF. The guideline in this thesis may provide greater inter-rater reliability and greater accuracy in calculating the human error probabilities when performing Petro-HRA.

Keywords: task complexity, framework, HRA, SPAR-H, PSF, petroleum, offshore, Petro-HRA, guideline.

Introduction

On April 20th, 2010 the Deepwater Horizon drilling rig in the Gulf of Mexico experienced a blowout explosion. The accident killed 11 workers, injured 16 and caused one of the largest environmental disasters in the United States history (Lehr et al., 2010).

More than thirty years earlier, on March 28th, 1979 the Three Mile Island nuclear plant in Pennsylvania experienced a partial nuclear meltdown in one of its reactors. The accident had no fatalities but is considered the biggest disaster in United States nuclear history (US NRC, 2013).

Both of these accidents had pre-existing problems leading up to the point of the accidents that can be traced partly back to human or organizational factors such as poor procedures, human-machine interaction (HMI), or the complexity of the operation (Meshkati, 1991; Skogdalen & Vinnem, 2012).

As we can see from these accidents, human error can contribute to devastating consequences. Some of the installations used, such as oil rigs or nuclear power plants, demand a very high reliability due to the potential fatal and disastrous consequences of accidents (Hollnagel, 1998). As such, these high reliability systems demand a very low probability of error, from both human and technical causes (French, Bedford, Pollard & Soane, 2011).

The Three Mile Island accident had a big impact on nuclear safety with regards to human and organizational factors (US NRC, 2013). The reliability of the technical components that are used in nuclear plants or oil rigs has improved to the point where they have very low chance of failing. As a consequence, the relative reliability of human operators has decreased (Marseguerra, Zio & Librizzi, 2006). After the Three Mile Island accident the Nuclear Regulatory Commission realized they needed more focus on human reliability. This signaled the start of the creation of the first Human Reliability Analysis (HRA) methods (Hollnagel, 1998).

Now, 30 years later, the petroleum industry is coming to the same realization. Skogdalen and

Vinnem (2011) stated that even though reliability analyses have been used in the petroleum industry for several decades, almost none of them take into account the human and organizational factors and their influence on risk.

Computerized automation has been adopted into the systems of many high-risk industries such as nuclear power, aviation, and the oil and gas industry. Humans do, however, still play an important role in the design, maintenenance, operation and supervision of such systems (Kim & Jung, 2003). Human reliability analyses try to take into account the human operator in these complex systems. These methods attempt to estimate and quantify the probabilities of error in human operated tasks.

One of the most frequently used HRA methods in nuclear power plants is the SPAR-H (Standardized Plant Analysis Risk – Human Reliability Analysis) method. This method has been developed by the Idaho National Laboratory (INL) in collaboration with the United States Nuclear Regulatory Commission (Gertman, Blackman, Marble, Byers & Smith, 2005). SPAR-H calculates the probability of human error based on eight performance shaping factors (PSF). These PSFs represent the contextual situation or environment where the operators perform their tasks. The PSFs are given numerical weights and combined with a nominal human error probability (HEP) they estimate the likelihood of human error. The eight PSFs in SPAR-H are «available time», «stress/stressors», «complexity», «experience/training», «procedures», «ergonomics/HMI», «fitness for duty», and «work processes» (Gertman et al., 2005). This thesis will examine one of these PSFs, complexity, and attempt to create a better theoretical foundation for this PSF.

Prior to the SPAR-H calculation of error probabilities, the risk analysts must describe and collect data about the task or situation being examined. This is usually done by performing task analysis and human error identification. Task analysis describe the operator's role in the system and the tasks performed by the operator, and human error identification describe the possible causes and types of errors in the situation (Kirwan, 1994a). Performing task analysis and human error identification yields qualitative data that can be used to determine the PSF multipliers, and thus the HEP for the SPAR-H calculation. This means that the SPAR-H method quantifies the HEP in a risk analysis based on more qualitative data collected earlier in the analysis.

A joint research project, funded by the Norwegian Research Council, between the Norwegian energy company Statoil, research foundations Det Norske Veritas and SINTEF, project owner Institute for Energy Technology (IFE) in Halden, the Norwegian University of Science and Technology, and Idaho National Laboratory, have started the task of developing guidance for a HRA method suitable for use in the petroleum industry as such a method do not exist at this point. This is called the Petro-HRA project. The quantification in the Petro-HRA method will be based on SPAR-H. SPAR-H is preferred over other existing HRA methods because it provides some guidance on assigning the PSFs, is not very resource demanding compared to other HRA methods, and provides worksheets that promote inter-analyst consistency. Other methods were also tested but were found to be too resource demanding, give unreliable error estimates, or be too cumbersome in use (Gould, Ringstad & van de Merwe, 2012).

This master's thesis will perform a literature review on complexity to examine the complexity PSF in SPAR-H and look at how this PSF can be described in a petroleum setting as part of a Petro-HRA method. At the moment there is an industry need for better theoretical foundations for the HRA methods and improved guidelines on using these metods. This masters thesis will attempt to meet some of these needs with three main contributions:

1. A literature review of complexity culminating in a theoretical framework of factors that contribute to the complexity of a task.
2. A description of these complexity factors, as well as a discussion regarding their suitability for a Petro-HRA method, and the factors' effect on operator performance. This will also make it easier for users of Petro-HRA to identify the appropriate complexity factors for the situation being studied.

3. A table that outline how the complexity factors affect the performance of operators. This will provide users of Petro-HRA with an easy-to-use guideline for identifying and assigning the complexity PSF in a Petro-HRA analysis.

As the situation is today there is little guidance on how to handle the PSFs associated with the HRA methods (Kariuki & Löwe, 2007). Stated earlier, the contributions of this thesis may provide a better theoretical foundation and a guideline for the complexity PSF in Petro-HRA and may provide higher inter-analyst reliability when performing HRA in the petroleum industry.

The problem statements for this thesis are:

What is complexity?

Which task characteristics contribute to the overall complexity of a task?

How should the complexity PSF be described in a Petro-HRA method based on SPAR-H?

Is it possible to provide some advice on how to assign the PSF multipliers in Petro-HRA?

In this master's thesis, complexity is used as task complexity. This is because the majority of research on complexity looks at the complexity of various tasks, and also because the complexity that SPAR-H and Petro-HRA is concerned with is the complexity of operator tasks.

This thesis aim to give a greater understanding of what complexity is and how this construct can be used in a HRA method in the petroleum industry. The thesis consists of a review of complexity and a conceptualization of complexity factors for Petro-HRA. The review part will start by explaining quantiative reliability analysis (QRA), HRA, and their role in the petroleum industry. Then a brief explaination on how HRA methods are used follows along with a description of the SPAR-H method, its PSFs, and how the HEP values are used in this method. Finally in the review part a thorough examination of the literature on complexity is undergone. The conceptualization part is started by a methods section explaining how the literature review was performed. Then factors that contribute to the complexity of a task are presented. The factors are then discussed for their suitability in the Petro-HRA method, and their effect on operator performance is presented. Based on the factors and performance effects, a guideline-table for Petro-HRA users is developed. Finally, strengths and weaknesses of the thesis are discussed and suggestions for future research are provided.

This thesis will not examine or evaluate whether or not the HEP values of SPAR-H will be appropriate for Petro-HRA. These values and their cutoff ranges might be needed to review as the method being developed is in a completely new domain, however this is outside of the scope of this thesis. The guideline-table developed here will nonetheless be just as useful should the HEP values of a Petro-HRA method be different from the values used in SPAR-H.

Theory

Quantitative Reliability Analysis and Human Involvement

Quantitative Reliability Analysis (QRA) are approaches that look at accident scenarios and evaluate the overall safety of a system probabilistically. The accident scenarios are composed of two failure components, human failure events (HFEs) and hardware (system/component) failure events (Kim & Jung, 2003).

QRA processes has been used by the offshore industry for more than three decades. Traditionally, QRA has focused on technical systems and capabilities. Human and organizational factors have been given less attention. Over the last ten years however, a growing research effort has been aimed to reveal, isolate and measure human and organizational factors and their influence on risk (Skogdalen & Vinnem, 2011).

The trend in the offshore petroleum industry is toward more extensive use of floating production systems and operations in the arctic and deepwater areas. This suggests that in order to mitigate hazards and control risks, operational aspects of safety will be more important in the future. Revealing the human and organizational error factors are therefore of great importance to the oil and gas industry (Skogdalen & Vinnem, 2011). While human and organizational malfunctions are inevitable, their occurance can be reduced and their effects mitigated by improving how systems are designed, operated and maintained (Bea, 2002).

Experience has shown that the primary hazard is not the ocean environment itself. The industry has learned how to engineer, build, operate and maintain structures that can endure the extreme weather, temperatures and sea floor soil movements that frequent the offshore environment. The primary hazard is associated with human and organizational factors that develop during installation lifecycles (Skogdalen & Vinnem, 2011). Human beings are arguably the weakest link in most engineering systems (Kariuki & Löwe, 2007). Even structural and equipment failure can be traced back to the design phase (Reason, 1990a; Skogdalen & Vinnem, 2011). Statistics from the 1990s show that half of the leaks from hydrocarbon systems on the Norwegian Continental Shelf were caused by human interventions in the system (Vinnem, Seljelid, Haugen, Sklet & Aven, 2009). Regulators have realized that the role of humans in system safety is not sufficiently addressed (Kariuki & Löwe, 2007). The Norwegian Petroleum Safety Authority stated that it is not sufficient to only focus on the improvement of technical solutions if human and organisational factors are not considered as well (Jernæs et al., 2005).

Even in systems that are largely technological, research shows that in the majority of cases there is a human element involved (French et al., 2011). Although technological innovations have made many tasks easier to perform, their effects have also made other tasks more complex than ever, especially in safety critical systems in dynamic environments (Liu & Li, 2011; 2012). Statistics show that human error is implicated in 90% of failures in the nuclear industry (Reason, 1990b), 80% of failures in the chemical and petro-chemical industries (Joschek, 1983; Bea, 2002), over 75% of marine casualities (Rothblum, 2000), 70% of aviation accidents (Helmreich, 2000), and over 62% of failures in drinking water distribution and hygiene (Wu, Hrudey, French, Bedford, Soane & Pollard, 2009). These data show how vulnerable our systems are and also show the importance of understanding how human behavior affect the risk in our systems (French et al., 2011). This illustrate the need to include probabilities for human error in quantitative reliability analyses, as the QRA methods generally are limited in their abilities to characterize human and organizational factors (Bea, 2002).

Human Reliability Analysis

To predict human reliability in the QRA processes, Human Reliability Analyses (HRA) are often used (Skogdalen & Vinnem, 2011). HRA takes part i QRA in trying to estimate the human failure events (Kim & Jung, 2003). Even though human factors are seen as an important contribution to accidents, research show that very few reliability analyses include HRA in the analysis process in the petroleum industry (Skogdalen & Vinnem, 2011). HRA are methods developed to calculate how the behavior of an operator can lead to system conditions that are in conflict with the expected or desirable (Hollnagel, 1998). In short, HRA methods are used to estimate the likelihood that humans make errors (Fujita & Hollnagel, 2004), also called the human error probability (HEP).

