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# **The Design of User Interfaces for the SPEEDD Prototype**

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# 0 Executive Summary

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In this report, the approach taken to designing User Interfaces for the SPEEDD project is described. The aim of this work package is to develop design and evaluation approaches which are informed by a robust theory of human decision making, which will extend theory and practice in Ergonomics / Human Factors and which will lead to the development of novel display design concepts.

The report provides a short introduction to the field of Visual Analytics before introducing the main strands of the Ergonomics / Human Factors theory developed for SPEEDD. This begins with an acknowledgement of the importance of Situation Awareness as a key (but often underplayed) aim for the design of Visual Analytics, and then explores approaches to decision making. In particular, SPEEDD is developing a novel approach to human decision which draws on concepts from cybernetics.

In order to study how operators use information in their environment to support decision making, SPEEDD employs eye-tracking to collect data (in the field and in laboratories). The next section reviews approaches to the analysis of eye-tracking data and explains how these approaches can be related to the theory of decision making.

The approach to visualization design used in SPEEDD follows principles from Cognitive Work Analysis (CWA) with the aim of developing Ecological Interfaces. The CWA approach used in SPEEDD is reviewed and the approach to Ecological Interface Design is considered in comparison to other design approaches. The CWA results in a set of design assumptions which complement the User Requirements proposed in deliverables 7.1 and 8.1. On the basis of these assumptions, it is possible to map User Interface layout in terms of specific functions which need to be supported. Assuming that each of these functions would be allocated its own area of results in a schematic layout of the UI. This schematic is then populated using objects which relate to these functions.

The next section reports the Road Traffic Management Use Case. The CWA views of the work activity are presented. These views allow the analysis to determine which type of decision making is performed in the system and what type of information would best support such activity. In particular, the analysis raises the question of how Situation Awareness is managed in the control room at present and how this could be supported in future designs.

The second case study involves the specification of the User Interface for Credit Card Fraud. In this report, we have drawn our analysis from informal discussions with bank staff and from reviews of related literature. This means that the description of activity is somewhat compromised by the lack of access that we have been able to obtain. However, it should be borne in mind that Fraud prevention is a highly secure environment and that banks are unwilling to publicly share information (for reasons of customer confidentiality, commercial sensitivity and crime prevention).

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# Introduction

## History of the document

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## 1.1 Purpose and Scope of the Document

This is the first report on activity under Work Package 5 (Real-time Visual Analytics for Proactive Decision Support). As stated in the Description of Work, “The primary objective of this work package is to explore the impact of real-time proactive decision computation on human decision-making in Big Data applications.” This requires two strands of research: the first focuses on Ergonomics / Human Factors, particularly in terms of understanding the nature of decision making in the SPEEDD use case domains; the second focuses on the design and evaluation of Visual Analytics to support such decision making. In order to meet the primary objective, the Work Package involves three tasks:

- T5.1: Modelling Decision-Making as a Socio-Technical Activity
- T5.2: Defining Objective Metrics for Evaluating Decision-Making
- T5.3: Real-Time Visualization for Human Decision-Making

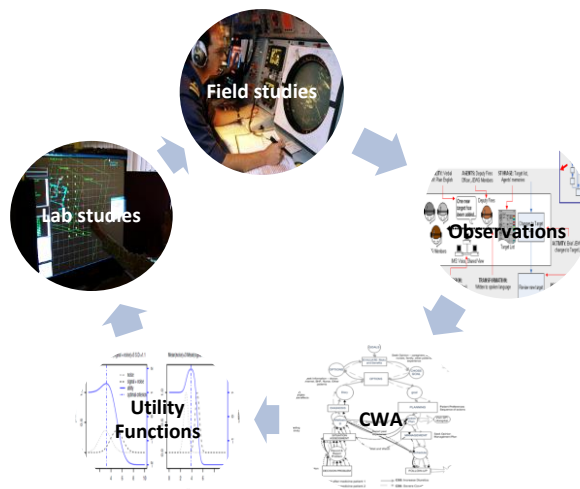


Figure 1: Strategy for WP 5

As figure 1 highlights, in Work Package 5, we take an Ergonomics / Human Factors approach in which work activity of practitioners is observed and described (using Cognitive Work Analysis) which leads to a description of decision strategy (in the form of utility functions) and requirements for user interface designs, which are evaluated through laboratory studies and presented to practitioners.

T5.1 involves field study (where possible) of practitioners in the case study domains. To date, this has only been possible for the road traffic management case study. We observed and interviewed operators in situ (in the DIR CE control room in Grenoble, France). An initial description of this study was provided in report 8.1, where we presented a Hierarchical Task Analysis of operator activity, together with a discussion of Situation Awareness and an initial set of user requirements for the user interface. In the current report, the analysis of operator activity is elaborated in the form of Cognitive Work Analysis, which provides a system-level view of activity in this domain.

A similar analysis is provided for the Credit Card Fraud case study, based on an extensive review of literature and informal (off-the-record) discussion with personnel in three banks in Europe. Gaining access to banks to discuss the manner in which Credit Card Fraud is managed has proved problematic for this project and, where we have managed to gain access, we have agreed to ensure that all discussion is anonymised and that no material which represents commercial or financial information is reported.

In this report, task 5.1 is reported and this represents the completion of this task (which was scheduled to run from month 1 to month 11). It is possible that, should further information be made available regarding the Credit Card Fraud use case, an addendum to this report is produced.

T5.2 involves the definition of objective metrics for decision-making. For the SPEEDD project, decision-making is considered as the rational response to available external information and user goals. This is described in terms of a novel theory of cognitively bounded rational analysis which is being developed as part of this project. To this end, we first need to develop an approach to the capture of operator activity which allows us to determine how information is sampled and used. For this project, we use eye-tracking as an approach to exploring information sampling and use. This approach was successfully applied to the DIR CE control room during our field study, and is being refined for use in laboratory studies for further investigation into decision strategies and as the basis for evaluating user interface designs. The manner in which we present information to users affects how easily they can sample this information, and also how easy it is for them to relate the sampled information to their current goals.

In this report, we outline the initial development of the theory being explored in SPEEDD. The aim, in this report, is to introduce the basic concepts. These concepts will be elaborated further during the phase of laboratory trials which are planned for year 2 of the project.

T5.3 involves the specification and build of user interfaces for the SPEEDD prototype. For this task, we needed to provide a clear translation from the observation of operator activity (in the form of Cognitive Work Analysis) to the specification of a user interface, and also to ensure that the designs operated effectively with the SPEEDD architecture in the form of a functioning prototype. This

report focuses on the translation from CWA to interface design and the ways in which concepts of Ecological Interface Design (section 6.2) have been applied. A functioning prototype has been produced and runs in the SPEEDD architecture. Future work will involve evaluation of the designs (through both user acceptance testing and through laboratory evaluations to determine the impact of different designs of decision-making) and the production of further generations of prototypes.

## **1.2 Relationship with Other Documents**

This report builds on the Hierarchical Task Analysis (HTA) of Road Traffic Management that was presented in D8.1 and to the description of the SPEEDD Architecture reported in D6.1. This report also links to the User Requirements for the Credit Card use case in D7.1.

In addition to the Ergonomics / Human Factors work in WP5, there has also been significant contribution to the work on SPEEDD architecture (6.1). The examples of User Interface design presented in this report not only relate to the underlying analysis and theory we present, but are also functioning prototypes which operate under the SPEEDD architecture.

# Visual Analytics

## 2.1 Introduction

In SPEEDD, a key aim of WP5 is to develop novel techniques for the design and evaluation of Visual Analytics for Big Data through understanding the ways in which the users of these displays make decisions. The concept of Visual Analytics arises from the merging of research into data analytics with research in visualization (Keim et al., 2010). Broadly, the role of data analytics is to discover patterns and trends in data and the role of visualization is to present these patterns and trends to the user who will then be able to interpret and understand them. Visual Analytics seeks to cement this relationship between analytics and visualization through close integration, such that the user can manipulate the visualization in order to create new queries for the analytics or can refine the analytics (perhaps through modifying the thresholds or parameters that the analytics are applying, in a form of directed learning). In this way, Visual Analytics is more than simply visualizing the output of data analytics and offers new ways to allow people to interact with Big Data and complex analytics.

As figure 2 illustrates, Visual Analytics is an amalgam of several disciplines, with visualisation at the core surrounded by data analytics and human perception, and the supporting (socio-technical) infrastructure and evaluation at the outside (Keim et al., 2010).

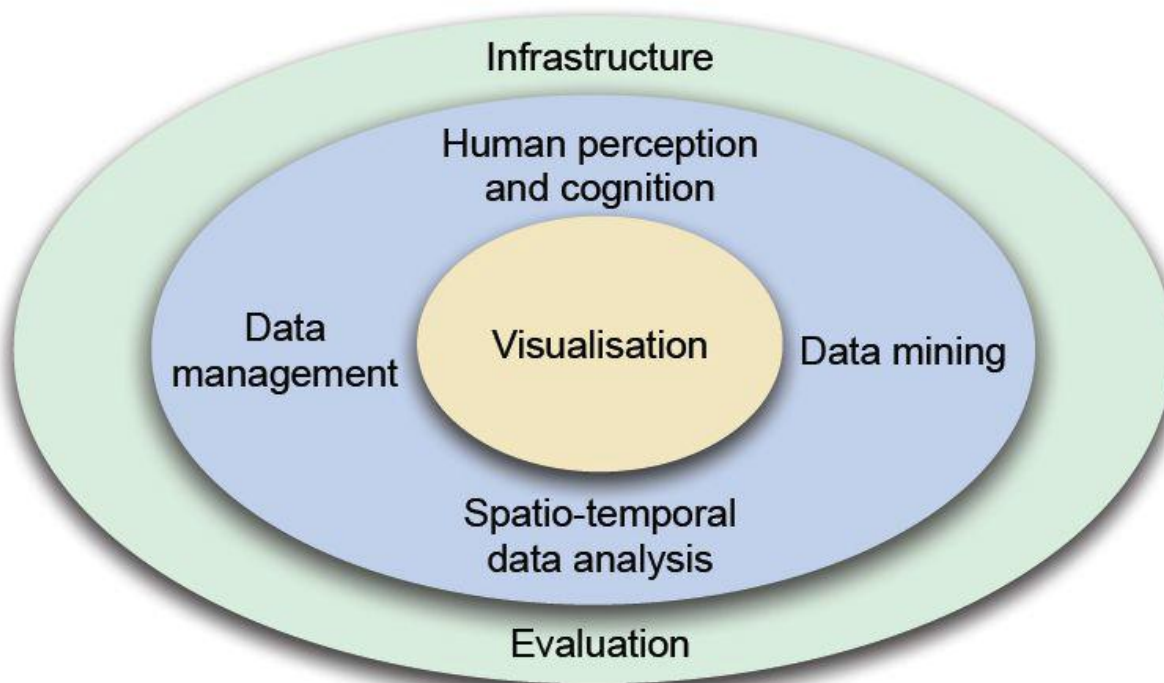
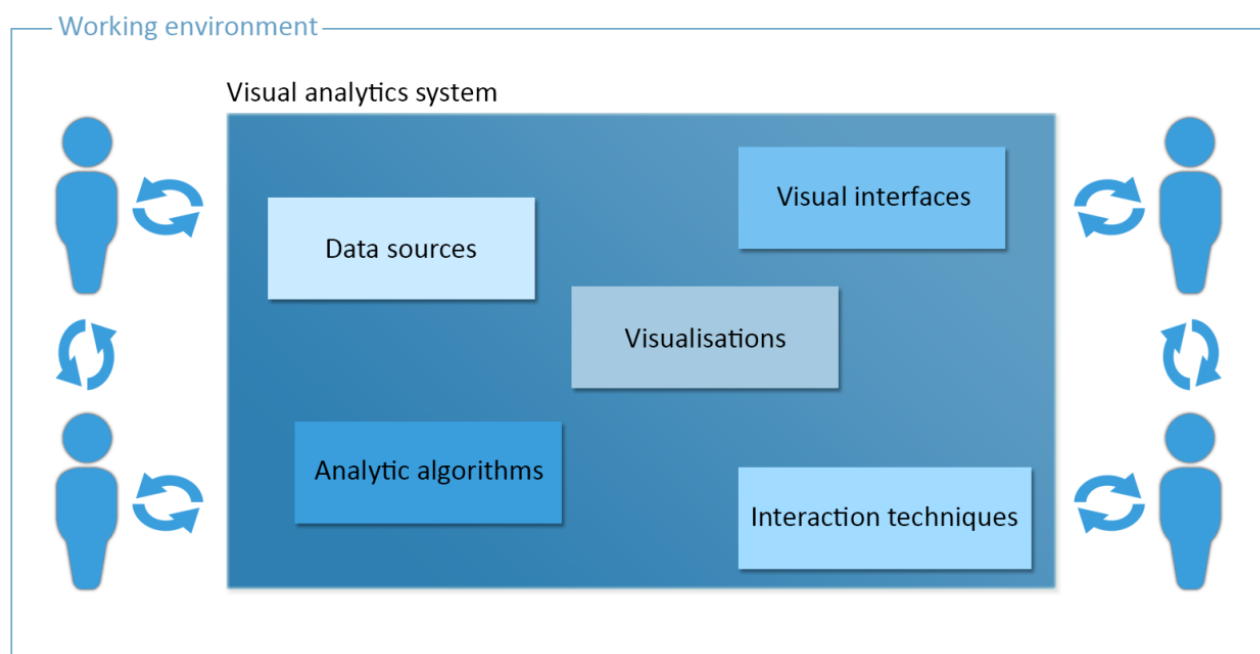


Figure 2: The building blocks of visual analytics research (from Keim et al., 2010, p. 12)

Figure 2 places ‘visualisation’ at the centre of Visual Analytics. This could imply that the interaction between human and computer will be through an individual interacting with a visualisation. Key to the development of Visual Analytics is an appreciation of the Socio-Technical Infrastructure in which the technology will be used (figure 3). This means that it is important to appreciate how Visual Analytics operates in a working environment in which other actors will share information with each other, or will interact with systems outside the core Visual Analytics system. While the data analytics for the SPEEDD project are dealt with in detail in other reports, this report focuses on the socio-technical challenge of managing and interpreting data in the two case study domains of the project. In the Description of Work, it was proposed that decision making (for the SPEEDD case studies) needs to be considered in terms of the socio-technical context in which the operations occur, and we have described these using Cognitive Work Analysis.



**Figure 3: Visual Analytics in a Socio-Technical System**

Visual Analytics combines human perception and cognition with automated data analysis techniques, allowing the analyst to control the construction of visualisations and the exploration of dynamic data (Keim et al., 2010). Visual Analytics has emerged because of the need to go beyond existing information visualisation research when tackling complex data. This means that Visual Analytics needs to be analyst-driven. In other words, it is not sufficient to see the analyst merely as the passive consumer of the output of data analytics but, rather, there is a need to design visualisations which support “...the exploration of information presented by visualisations [in] a complex process of sense-making” (Keim et al., 2010, p. 116). The question of how people make sense of the output of data analytics, both in terms of their decision making and in terms of developing and maintaining situation awareness, is discussed in section 3.