In HRA methods, the HEP is calculated by looking at the task at hand and how various aspects of it affect the probability for human error. HRA methods are either holistic or atomistic. Holistic methods make judgments based on the overall event, while atomistic methods make judgments on subcomponents that are combined into a final HEP (Boring, Gertman, Joe & Marble, 2005). Atomistic HRA methods calculate the HEP by factoring in environmental conditions, which are called performance shaping factors (PSF) (Marseguerra, Zio & Librizzi, 2006). These PSFs usually include variables such as available time, the complexity of the task, training of the operators, among others (Hollnagel, 1998).

SPAR-H

SPAR-H is a HRA method developed by the Idaho National Laboratory. This method was initially called Accident Sequence Precursor Standardized Plant Analysis Risk Model (ASP/SPAR) and was developed for use in nuclear power plants in 1994 (Gertman et al., 2005). ASP/SPAR was developed as a closely related alternative to two popular HRA approaches at the time, THERP and ASEP. THERP required considerable training to perform and ASEP was a simplified THERP that was most often used as a screening HRA (Blackman, Gertman & Boring, 2008). The model was updated in 1999 and renamed to the current name: Standardized Plant Analysis Risk-Human Reliability method (SPAR-H) (Gertman et al., 2005). This method was a further simplification and generalization from THERP and ASEP and uses performance shaping factors to generalize human performance (Blackman et al., 2008). The U.S. Nuclear Regulatory Commission has since then used SPAR-H to perform various risk analyses in nuclear power plants (Gertman et al., 2005).

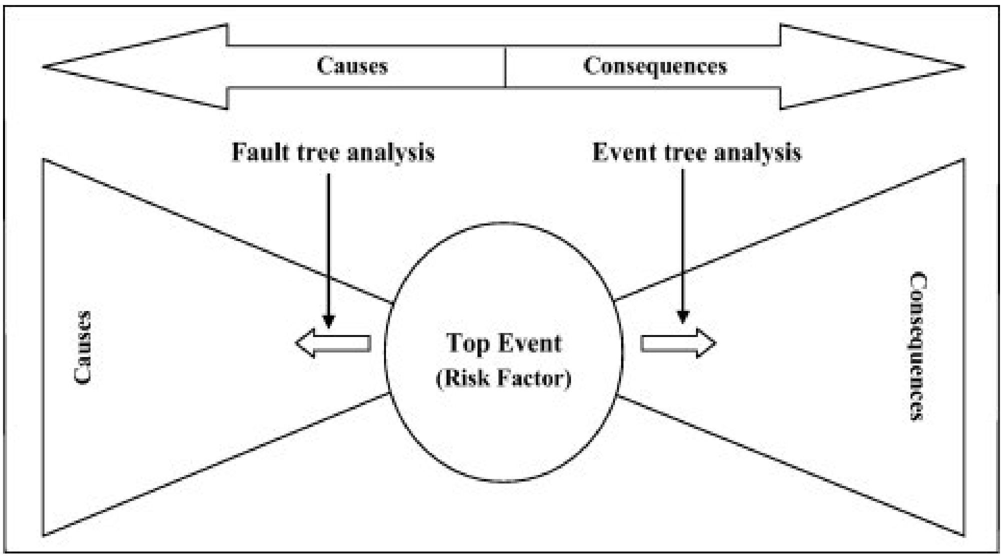
The SPAR-H is an atomistic cognitively based HRA method that calculate HEPs associated with operator crew actions at nuclear power plants (Gould et al., 2012) on the basis of a nominal HEP and eight performance shaping factors (PSFs). A PSF is an aspect of the human's individual characteristics, environment, organization, or task that decrements or improves human performance, thus respectively increasing or decreasing the likelihood of human error (Boring & Blackman, 2007). The use of mapping error probabilities related to PSFs instead of mapping whole scenarios brought greater generalizability to HRA and greater inter-analyst reliability (Lois et al., 2009). The eight PSFs in SPAR-H are available time, stress and stressors, complexity, experience and training, procedures, ergonomics and human-machine interface (HMI), fitness for duty, and work processes. The PSFs multiply the HEP based on their influence on the error probability (Gertman et al., 2005; Lois et al., 2009). When there is no indication that the PSF has a significant contribution, or there is not enough information to rate the PSF, the PSFs multiplier is set to the nominal value of 1.0, indicating that this PSF does not affect the overall HEP. When there is an indication that the PSF contributes to the HEP, the multiplier is either set as greater than 1.0, indicating an increase in error probability, or less than 1.0, indicating that there is a decrease in error probability and thus the PSF contributes positively to the overall HEP (Lois et al., 2009).

SPAR-H is used for analyzing two kinds of tasks, diagnosis tasks and action tasks. Diagnosis in SPAR-H refers to cognitive processing, from the very complex process of interpreting information to the very simple process of deciding to act, while action refers to a physical action such as pressing a button or turning a lever (Whaley, Kelly, Boring & Galyean, 2011). The nominal baseline HEP is 0.01 for a diagnosis task, and 0.001 for an action task (Boring & Blackman, 2007). This means that the probability for human error if all PSFs also are nominal is one in a hundred for a diagnosis task and one in a thousand for an action task. As stated earlier, the PSFs contribute to the nominal HEP by increasing or decreasing the likelihood of error based on the operator's contextual situation. The contributions of HEP values for the different PSFs are determined using expert judgment, something that has been cited as a problem for inter-rater reliability in HRA methods (Swain, 1990).

Using SPAR-H

SPAR-H is a method that is used in post-initiating events. An initiating event is a scenario that may cause an undesirable system state (Gertman et al., 2005), such as the loss of well control or a gas leak. In the bow-tie model (e.g. Mokhtari, Ren, Roberts & Wang, 2011; see Figure 1), which illustrate the causes leading up to an initiating event (here called «Top Event») on the left side of the bow-tie, and the potential consequences of the event on the right side of the bow-tie, SPAR-H is concerned with the right side of the bow-tie. SPAR-H attempt to identify where the probabilities for human error is greatest after an initiating event has occured, so improvements can be made and potential consequences can be avoided.

Figure 1. Example of the bow-tie model (Mokhtari et al., 2011)



After an initiating event, safety barriers are used to reduce the risk of accidents (Sklet, 2006). These barriers can be technical systems that automatically start when sensors indicate an initiating event, or they can be human operators that manually try to restore the system. HEPs calculated by SPAR-H quantify the probabilities that these human barriers fail, resulting in a human failure event (HFE) (Whaley et al., 2011).

A SPAR-H analysis is performed by first categorizing the HFE into diagnosis or action. The SPAR-H worksheets (Gertman et al., 2005; see Figure 2) includes columns for both action and diagnosis tasks. Usually both diagnosis and action are identified and either used as seperate HFEs or combined into a single HFE (Whaley et al., 2011). Once the HFE has been categorized, the analyst should identify the most important performance drivers, i.e., the characteristics of the situation that influence operator performance, both negative and positive. The eight PSF's are then rated according to the performance drivers that are identified, and the HEP is calculated (Whaley et al., 2011). The final HEP is a product of the nominal HEP and the PSF multipliers. When action and diagnosis are combined into a single HEP, the two HEPs are calculated seperately and then summed into a combined HEP (Whaley et al., 2011).

Figure 2. Extract from the SPAR-H worksheet for assigning PSFs (Gertman et al., 2005).

A. Evaluate PSFs for the Diagnosis Portion of the Task, If Any.

PSFs	PSF Levels	Multiplier for Diagnosis	Please note specific reasons for PSF level selection in this column.
Available Time	Inadequate time	P(failure) = 1.0 ☐	
	Barely adequate time (≈2/3 x nominal)	10 ☐	
	Nominal time	1 ☐	
	Extra time (between 1 and 2 x nominal and > than 30 min)	0.1 ☐	
	Expansive time (> 2 x nominal and > 30 min)	0.01 ☐	
	Insufficient information	1 ☐	
Stress/ Stressors	Extreme	5 ☐	
	High	2 ☐	
	Nominal	1 ☐	
	Insufficient Information	1 ☐	
Complexity	Highly complex	5 ☐	
	Moderately complex	2 ☐	
	Nominal	1 ☐	
	Obvious diagnosis	0.1 ☐	
	Insufficient Information	1 ☐	

One of the problems of HRA in general is that the PSF's are assigned using expert judgments, which are more or less based on arbitrary scales, and lack a solid theoretical foundation that guide the experts (Mosleh & Chang, 2004). These disadvantages might result in unreliable HEP values that indicate higher or lower risk than the situation warrants. Even so, most risk analysts acknowledge that the value of HRA come from not the exact probability values, but the insight into sources of vulnerability and risk (Boring et al., 2009). This means HRA can be used as a ranking tool to identify which situations and tasks that are most vulnerable to human error. As Bea (2002, p. 3) so elegantly put it, «[...] the objective is detection and not prediction».

Complexity for Petro-HRA

When developing a HRA method for the petroleum industry it is important to know that the method being developed and put to use has a sound theoretical foundation. What works for the nuclear industry may not work for the petroleum industry. HRA in general has also been criticized for a lack of theoretical basis for the PSFs (Mosleh & Chang, 2004). The concept of complexity is one of the building blocks of the SPAR-H method and so it is important that this PSF is thoroughly examined if it is to be used in a different domain.

The end users of Petro-HRA are often consultants with varied backgrounds. These consultants might have different views of what complexity is or what to add to the term. Complexity might be significantly different from a psychology perspective than an engineering or chemistry perspective. A solid theoretical foundation for this PSF will contribute to a similar starting point for most users of Petro-HRA.

Task complexity is a conceptual construct that is known to influence human performance in several ways, such as cognitive usage, mental workload, and human error (Ham, Park & Jung, 2011; Liu & Li, 2012). A comprehensive study of complexity is important if the goal is to understand and improve human performance (Ham, Park & Jung, 2012).

What is Complexity?

Complexity has shown to be a difficult term to define. There have been many attempts at answering the question "What is complexity?", but this question has been very hard to answer and the term is often used without definition (Ham et al., 2011; Liu & Li, 2012). The difficulty exist because complexity depends on which aspect you are concerned with (Xing & Manning, 2005). Most definitions of complexity are operational and usable only in the specific domain of the researcher (Xing, 2004; Xing & Manning, 2005). Indeed, some researchers claim that a single concept of complexity will not be usable because it needs to be approached from varying perspectives (Ham et al., 2012). The majority of research on complexity and complex tasks has operationalized complexity for its research purpose without trying to generalize the term.

Some researchers argue that most importantly is not the definition of complexity in itself, but to identify the underlying factors that contribute to complexity (Ham et al., 2011). A common approach to evaluate the complexity of a task has been to identify task complexity factors and measuring these factors (Ham et al., 2012). Several studies have tried to identify complexity factors that are specific to their domain, such as air traffic control (Mogford, Guttman, Morrow & Kopardekar, 1995), nuclear power control (Braarud & Kirwan, 2011), auditing (Bonner, 1994), and information search (Byström & Järvelin, 1995), but none of these have identified factors that are specific to the offshore petroleum domain, and we are still lacking a conceptual framework that can be used independently of domains (Ham et al., 2011; 2012). The numerous studies that have identified complexity factors have resulted in a confusion of individual and task characteristics (Liu & Li, 2012).

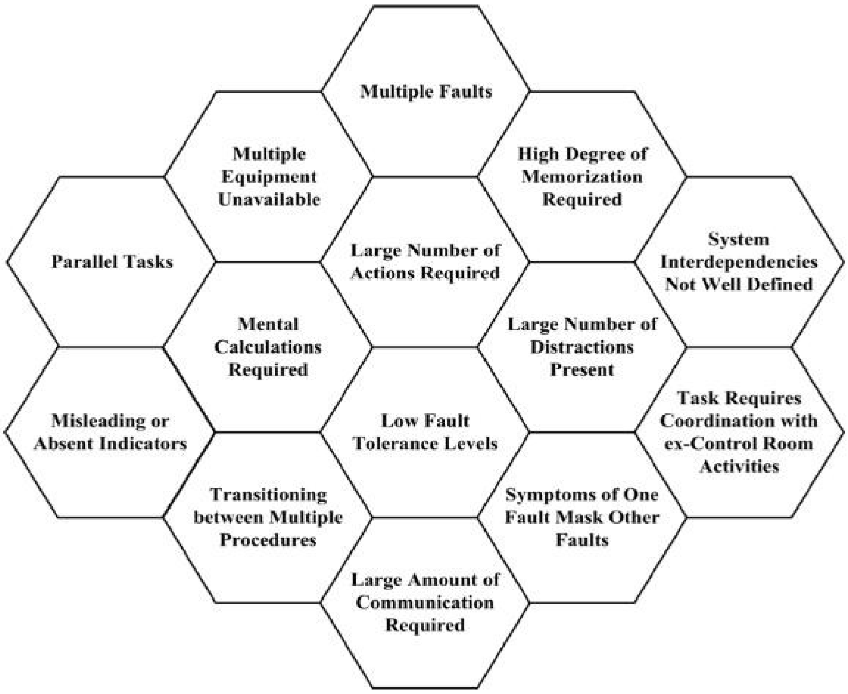
Complexity in SPAR-H

SPAR-H's complexity PSF originated from the HRA method THERP, and the multipliers used are the same as THERP's levels. THERP does not have a specific complexity PSF, but the method covers tasks involving complexity. SPAR-H has extended these descriptions into a general PSF (Boring & Blackman, 2007).

In SPAR-H the complexity PSF is divided into four multiplier levels; highly complex, moderately complex, nominally complex tasks and obvious diagnosis tasks (Gertman et al., 2005). Highly complex tasks are described as tasks that are very difficult to perform and have many variables with ambiguous and concurrent diagnoses and actions. In SPAR-H, highly complex tasks multiply the HEP by five for both action and diagnosis tasks. Moderately complex tasks are described as somewhat difficult to perform, where there is some ambiguity, several variables, and perhaps some concurrent diagnoses or actions. The moderately complex tasks multiply the HEP by two for both action and diagnosis. Nominal tasks are tasks that are not difficult to perform, with little ambiguity, and few variables involved. A nominal task will not affect the overall HEP and thus the multiplier is one. Obvious diagnosis is a task where diagnosis is severely simplified. In this situation the problem is obvious to the extent that it is difficult for the operator to misdiagnose it. Much validating and convergent information is available to the operator and so the HEP multiplier is 0.1 for obvious diagnosis tasks, indicating a decrease in HEP. SPAR-H does not have a multiplier for obvious action tasks as easy to perform actions tasks are captured under the nominal multiplier. If the rater does not have sufficient information to choose a complexity multiplier, the SPAR-H manual suggests using a nominal HEP (Gertman et al., 2005).

The SPAR-H manual suggests a guideline of 14 factors that contribute to task complexity (Gertman et al., 2005; see Figure 3).

Figure 3. Factors contributing to complexity in SPAR-H (Gertman et al., 2005).



Subjective and Objective Complexity

Despite the many different definitions of complexity, the literature show that many researchers agree that task complexity can be divided into two different complexity types: Subjective and objective complexity (e.g. Bonner, 1994; Li & Wieringa, 2000; Ham et al., 2012; Liu & Li, 2012). According to Ham et al. (2011), the factors that contribute to complexity can be covered by either very subjective features that depend on the knowledge, training and personal attributes of the operator, or objective features that pertain to the characteristics of the task itself, such as the number of elements, objectives, constraints, and the overall size of the problem. Objective complexity is determined by technical features and situational factors, while subjective complexity is the operators' perceptions of the objective complexity and is highly dependent on their knowledge and experience (Ham et al., 2012). Objective complexity is in other words independent of task performers, while subjective complexity is a joint property of task and performer (Liu & Li, 2012).

Review of Literature on Complexity

To identify the most important factors that contribute to task complexity, a review of relevant literature was performed. The list of articles used in this review can be found in Table 1 in the methods section. The following paragraphs attempt to outline some of the different approaches and findings of earlier research on complexity. This is done to get an overview of how complexity has been used or described in previous research.

Campbell (1988) examined task complexity in the context of goal setting and strategy development. He classified complexity into three schemes: (a) as a psychological experience, (b) as an interaction between task and person characteristics, and (c) as a function of objective task characteristics. These three schemes can be divided into the subjective (a and b) and objective (c) types of task complexity described previously. Psychological complexity can be described as the perceived complexity of the operator that is affected by feelings of significance, autonomy, and enrichment. Person-task complexity is the complexity of the task relative to the capabilities of the person performing the task. Objective complexity is the characteristics of the task and is described as the magnitude, variation, and amount of stimulation (Campbell, 1988). On the basis of earlier research on complexity, Campbell (1988) created an integrative framework of objective complexity which includes four factors that contribute to task complexity: (a) the presence of multiple paths toward a desired end-state, (b) the presence of multiple desired outcomes to be attained, (c) the presence of conflicting interdependencies among paths to multiple outcomes, and (d) the presence of uncertain or probabilistic links among paths and outcomes.

Bonner (1994) looked at task complexity in the auditing domain. This research divided task complexity into difficulty and structure, where difficulty is the subjective qualities and structure is the objective qualities of a task. Bonner argue that those who believe that task complexity is a function of objective qualities of the task itself appear to believe that the complexity is perceived equally by all persons at the input stage and that personal attributes affect judgment and performance differently at the processing and output stages (Bonner, 1994). Input, processing and output are the three stages of Bonner's complexity model. These stages are then divided into amount and clarity of information at each stage. Factors that contribute to complexity at the input stage include number of alternatives and number of cues (amount), and cue specification and cue measurement (clarity). Similar factors are found at the processing and output stages (Bonner, 1994).

Xing and Manning (2005) tried to identify factors relevant for air traffic control. In their review of complexity literature, they found that most definitions of complexity correspond to three factors of complexity: the numeric size of the basic elements, the variety of the elements, and the structural rules of the elements. Three types of complexity appeared from their review: information complexity, cognitive complexity, and display complexity. While these three focuses on different aspects of human or machine systems, there is an overlap among the types and all three are partially concerned with the three basic concepts of size, variety, and structure (Xing & Manning, 2005). The researchers do however feel that size, variety and structure is a weak definition of complexity factors, and that the structural rules of a system contributes most to complexity (Xing & Manning, 2005). This can be illustrated with an example of counting peas: Variations in amount and size of the peas will require longer time to complete the task, but will not make the task more complex (Xing & Manning, 2005).

Endsley and Jones (2004) suggested a framework of complexity types from research on situation awareness. The types range from technical system complexity to human perceived complexity. The authors suggest that several different factors contribute to the degree of complexity humans have to cope with when using a system. Endsley and Jones (2004) distingiushed between technical complexity, operational complexity, and apparant complexity. These three factors are respectively the system's functional complicatedness, the complexity that the operators have to deal with to use the system, and the complexity that is brought about by the system's user interface.

Harvey and Koubek (2000) looked at complexity in their research on team collaboration.

From their perspective, task complexity is based mainly on research by Campbell (1988), Wood (1986), Byström & Järvelin (1995), and Rasmussen (1990), and is determined based on three classes of task characteristics: Scope, structurability, and uncertainty (Harvey & Koubek, 2000). A task is here defined by products, acts, and information cues, and the complexity of the tasks are determined by their variety, uncertainty, amount of information, number of meta-operations, task presentation, information presentation, number of acts, number of dependencies between inputs and outputs, automaticity of the task, and time to complete the task (Harvey & Koubek, 2000). From these, the authors emerge at the three previously mentioned characteristics: Scope, structurability, and uncertainty. Scope is the breadth, extent, range or general size of a task, and is affected by the number of subtasks and amount of information to be processed. Structurability represents the degree of sequence and relationship between subtasks, and is affected by analyzability, alternatives, and coordination. Finally, uncertainty attempts to measure complexity based on the degree of predictability or confidence that can be achieved in a task (Harvey & Koubek, 2000).

Braarud and Kirwan (2011) summarized research in studies of nuclear operator crews in complex and realistic scenarios. Based on a brief literature review, four factors were identified, process complexity, task complexity, interface complexity, and subjective complexity (Braarud & Kirwan, 2011). Process complexity is the number and relationships of inputs, outputs and system variables, state variables, and the number of dynamically changing variables. Process complexity is the most objectively definable as it deals mostly with factual data about the system. Task complexity is a factor that relates to the number of underlying problems in a scenario such as conflicting goals, number of alarms, tasks, goal pathways, time available, and number of decision options. Task complexity is found in the diagnostic behavior of the operator that occur between system and operator performance. The third factor, the interface complexity of the system represents the computer screen formats and procedures. This refers to the degree that the operator instrumentation is consistent with the operator's information needs and diagnostic approach. Finally, subjective complexity includes the operator's perceived level of complexity. Subjective complexity is primarily a function of the operator's training and experience (Kirwan, 1994b). Based on these factors a complexity questionnaire was developed and submitted to operators that had completed simulated accident scenarios (Collier, 1998). The questionnaires yielded eight complexity dimensions: ambiguity, spread/propogation, coordination requirements, information intensity, familiarity, knowledge, severity, and time pressure/stressors (Braarud & Kirwan, 2011). These dimensions were found to be highly correlated (Braarud, 1998), and this point to the discovery that complexity factors will be overlapping and dependent of each other (Braarud & Kirwan, 2011). The authors tested their complexity dimensions in a simulated nuclear power plant control room and found higher variability in complex scenarios, which in some cases lead to differences in outcomes (Braarud & Kirwan, 2011).

Byström and Järvelin (1995) examined the effect task complexity had on information seeking and use from a problem-solving viewpoint. They identified task characteristics related to complexity from literature on task complexity. These include repetitivity, analyzability, a priori determinability, number of alternative paths, ouctome novelty, number of goals and dependencies among them, uncertainties between performance and goals, number of inputs, cognitive and skill requirements, and time varying conditions (Byström & Järvelin, 1995). These characteristics were grouped into two dimensions: characteristics related to the a priori determinability of tasks, and characteristics related to the extent of the task. The extent dimension refers to the overall size of the task, while the a priori determinability dimension relates to the degree of a priori uncertainty or structure of the task. The authors use the dimension of a priori determinability to classify tasks into five categories based on how well the task can be determined prior to problem-solving. A task where the answer is easily determinable is less complex than a novel and unstructured task where the result, process, or information requirements are unknown (Byström & Järvelin, 1995).