Keim et al. (2010) described the visual analytics process as a feedback loop between knowledge and data, involving the following stages: data, models, visualisation and knowledge (figure 4). The process begins with data acquisition and transformation. These data can be heterogeneous and may require integration based on the meaning of the data rather than type, a process described by Thomas and Cook (2005) as 'information synthesis'. Adjustments made by an analyst using interactive visualisations will refine the data model(s). The final stage, knowledge, can arise from the analyst gaining insight from the data and models, which then allow the analyst to seek more data or refine the models which, in turn, support automatic acquisition of data. Critical to this process, from the analyst's perspective, is the question of what constitutes 'insight'.

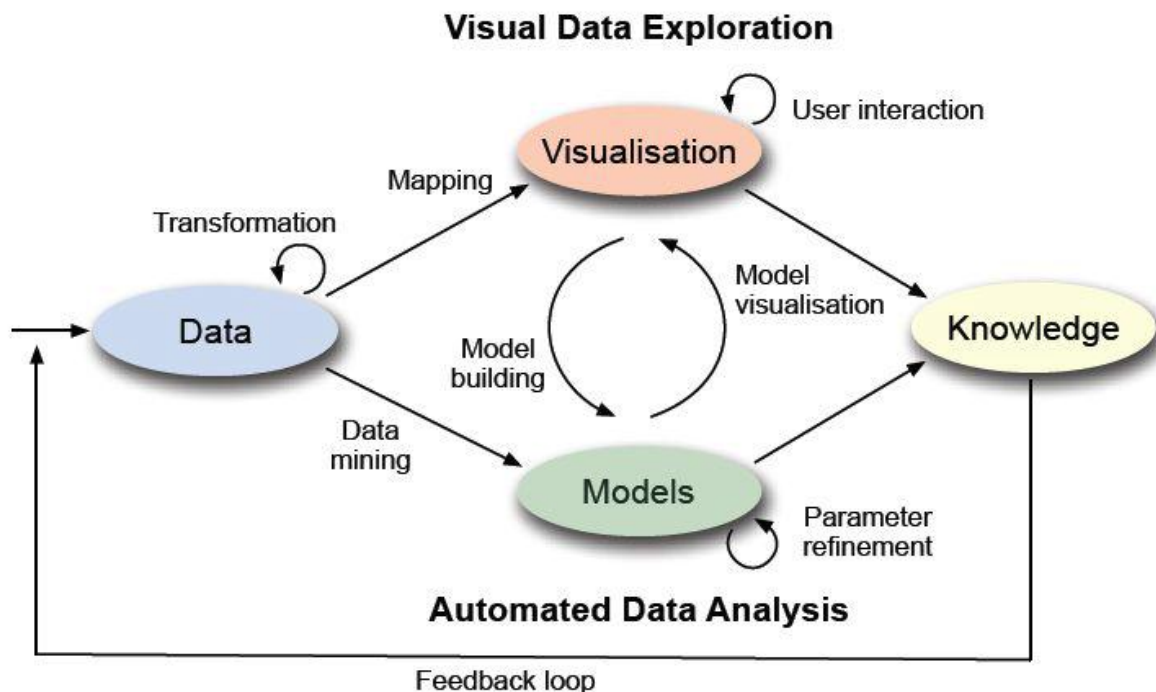


Figure 4: The visual data exploration loop (from Keim et al., 2010, p. 10)

A repeated claim for Visual Analytics is that it can help analysts gain 'insight' into the problem that they are facing (Thomas and Cook, 2005; Pousman et al., 2007). Insight has long been a subject of debate in Cognitive Psychology, i.e., does insight arise as a sudden 'ah-ha' realisation of the solution to a problem or is it the gradual piecing together of disparate information? (Bowden et al., 2005). In the field of Visual Analytics, insight is a somewhat looser concept which relates to the capability of the analyst to spot patterns in the data. This implies that, rather than a solution 'popping out' of the displayed information, there is an analyst-driven process in which displayed information is combined with analyst knowledge in order to discover patterns. In a study of bioinformatics researchers, Saraiya et al. (2006) concluded that most 'insights' were not revealed by the visualisation but by the experience of the analysts. Similarly, Ishack, Baber and Duncan (2015) suggest that the manner in which people interact with Visual Analytics is not simply a function of what is displayed to them, but a matter of how this display corresponds to their existing knowledge. Further, it is a commonly known effect in cognitive psychology that people are reluctant to revise

an opinion once formed, even in the face of strong evidence. With our User Interface design, we hope to address this issue and establish trust of the user in the Visual Analytics tool and to ‘keep an open mind’ regarding emerging trends.

If interaction with Visual Analytics is influenced by domain knowledge then one cannot assume that a ‘good’ visualisation will guarantee that the person using it will be able to *see* patterns in the data, if such patterns exist. For instance, it might be possible (following assumptions from Gestalt theory) that a ‘pattern’ could be seen in the data even when no such pattern exists, i.e., to see a visual pattern when there is no statistical pattern. This problem is made worse by the quantity of data which are being displayed in Visual Analytics because the quantity of data, coupled with the selection and editing of parameters by the analyst, could create correlations which are statistically reliable but practically meaningless (or at least misleading). Thus, allowing the analyst to play around with parameters could lead to visually compelling patterns which are artefacts of the data rather than reflections of reality. Such nonsense correlations are for example shown on this website: <http://tylervigen.com/>, with e.g. trends for the number people who drowned by falling into a swimming-pool mapping onto the the number of films Nicolas Cage appeared in. This also implies that the manner in which someone interacts with a given visualisation *could* be affected by their domain knowledge. For example, assume that insight might arise when disparate pieces of information are presented together to present an interesting and unexpected relationship in the information. This highlights that interaction between the person and the visualization results in the pattern and, consequently, this interaction becomes a form of thinking (rather than simply the manipulation of a display). Furthermore, if the person already knows some of this information, they might not seek to display it. As such, it is plausible that the expert could miss connections simply because information was not displayed in relation to other information, or the novice could miss connections simply because they were unable to appreciate the meaning of different pieces of information.

## 2.2 Challenges for SPEEDD

While the design of user interfaces / visualizations will involve software development and graphic design (and integration with the SPEEDD architecture, D6.1), we also want to develop a methodology which allows us to create designs from understanding operator activity. This requires the development of a process which takes us from the observation of operators to the specification of the visualization. By creating such a process, it is possible for design decisions to be evaluated and audited. For Work Package 5, this process involves the development of an approach which helps make a transition from operator activity (described using Cognitive Work Analysis) to the layout of the user interface (reflecting assumptions of Ecological Interface Design, see 6.2).

In addition, this Work Package involves the evaluation of the designs. We wanted to ensure that the evaluation is informed by theory, and intend to develop a novel theory which addresses the relationship between decision making and the visualization which is presented to support the decision maker. From this perspective, it should be possible to provide objective evidence for the ways in which visualization (and the output from the SPEEDD project) enhance or impair operator decision making abilities.

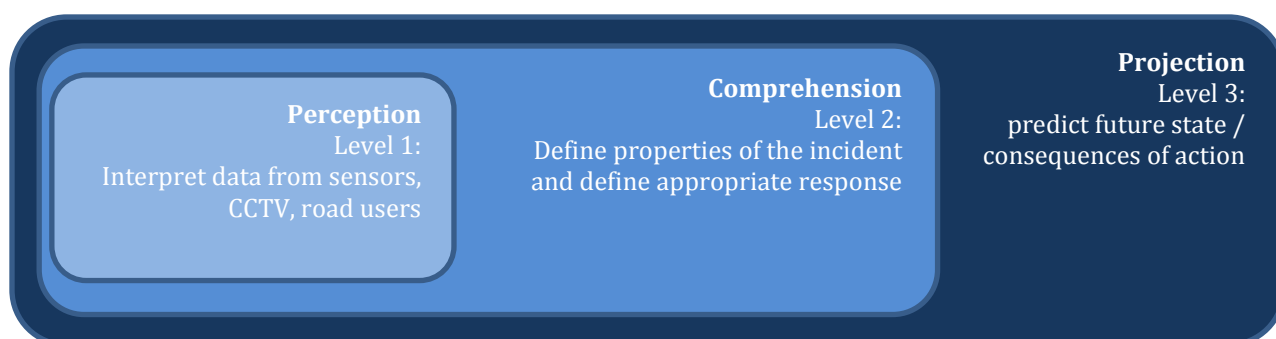
## 3 Situation Awareness and Decision-Making

### 3.1 Introduction

In order to understand human cognition, this section discusses how the SPEEDD project will result in developments in theories of Situation Awareness and decision making, and the contribution of these theoretical developments to the work being undertaken in the SPEEDD project.

### 3.2 Situation Awareness

In D8.1, it was proposed that a core requirement of the SPEEDD system to support the use case of Road Traffic Management was the capability to enhance operator Situation Awareness. At its most basic, Situation Awareness refers to the ability to know what is going on at a given moment in time. The most commonly cited definition of Situation Awareness, is as follows: “...the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” [Endsley, 1995]. This definition is illustrated by figure 5, with reference to SPEEDD’s Road Traffic Management case study.



**Figure 5: Levels of Situation Awareness [from Endsley, 1995] applied to Road Traffic Management Case Study**

Figure 5 implies that the role of the Road Traffic Management ‘system’ (i.e., the combination of operators, sensors, algorithms etc.) is to collate sufficient information to allow a clear, consistent and unambiguous definition of the current situation. For routine behavior, this ‘perception’ requires checking that the road and its users are performing according to expectations and not showing any deviation from this. When deviation from normal does occur, i.e., an event or an incident interrupts the normal state, then the ‘system’ needs to define which information is important and comprehend the nature of the incident. In both perception and comprehension, the key challenge lies in determining which information is salient, with further challenges arising from the need to monitor multiple information sources sequentially. Following perception and comprehension, the next step is to make predictions of what is likely to happen next, either in terms of how the incident might develop or in terms of how the incident might respond to the

interventions that the operators have made. A key challenge here lies in the ability of the system to make reliable predictions, over short or longer time scales.

### 3.3 Qualitative Descriptions of Decision Making

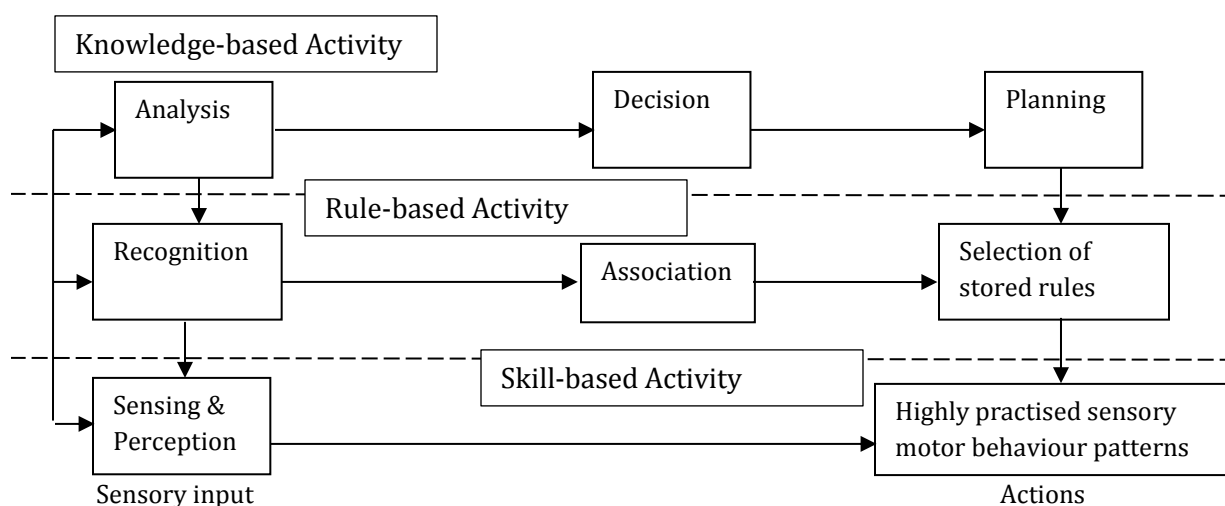
For the individual operator, Situation Awareness involves selecting the most appropriate information source and then analyzing the content of this source in order to make sense of it with a view to understand the ‘true’ global situation. While figure 5 helps to understand the scope of this activity, there is little here to explain *how* the actions are performed. This means that the SPEEDD project requires a means of theorizing the cognitive activity that operators perform in order to interpret the displayed information. Relating Situation Awareness to Ecological Interface Design (EID), we might expect operators to be able to spot patterns in the data and then respond to these by selecting a course action based on a perceived event category. It is interesting to contrast guidance for the design of User Interfaces from the perspective of Situation Awareness with that presented for EID. As Table 1 shows, there are strong similarities between the approaches (even if the underlying theory and the terminology used differ). Both emphasise the benefit of ‘direct’ display of information and both imply the need to represent the system in terms of user goals and in terms of different levels of system operation and performance. For this report, the way in which these different levels are reflected is through the Cognitive Work Analysis Abstraction Hierarchy (i.e., in terms of the system’s Functional Purpose, which corresponds to the ‘goals’ that the system is intended to achieve; the Values and Priorities, which act as constraints on system activity; the Purpose-related and Object-related Functions, which define the sub-goal and task structure of system activity; the Objects, which define the information sources contributing to system activity).

Design for Situation Awareness	Ecological Interface Design
Relate to operator’s major goals	Represent function and meaning in the image of a the task ecology
Present information directly	Design to support direct perception of visual information
Assist system projection	
Display global status	Reveal underlying system process and constraints
Support global-local trade-offs	
Support perception-action schemata	
Take advantage of human parallel processing capability	Integrated capabilities permit more work with less cognitive effort
Filter information judiciously	

**Table 1: Comparing EID and SA**

Rasmussen (1983) proposed three modes of human activity which he termed SRK (skill-based, rule-based and knowledge-based) activity (figure 6). Skill-based activity involves the sort of direct perception that has been alluded to in our discussion of Ecological Interfaces and Direct Perception.

In the use of visualizations, this results from the viewer spotting the ‘current state’ of a system in order to notice deviations (against some notion of a ‘desired state’ or simply in terms of changes to state). Typically, the viewer would be assumed to have a ‘schema’ of the ‘intended state’ and will match this to the displayed information. The schema might reflect the knowledge and experience of an operator, or it might reflect the output of the SPEEDD analytics, e.g., in terms of predicted deviations in system performance or in terms of suggested changes to the system state. In the Fraud Use Case, the current state could, for example, represent the average (financial) value of transactions on credit cards in a given location, and the schema could relate to outliers against these averages, i.e., such that transactions which are too high or too low could be flagged to the operator. In skill-based activity, recognition of these patterns relies on being able to spot such changes in the displayed information.