Lazzara, Pavlas, Fiore and Salas (2010) started the work of developing a framework for task complexity with examples from simulated planning tasks of military missions. These authors focused on objective task qualities and used Campbell (1988) and Woods (1986) as their starting point. In the framework developed by Lazzara et al. (2010) complexity is divided into coordinative complexity, which is the degree of interaction and integration required from team members, and component complexity, which is the number of distinct acts and elements that needs to be processed in completing a task. Coordinative complexity includes complexity factors such as task ambiguity, number of decisions, interdependencies between team members, solution diversity, and number of global restrictions of the task. Component complexity includes the number of local restrictions, at the individual level, and the amount of information needed and received (Lazzara et al., 2010).

Ham, Park & Jung (2011) were concerned with the lack of a theoretical basis for categorizing the many complexity factors that previous literature had found. The authors attempted to develop a framework with a more systematic approach to the many factors identified by earlier research. In this framework the task complexity term acts as a bridge between objective and subjective complexity as it is seen in relation to human capabilities and limitations (Ham et al., 2011). The authors also identified other types of complexity than task complexity, such as cognitive complexity, system complexity, and operational complexity. Furthermore, each type of complexity has its associated complexity shaping factors that contribute to the degree of complexity found (Ham et al., 2011). Ham et al. (2011) proposed a model where the complexity shaping factors of different domains (i.e. knowledge complexity, cognitive complexity, interaction complexity) can be identified on the basis of three aspects of the domain concerned: (a) the spatial aspect, relating to the logical scope and size of the domain, (b) the relational aspect, dealing with causality and connections within the domain, and (c) the temporal aspect (Ham et al., 2011). The model is meant to be applicable for any domain, context or user (Ham et al., 2012). They noted that the framework and model does not automatically generate complexity factors or guarantee that the identified factors are complete. As for any conceptual framework, subjective judgment and analysis is needed in identification. The qualitative identification of factors can however be more complete and systematic when assisted by this framework (Ham et al., 2011). On the basis of this framework, Ham et al. (2012) identified 21 complexity factors based on the three dimensions size, variety, and structure/organization. These complexity factors include, among others, number of steps, number of goals, number of subjective judgments needed, number of preconditions, and logical relationship between steps.

Liu and Li (2012) reviewed operational definitions and models of complexity and organized these into three viewpoints. The first viewpoint is the structuralist view, where task complexity is understood as the structure of a task. This view implies that task complexity is a function of task components and is as such what several other researchers define as objective task complexity. An example here is the number of elements of which the task is composed, and the relationship between these elements (Liu & Li, 2012). The second viewpoint is the resource requirement of the task. In this view, task complexity is affected by its cognitive, physical and mental demands, and requirements of memory, knowledge, skill, and time on the operator (Liu & Li, 2012). The last viewpoint is the interaction view and is concerned with the interaction between task and task performer characteristics. This viewpoint is mostly concerned with the task performer's subjective complexity. Researchers who hold this viewpoint argue that the performer's perceived complexity must be considered because each performer may interpret the same objective task differently (Liu & Li, 2012). Based on their reviews the authors grouped the various task complexity definitions found in other literature, creating 24 complexity contributory factors. These were again organized into 10 complexity dimensions which formed their task complexity model. These dimensions are size, variety, ambiguity, relationship, variability, unreliability, novelty, incongruity, action complexity, and temporal demand (Liu & Li, 2012).

In addition to the research mentioned here, several others have also studied complexity theoretically or experimentally. Some of these researcher's work can be found in Table 1 in the methods section.

To summarize, the research on complexity constitutes a vast and multidisciplined field of work. One simple definition can hardly encompass all that is complexity, thus the construct is best understood with respect to the specific domain in question. Many researchers agree that a qualitative distinction can be made between subjective and objective complexity. Those who have tried to identify complexity factors usually find similar and overlapping results. A few factors seem to be repeated regardless of research domain, such as size of the problem space, variety of its components, the stucture and logic of the task, its ambiguity, and the uncertainties that the task-doer face.

Method

To find complexity contributing factors, a review of relevant literature was performed. The research method used was thematic analysis. This method was chosen because it permits the researcher to use both textual data and interviews (Howitt, 2010) in addition to being a theoretically flexible approach to analysing data (Braun & Clarke, 2006), which is useful in a literature review of a psychological construct such as complexity. Thematic analysis attempt to describe the major features of the data to identify the major themes (Howitt, 2010). In this thesis the goal is to identify what complexity is and identify the underlying factors that make up complexity. Themes in this thesis were defined on two levels: Elements that contribute to task complexity, and the categories where these elements fit together.

The literature search was performed using the search engines available in the PsycNET database (psycnet.apa.org), Google Scholar (scholar.google.com), and the library search engine BIBSYS Ask (ask.bibsys.no), as well as using the reference lists of relevant articles. The keywords used in the search engines were: Complexity, task complexity, complexity review, complexity performance, complexity decision making, complexity framework, what is complexity, complexity model. During the literature search, coding was performed in the form of notes that identified the complexity contributing factors in the articles used. The search was ended when the literature yielded no new relevant articles and the author felt that theoretical saturation was acquired.

When the literature review was completed, the notes and codings from the articles were analyzed. This analysis presented many different elements that contribute to complexity. These elements were organized into factors that identifed the main categorized themes of the literature. A list of articles used in the literature review that were subject to the coding process can be found in Table 1.

After the complexity factors had been created, a guideline table for Petro-HRA consultants was made based on the factors and their effect on operator performance (see Table 3 in the "Results and Discussion" section). To establish the usability of this guideline table, subject matter experts on HRA in the petroleum industry were contacted and interviewed about the factors' suitability and use in the petroleum industry. Four persons were interviewed; three by telephone, and one face to face. The experts were informally consulted on the usability of the guideline table for Petro-HRA. Prior to the interviews the experts were given the guideline table and the description of the factors. The interviewees were then asked questions on how they determine complexity and the HEP cutoff values when performing SPAR-H today, whether or not the factors are covering for tasks in the petroleum domain, and whether the guideline table was understandable and practically applicable for Petro-HRA analysts. This was done due to the author's lack of knowledge on specifics in the petroleum domain such as operator tasks and operations, and if a guideline were to have practical use, experts in the field of use had to be consulted.

Table 1. Research and literature reviewed.

Author and Publication Year	Title
Abdolmohammadi & Wright (1987)	An Examination of the Effects of Experience and Task Complexity on Audit Judgments
Bell & Ruthven (2004)	Searchers' Assessment of Task Complexity for Web Searching
Bonner (1994)	A model of the effects of audit task complexity
Braarud & Kirwan (2011)	Task Complexity: What Challenges the Crew and How Do They Cope?
Byström (2002)	Information and Information Sources in Tasks of Varying Complexity
Byström & Järvelin (1995)	Task complexity affects information seeking and use
Campbell (1984)	The effects of goal-contingent payment on the performance of a complex task
Campbell (1988)	Task Complexity: A Review and Analysis
Chen, Casper & Cortina (2001)	The Roles of Self-Efficacy and Task Complexity in the Relationships Among Cognitive Ability, Conscientousness, and Work-Related Performance: A Meta-Analytic Examination
Chipbarupa, Larson, Brucks, Draugalis, Bootman & Puto (1993)	Physician prescribing decisions: The effects of situational involvement and task complexity on information acqusition and decision making

Cummings & Tsionis (2005)	Deconstructing Complexity in Air Traffic Control
Endsley & Jones (2004)	Designing for Situation Awareness. An Approach to User-Centered Design
Gell-Mann (1995)	What is Complexity?
Ham, Park & Jung (2011)	A Framework-Based Approach to Identifying and Organizing the Complexity Factors of Human-System Interaction
Ham, Park & Jung (2012)	Model-based identification and use of task complexity factors of human integrated systems
Harvey & Koubek (2000)	Cognitive, Social, and Environmental Attributes of Distributed Engineering Collaboration: A Review and Proposed Model of Collaboration
Horsky, Kaufman, Oppenheim & Patel (2003)	A framework for analyzing the cognitive complexity of computer-assisted clinical ordering
Hwang (1995)	The Effectiveness Of Graphic And Tabular Presentation Under Time Pressure And Task Complexity
Jacko & Ward (1996)	Toward establishing a link between psychomotor task complexity and human information processing
Kanfer & Ackerman (1989)	Motivation and Cognitive Abilities: An Integrative/Aptitude-Treatment Interaction Approach to Skill Acquisition
Kerstholt (1992)	Information search and choice accuracy as a function of task complexity and task structure
Kirwan (1994)	Human error project experimental programme
Kuhlthau (1999)	The Role of Experience in the Information Search Process of an Early Career Information Worker: Perceptions of Uncertainty, Complexity, Construction and Sources
Lazzara, Pavlas, Fiore & Salas (2010)	A framework to develop task complexity
Li & Wieringa (2000)	Understanding Perceived Complexity in Human Supervisory Control
Liu & Li (2011)	Toward Understanding the Relationship between Task Complexity and Task Performance
Liu & Li (2012)	Task complexity: A review and conceptualization framework
Lois et al. (2009)	International HRA empirical study – pilot phase report. Description of Overall approach and First Pilot Results from Comparing HRA Methods to Simulator Data
Marshall & Byrd (1998)	Perceived task complexity as a criterion for information support
Mascha & Miller (2010)	The effects of task complexity and skill on over/under-estimation of internal control
Mogford, Guttman, Morrow & Kopardekar (1995)	The Complexity Construct in Air Traffic Control: A Review and Synthesis of the Literature
Park, Jung & Ha (2001)	Development of the step complexity measure for emergency operating procedures using entropy concepts
Payne (1976)	Task Complexity and Contingent Processing in

	Decision Making: An Information Search and Protocol Analysis
Pieschl, Stahl, Murray & Bromme (2011)	Is adaptation to task complexity really beneficial for performance
Rothrock, Harvey & Burns (2005)	A theoretical framework and quantitative architecture to assess team task complexity in dynamic environments
Sintchenko & Coiera (2003)	Which clinical decisions benefit from automation? A task complexity approach
Sintchenko & Coiera (2006)	Decision Complexity Affects the Extent and Type of Decision Support Use
Snowden & Boone (2007)	A Leader's Framework for Decision Making
Speier, Vessey & Valacich (2003)	The Effects of Interruptions, Task Complexity, and Information Presentation on Computer-Supported Decision-Making Performance
Tiamiyu (1992)	The Relationship Between Source Use and Work Complexity, Decision-Maker Discretion and Activity Duration in Nigerian Government Ministries
Topi, Valacich & Hoffer (2005)	The effect of task complexity and time availability limitations on human performance in database query tasks
Vakkari (1999)	Task complexity, problem structure and information actions. Integrating studies on information seeking and retrieval
Weingart (1992)	Impact of Group Goals, Task Component Complexity, Effort, and Planning on Group Performance
Wood (1986)	Task complexity: Definition of the construct
Wood, Mento & Locke (1987)	Task Complexity as a Moderator of Goal Effects: A Meta-Analysis
Xing (2004)	Measures of Information Complexity and the Implications of Automation Design
Xing (2007)	Information Complexity in Air Traffic Control Displays
Xing & Manning (2005)	Complexity and Automation Displays of Air Traffic Control: Literature Review and Analysis
Xu, Song, Li, Zhao, Luo, He & Salvendy (2008)	An ergonomics study of computerized emergency operating procedures: Presentation style, task complexity, and training level
Xu, Li, Song, Luo, Zhao & Salvendy (2009)	Influence of step complexity and presentation style on step performance of computerized emergency operating procedures
Zhang, Li, Wu & Wu (2009)	A spaceflight operation complexity measure and its experimental validation
Zhang, Wu, Zhang, Quanpeng & Liu (2011)	Task Complexity Related Training Effects on Operation Error of Spaceflight Emergency Task

Results and Discussion

The literature review identified many elements that contribute to complexity. These elements were organized into 13 categories that grouped similar elements together into parent complexity contributing factors, thus creating a conceptual framework – a descriptive model of complexity that synthesize information from a variety of domains. A similar, albeit more simplified, task was undertaken by Gertman (2012), where he identified complexity subfactors to guide users of SPAR-H in assigning the PSF multiplier. Gertman (2012) performed a brief literature review and used the factors found by Xing and Manning (2005), quantity, variety and relations. The factors identified in this thesis can be seen as an expansion of the work by Gertman (2012).

The 13 complexity factors and their contributing elements can be seen in Table 2. In the coming section of this thesis, these 13 factors are described and a discussion follows regarding the different factors' suitability for describing complexity in a Petro-HRA method. Of the 13 factors, seven are found to be appropriate for Petro-HRA. These seven factors effect on operator performance is examined, and a guideline table for Petro-HRA is created.

Conceptual Framework of Task Complexity

Table 2. Conceptual framework of complexity factors.

Factor	Elements	Source
Goal complexity	Multiple paths to desired end-state/goal Multiple end-states/goals Competing ideas, paths or alternatives Competing goals Conflicting interdependencies between paths and goals Multiple faults Number of goals Number of tasks Number of parallel tasks	Campbell (1988) Braarud & Kirwan (2011) Kirwan (1994b) Byström & Järvelin (1995) Payne (1976) Bonner (1994) Chinbarupa et al. (1993) Lazzara et al. (2010) Snowden & Boone (2007) Campbell (1988) Ham et al. (2011) Gertman et al. (2005)

Step complexity	Number of unique actions Number of unique steps Number of unique inputs Number of unique outputs	Weingart (1992) Lazzara et al (2010) Ham et al. (2011) Zhang et al. (2009) Xing (2004) Liu & Li (2012) Gertman et al. (2005) Braarud & Kirwan (2011) Park et al. (2001)
Size complexity	Number of information cues Number of task elements/components Amount of information Information intensity Size of problem space/scope/spread Number of sub-tasks Memorization requirements	Speier, Vessey & Valacich (2003) Bonner (1994) Ham et al. (2011) Li & Wieringa (2000) Lazzara et al. (2010) Braarud & Kirwan (2011) Xing (2004) Xing & Manning (2005) Harvey & Koubek (2000) Sintchenko & Coiera (2006) Liu & Li (2011) Gertman et al. (2005)
Interaction complexity	Amount of interaction/commnication between individuals Coordination demands/interdependence between individuals	Woods (1986) Gertman et al. (2005) Sintchenko & Coiera (2003) Braarud & Kirwan (2011) Lazzara et al. (2010)
Connection complexity	Relation between elements/components Relation between inputs and outputs Number of connections between elements/parts Strength of connections between elements/parts Dependencies between tasks or elements/components	Ham et al. (2011) Xing & Manning (2005) Xing (2004) Braarud & Kirwan (2011) Kirwan (1994b) Liu & Li (2012) Li & Wieringa (2000) Gertman et al. (2005)
Uncertainty	Uncertainty of paths/process and end/outcome A priori determinability Number of known factors Number of known connections Clarity of information/task Completeness of information	Campbell (1988) Byström & Järvelin (1995) Li & Liu (2011) Vakkari (1999) Byström (2002) Ham et al. (2011) Mascha & Miller (2010) Bonner (1994) Kirwan (1994b) Sintchenko & Coiera (2003) Kerstholt (1992) Lazzara et al. (2010) Braarud & Kirwan (2011)
Dynamic complexity	Unpredictability Environmental predictability / weather Noise/irrelevant information Masking of faults	Snowden & Boone (2007) Jacko & Ward (1996) Liu & Li (2011) Mogford et al. (1995) Wieringa & Stassen (2000) Gertman et al. (2005)

	Change/stability of task Dynamics of process/paths Ambiguity	Braarud & Kirwan (2011) Kirwan (1994b) Chen et al. (2001) Ham et al. (2011)
Variation complexity	Outcome novelty Task novelty Task variety/diversity Variety of elements	Byström & Järvelin (1995) Liu & Li (2012) Ham et al. (2012) Xing & Manning (2005) Li & Wieringa (2000) Wieringa & Stassen (2000)
Structure complexity	Structure of task Order/organization of task Rules of task Conflicting rules Task logic/logic of component relations	Abdolmohammadi & Wright (1987) Ham et al. (2012) Liu & Li (2011) Harvey & Koubek (2000) Bonner (1994) Xing & Manning (2005) Lazzara et al. (2010) Zhang et al. (2009)
Temporal complexity	Time pressure Temporal demanad	Sintchenko & Coiera (2003) Braarud & Kirwan (2011)
Knowledge complexity	Domain knowledge Depth of knowledge Engineering decision knowledge	Ham et al. (2012) Braarud & Kirwan (2011) Kirwan (1994b)
HMI complexity	Operation instrument information Misleading/absent indicators Presentation homogeneity/logic	Zhang et al. (2009) Gertman et al. (2005) Liu & Li (2011) Kirwan (1994b)
Procedure complexity	Number of procedures Procedure homogeneity Procedure executability	Bonner (1994) Kirwan (1994b) Xu et al. (2008)

The following section is a description of the complexity factors in Table 2 and what contributing elements the factors are categorized from.

Goal complexity can be described as the multitude of paths or alternatives an operator can take to reach the goal of a task. The complexity will increase if there are more paths or goals (Bonner, 1994), or if the paths or goals are incompatible with each other (Campbell, 1988). This increase in complexity is due to an increase in information load on the operator (Campbell, 1988). This may happen if there are several parallel paths, competing paths or goals and no clear indication to which is the better choice (Bonner, 1994), or if there exists conflicting interdependencies among paths (Campbell, 1988). Under conditions of high goal complexity the operators may observe several paths as possibilities but only one lead to goal attainment, or that several paths lead to goal attainment, but differ in their efficiency and the operator must find the most efficient path (Campbell, 1988). The presence of conflicting interdependencies among paths mean that attaining one desired goal will conflict with the achievement of reaching one or more different goals, thus also making it a matter of prioritizing. This may for example be that quality will exclude quantity (Campbell, 1988). However, not all increase in paths will lead to higher goal complexity. If multiple paths lead to the task goal, this redundancy in paths will actually decrease the complexity of the task (Campbell, 1988).

Step complexity. This factor refers to the number of unique cognitive acts, actions or steps that are required by the operator to complete the task **(**Lazzara et al., 2010; Sintchenko & Coiera, 2003). A step is unique when it is qualitatively different from other actions in the same knowledge or skill domain and specific domain knowledge or skills do not generalize to that step (Wood, 1986). The number of continuous steps will also contribute to the complexity of the task. This is due to information requirements for not only the current step, but also for the continuous action steps. This increases the amount of information that is needed to perform the actions (Park, Jung & Ha, 2001). A higher number of steps will make a task more complex.

Size complexity is the overall size or scope of the problem space. This factor is perhaps the most straightforward measure on complexity and most research use some variation of size complexity (Xing & Manning, 2005). Size complexity is associated with the numeric size of the elements or information cues. These are the basic units of thought needed to complete a task (Sintchenko & Coiera, 2003). This is related to the amount and intensity of information that an operator has to process. A high number of alarms, cues, or information needed to complete the task, as well as differentiating important from less important information will contribute to size complexity (Lazzara et al., 2010; Braarud & Kirwan, 2011). Information cues are the pieces of information used to make a judgment during problem solving (Harvey & Koubek, 2000; Liu & Li, 2012). Sometimes task size is described as task scope, which is a function of the subtasks, products, and information processing requirements (Harvey & Koubek, 2000). The two terms, scope and size, can be said to describe the same elements, amount of information that needs to be processed. A higher amount of information, or high memorization demands (Gertman et al., 2005), will require the operator to use more cognitive resources to process the information load, making the tasks more complex (Lazzara et al., 2010).

Connection complexity refers to the relationship between the elements of the task. This factor depends on the number, strength and dependencies of the connections between the tasks or elements in a system (Li & Wieringa, 2000). Connection complexity increases when the task elements or tasks are highly connected and the output of one element depend on the input of another (Kirwan, 1994b), or if the dependencies of the system are not well known or poorly defined (Gertman et al., 2005).

Uncertainty. The uncertainties an operator face when performing a task is a contributing factor to complexity according to several researchers (Campbell, 1988; Byström & Järvelin, 1995; Bell & Ruthven, 2004), and is often used as one of the main characteristics of complexity along with task size and structure (Harvey & Koubek, 2000). Uncertainty can be linked to the number of known factors of a task (Byström, 2002) or to what extent the task can be determined by the operators prior to undertaking it. Less *a priori determinability* of a task yields higher complexity (Byström & Järvelin, 1995). Uncertainty also relates to how clear, consistent or complete the information about the task is, as well as the clarity of the task itself (Kerstholt, 1992; Bonner, 1994; Mascha & Miller, 2010).

Dynamic complexity can be described as the unpredictability of the task or the environment where task is performed. According to Woods (1986) this is the stability of the relationships of task components in a changing external world. This factor includes the unreliability and inconsistency of the task (Liu & Li, 2012) and the environmental noise where the task is performed (Ham et al., 2011). Dynamic complexity is affected by the ambiguity, change or stability of the task or system characteristics over time, which contributes to difficulty in predicting what will happen (Snowden & Boone, 2007; Lazzara et al., 2010; Liu & Li, 2012). Inconsistencies and masking of faults also fall under the dynamic complexity category. If one fault masks another fault task complexity will increase (Gertman et al., 2005; Lois et al., 2009).

Variation complexity refers to the novelty of the task, its components and goals. A task that is irregular and not a routine event for an operator will be more complex than one that is a frequent problem in the domain (Liu & Li, 2012). Similarly, the variety of the components or elements of a task will also contribute to complexity (Xing, 2004).

Structure complexity can be described as the order or organization of the task. It represents the structural rules of a system or task, and these rules determine the interconnections or relationships between the task components (Xing & Manning, 2005; Harvey & Koubek, 2000). The logical sequence or relationship of these components will also contribute to the task's structural complexity (Zhang, Li, Wu & Wu, 2009). The complexity of a task will depend on whether or not the structure of the task is logical, as well as the number of rules and whether or not these rules conflict with each other. Tasks that have many or conflicting rules, e.g. requirements of both speed and accuracy are believed to be more complex than tasks with fewer rules (Lazzara et al., 2010).