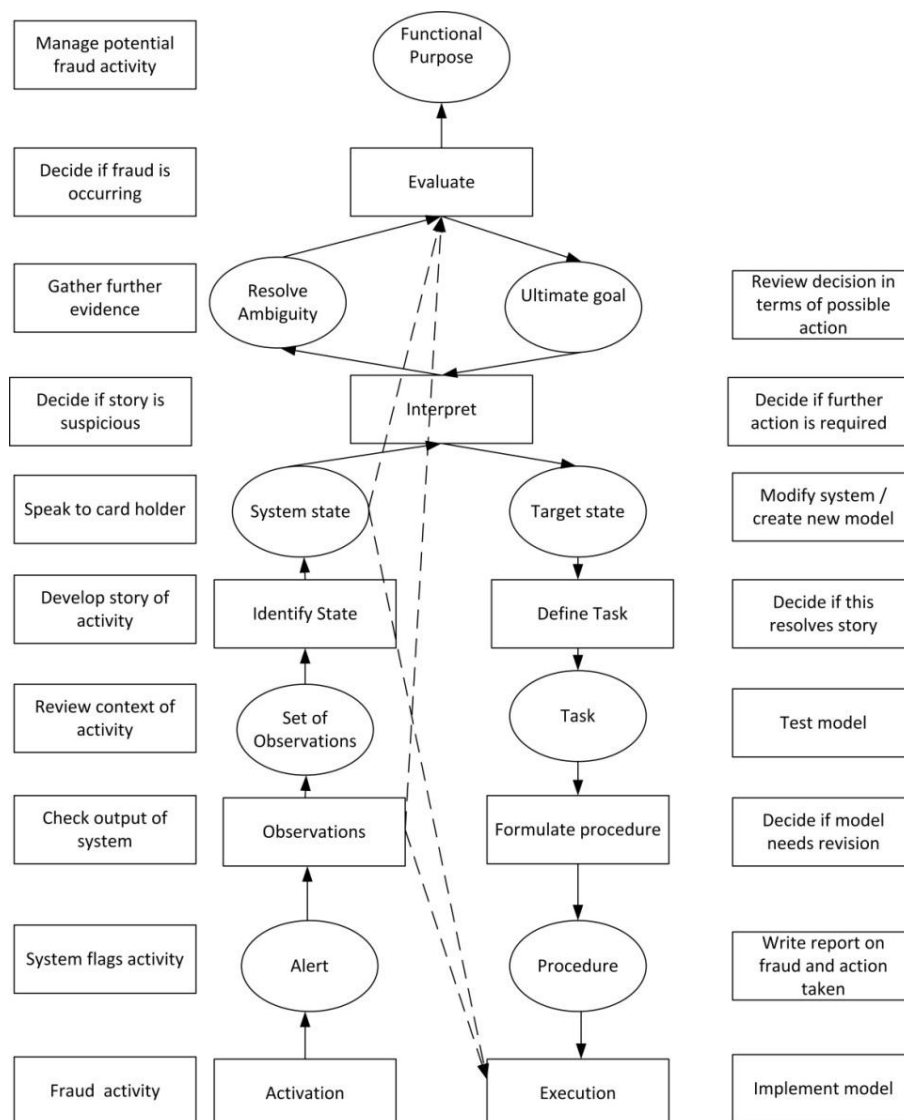
**Figure 6: Rasmussen’s Skill-based, Rule-based and Knowledge-based levels of Human Activity**

Rule-based activity, on the other hand, involves the application of known procedures to search for deviations and to compare and check parameters in the state of a system. In this case, the viewer would have a learned set of procedures and rules which he/she follows in order to interpret the displayed information. In terms of User Interface design, this could mean that the user would need to be able to select (or enter) queries and search terms to call up data which is not currently displayed. The ability to decide which query to make would depend on operator experience and the context in which he/she is operating.

The knowledge-based approach, finally, involves the viewer generating ‘what-if’ questions to explore the system in terms of its likely changes from the current state. In this case, the operator would not be able to directly spot patterns of interest nor be able to apply known rules or procedures. Rather the operator would need to engage in some form of investigation in order to generate and test hypotheses to explain a set of observations.

Often, SRK is presented in the form of a ‘decision ladder’ in which the high-level, goal-based actions correspond to knowledge-based activity, mid-level sequences of action correspond to rule-based

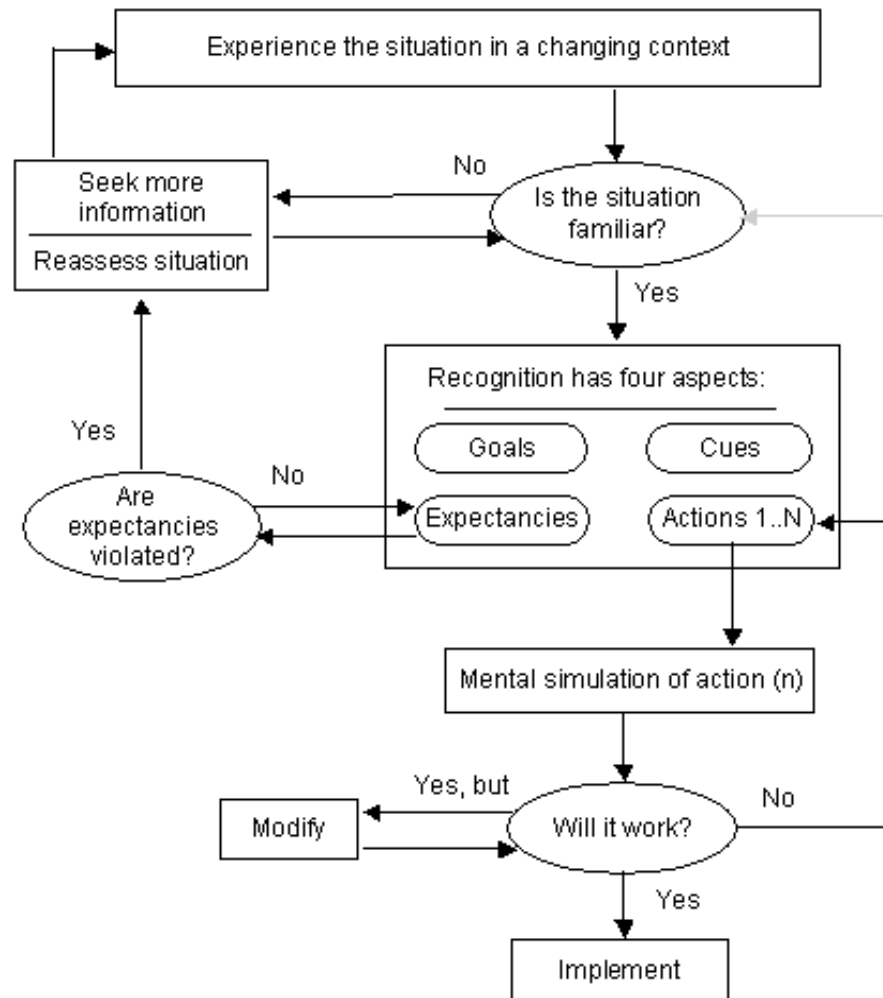
activity, and low-level actions (indicated as 'short-cuts' on the ladder) represent skill-based activity. Figure 7 shows the decision ladder that was developed to describe fraud analysis.



**Figure 7: Decision Ladder (Control Task Analysis) for generic Credit Card Fraud Analyst Activity**

Each of the different levels of activity identified in SRK requires different information and, thus, each could require different approaches to user interface design. While Visual Analytics often expresses the goal of supporting 'insight' in operators (in terms of presenting a pattern of data which can create the sort of 'a-ha' recognition of the correct interpretation) it is equally important to design the displays to allow operators to develop their own knowledge and experience. Thus, what is required for SPEEDD is, on the one hand, a theory which can support the concept of Ecological Interface Design, i.e., to explain how 'skill-based activity' is supported by the user interfaces, and on the other hand, a theory which can allow us to consider how operators select information from multiple displays and how these selections form the basis of their decision making.

In order to address the question of skill-based activity further, we take the idea of Recognition-Primed Decision Making (RPD) from Klein et al. (1986). An example of RPD is shown in figure 8.



**Figure 8: Process model of Recognition Primed Decision Making (from Klein, 1989)**

As figure 8 illustrates, RPD combines situation assessment (in terms of the activity beginning with the operator experiencing the situation and determining whether or not it is familiar) with mental simulation of responses to that situation, in order to define a plausible course of action. 'Recognition' gives sense of how typical the situation is (in terms of the person's experience) and this, in turn, gives an idea of reasonable actions to take. The processes in RPD, thus, involve defining goals; identifying critical cues and expectations in available data through matching features of the situation to the knowledge and experience of the person; and then performing some form of evaluation of possible courses of action in order to select an appropriate one. The complexity of decision making arises from the need for evaluation (and the difficulties involved in defining goals, cues and expectancies).

Klein (1999) elaborates on this process through the following actions which the operator might perform:

1. **Feature matching** refers to the use of predefined and context-free features to adopt a hypothesis or to select between hypotheses.
2. **Holistic matching** involves generating inferences about the situation that lead to a meaningful whole in terms of coverage and coherence.
3. **Seeking more information** involves the decision maker seeking more information regarding the situation when unable to make a clear diagnosis.
4. **Story building** refers to the process of constructing stories in order to infer how a current situation might have evolved from an earlier state.
5. **Step-by-step belief updating** refers to the way in which people change their judgments or beliefs over time, as they become aware of new information; it involves generating a hypothesis and modifying it on the basis of new information.
6. **Global belief updating** refers to the aggregation of all evidence in order to update one's diagnosis regarding the situation.
7. **Mental simulation** involves the construction of a causal chain between the inferred, prior state and the current, observed state.
8. **Analogical reasoning** involves the retrieval of a match to a prior case that can serve to identify the dynamics of the situation.

From this brief discussion, the goal of interface design for SPEEDD will be to support Ecological Interface Designs in ways which can allow operators to draw on skill-based activity and Recognition-Primed Decision making. However, it should be apparent that neither SRK nor RPD offer quantifiable models of human decision making. This means that, while it is possible to use these approaches to inform and inspire design ideas, they cannot, by themselves, provide a means of *measuring* decision making. The measurement of decision making is essential to the SPEEDD project because we intend to explore whether Visual Analytics can result in measurable (quantitative) changes in the ways in which people make decisions and to test whether decisions are optimal.

### 3.4 Quantifying Decision Making

Both the SRK and RPD descriptions provide convenient qualitative descriptions of how people might make rapid decisions. However, these lack the quantitative dimension that can allow us to formally make predictions of decision making. There are several approaches that could be taken. We could, for example, simply construct checklists (drawing on SRK or RPD) to determine when (and for how long) operators engage in the types of task that these frameworks assume. Similarly, we could use concepts from heuristic decision making (Gigerenzer & Gaissmaier, 2011). Heuristics are rules that are hypothesised to generate behaviours, which ignore some of the available

information in order to allow operators to make fast decisions. Very broadly, heuristics correspond to Rasmussen and Vicente's rule-based decision making. For example, one of the most popular heuristics in information gathering and decision-making is Take-The-Best (TTB), which claims that people search the information according to its reliability, and make the decision immediately after the discriminating information (e.g., positive for one choice and negative for the other choice) between choices is found. Relating this to visualization, one might expect to capture the heuristics that operators use, e.g., through observation and interview, and then seek to create designs which reflect these heuristics. Such an approach *could* be effective in situations in which operators find it easy to articulate their heuristics, where the tasks they perform are fairly consistent and standard, and where it can be expected that (through training and experience) the operators approach the task in much the same way. An initial study conducted for SPEEDD showed that the operators in the Grenoble DIRCE have developed idiosyncratic approaches to their work (Starke et al., 2015). This suggests that designing for heuristics might, in this instance, result in designs which satisfy some of the operators but which are unusable for others.

An alternative approach is to employ a Bayesian explanation of decision making which posits that a behaviour is explained to the extent that it corresponds to the optimal behaviour in the adaptation environment (Oaksford & Chater, 2007). In terms of designing visualisation, this implies that the manner in which the operator searches for information will change in terms of the layout of the display and in terms of the 'value' of information to different tasks.

For SPEEDD we adopt a cybernetic approach to human decision making (Baron & Kleinman, 1969; Lewis, Howes and Singh, 2014). The cybernetic approach explains decision making policies as adaptations to feedback driven control.

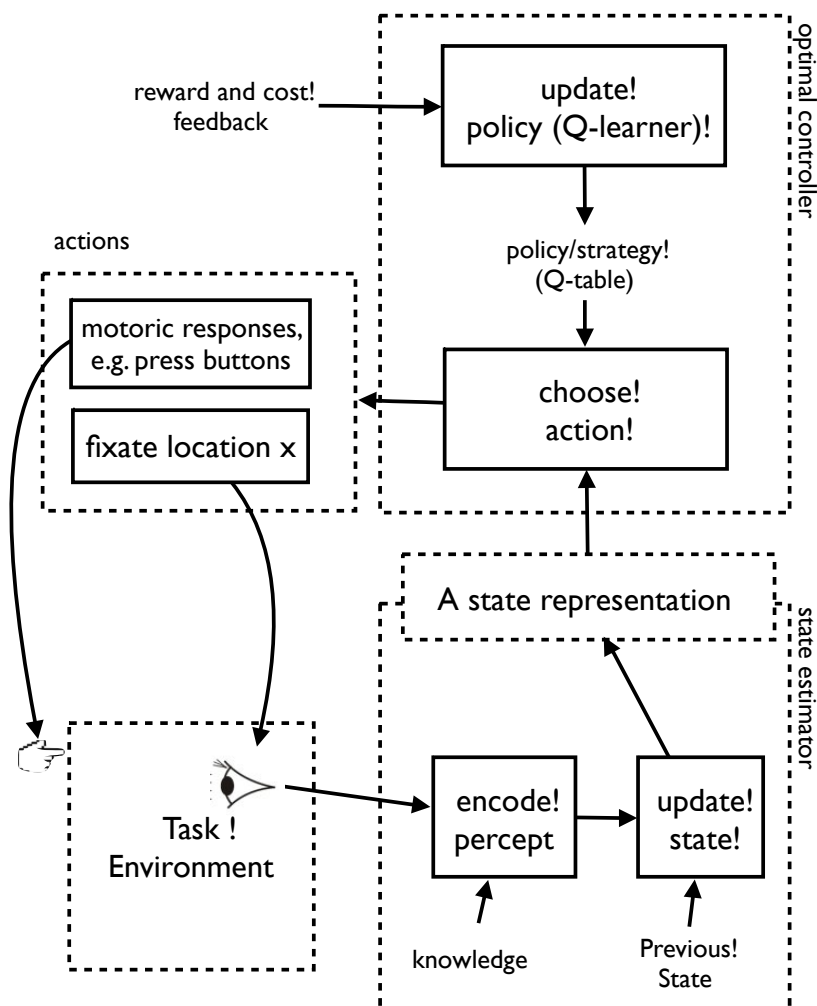
### 3.5 A Cybernetic Decision-Making Theory

A cybernetic approach explains decision-making policies as adaptations to feedback driven control. In our approach, we assume that the operator's behaviours can be predicted by the control policy. The control policy is a probabilistic mapping from states to actions, where states and actions are customised for the task. The control policy is continually adjusted and tuned in response to feedback. The optimal control policy is the policy that maximises the reward feedback signal. The predicted behaviours maximise the reward feedback signal given the constraints imposed by the temporal and spatial requirements of the technological system and hypothesised human information processing system. Reward is commonly associated with a utility function.

The roots of our approach are in the work of Baron and Kleinman (1969) (see Lewis, Howes and Singh, (2014)), and also in work on active vision (Hayhoe and Ballard, 2014). In particular, Baron and Kleinman exploited control theory to model the operator of complex dynamical systems including a range of cockpit scenarios. In their model of cockpit instrument modelling, the visual sampling problem, for example, is considered in parallel with the control problem. Using a model of the operator with a high-resolution fovea and low-resolution parafovea, they showed how cockpit instrument-monitoring behaviour depends explicitly on the control task. More recently, members of the project team, Chen et al., (Vision Research submitted; ACM CHI submitted), show that this approach can be used to well-known phenomena concerning visual search in both applied and

laboratory tasks. Specifically, an optimal control model embedded with the assumptions of human visual mechanisms (e.g., visual acuity degradation away from fovea, saccadic duration, and fixation duration) offers explanations for the observed human behaviours in these visual search tasks (e.g., the gaze distribution, the search time, the saccadic selectivity across colour and shape). Unlike previous approaches to modelling decision-making, skills and rules are an emergent consequence of rational adaptation to (1) the ecological structure of interaction, (2) cognitive, perceptual and motor limits (e.g., visual and/or motor constraints), and (3) the goal to maximize the reward signal.

An overview of the optimal control approach is presented in Figure 9. In general, the optimal strategy could be derived by many formal approaches that require utility and reward functions, e.g., optimal control theory, dynamic programming or reinforcement learning. In the pilot work that we have done for the project we have used Q-learning, a reinforcement-based learning technique.



**Figure 9: An overview of a cybernetic approach.**

In the optimal control approach, both the technological system and the human information processing system (e.g., visual system and/or motor system) are considered. Figure 9 illustrates one way of integrating the technological system and human information processing system constraints (e.g., visual system and/or motor system) into a control problem. Applied to the SPEEDD road traffic control task (see Section 5), this approach will help us answer difficult design conundrums. We are considering four case studies: (1) how to arrange information sources, including traffic camera displays, maps, forms, etc. over the entirety of the operator's visual field, especially when the visual field, and therefore the display size, can be extended by reasonable head and upper-body movements? (2) How to integrate advice from Artificial Intelligence with the available situation information? (3) How to manage operator workload? And, (4) how to facilitate communication between operator and other service personnel?

Consider in more detail the simple problem of arranging and scaling displays. One issue here concerns the trade-off between clutter and salience. The more spread-out a display (perhaps over an entire wall of monitors) then the less cluttered and more readily perceptible individual displays become. However, also as displays are more spread-out, unattended displays can become less salient because the large-scale arrangement of the monitors means that more information falls into low-acuity peripheral vision (see Section 4) or may be inaccessible due to the need for substantial and repeated head movements. The optimal control model can help us derive the optimal scaling and spread parameters for the displays.

By way of contrast, consider what other approaches to decision making could tell us about this design problem. The recognition-primed decision-making offers limited guidance for solving this problem. While it tells us that experts do not do search and problem solving, it fails to help the designer to understand the consequences of visual acuity and display arrangement for behaviour, even for expert operators. The heuristic decision making approach (Gigerenzer & Gaissmaier, 2011) tells us that decision makers are likely to use non-compensatory strategies, sometimes referred to as fast-and-frugal strategies, in an effort to maintain high accuracy while minimising time costs. These heuristics are claimed to be ecologically rational but it is unclear how they might be adapted through extensive experience with a particular task environment such as those found in control rooms. The Bayesian approach can offer deep explanations of why people behave as they do and indeed this approach has been exploited in Ideal Observer Theory (Geisler, 2011). But the goal in Ideal Observer Theory is to establish the best possible estimate of the state; heuristic control assumptions (e.g., maximizing the information gain or 'maximum a posteriori') are then required to model behaviour.

In contrast to the other approaches, the optimal control approach derives predictions of the operator's behaviour from a model of the temporal costs of eye and head movements, a model of how visual acuity degrades with eccentricity from the fovea, and the assumption that operators optimise speed/accuracy trade-offs. Unlike heuristics or RPD, no *a priori* assumptions are made about *how* decisions are made in our approach. Through feedback, and experience, the behaviour of the control policy comes to resemble decision heuristics, or recognition-primed decisions or Bayes optimal solutions. The SPEEDD decision model will be built on ideas outlined in Chen et al. (2013)

and Payne and Howes (2013). It will be calibrated to eye and head movement data collected during the project (see section 4), and will be used to predict the consequences of information visualisation systems being designed in Birmingham.

In detail, our approach is to model state-dependent actions that minimise a measure of cost or maximise a measure of goodness, given the specifications of both the technology system and human information processing mechanism. In the bottom left of Figure 5, the information from the external task is encoded by noisy perceptual processes (e.g., noisy vision system) to generate a task relevant perception. This new observation is then integrated with the previous state into a new state representation (the bottom right). The state estimation module implements the psychological constraints imposed by visual and cognitive mechanisms. Subsequently, the optimal controller module chooses an action on the basis of the new state and the current policy. The initial policy has no control information and results in random action selections. The control policy is updated incrementally (learned) as reward and cost feedback is received from the interaction. Hence, through reward guided control optimisation, the policy converges on the optimal control policy that maximises the reward. This interaction is thereby defined as a reinforcement-learning problem. The predicted response can then be compared to empirical data.

### 3.6 Challenges for SPEEDD

Having established a theoretical framework which allows us to relate information search to decision making, challenges for SPEEDD involves the collection of data (in the field and the laboratory) which allow this theory to be tested. To this end, WP5 requires the development of predictive (computer) models of decision making which are populated with data from human decision making. The data that these models employ can be drawn from the eye-tracking studies that are being undertaken. The rationale for these studies is given in the next section. Ultimately, the models will allow us to explore and evaluate alternative User Interface designs prior to presenting to users.

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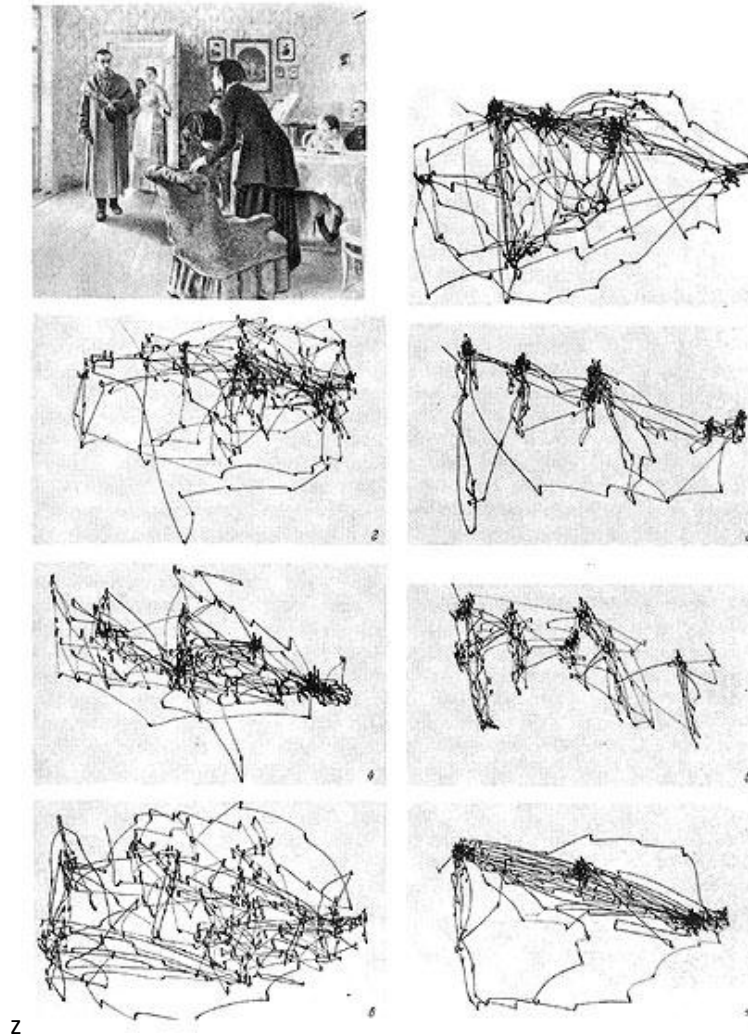
## 4 Using Eye-tracking as a Metric for Operator Performance

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### 4.1 Active Vision

The striking feature about vision is the discrepancy between perceived and ‘true’ objectivity of visual perception: processing of visual ‘raw’ information from the retina results in information that, fused with memory, results in the impression of a complete and accurate rendering of the scene which we are examining (Snowden et al., 2012). However, this is an illusion. An important aspect in vision is the distribution of photoreceptors within the retina and the representation of this recorded information in the visual cortex. Since a uniform sensor distribution on the retina would result in an unmanageable amount of incoming information (Snowden et al., 2012), there is a high density of cones within up to  $1.5^\circ$  to  $2^\circ$  visual angle (foveal vision with high acuity) which rapidly falls off towards the periphery (Snowden et al., 2012). As a result, only a small fraction of what we see at any one point is rendered in high resolution, the remaining visual field rapidly falling off into blur. This non-uniform information representation is further exacerbated by the disproportionate attribution of brain area to areas on the retina, commonly referred to as the ‘cortical magnification factor’ (Cowey and Rolls, 1974, Rovamo et al., 1978). In order to assemble an accurate rendering of a scene, we move our eyes in order to utilise processing abilities to an optimal extent. These eye movements typically occur 3 times per second during natural scene viewing (Henderson, 2003), i.e., ‘saccades’. Attention to areas of interest is termed ‘fixation’, while tracking a moving subject is called ‘smooth pursuit’ (Kowler, 2011). In order to quickly and efficiently create a visual representation of a scene, eye movements are directed strategically towards relevant information sources (Hayhoe and Ballard, 2005), allowing us to make inference from eye movement patterns to underlying cognitive processes (Henderson, 2003, Hayhoe and Ballard, 2005). There remains a debate as to whether we build up a global representation of the viewed environment, or whether we employ a ‘local, transient scene representation’ (Chapman, 2005). In addition, it has been highlighted that the perception of an accurate scene rendering stems from familiarity, without the ability for recollection of specific detail (Chapman, 2005). This is relevant in control room scenarios, where the perceived awareness of the situation status may be an illusion resulting from familiarity effects, potentially leading to the omission of important available data.

Early research on eye movements (e.g., Buswell, 1935, Yarbus, 1967) highlighted the relationship between eye movement patterns and the search goal of observers. Yarbus (1935) asked people to look at pictures and answer questions about the scenes depicted. He showed that observers would look at question-specific regions of the image (Figure 10). A recent study repeated Yarbus’ experiments, supporting the original claims that tasks can be decoded from attended regions (Borji and Itti, 2014).



**Figure 10: Alfred Yarbus' eyetracking records for viewing I.E. Repin's picture 'An unexpected visitor'. Eye movement patterns depended on the information sought – each panel represents the observer seeking information relating to one of seven different questions. From Yarbus (1967): Eye Movements and Vision, page 174.**

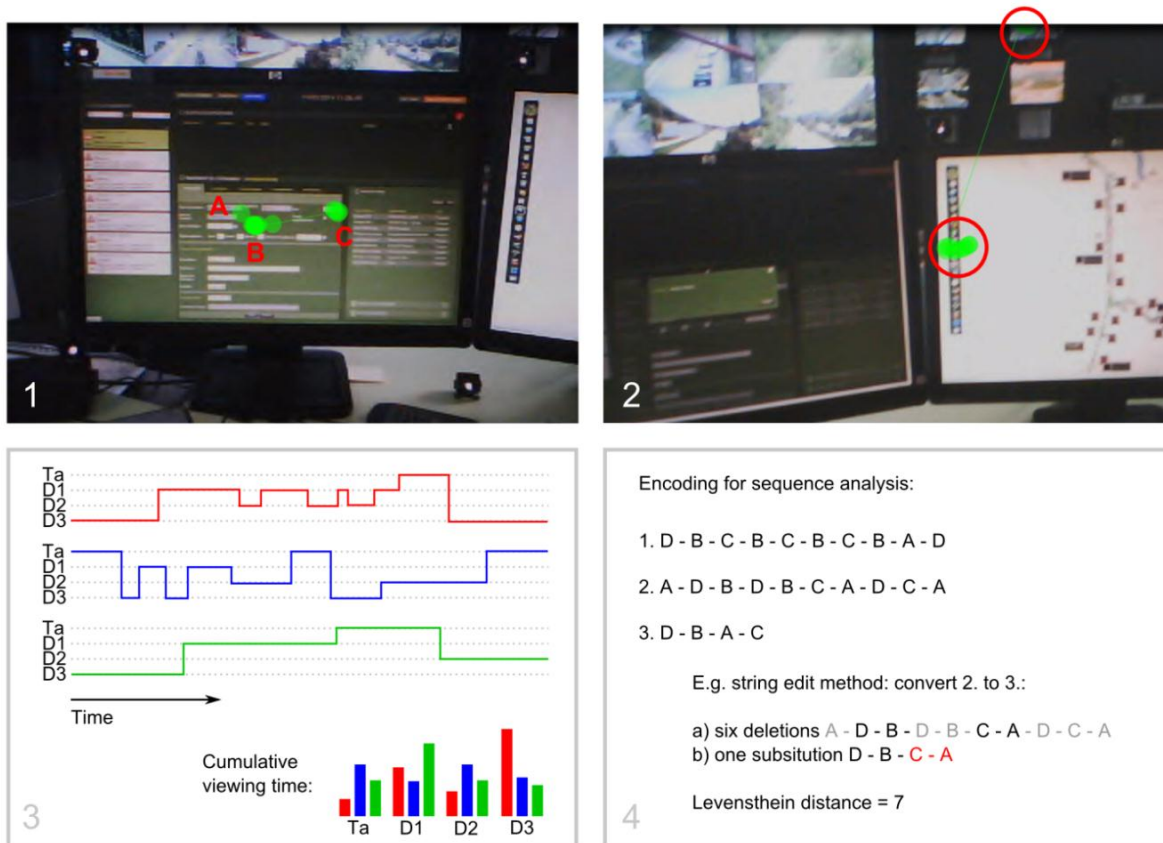
Since Buswell's and Yarbus' early work, the assumption that an observers' intent and goals guide eye movement has led to the research area of Active Vision (Findlay and Gilchrist, 2003). Active Vision assumes that we direct foveal vision to parts of a scene that is likely to hold information we are seeking, typically performed 'just-in-time' (Hayhoe and Ballard, 2005). Active gaze direction is 'knowledge-driven gaze control' tasks (Henderson, 2003). For tasks such as control room activities and detection of patterns from multiple information sources in financial fraud analysis, we propose that the active vision and knowledge-driven gaze control framework will provide insightful and relevant metrics to understand human decision making based on eye-tracking data.