Interaction complexity can be described as the degree of interdependence among team members (Lazzara et al., 2010). The amount of communication or interaction that is required between individuals will contribute to the complexity of the task (Sintchenko & Coiera, 2003; Gertman et al., 2005). Tasks that rely on distributed knowledge, where individual team members only have access to some of the information required to complete the task have more interaction complexity than tasks where all participants have all the information required (Lazzara et al., 2010). This type of complexity is important in team tasks.

Temporal complexity is the time pressure the operator is subjected to. The temporal demand of a task has a significant contribution to task complexity (Liu & Li, 2012). Both the experience of simultaneous tasks and time pressure will contribute to temporal complexity due to the difficulty of coordinating the execution of the tasks (Braarud & Kirwan, 2011; Liu & Li, 2012). This is sometimes referred to as temporal load and will contribute to worse information selection and decision efficacy by the operator. Temporal demands are often caused by little available time, urgency, or risk (Liu & Li, 2012).

Knowledge complexity refers to the knowledge the operators need to have about their domain to complete a task (Ham et al., 2012). This factor also includes knowledge depth that entails a detailed understanding of how the different components, systems and subsystems are interrelated (Braarud & Kirwan, 2011). In an accident scenario an operator needs to have knowledge about how the fault interacts with neighbouring systems that may be affected (Braarud & Kirwan, 2011).

HMI complexity is the complexity of the operation instrument information. This factor includes the type and number of monitors and controllers (Zhang et al., 2009) and how the information is displayed or presented (e.g. Bonner, 1994). An interface that is less intuitive or hard to undestand for the operator will contribute to a higher task complexity. Examples include missing or misleading indicators, or unavailable equipment (Gertman et al., 2005).

Procedure complexity referst to the number of and the presentation of procedures that the operators use to complete tasks. According to Zhang et al. (2009) it is important to ensure the procedure is technically correct, understandable without introducing task overload, and possible to execute without mistakes, in order to minimize the complexity of the task.

General Discussion on Complexity in Petro-HRA

As we have seen, complexity is often described as objective or subjective. This distinction should be kept in mind when examining complexity for the Petro-HRA method. SPAR-H, and Petro-HRA, assumes an average operator and is interested in finding the probability of error of this general or average operator. When assigning the complexity PSF, the method is best served with assuming that all operators performing a complex task affect the HEP with the same magnitude, thus assuming that all operators are average. If there is variation in the characteristics of the operator, PSFs such as experience/training, stress/stressors, or fitness for duty will identify this variation and the HEP will be altered. Complexity can also be related to task characteristics that increase information load and memorization requirements (Campbell, 1988; Collier, 1998). This means that complexity can be defined objectively and determined independently of any particular task-doer (Campbell, 1988). This does not mean however, that all task-doers or operators will perform equally well when faced with high information load or a particularly complex task. It just means that the complexity PSF is best served with identifying the objective characteristics of the task and leave the variance in operator performance to other PSFs. In addition, it is important to remember that the HEP is a probability and not a fixed number, and thus it is also susceptible to variance.

In the subjective view of complexity, the knowledge, experience and training of the operator are the most important determinants of complexity (Ham et al., 2012). This view looks at the complexity of the task as a "state of mind" and argue that there can hardly be lack of knowledge or increased information load without a person (Liu & Li, 2012). This can also be described as perceived complexity or difficulty, which can be found in the intersection between task and task-doer. It is the task-doer's subjective complexity that determine the performance. The perceived complexity of a task will be in relation to the task-doer's knowledge, skill and motivation. In other words how difficult the task-doer finds the task. However, it can also be argued that the complexity of a task can be "rated" as objectively more or less complex regardless of the operator. Arguably, fifty information cues of a task in constant change is more complex to perform than a more linear task with just five information cues regardless of whether an expert or a novice is performing the task. The expert however, will probably perceive the tasks as less complex than the novice and will probably perform better. The HRA methods however, do not attempt to identify individuals that perform a task well, but rather find situations with high probabilities of human error. This means that it is not the performance of the individual, but the objective complexity of the situation that is the most important factor for the Petro-HRA method.

Another point that is worth mentioning is that decision-making in complex domains can be viewed as a function of the decision task and the expertise of the decision maker. If the expertise of the decision maker is controlled for, e.g. everyone are experts, which often is the case for operators in the petroleum domain, the objective task will be the main variable for performance (Sintchenko & Coiera, 2006).

Complexity Factors Excluded in Petro-HRA

As mentioned earlier, six of the 13 factors that the literature review identified as important for task complexity were found not to be appropriate for the complexity PSF in Petro-HRA. This means that users of Petro-HRA should not include these when assessing the complexity of a situation or task.

Five of these excluded factors are procedure complexity, temporal complexity, HMI complexity, knowledge complexity and interaction complexity. The factors all contribute to the overall complexity of a task. However, the SPAR-H method include PSFs for all of these factors. This means that their effect on the HEP is taken into account in other parts of the HRA and an inclusion of these factors into the complexity PSF as well would contribute to double counting these factors in the analysis, thus making their contribution to the HEP greater than it should be.

Procedure complexity is identified in the "procedures" PSF and this PSF includes the existance and usability of operating procedures of the tasks under consideration (Gertman et al., 2005). *Temporal complexity* refers to how much time pressure or temporal demand there is on the operator. This factor is covered by the "available time" PSF in SPAR-H. *Knowledge complexity* refers to the depth of knowledge possessed by the operator. This factor is highly dependant on the operator's skills and expertise in their domain and is covered by the "experience/training" PSF in SPAR-H (Gertman et al., 2005). *HMI complexity* is a factor that several researchers include in a description of task complexity. This factor refers to the equipment, displays, quality and quantity of information available from instrumentation. In SPAR-H, the complexity of HMI is covered by the "ergonomics/HMI" PSF (Gertman et al., 2005). The *interaction complexity* factor describes the degree of dependence among team members. Poor or missing communication and a distribution of knowledge or actions among team members or shifts will decrease performance. However, the planning, communication, and coordination is covered by the "work processes" PSF in SPAR-H (Gertman et al., 2005).

The sixth excluded factor is uncertainty. *Uncertainty* is a factor that contribute to task complexity according to several researchers (Campbell, 1988; Byström & Järvelin, 1995; Bell & Ruthven, 2004). It is possible to argue that this factor should not be included into a Petro-HRA analysis because it is a subjective measure that is in relation to other aspects of a task and in relation to the operator's knowledge. Uncertainty in other aspects of the task can be uncertainty with regards to task variety (Vakkari, 1999), task outcomes, information requirements (Byström & Järvelin, 1995), or connections between components or sub-tasks (Harvey & Koubek, 2000). It can be argued that uncertainty affects the other complexity factors. This would mean that uncertainty in the amount of information available or the size of the problem, uncertainty in processes or goal achievement, the structural rules, variety, or the dynamic environment of the task will contribute to complexity, and not uncertainty in itself. Uncertainty can, in other words, be viewed as a lack of knowledge or information about a situation that concludes in the operator not knowing how to proceed. This means that uncertainty is tightly connected to the subjective and perceived complexity of the operator.

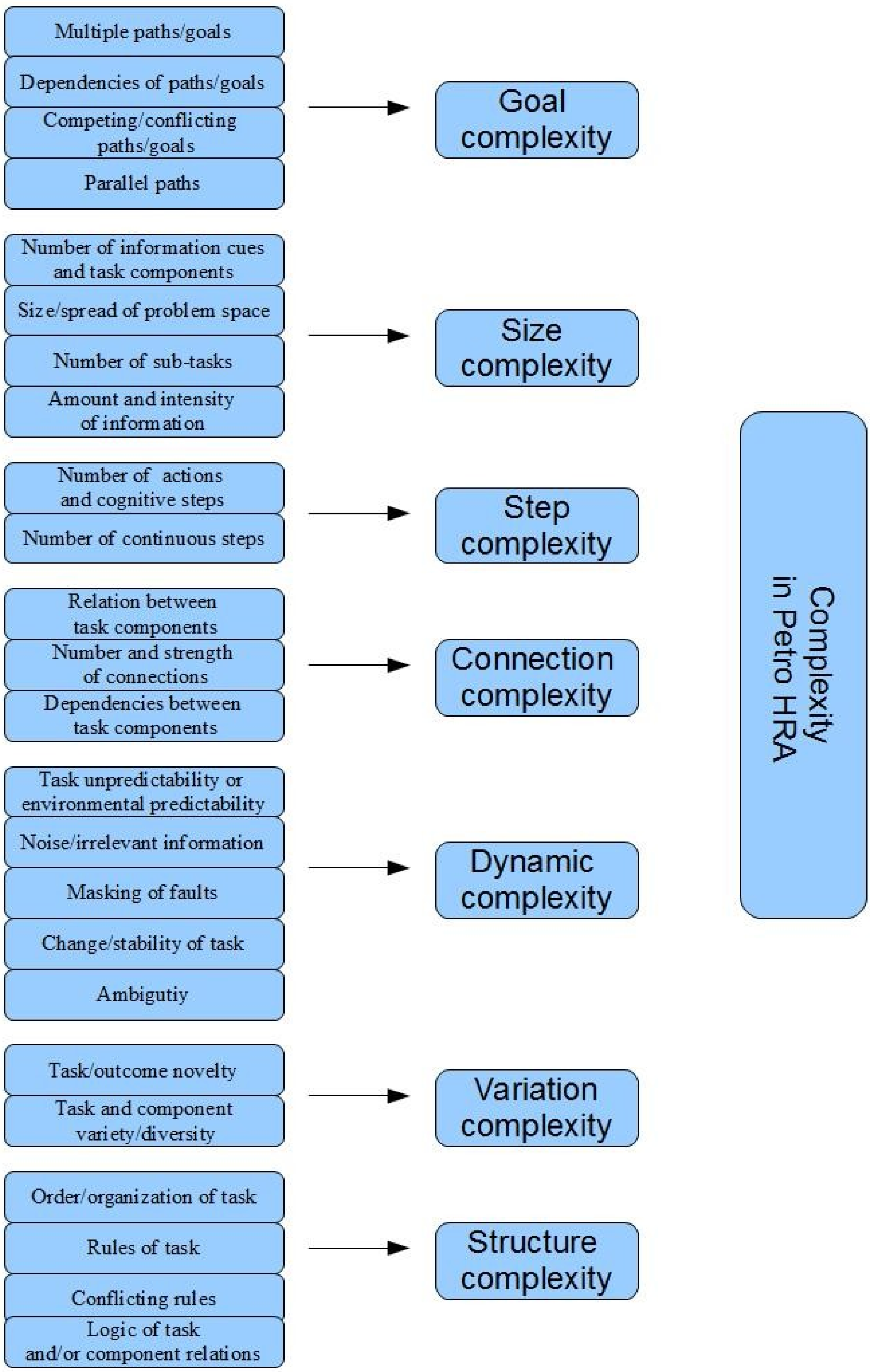
Complexity Factors for Petro-HRA

Based on the difference between objective and subjective complexity, the average operator in SPAR-H, and the other PSFs of SPAR-H, seven complexity contributing factors were extracted from the literature review as being usable in a Petro-HRA method. These factors are goal complexity, size complexity, step complexity, connection complexity, dynamic complexity, variation complexity, and structure complexity. The structure of these factors and their contributing elements can be found in «Figure 4».