## 4.2 Eye-tracking related to information sampling / decision making

In D8.1, we presented a cursory overview of the eye-tracking studies conducted in Grenoble DIRCE. In this section, we elaborate on the analysis process. The first step to data analysis typically requires defining regions of interest (ROIs) within the examined scene. Here, it is important to allow for pupil-size related error in gaze estimate from the eyetracking apparatus, which is typically in the region of several millimetres and depends on the distance from the screen (accuracy is hence typically given in degrees visual angle). In a control room task, these ROIs can correspond to individual screens. In tasks such as fraud analysis, these regions could correspond to menus, graphs and specific data sources. The definition of ROIs allows us to quantify parameters associated with visual attendance to known information sources. In addition, basic metrics relating to saccade amplitudes and dwell times can be defined independent of ROI definitions. A comprehensive description of eye-tracking metrics is provided in a recent book (Holmqvist et al., 2011), which details around 120 eye-tracking metrics in four categories: movement measures, position measures, numerosity measures and latency measures. In the following, we will describe selected metrics that allow us to understand an operator's information sampling behaviour and more complex parameters such as goal structure and schema. We intend to employ these metrics for the analysis of our experimental eye-tracking work in year 2 of the SPEEDD project, and we have already started doing so when analysing data from year 1 (Starke et al., 2015). Selected metrics are visualised in Figure 11.

### Saccade frequency and amplitude

The two most commonly used metrics related to basic eye movements across a scene are saccade frequency and saccade amplitude. Saccade frequency reflects the number of eye movements per second. The 'normal' saccade frequency depends on the task – whereas the most commonly quoted figure for regular scene viewing is 3 saccades per second, reading for example is associated with a higher saccades frequency of 4 to 5 saccades per second (Henderson, 2003). Even when attending to a defined ROI, participants commonly show saccades, perhaps to navigate between specific items within a ROI such as different text passages or image content. Saccade amplitude reflects the size of a gaze shift. In regular scene viewing, saccade amplitudes tend to be small or moderate, early work highlighting that 15° or smaller is normal (Bahill et al., 1975, Zangemeister and Stark, 1982). The saccade amplitude reflects the integration of peripheral information as well as prior knowledge: for smaller amplitudes, it is more likely that the gaze shift was triggered after a feature in the periphery demanded visual attention. This could be a flashing data field or the change in a graph. For larger saccade amplitudes, especially those that require significant head or even body movement, it is more likely that the gaze shift was triggered by internalised knowledge. This could be a gaze shift to a monitor of known location.



**Figure 11: Visualisation of selected eyetracking metrics. Panel 1: a small (A to B) and moderate (B to C) saccade amplitude. The high intensity green at B indicates a fixation in between the two saccades. Panel 2: a large saccade amplitude, corresponding to a gaze shift between two regions of interest (from a monitor displaying a road map to a CCTV feed). Panel 3: illustration of dwell times and cumulative viewing times, simplified for explanatory purposes for three hypothetical observers. Dwell times correspond to a continued attendance to a region of interest (here Ta, D1, D2, D3) whereas the cumulative viewing time is the sum of all dwell durations. Panel 4: representation of switches between regions of interest (taken from panel 3) for scan pattern analysis.**

### Fixation duration and number of fixations

Directly related to saccade frequency are fixation duration and number of fixations. A higher saccade frequency logically results in lower fixation durations. Fixation duration is an important metric related to information extraction. In visual search tasks, items attended to for less than a second are commonly not remembered on subsequent enquiry (Chapman, 2005). In static images, fixation duration is a very useful measure to understand decoding of different elements in a scene. In tasks such as control rooms or analytics, where displayed information is dynamic rather than static, an element of uncertainty is added: extended fixation durations may now correspond to the monitoring of an evolving scene, or to problems understanding displayed information. It is therefore important to understand and define stimuli characteristics before interpreting results from tasks related to the SPEEDD project.

### **Dwell time and cumulative viewing time**

Dwell time is similar to fixation duration; however, while fixation duration relates to the raw eye movement (typically thresholded to be within a defined range of movement and velocity), dwell time relates to the duration for which the observer looks at a defined ROI; it is the time from entry to exit within a ROI. Long dwell times can either reflect normal decoding of a complex stimulus with all attentional resources or the failure to decode a stimulus efficiently / effectively, respectively the failure to understand a visual input. Concurrently, short dwell times may correspond to efficient pattern recognition or 'skipping' of an information source. Cumulative viewing time is the total time an observer attends to each ROI, which is typically expressed as a fraction of the total viewing trial for that trial. Dwell times and cumulative viewing times allow to understand higher level goals of an observer and also to evaluate UI design. Inferences can be drawn on how an observer structures information accumulation across the available information sources, how long he/she interacts with UI components (compared to expected usage time) and how the ROI is being used, for example frequently and for a short time or infrequently but for a long time.

### **Time to first hit**

The 'time to first hit' quantifies the elapsed time until gaze is directed to a specified ROI for the first time. This metric is useful for understanding the prioritisation of specific information sources: when examining a scene, it is thought that gaze is directed towards the perceived most important information source first (ref). Hence, contrasting time to first hit between different UI designs and between different observers allows us to understand how displayed information is weighted and how reliable it is judged to be.

### **Scan patterns**

Scan patterns describe the sequence of fixated regions in a scene; the term has been proposed to replace the term 'scan paths', since the latter is associated with partially flawed assumptions in the scientific community (Henderson, 2003). Scan patterns can be compared between observers and scenes in many different ways. Historically, amongst the simpler methods is the string edit method. It allows to compare similarity between scan paths by calculating the Levenshtein distance based on the number of insertions, deletions and substitutions necessary to convert one string into the other (Brandt and Stark, 1997, Salvucci and Anderson, 2001). Using scan pattern analysis facilitates the comparison of an observed usage pattern to an expected pattern (which a UI is designed for) or to examine repeatability and variability in the scanning method between UIs, observers, information arrangements etc.

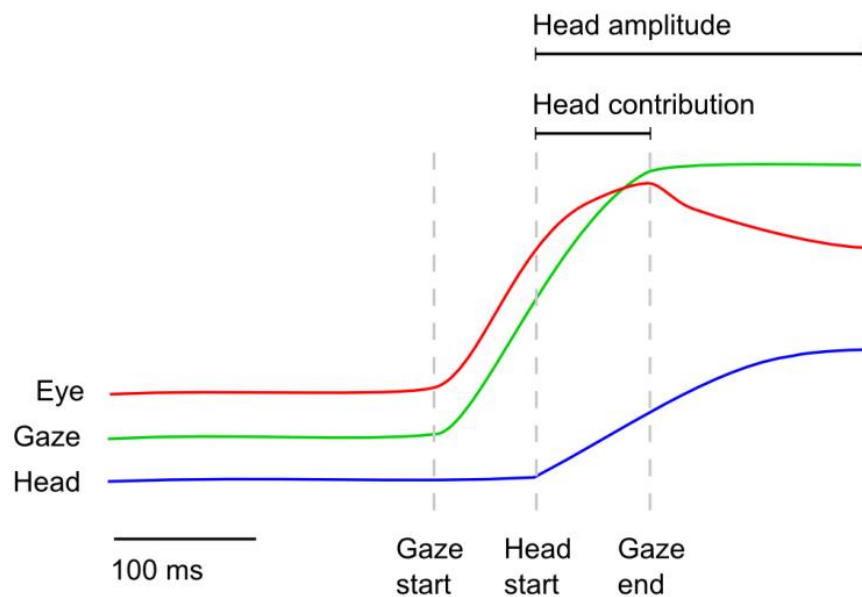
### **Pupil dilation**

Pupil dilation is a metric not related to eye movements but rather to dynamic changes in pupil diameter while performing a visual task. This metric can be derived from eye-trackers as they estimate pupil diameter for each recorded sample as part of the technical protocol. Pupil diameter can change for two very different reasons. Firstly, pupils contract and expand based on the luminance of the examined scene in order to control the amount of incoming light just as the aperture of a camera. In this case, changes in diameter are a purely mechanical result of the scene characteristics, which does not allow direct insight into cognition of the observer. Secondly, the pupil diameter can change as a physiological co-correlate of mental task and decision process (de

Gee et al., 2014). In this case, pupil diameter allows a direct insight into (pre-) conscious decision making. By tracking the pupillary response, one can determine the feature of the examined scene that is associated with or triggered fundamental cognitive attributes such as cognitive load (Kahneman and Beatty, 1966), problem solving (Hess and Polt, 1964, Beatty, 1982) or surprise (Preuschoff et al., 2011). Recently, pupillometry has been used to monitor decision making and associated factors such as responses in context of individual criterion and bias with great sophistication in simple tasks that require a yes/no response (de Gee et al., 2014). This exciting work suggests that pupil state in fact reflects the continuous decision making process and tracks brain processes (de Gee et al., 2014), rather than solely reflecting the post-decisional state. It is important that to utilise pupil dilation as a decision making metric, experimental design has to tightly control for luminosity of the stimuli; this requires laboratory experiments.

### 4.3 Head movement and gaze shifts

Depending on their amplitude, gaze shifts can be executed by eye movement alone or accompanied by head movement and whole body movement. The integration of these three components depends on physiological requirements and individual propensity: gaze shifts larger than  $45^\circ$  to  $50^\circ$  visual angle have to be executed in part by head movement simply because the eyes will not rotate further within the head (Proudlock and Gottlob, 2007). Gaze shifts larger than  $75^\circ$  to  $90^\circ$  additionally need rotation of the upper body due to the functional limits of head/neck rotation (Proudlock and Gottlob, 2007). For gaze shifts that can be executed without head movement, studies have noted pronounced individual variation in the relationship between gaze shift with head movement (Fuller, 1992, Stahl, 2001, Chapman and Corneil, 2008, Thumser et al., 2008, Thumser and Stahl, 2009). As a general rule, gaze shifts  $< 15^\circ$  are typically not accompanied by substantial head movement (Proudlock and Gottlob, 2007, Freedman, 2008). Due to inertia of head and body, there is commonly a lag found between the onset and termination of rotational movements (see Figure 12), where often movement commences in the order eyes – head – trunk – feet (Scotto Di Cesare et al., 2013). In the 1980s, eye-head coupling was categorised into four different types (Zangemeister and Stark, 1982): Type I refers to synchronous eye and head ‘controller signals’ where a fast saccade was accompanied and followed by slower head movement, stabilising gaze while the head moved. This pattern was found in 35% of subjects. Type II refers to head movement onset following eye movement completion, a pattern only rarely observed unless related to pathology. Type III refers to early head movement which starts before the eye saccade and results in an initial velocity of the eye before moving for the saccade; this type was found in 43% of subjects especially for larger gaze shifts. Type IV refers to very early head movement, which is completed before the eye saccade begins. This coupling type was observed infrequently, especially when targets moved with large amplitude, when subjects attempted very fast gaze shifts and when targets had low brightness. In this scenario, head movement may be more indicative of attention relocation than the delayed gaze shift. Movement patterns between eyes and head are hence commonly not perfectly synchronised with a gaze shift; rather, a gaze shift is often completed long before head and body come to a halt, accomplished by the intricate interplay between ocular reflexes (Proudlock and Gottlob, 2007). Subtle differences in the latency between the onset of eye- and head movement have further been attributed to stimulus characteristics (Doshi and Trivedi, 2012).



**Figure 12: Movement sequence for a 60° gaze shift executed via both eye- and head movement. Redrawn and adapted from Corneil (2011).**

### Inferences on cognitive activities from eye-head coupling

While physiological requirements and limits impose basic patterns on the coupling of eye and head movement, variation in the detailed contribution of head movement to the gaze shift as well as the coordination between eyes and heads has been highlighted both between different participants and tasks (Proudlock and Gottlob, 2007, Corneil, 2011). Part of the variation may stem from sometimes artificially simplified laboratory settings that may not be representative of gaze shift behaviour in the real world (Herst et al., 2001). However, it is becoming ever more apparent that cognitive / subconscious factors may influence coupling characteristics. Eye- and head coupling has received recent research interest in context of cue characteristics: in context of monitoring driver behaviour, quantifying the latency between eye and head movement onset has given hope that the nature of the gaze shift can be classified as endogenous (triggered by the observer's goal) or exogenous (triggered by scene characteristics without conscious control of the driver) and hence can serve to warn drivers of dangerous attention relocation (Doshi and Trivedi, 2012). Recent work has further highlighted that aligning eyes and head may produce better performance during visual search tasks: participants who performed standard visual search tasks underperformed when executing visual search tasks with the eyes rotated laterally (Nakashima and Shioiri, 2014). While this finding relates to basic image processing abilities, it has also been hypothesised that aligning eyes and head after a gaze shift may disclose expectations of an observer regarding future gaze shifts: aligning eyes and head would result in a new neutral orientation of the eyes, which makes a subsequent gaze shift independent of the previous one (Proudlock and Gottlob, 2007). If only the eyes were moved without a head movement, a future gaze shift would be constrained by this abaxial eye orientation. Eye and head coupling may hence also be expectation driven.

### Eye-head coupling metrics

Several metrics have been employed to characterise eye-head coupling during gaze shifts. The *eye-head or latency* (Scotto Di Cesare et al., 2013) is the time between the onset of eye- and head movement; depending on the definition, this can take positive or negative values depending on which is moving first. The *head contribution* (see Figure 12) is defined as “change in position of the head that occurs during the gaze shift and actually contributes to the overall change in the direction of the line of sight” (Freedman, 2008). This is in contrast to the *head movement amplitude* (see Figure 12), which is defined as the “change in head position from the beginning to end of head movements” (Freedman, 2008). Head movement amplitude is typically greater than head contribution, since the head continues rotation while gaze has already reached a stationary fixation. Other metrics include *compensatory eye movement* which serves to stabilise the gaze during continuing head movement (Schwab et al., 2012) or features related to rotational velocity or acceleration (Doshi and Trivedi, 2012).