These seven factors are objective measures of a task that all contribute to the overall complexity of the task. Some of the factors can be viewed as both subjective and objective. Variation complexity, which include task novelty, is an example. Task novelty can be viewed as a subjective quality of a task, given that the novelty of a task is seen in relation to the experience of a task doer, e.g. if the task has been performed before. However, in Petro-HRA, task novelty or variety should be seen as whether or not the task is novel in the operator's domain. For instance, is it novel for any operator performing this task in this context? When using the complexity factors for a Petro-HRA analysis the average operator should always be kept in mind as the task-doer.

Most of the complexity factors for Petro-HRA are arguably diagnosis oriented. However, there is no indication that these factors can not be used in action tasks. Two HRA experts in the petroleum domain also stated that diagnosis is, in the vast majority of cases, the most complex tasks facing operators. This is partly due to the problem solving and mental calculation requirements of diagnosis tasks, as well as due to the fact that most action tasks in this domain are simple by design. The usability of these seven factors in both action and diagnosis tasks were underlined by the HRA experts in interview.

Figure. 4. Complexity factors for Petro-HRA



Dependancies of the Factors

Even though the factors describe different objective features of a task the complexity factors should not be seen as orthogonal to either each other or to the other PSFs in SPAR-H. Collier (1998) identified similar complexity factors (ambiguity, spread, information intensity, severity) on the basis of questionnaires given to control room operators. The complexity factors were analyzed and these analyses showed that the complexity factors were highly correlated among themselves (Braarud, 1998). We can assume the same for the factors found in the current framework.

The complexity PSF also stands out as a factor that is influenced by and influences other PSFs (Boring, 2010). Correlations and factor analyses for SPAR-H show that complexity is correlated with every other PSF in an action task, and is correlated with the stress/stressors, experience/training, procedures, and work processes PSFs in a diagnosis task (Boring, 2010). This problem was also identified by one of the experts on HRA in an interview, where it was stated that it is often hard to know where to classify a performance driver in an analysis. The complexity of a task can be influenced by HMI, knowledge, and a high mental workload. Which PSF is then the performance driver? The PSFs are often highly related in a task and this leads to similar problems when assigning the PSF values. This is also illustrated by the fact that five of the complexity factors discovered in this thesis are measured by other PSFs in a SPAR-H analysis.

Performance Effect of the Complexity Factors for Petro-HRA

The seven factors included for Petro-HRA, goal complexity, size complexity, step complexity, connection complexity, dynamic complexity, variation complexity, and structure complexity, all contribute to task complexity. Based on research performed on complex tasks in various domains, indications can be made as to how each of these seven complexity factors affect operator performance. From these indications, some general recommendations can be made as to the assignment of the HEP multiplier in the complexity PSF.

Much of the research presented in this section does not measure human error or accuracy, but measure time spent to complete a task. It is important to keep in mind that the two variables, error rate and time spent, are not the same performance measures. However, time spent can be an indication of performance in time pressed situations that occur after an initiating event.

Goal complexity and performance. Elements that contribute to goal complexity has been studied by several researchers. Payne (1976) studied the effects of several alternative goals on choice strategies. He found that subjects spent less time for each alternative goal, in an effort to reduce cognitive load, but spent more time overall as the number of goals increased. Onken, Hastie & Revelle (1985) did a similar experiment and found that decision time increased almost linearly with number of alternatives. Depending on size complexity, the subjects spent 10-25 seconds when two alternatives were present, 15-35 seconds when four alternatives were presented, 15-50 seconds for six alternatives, and 20-60 seconds for 12 alternatives (Onken et al., 1985). It seems that time spent for each alternative is slightly less when the number of alternatives increase, but the overall decision time increases due to the need to consider more alternatives. The research of Chinbarupa et al. (1993) suggest the same.

Research on alternative paths and goals indicate that as the number of paths or goals increase, the decision time increase as well. Six alternative paths or goals indicate a large effect on performance, while 3-5 alternatives indicate a moderate effect, and two or less alternatives indicate low or no effect on operator performance. Based on this, a general recommendation for the goal complexity factor's effect on HEP is nominal to high depending on the number of paths or goals, while keeping in mind the potential effects of conflicting goals and paths on the mental workload of the operators.

Size complexity and performance. Research has indicated that task size is an important contributor to performance. Bonner (1994) performed a review on complexity and the number of information cues in the input and output stages of a task. This research showed an indication that performance was better at lower number of information cues at the input stage, while the output stage was not as important. Li and Wieringa (2000) studied students on systems and subsystems that varied in their connectability and size. They found that more than 15 unconnected subsystems, or eight connected subsystems, dramatically increased the task complexity and lead the students to exceed a 30 minute operation time limit. Half the amount of unconnected subsystems, eight, were more manageable, while three or less had no effect on performance (Li & Wieringa, 2000). Similar results have been found by Park and Jung (2008) who measured size complexity and found a clear relationship between task size and time to complete a task.

Sintchenko and Coiera (2006) tested both time spent and decision accuracy in two different tasks. They showed that more information (36 information components in the low complexity task, and 68 components in the high complexity task) resulted in more time taken for a decision and a lower decision quality with 80% correct decisions in 125 seconds in the low complexity task, and 64% correct decisions in 156 seconds in the high complexity task (Sintchenko & Coiera, 2006). Research by Speier, Vessey and Valacich (2003) suggested similar findings. These researchers had students do a simple task consisting of 2-8 cues and 1-4 calculations and a complex tasks with 30 cues and 15 calculations. They tested the effects of interruptions on decision time and quality. Results showed that accuracy on the simple task was in the 73-80% range and time spent was in the 42-55 seconds or 138-165 seconds range, depending on presentation format. Accuracy on the complex task was between 70-76% or 44-55% depending on presentation format and time spent was from 1307 to 1774 seconds (Speier et al., 2003).

Research on task size indicate that size complexity is an important factor of complexity and greater size complexity leads to increased decision time and decreased decision accuracy. The research showed here also indicate that size complexity is highly connected with other aspects of the task, such as connection complexity and presentation format or HMI. Based on this research a general recommendation is that size complexity has a nominal to high effect on HEP depending on the number of information cues, elements or subsystems.

Step complexity and performance. Research on step complexity and performance has been more inconclusive than size complexity. On one hand research by Park and Jung (2008) indicate a relationship between step complexity and time to complete a task. On the other hand, Zhang et al. (2009) also measured step complexity and its effect on error rate and operation time. They found that out of four measures of complexity (size, step, logic and HMI complexity), step complexity is the least important to the overall complexity of the task. Similar results were reported by Weingart (1992), who found that higher step complexity lead to greater uncertainty, but no direct link were found between step complexity and performance. Park and Jung (2008) argue that there will be an interrelation between size complexity (amount of information) and step complexity (amount of actions) because operators have to process a set of information to understand the steps they have to perform.

Research indicates that step complexity is not as important as size complexity to the overall complexity of a task, and a general recommendation for step complexity's effect on HEP would be nominal to moderate, depending on size complexity. In action tasks however, step complexity might be a greater contributor to complexity than in diagnosis tasks.

Connection complexity and performance. Li and Wieringa (2000) found that connections between subsystems greatly increases complexity. When parts of the system or task are connected, task size can be lower while the task is still highly complex. Eight or more connected subsystems is similar to 15 or more unconnected subsystems, and the complexity increase from system connectivity lead to an increase in task operating time (Li & Wieringa, 2000).

The indication from Li and Wieringa (2000) is that connection complexity decreases the performance of a task and that tasks with smaller size complexity can still be highly complex when the components, elements or subsystems are strongly connected. A general recommendation for connection complexity is a moderate to high effect on HEP, depending on size complexity.

Dynamic complexity and performance. The elements of dynamic complexity vary in their effect on performance. Noise does not seem to be a driving factor of complexity as the operators are highly trained specialists, and environmental noise does not challenge their prioritization (Braarud & Kirwan, 2011). The masking of faults however, were found to be a dominant factor of operator performance, and time spent on a task increased from 7 minutes on a simple task, to 21 minutes on a complex task where faults were masked (Braarud & Kirwan, 2011).

Ambiguity of information is also an element that contribute to dynamic complexity. Analysis from questionnaire ratings (see Braarud & Kirwan, 2011), as well as studies to identify factors of human error identified ambiguity (Lois et al., 2009) or salience of information as an important performance driver (Follesø, Drøivoldsmo, Kaarstad, Collioer & Kirwan, 1995). Mascha and Miller (2010) also identified the clarity of information as a more dominating factor than amount of information on judgment performance.

Parts of dynamic complexity has a high effect on performance, such as the ambiguity of the task and the masking of faults. Other parts, such as environmental noise seems to have a lower effect. Based on this, the recommendation for dynamic complexity's effect on HEP is from moderate to high, depending on which elements are present in the task.

Variation complexity and performance. Task variety does not appear to have a major influence on task-doer performance. However, Byström and Järvelin (1995) found that task success decreased as tasks became less routine and more unknown and novel. Several researchers refer to the problems of task unfamiliarity, which can be viewed as similar to task novelty (Goodman & Shah, 1992; Braarud & Kirwan, 2011). Braarud and Kirwan (2011) identifed a complex scenario as a task that had not previously been trained, and as such was unfamiliar to the crew. Similarly, Goodman and Shah (1992) summarize experts as people who excel mainly in their own domain, and perceive large and meaningful patterns in their domain. Less familiarity, such as task novelty, results in operators being less aware of making errors and make less automated responses

(Goodman & Shah, 1992). The authors discovered that less familiar tasks had a considerable higher accident rate (1,24 accidents per 200 days) than tasks that were more familliar (0,511 accidents per 200 days). They argue that this is due to lack of knowledge of the tasks, due to unfamiliar work processes such as shift changes, changes in equipment (Goodman & Shah, 1992), or lack of experience and training (Braarud & Kirwan, 2011). This could indicate that task novelty is dependant on other PSFs.

Based on this research there is an indication that variation complexity affects performance depending on the other PSFs. Keeping this in mind, the general recommendation for variation complexity is from nominal to moderate, depending on the other PSF's involvement. This conservative recommendation is made to avoid the potential problem of double counting factors when other PSFs also are performance drivers.

Structure complexity and performance. Research on task structure has shown that more unstructured tasks contribute to greater perceived complexity by the task-doer (Abdolmohammadi & Wright, 1987). More objective measures has also been found, Zhang et al. (2009) identified task logic as a more important factor to the complexity of a task than size, instrument (HMI), or step complexity. They found that error rate and operation time are linearly related to task logic. Similar results were found by Park and Jung (2008), who show a negative relationship between time to complete the task and the logic of the task steps. That is, as task logic decreases, time spent on the task increases.

These results indicate that the structure of the task, and especially task logic is dependant on the size of the task, and affects the complexity of the steps needed to perform. This would mean that task structure both influences and is influenced by size complexity and step complexity. A general recommendation for structure complexity is an effect on HEP from nominal to high, depending on size complexity, and its effect on step complexity should be kept in mind if step complexity is an important part of the task.

Guideline-Table for Users of Petro-HRA

Based on the complexity factors that were found to be usable for Petro-HRA and the performance effect of these factors, a guideline table was created (see Table 3). The first column lists the complexity factors. The second column lists the main elements that make up the factors and contribute to task complexity. Next, the third column describes the factors so the users of this table can identify which factors are present in a task. This column is an abbreviation of the descriptions given earlier in this thesis. The fourth column suggests, on the basis of research on similar factors, how the elements in this factor affect operator performance. In addition, a general suggestion is made as to how much the factor affects the HEP in the complexity PSF. Finally, the fifth column refers to which research articles are used for the performance estimates.

The purpose of this table is to assist users of Petro-HRA to identify when the complexity PSF is a performance driver, and guide consultants in what multiplier level to assign. The table will also assist in determining the cutoff values, e.g. when a task is highly complex or when it is moderately complex. According to an interviewed HRA expert, the cutoff values are usually determined by asking operators how complex the task was. This approach will be highly determinant on the operator's knowledge, experience and training and will be a subjective measure of complexity. The operator's subjective perception of complexity will be more related to other PSFs, and to a less degree be dependant solely on the complexity of the task.

The table is a quick and easy-to-use tool for time challenged consultants while still retaining the potential for high accuracy and stronger inter-rater reliability. It is however important to note that the table should still be used together with the expertise of the HRA analysts. Most of the research used for the performance estimates are from fields outside of the HRA or petroleum domain and might measure variables other than the complexity factors. It is important that HRA analysts use their judgment in assigning the PSF multipliers as the recommendations given in the guideline table are not enough on their own to assign a complexity level. However, the use of this table can lead to a more systematic and complete approach to the complexity PSF in Petro-HRA. This was also stated by two of the HRA experts in interview as a benefit of having such a guideline.

Factor	Elements	Description	Effect on performance/HEP	Source of HEP estimates
Goal complexity	Number of paths. Number of goals. Competing goals. Parallel tasks. Conflicting interdependencies between paths and goals, or among different paths.	Goal complexity is the multitude of paths or alternatives to one or more goals. Complexity will increase with more paths or goals, and if these are incompatible with each other. E.g. parallel or competing paths/goals, and no clear indication of the best path/goal.	6 or more alternative paths/goals – high. 3-5 alternatives – moderate. 2 or less alternatives – low. Linear relationship between number of paths/goals and performance. General recommendation for PSF multiplier: **nominal to high**, depending on number of paths/goals.	Payne (1976) Onken et al. (1985) Chinbarupa et al. (1993)
Size complexity	Number of information cues or elements. Information intensity. Size of problem space. Memorization requirements.	Size complexity is the numeric size of the basic elements or information cues. This includes task scope, which includes the sub-tasks and spread of faults to other areas/tasks. Complexity will increase as the amount and intensity of information an operator has to process increases.	15 or more information cues – high. 8-14 information cues – moderate. 8 or less information cues – nominal. General recommendation for PSF multiplier: **nominal to high**, depending on number of cues.	Bonner (1994) Li & Wieringa (2000) Sintchenko & Coiera (2006) Mascha & Miller (2010)
Step complexity	Number of unique cognitive actions, physical actions or steps. Number of continuous steps.	Step complexity is the number of acts, steps or actions that are qualitatively different from other steps in the task, meaning that knowledge do not generalize to the steps. This includes the number of continuous/sequencial steps required. Complexity increase as the number of steps increase, even more so if the steps are continuous.	Less effect on HEP than size complexity, but similar. More important for Action than Diagnosis. Linear relationship between number of steps and performance. General recommendation for PSF multiplier: **nominal to moderate**, depending on size complexity.	Park, Jung & Ha (2001) Weingart (1992) Zhang et al. (2009)

Connection complexity	Relation between elements, inputs, or outputs. Number and strength of connections between elements. Dependencies between elements or tasks.	Connection complexity is the relationship and dependencies of the elements of a task. Complexity will increase if the elements are highly connected and it is unclear or poorly defined how the input of one element will affect the output of another.	Connections between subtasks or elements greatly increases size complexity. > 8 connected information cues – high. General recommendation for PSF multiplier: **moderate to high**, depending on size complexity.	Li & Wieringa (2000)
Dynamic complexity	Unpredictability. Change/stability of task. Environmental predictability/weather. Information clarity. Noise. Masking of faults. Ambiguity	Dynamic complexity is the unpredictability of the environment where the task is performed. This includes the change, stability, or inconsistency of task elements. Complexity will increase as the ambiguity or unpredictability of the environment increases. This includes the masking of faults.	Noise – low. Clarity of information – moderate. Less important than amount of information. Masking of faults – high. Ambiguity of the task – high. General recommendation for PSF multiplier: **moderate to high**.	Braarud & Kirwan (2011) Braarud (2000) Lois et al. (2009) Mascha & Miller (2010)
Variation complexity	Task novelty. Element variety. Task diversity.	Variation complexity refers to the regularity or similarity of the task compared to other tasks in the same domain. Variety of the elements and sub-tasks is also included. Complexity increases as the novelty of the task increases, this includes the variety of sub-tasks or task elements.	Novelty may cause other factors/PSFs to be a problem. Novelty – low to moderate. General recommendation for PSF multiplier: **nominal to moderate**.	Braarud & Kirwan (2011) Byström & Järvelin (1995) Goodman & Shah (1992)
Structure complexity	Order/organization of task. Number of task rules. Conflicting rules. Logic relations.	Structure complexity represent the order of the task. Order is determined by the number and availability of rules. This includes whether the rules are conflicting and whether the sequence and relationships of elements/sub-tasks are logical. Complexity will increase if there are many or conflicting rules, or if the structure of the task is illogical.	Task logic – moderate. Higher effect than size or step complexity. General recommendation for PSF multiplier: **nominal to high**, depending on size complexity.	Zhang et al. (2009) Park & Jung (2008) Abdolmohammadi & Wright (1987)

Table 3. Guideline table of complexity factors for Petro-HRA.

Strengths and Limitations

One of the major strengths of this thesis is that the conceptual framework of complexity factors presented in this thesis is based on a thorough review of literature on complexity in a varied range of research domains. This means that the factors presented here are important components that make up complexity of a task regardless of task domain. The seven factors used in the guideline table for Petro-HRA are based on the same conceptual framework thus giving them the same theoretical rigour. A rich selection of factors, or PSFs, will aid the analyst in identifying the correct factors that might otherwise be overlooked (Boring, 2010). Another strength of the complexity factors and the guideline table is an increase in inter-rater reliability in the complexity PSF when performing Petro-HRA. This is due to the analysts looking at the same complexity factors when analysing similar tasks, and will thus find results and HEPs more consistant with other analysts than if they worked out of their own preconceptions of complexity.

A limitation of this thesis can be that the factors' effect on performance is based on research with variables similar to the complexity factors in situations that might not be relevant for the petroleum industry or HRA. As a consequence of this, it is difficult to make accurate recommendations for the different factors' effect on performance. This means that the expert judgment of the HRA analyst should still be the deciding factor when deciding on the complexity multiplier. Still, several HRA experts in interviews expressed that having some tangible evidence of the performance effects is better than not having any.

Theoritical and Practical Implications

The theoretical implications of this thesis is a greater understanding of what complexity is, and what factors complexity consist of. The framework of complexity factors should be an promising starting point for other researchers to build on and expand our understanding of the construct. The framework and its contributing elements can also contribute to modeling complex behavior and scenarios by using the complexity factors as modifiable experiment variables. This will again increase our understanding of the effect of complexity on operator performance.

The practical impliactions of this thesis are that users of the Petro-HRA method may have a better understanding in what to look for, and what to exclude, when assigning the complexity PSF. In addition, the guideline developed in this thesis may provide greater inter-rater reliability, and at the same time reduce analysis time, making the method both more reliable, and more cost-efficient.

Future research

There are several interesting paths to take with regards to complexity in a HRA method for the petroleum industry, and for the Petro-HRA method on the whole. The complexity factors found here should be validated and their performance effect should be examined in relevant scenarios. Ideally, this could be done by creating experiments where one or more factors are varied while others are kept constant and then measure operator performance. In addition, more research on complexity, decision making, and cognitive psychology should be undertaken to identify more potential complexity factors, or to eliminate superfluous or erroneous factors.

The PSFs themselves should also be examined and reviewed when the SPAR-H method is developed for a new domain. The offshore petroleum industry might have other and different challenges than nuclear power control rooms, and thus the PSFs used in SPAR-H could be different than the PSFs required for this new domain. In addition, similar to this thesis, literature reviews or other experiments should be performed to create solid theoretical foundations for the other PSFs in the Petro-HRA method.

The HEP values for the Petro-HRA method should also be examined, both for complexity and for other PSFs. The HEP values that are identified and validated for the nuclear industry might not be as accurate when used in an offshore petroleum domain.

Conclusion

This thesis has attempted to identify complexity factors for the purpose of strengthening the complexity PSF in Petro-HRA, a HRA method being developed for the petroleum industry based on SPAR-H. Based on a thorough review of literature on complexity, a conceptual framework of task complexity was created. This framework consists of 13 factors that contribute to task complexity. The factors are goal complexity, size complexity, step complexity, connection complexity, dynamic complexity, variation complexity, structure complexity, uncertainty, knowledge complexity, temporal complexity, HMI complexity, interaction complexity, and procedure complexity. These factors are created based on research in multiple fields and constitute a rich variety of elements, making the framework usable in a wide variety of domains.

All of the complexity factors in the conceptual framwork however, are not suitable for identifying complexity in a Petro-HRA method based on SPAR-H. This is because the SPAR-H method already identifies several of the complexity factors as potential performance drivers in other PSFs. The complexity factors knowledge complexity, temporal complexity, HMI complexity, interaction complexity, and procedure complexity should not be used when identifying task complexity for the Petro-HRA method as they are included in others parts of the analysis and an inclusion in the complexity PSF would contribute to double counting these factors in the analysis. The complexity factor uncertainty should arguably also be excluded from complexity in Petro-HRA due to this factor being highly subjective and in relation to the task-doer while Petro-HRA attempts to identify the objective features and situations that contribute to task complexity and decreased operator performance.

The seven complexity factors found to be suitable for describing complexity in Petro-HRA are goal complexity, size complexity, step complexity, connection complexity, dynamic complexity, variation complexity, and structure complexity. A guideline table for users of Petro-HRA have been developed on the basis of these seven complexity factors and their effect on operator performance. This guideline table might help the users of Petro-HRA in identifying complexity as a performance driver and assist in assigning the multiplier of the complexity PSF as well as improve the inter-rater reliability of the Petro-HRA. The guideline table will not identify complexity as a performance driver or decide how to assign the PSF multiplier on its own. Expert judgments performed by the analyst should still be the main decider when performing HRA. The guideline table can however shorten the time an analysis take, help the analyst in identifying complexity factors, and increase inter-rater reliability.

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