## 4.4 Challenges for SPEEDD

The primary challenge for SPEEDD is the development of metrics to analyse eye-tracking data. Indeed, our initial work has resulted in advice to Tobii (in terms of dealing with missing infrared markers defining a global reference frame within the field of view in the analysis; Starke et al. 2015, submitted to ACM TiiS). It is proposed that the relationship between head and eye movement warrants further investigation in the framework of natural tasks, building on the substantial body of work established from laboratory stimuli and recordings, particularly focussing on in field studies, and SPEEDD will make a significant contribution to this area. Eye-tracking provides an essential means by which an operator’s information search can be recorded. This will not only feed directly into the decision models, but also provide a quantitative metric of the usefulness of information in different visualization designs developed during the project. It also allows us to compare information search in current operations with potential changes arising from new User Interface designs.

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## 5 Cognitive Work Analysis (CWA)

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### 5.1 Introduction

The two case studies in SPEEDD lend themselves to different system characteristics. Rasmussen et al. (1994) proposed that systems can be defined in terms of a continuum of characteristics which range from causal (i.e., governed by definable laws) to intentional (i.e., governed by the intentions of actors). In addition to this continuum, Rasmussen et al. (1994) classify systems in terms of their coupling to the environment, such that causal systems tend to be tightly coupled to their environment, while intentional systems tend to be loosely coupled. The road traffic management case study focuses on a system which is tightly coupled to its environment and which is primarily causal. In other words, while the behaviours of individual road users might be regarded as intentional, the flow and behaviour of traffic as a whole can be described in terms of laws and the role of the traffic managers could be seen as ensuring that the laws of this system are being adhered to. In terms of describing this case study as a socio-technical system, the key issues would be to appreciate the ways in which coupling within the system is managed and the nature of the 'laws' which are being applied by the different stakeholders. When incidents arise, the tight coupling between system and environment breaks down and the 'laws' no longer apply. The role of traffic management thus becomes one in which the key purpose is to re-establish the tight coupling and ensure that the 'laws' are once again applied.

In contrast, the credit card fraud case study could be considered as a system which is predominantly intentional, in that fraudsters are continually seeking novel ways to disrupt a system which, as a result, oscillates between tight and loose coupling with its environment. This oscillation is meant to indicate that, in a well regulated system of credit card transactions (i.e., one in which there is no fraud), there will be close coupling between the different components of the system and the environment in which they operate and where there will be causal (i.e., rule-governed) system activity. From this perspective, fraud is an attempt to destabilize this tight coupling in order to subvert the rule-governed activity. In addition, fraudsters often aim to minimize this obvious destabilization in order to prevent detection. The case study can be considered as primarily an intentional system with loose coupling with the environment. From the perspective of a socio-technical system, it is necessary to understand the nature of the 'laws' that the system applies (i.e., what would constitute 'normal' in system operations) and the manner in which coupling shifts from tight to loose. Given the wide variety of fraudulent activity it is not obvious how this shift in coupling can arise, and given the secrecy with which banks protect their 'laws' it is not easy to determine how such shifts are handled or how stability is restored.

In order to understand both case studies, it is important to appreciate how coupling between system and environment is established and managed, and in order to do this it is beneficial to explore them as socio-technical systems which are seeking to fulfil a specific purpose. Cognitive Work Analysis provides a suite of methods which are intended to be used for such an exploration.

## 5.2 The Phases of CWA

Cognitive Work Analysis (CWA) focuses on what a system *could* look like rather than what it *does* look like (Rasmussen et al., 1994). In particular, the analysis seeks to move from the physical appearance of the current system to the high-level goals that the systems and its operators are seeking to achieve. Consequently, a primary focus of CWA lies in mapping the constraints within which decision and task activity can occur. In this respect, the term ‘constraint’ refers to the decision envelope in which operators can make decisions, e.g., in terms of the competing goals that the operators and their system will be managing. It is this focus on the trade-off between competing goals that makes CWA different from other Ergonomics / Human Factors approaches which often focus on the tasks that operators perform.

CWA consists of five phases (Bisantz et al., 2008; Burns et al., 2008; Chin et al., 1999; Jenkins et al., 2009; Naikar et al., 2006; Naikar and Sanderson, 2001; Rasmussen et al., 1994; Vicente, 1999). The order in which the phases are performed tends to work from the outside in, i.e., from organisational considerations to individual skill profiles.

The first phase is Work Domain Analysis (WDA). WDA maps the ‘big picture’ of the work domain in terms of the relationship between the goal (or Functional Purpose) of the system as a whole. Work Domain Analysis describes the ways in which the Functional Purpose of a system (on the first row of figures 16 and 23) is achieved through the use of specific actions on specific physical objects, and against specific constraints in the system. For this analysis, the ‘constraints’ are defined by those aspects of performance which the system values and which it seeks to prioritise. This system-level view shows how different elements of the system might contribute to the Functional Purpose (rather than assuming, for instance, that there is only a single entity controlling the system). The first pass of building the Abstraction Hierarchy is to work downwards from the Functional Purpose to the values and priorities which contribute to, and constrain, the achievement of this purpose, and then to work upwards from the objects that actors are able to use and the activities that they perform. Thus, the next step is to consider the Physical Objects (the fifth row of figure 1) that are used to support activity. The objects that we have included here are illustrative (rather than a complete set). The intention is to indicate the range of sources of information which the system uses in its activities. From these objects, we define Object-related functions, which indicate ways in which actors in the system make use of these objects. This, in effect, captures the material from the observations, interviews and literature review to help explain the processes that people in the system are likely to follow. In this step, the aim is to work upwards from the bottom of the hierarchy to the Values and Priorities of the system. In order to do this, the final step is to relate the Purpose-related Function to the Values and Priorities through the Purpose-related Functions of the system (which, in effect represents the ‘goals’ of the actors in the system), and, hence to the Functional Purpose. The Functional Purpose in WDA refers to the total system and the individual physical objects represent the components or subsystems as shown in Abstraction Decomposition Hierarchy (ADH). This diagram maps the elements of the WDA on to an abstract concept of the system as a whole: decomposed in terms of System, Subcomponent and Component.

The second phase is Social Organization and Cooperation Analysis (SOCA), which concerns the division of functions between actors in the socio-technical system. This takes the Object-related Functions from the ADH and maps these to the actors who might perform them (figures 17 and 24). The aim of this analysis is to indicate which functions are performed by individual actors and which might be performed by more than actor. In cases where a function is performed by more than actor, the question arises as to how these different performances might either overlap or otherwise influence each other.

The third phase is Control Task Analysis which establishes what needs to be done for the system to fulfil its purpose, exemplifying possible pathways between input states and output decisions. It is a mapping of information processing structures that the system as a whole needs to navigate. Typically, Control Task Analysis is presented in the form of a 'decision ladder' (figures 18 and 25).

The fourth phase, Strategies Analysis, concerns the routines that could be used to carry out the activities identified in Activities Analysis. We do not explore Strategies Analysis in this report.

The fifth phase, Skills and Worker Competency Analysis, concerns the mapping between the required competencies of workers and the system constraints, and is typically performed using the SRK taxonomy (Skill-based, rule-based or knowledge-based (Rasmussen et al., 1994; Vicente, 1999)). These are also not the focus of this report.

### **5.3 Challenges for SPEEDD**

While the methods for conducting CWA are generally well established, the process of translating from CWA description to User Interface design remains more of an art than a science. A challenge for SPEEDD is to refine the approach to Ecological Interface Design in a way which allows for consistent and coherent generation of User Interface designs from CWA.

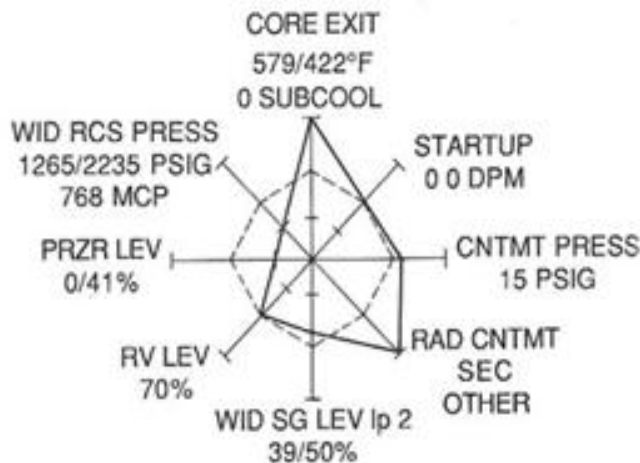
# 6 Principles of Display Design

## 6.1 Proximity Compatibility Principle

The Proximity Compatibility Principle (PCP) is based on the assumption that associated information should be positioned together. This might seem obvious, but it raises two difficult challenges for Human Factors. The first is what one means by ‘associated’ and the second is how this translates into a design recommendation. Wickens (1997) suggested two forms of ‘proximity’ which will be considered here:

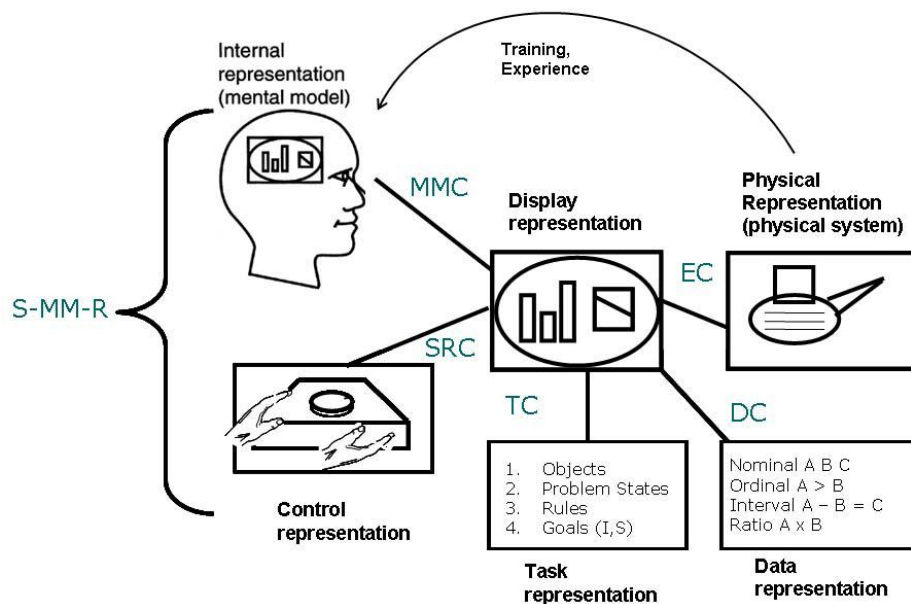
- i. ‘Display proximity’, i.e., people will see displays as being associated not simply because they are adjacent to each other, but also because they share common features, such as colour, scale, shape, code. Imagine a display which has a ‘traffic-light’ coding (i.e., red, amber, green) for warnings against different measures, and that this display has a series of line-graphs indicating different aspects of system performance. If three of these measures reach the ‘alarm’ state, and a corresponding red indicator appears above the line-graphs, it is plausible to assume that the operator will group those three red indicators into a single percept and then seek to interpret this alarm state (as opposed to responding to each indicator in turn and then combining this information into an explanation).
- ii. ‘Task / processing, proximity’, which is defined by the attentional demands involved in obtaining information about a particular system state. There are two main forms of task / processing proximity. Non-integrative proximity relies on similarity of cues, while integrative processing proximity relies on the active combination of information through computation and decision making. When a task demands attention to be divided between several sources of information, then an integrative display produces superior performance, but when the task demands attention be focused on single sources of information then non-integrative display produces superior performance (Carswell and Wickens, 1987; Carswell, 1992; Wickens and Carswell, 1987, 1995). This supports Woods (1988) proposal that design should aim to support information extraction by the operator (in terms of allowing the operator to respond to emergent properties which they can interpret on the basis of their experience and knowledge) rather than simply for information availability which requires the operator to search and combine specific pieces of information.

The question, therefore, that PCP raises is how best to define the ‘task proximity’? Consider the polygon display in figure 13. At one level, the polygon display presents parameters which the operator needs to monitor and manage. At another level, it presents the ‘operating envelope’ of the system. Rather than seeking to maintain control of each parameter separately, the operator will (more likely) trim the process in order to keep the envelope within limits and, as this envelope becomes distorted, the operator will focus attention on specific parameters.



**Figure 13: Example of a Polygon Display**

Hollands (2012) offers the General Compatibility Framework (figure 14), which takes as its input the notion of Stimulus – Mental Model – Response (S-MM-R). The S-MM-R draws on two representations: the mental model of the person and the layout of the controls to which the person has access. The representations link to the display representation via Mental Model Compatibility (MMC) and SRC, and these relationships further evoke Task Compatibility (TC), Data Compatibility (DC) and Ecological Compatibility (EC). While TC and DC are covered by the concept of PCP, the question of Ecological Compatibility is considered in the discussion of Ecological Interface Design in the next section.



**Figure 14: General Compatibility Framework (Hollands, 2012)**

## 6.2 Ecological Interface Design

The concept of Ecological Interface Design (EID) developed from Cognitive Work Analysis (see section 5). In this approach, the word ‘ecological’ has two connotations. The first, borrowing from Gibson’s (1969) concept of direct perception (later encompassed by the ‘ecological psychology’ movement) is that people excel at perceiving patterns. For User Interface design, this leads to the assumption that people are able to perceive meaning of objects *directly* (i.e., with no need for cognitive intervention) when the situation in which they encounter those objects provide a suitable context for interpretation. Thus, viewers can directly perceive physical objects as being separate from their background, that these objects can be picked up and that, having been picked up, the objects can be used for specific purposes, e.g., clicking, dragging etc.

In order to be effective, diagrams like figure 13 require a statement of the key parameters that define a system and a clear indication of what ‘steady state’ looks like. This introduces the second connotation of ‘ecology’ in EID: a User Interface exists in a task ecology. In other words, the system constrains the ways in which information is interpreted and defined to be salient or meaningful. Within this task ecology, it is plausible to assume that different people will interpret the information in different ways (according to their current tasks, goals, experience and training). Thus, the ‘task ecology’ of a system is defined by the range of states in which it can develop and the constraints that these states place on people interacting with the system. This means that, in addition to presenting information in a manner that the viewer can directly perceive, it is also important to represent the structure of the system with which the person is interacting (and the actions which are possible for that person). The questions which immediately arise, therefore, are what is the ‘system’ that is being worked with, and what constraints might affect interaction with this system. In other words, the focus is on human activity in a ‘system’ and the ecology can be described in terms of the problem space in which humans make decisions, the sort of tasks and decisions that humans perform and make and the constraints which affect performance of these activities.

If a goal of User Interface design is to provide a view of the ‘system’, then it is important to ensure that this view supports the Situation Awareness (section 3) of the stakeholders who engage with the system. We reiterate that the stakeholders need not be represented by a single group of users but could be different groups with different information needs. In this report, the SPEEDD User Interface design is primarily focused on those stakeholders who will be directly interacting with the outputs of the analytics (e.g., traffic control room operators and fraud analysts). However, subsequent work will consider ways in which User Interfaces for other stakeholders *could* be designed.

### Visualising Functional Purpose and Values and Priorities

At the highest level, the CWA Abstraction Hierarchy presents the Functional Purpose of the system as a whole. This indicates the intended purpose of the system. It is possible that a simple display of performance against this purpose could be presented. For example, if the system is intended to respond to incidents as quickly as possible, then this display could show the average time spent responding to incidents, perhaps over time and perhaps against targets or against historical data.

Obviously the usefulness of such a display would depend on the nature of the work and the perceived benefit that stakeholders feel it provides.

At the next level of the Abstraction Hierarchy, the Abstract Function (values and priorities) would be reflected by the main parameters that the 'system' is seeking to balance and the causal relations between these. Often EID is applied in Process Industries and so these variables tend to be mass, energy, flow etc. Figure 15 shows an example of the User Interface designed for a cement processing plant (Passen, 1995). By way of explanation of the Functional Purpose and Values and Priorities of the system, it is not possible for the operator to directly observe how finely cement powder is being ground (but the fineness of the powder dictates the flow through the process but also the speed with which the process is completed). In figure 15, the Functional Purpose is represented by the milling efficiency curve, and the energy balance graphs at the top of the display. The Values and Priorities are represented as 'goals' of the system (displayed in the centre of the display: thermal energy, milling energy, temperature, specific mixing energy). The operator is seeking to maintain these outputs within tolerable limits. At the bottom of the display, data relating to the Objects under consideration are displayed, i.e., parameters for particular aspects of the process. The relationship between the different displays is indicated by the lines on the display.

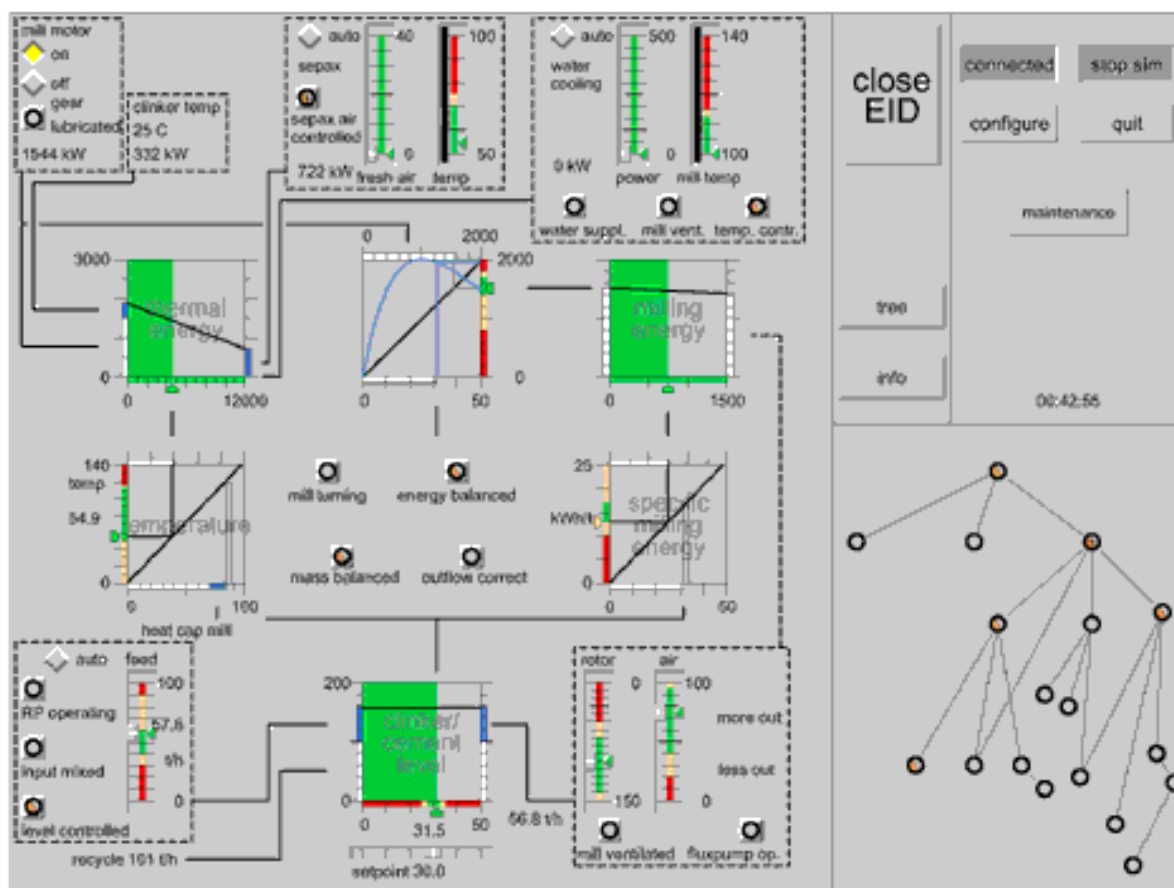


Figure 15: Example of EID for cement processing plant (Passen, 1995)

**Visualising Purpose-related / Object-related Functions and Physical Objects**

While figure 15 illustrates how the system's Functional Purpose and Values and Priorities might be displayed, it can also be beneficial to present views of the subgoals (Purpose-related functions), tasks (Object-related functions) or information sources (Physical objects). These can either provide cues for the operators to interact with the system at a lower level or can provide alternative means of alerting operators to change in system state. Thus, for example, the output of a CCTV (Physical Object) could be manipulated by the operator (Object-related function) in order to determine the location of an incident (Purpose-related function). In this situation, it might further be useful for the operator to be able to directly mark and record this information, say by marking this video frame (and its associated metadata defining location, direction of view, time etc.) and capturing this directly into the report.

# 7 Case Study 1: Road Traffic Management

## 7.1 Introduction

As noted in D8.1, “Road Traffic Control involves the monitoring of traffic, responding to incidents and influencing road user behaviour through the use of signs which can be updated remotely from the control centre”. Following the Hierarchical Task Analysis, in D8.1, we concluded that the primary goals of operators in the control room could be summarized as:

- Receive notification (from sensors, patrols, road users)
- Determine incident type
- Determine incident location
- Determine incident impact
- Initiate response
- Monitor road user compliance
- (Open) / Close incident log

While this provides an indication of how the operators might perform their task, the focus is very much on individual performance and less attention was given to the ‘road traffic management’ system as a whole. Using Cognitive Work Analysis, it is possible to extend this description to consider all of the actors who contribute to the operation of the system.

## 7.2 Abstraction Hierarchy

In figure 16, we have used the phrase ‘manage road network’ as the Functional Purpose of the system.

Having defined a Functional Purpose, the next step is to define the Value and Priority Measures of the system (the second row of figure 16). These represent those aspects of performance that the system could use to indicate how well it is performing. Through the interviews, we defined the following aspects:

- To ensure minimal congestion in the road network
- To ensure minimal risk to road users
- To enable minimal journey times for road users
- To ensure informed road users
- To support maintained infrastructure
- To encourage compliant road users
- To support immediate response to incidents
- To produce an auditable record of activity

These aspects map quite nicely on to a generally accepted set of objectives for traffic management which Folds et al. (1993) proposed and which have been well cited in the traffic management literature:

- Maximize the available capacity of the roadway system

- Minimize the impact of incidents (accidents, debris, etc.)
- Contribute to demand regulation
- Assist in the provision of emergency services
- Maintain public confidence in the control centre operations and information provision

The main difference between the set that we derived and those offered by Folds et al. (1993) concern the issues of providing support to the emergency services (although we have ‘immediate response to incident’ which we suggest would include this), and maintaining public confidence in control centre provision (which we do not include but which could relate to the priority for ensuring ‘compliant road use’).

In order to develop the initial concept for a User Interface, it is useful to consider the relations between the different Values and Priorities in the Abstraction Hierarchy. Taking the perspective that the ‘system’, as a whole, requires this information in order to fulfil its Functional Purpose provides a high-level, Socio-Technical Systems perspective on operations. This also raises the question of *who* can be considered part of the system, which is explored using the Social Organisation and Cooperative Analysis (SOCA) diagram in the next section.

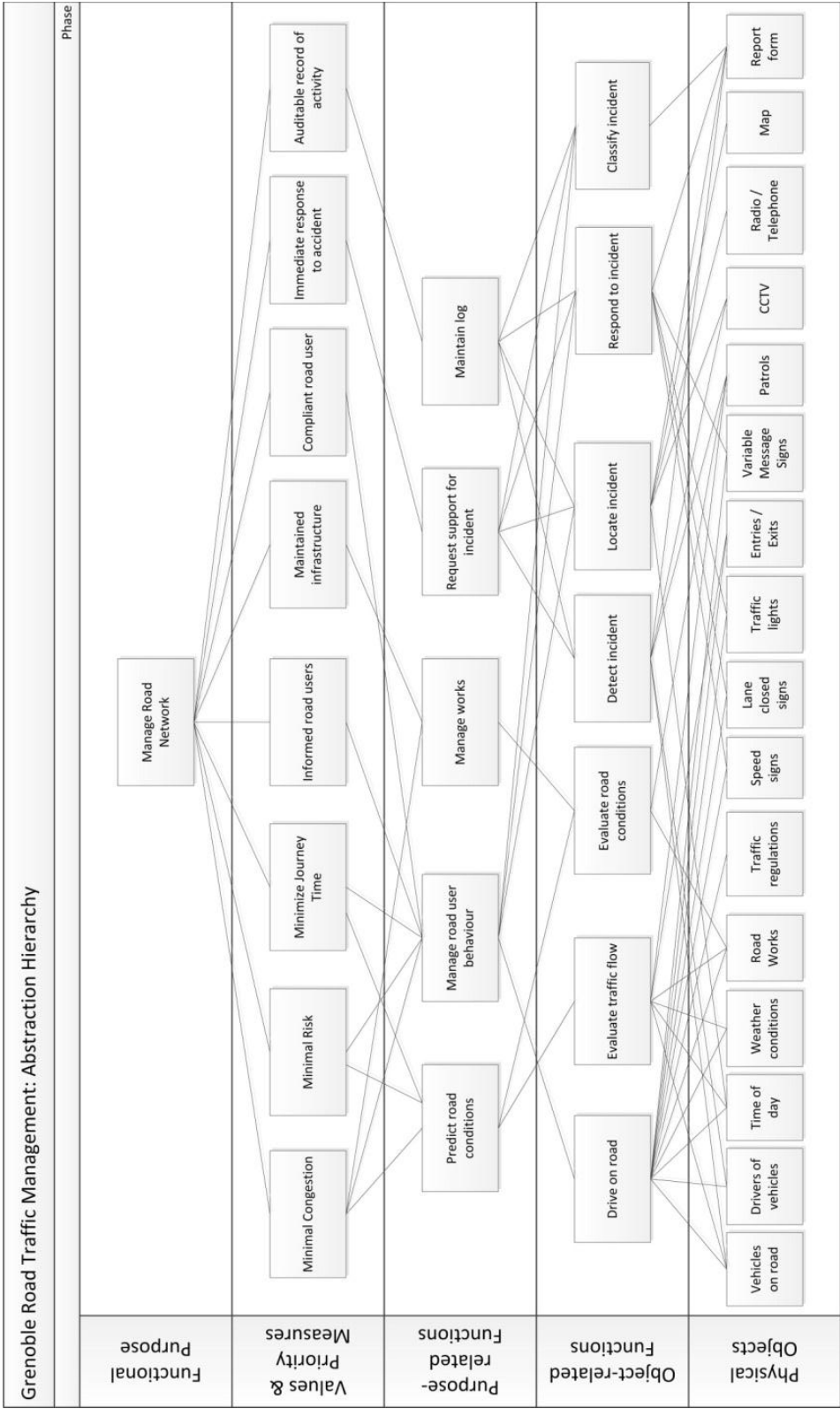
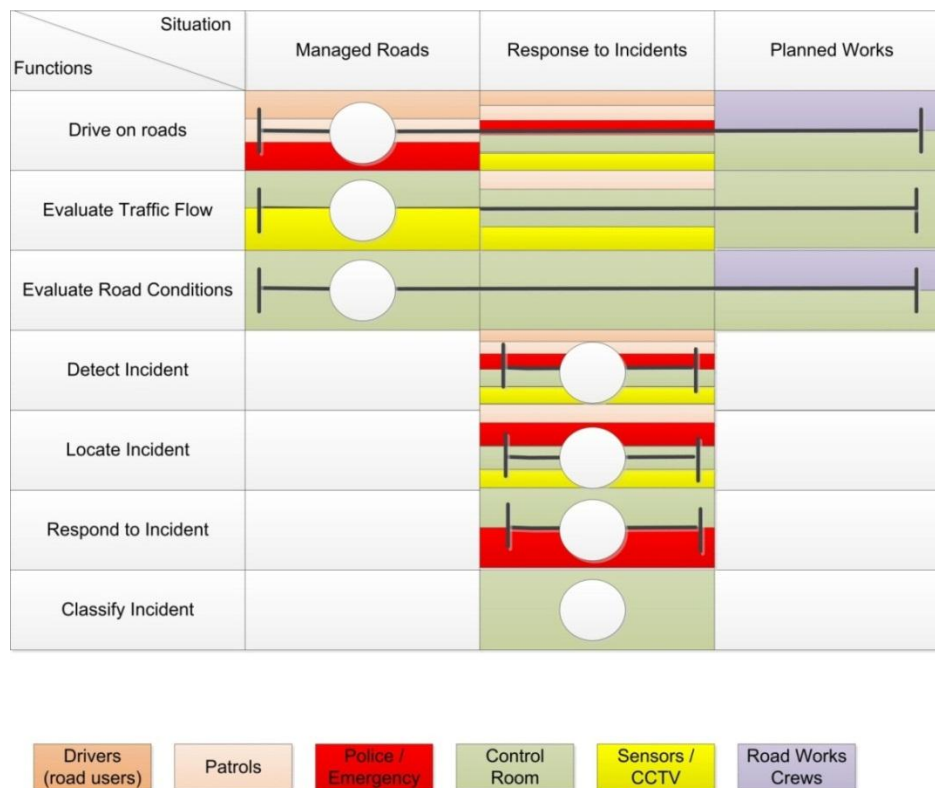


Figure 16: Abstraction Hierarchy for Road Traffic Case Study

### 7.3 Social Organisation and Cooperation Analysis

In any Socio-Technical System, there will be a wide range of actors who perform different functions in order for the system to achieve its Functional Purpose. In the case of road traffic management, for instance, there will be the individual road users who are driving vehicles through the road network and whose behaviour the operators in a control room are seeking to influence. In addition, there might be specialized roles, dedicated to maintaining the infrastructure of the road network or to dealing with accidents and incidents, which are called upon at specific times. Figure 17 takes the Object-related Functions (from figure 16) and shows how these can be performed by different actors (shown by colour coding) and in different circumstances. In this figure, the circumstances are presented as examples of different ‘modes’ in which the system could be assumed to operate, i.e., normal conditions (managed roads), disrupted conditions (response to incidents), or scheduled disruptions (planned works). Figure 17 shows how the different circumstances can lead to different distribution of these object-related functions across the range of actors.



**Figure 17: SOCA for Road Traffic Case Study**

It can also be assumed (as illustrated by Houghton et al., 2014), that actors which can perform the same object-related function in the same circumstance could have a requirement to share information or otherwise communicate with each other. For example, the ‘evaluate traffic flow’ function, under ‘managed roads’, is performed by both the <sensors / CCTV> actor and the <control room> actor, signifying a need to share information between these actors; the ‘drive on roads’ function, under ‘response to incidents’, is performed by <drivers>, <patrols>, <police / emergency>,

<control room>, <sensors / CCTV>, suggesting a need to share information between *all* of these actors. While it is clear how the former case can be (and is currently) supported by the design of the control room, it is less clear how the latter case can be supported.

## 7.4 Control Task Analysis ('decision ladder')

The initial description of Road Traffic Management that we have derived from our field studies (reported in D8.1), suggest a series of actions that the operator will seek to perform. These are illustrated by figure 18, which is intended to be a generic description of how analysis *might* be performed. The primary tasks are derived from the Object-Related Functions in figure 16, which represent a form of task analysis. This task analysis is complimentary to the Hierarchical Task Analysis reported in D8.1, illustrating how different Ergonomics / Human Factors methods can be used to represent field observations. The 'decision ladder' in figure 18 should be read from the bottom left (beginning with an input to the operator) up to the top (Functional Purpose, or overall goal of the operator / system). From the Functional Purpose, the right-hand leg of the ladder descends to the action that the operator will make. The key point to note here are that we suggest that there are various 'short-cuts' that the experienced operator might apply (indicated by dotted lines), perhaps in light of particular patterns of data or reports from previous responses.



## 7.5 User Interface Concept

Taking the CWA analysis, the next step is to develop an initial concept for the information which might be presented in the User Interface for this case study. In broad terms, we would expect the User Interface to convey information which could be perceived in terms of Associative and Selective perception, i.e., patterns which could convey coarse relations between forms of data, or to convey information which can be read (and interacted with) in a more Quantitative form. Deciding how much of the User Interface to design in terms of Associative / Selective and how much to design in terms of Quantitative obviously depends on the nature of the task, the preferences of the operators and the type of data. For the initial prototype, a set of User Interfaces will be designed which vary in the relative emphasis of these types of perception. However, this report will concentrate on the design which emphasizes Associative / Selective perception (for the simple reason that this is more indicative on the assumptions which underlie EID).

Taking the Abstraction Hierarchy, we can begin to relate the information requirements for each level to a Generic Representation and to the needs of different stakeholders in the system. For this report, we are only considering Control Room Operators but it is useful to note that other stakeholders (in this case, road works crews or road users) might have different or similar requirements.

	Generic Representation	Control Room Operators	Road Works Crews	Drivers (Road users)
Domain purpose	Overview			
Values Priorities	Balances, contrasts	Congestion Incident Record activity	Congestion Infrastructure	Congestion Risk Journey time Information
Knowledge semantics insight	Relations, affordances, status	Support to response Update log	Conditions {repair / works, weather, traffic flow / density, environmental}	Driver behaviour Compliance
Facts ideas opinions	States, trajectories, capabilities, magnitudes, persistence, availability, projection...	Availability {signage, CCTV}	Availability {lane, road, exit / entry}	Movement Accident
Source objects	Topography, layout, location, size, time...	Location {signage, CCTV} Content {signage, CCTV}	Map	Vehicles Motion Compliance

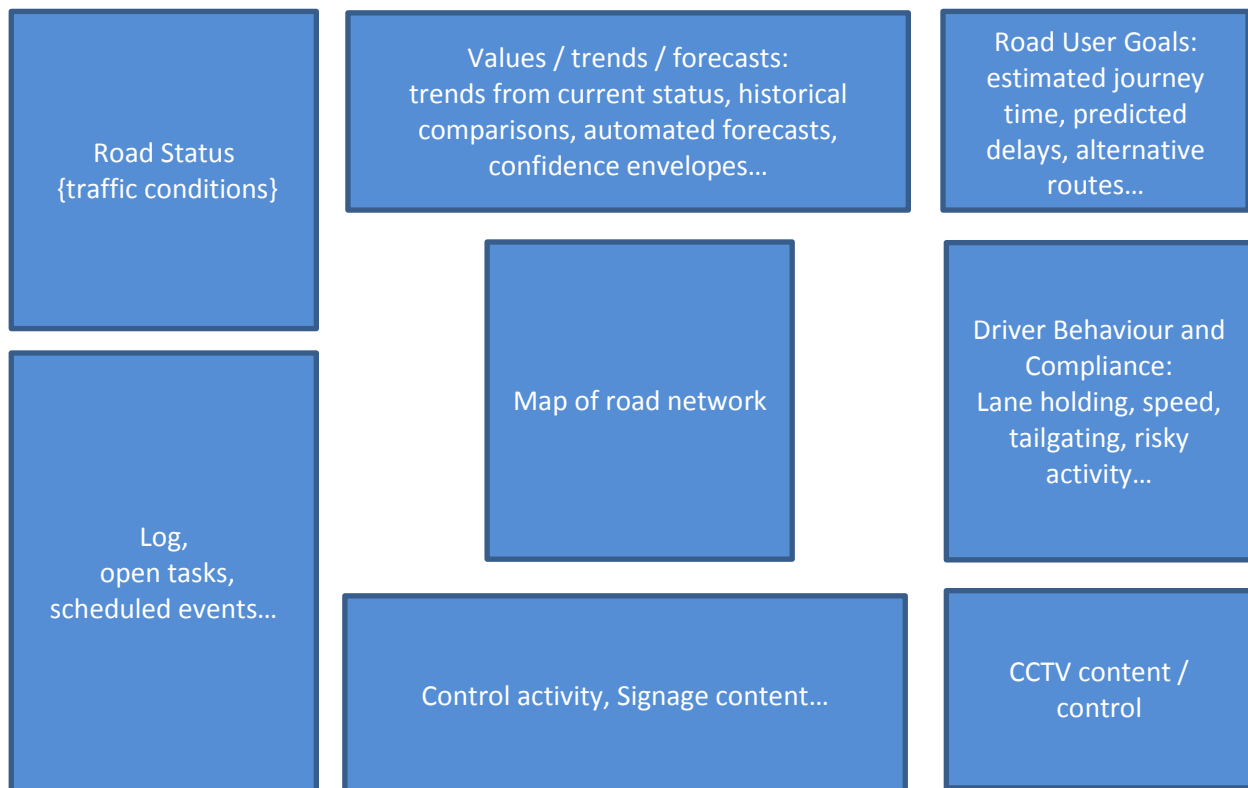
**Table 2: Relating Information Requirements for different Stakeholders to the levels of Abstraction Hierarchy**

In table 2, these relations are mapped and examples of the type of information which might be used in the system to support these relations are indicated. This provides a simple means of eliciting the information which *might* be useful for this system. We do not assume that all of this information needs to be presented to a single operator (or even to a single type of operator, e.g., some of the information might be useful to control room staff while other information might be useful to road users).

	Congestion	Risk	Time	Inform	Infrastructure	Comply	Respond	Record
Congestion	-	Speed x density	Traffic flow x density	Advisory (delays)	Available lanes x density	Inter- vehicle distance x speed	Available lanes (ER)	
Risk		-	Upper ranges of speed	Advisory (weather)	Road weather x	Variability in driving behaviour	Available ER resources	
Time			-	Advisory (x mins to y)	Available lanes x density x speed	Upper ranges of speed	ER time to accident	
Inform				-	Advisory (works)	Advisory (speed, regs)	Advisory (accident)	
Infrastructure					-	Advisory (lane use)	Available lanes (ER)	
Comply						-	Advisory (drivers pull over)	
Respond							-	
Record								-

**Table 3: Relations between Values and Priorities for Road Traffic Case Study**

Finally, taking the relationships defined in table 3, we sketch the concept layout (figure 19) for the User Interface. The aim, at this stage, is not to populate this with graphics but determine the display objects and their relative location and function. Options for the graphics are considered in the next section and the final design will be presented in section 9.



**Figure 19: Schematic User Interface layout for Road Traffic Case Study**

## 7.6 Graphic Options for the Different Regions of the User Interface

Figure 19 contains 8 regions. The following list outlines some of the options that are being considered in the design. Items marked \* correspond to existing information displays in the control room.

- Road status (traffic conditions): displayed (perhaps) as a fundamental diagram (as used in D8.1). This could also compare current traffic conditions with the same time last week or averaged across multiple timepoints, and predicted traffic conditions and likely trends;
- Values / trends / forecasts: this display could provide operators with views of the predicted traffic, or driver behaviour, to allow comparison between alternative courses of action;
- Road user goals: this display could indicate information which might be relevant to road user activity, for instance, alternative routes which drivers might take if there is congestion;
- Driver behaviour and compliance: this display could indicate how road users are behaving. This could include average speed in each lane or average distance between vehicles;
- CCTV content / control\*: this display would present the images from the selected CCTV camera to the operator, and allow the CCTV camera to be controlled;
- Control activity, signage content\*: this would show the actions that the operator is able to perform and the content which could be presented on variable message signs;

- Log, open tasks, scheduled events\*: this would show the log of the current incident that the operator is working on, together with open tasks or any scheduled events that need to be dealt with;
- Map of road network\*: displayed as a map of the ring road (either a schematic as in the current design or a more detailed map of Grenoble and the road network), with key Objects indicated, e.g., CCTV and sign locations, junction (ramps) etc. This could also be used to display the location of incidents, such as congestion.

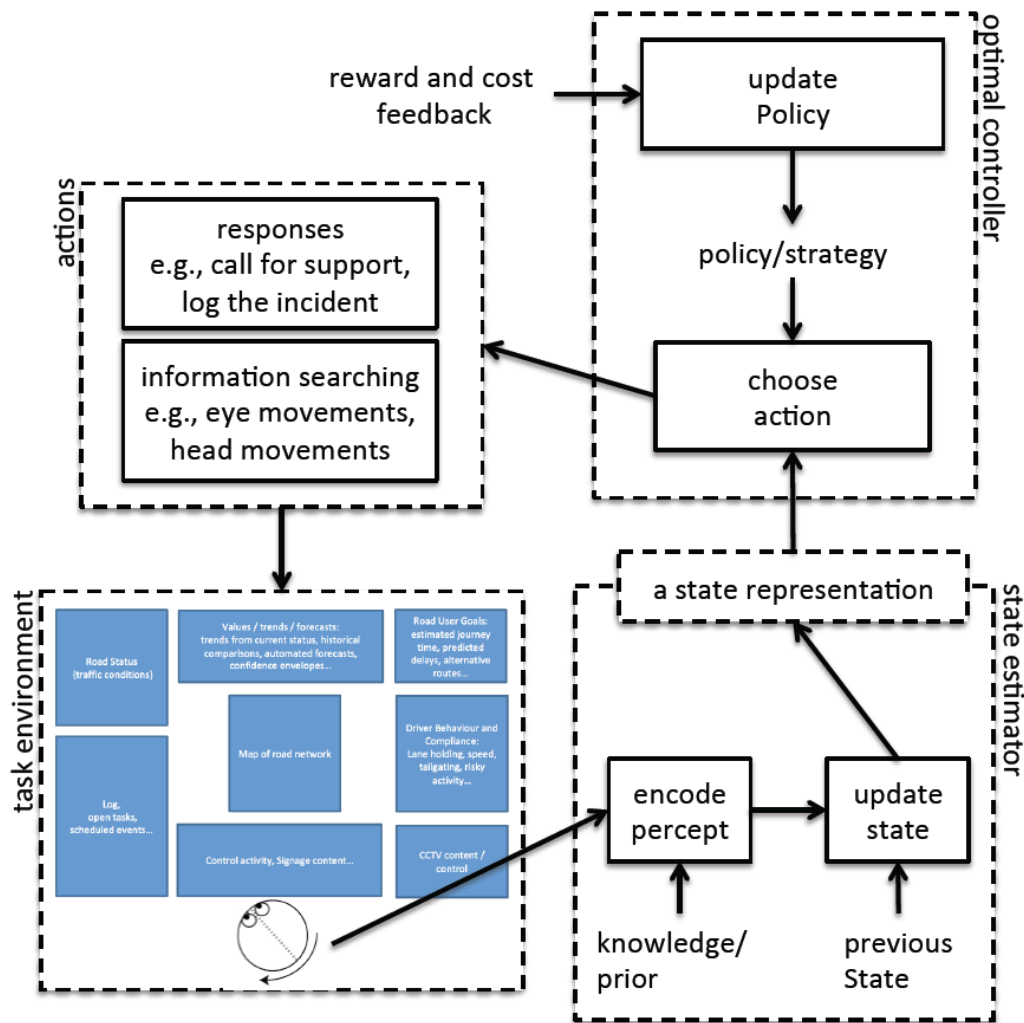
## 7.7 Cybernetic Decision Model for Road Traffic Case Study

We plan to use the cybernetic decision (optimal control) model of operator decision making introduced in Section 3.5 to assist in the design of visualisations for operator decision-making. The first hypothesis is that the efficiency of detecting, identifying and localizing the accident/congestion are affected by the arrangement and scale of the displays, as well as the visual, motor, and cognitive mechanism constraints. For example, the more spread-out a display, the less cluttered and more readily perceptible individual attended displays become. However, also as displays are more spread-out, acuity rapidly drops towards the periphery.

We aim to derive predictions of the operator's behaviours from a model of the temporal costs of eye and head movements, a model of how visual acuity degrades with eccentricity from the fovea, and the assumption that operators optimise speed/accuracy trade-offs.

Figure 20 shows an overview of the model. Before illustrating the model, we first specify the task to be modelled. The operators' basic behaviours include monitoring the traffic flow, detecting congestion, incidents, responding to these situations, recording activities, e.g., updating log. The crucial part of this process is to detect the incidents as quickly and accurately as possible. To do this, the model will update and evaluate a representation of the traffic conditions by gathering information from the available devices, e.g., CCTV or Map(s) of the road network. When a problem, e.g., an accident, or congestion, is identified and localized, proper responses are required to be executed, e.g., putting up signage or calling for outside support.

This modeling work is related to at least two lines of work about human behaviour. First, it is related to human visual search behaviour, e.g., the target detection task from a visual display. Second, it is related to inference in human probabilistic inference tasks. In this task a person needs to infer which of two choices is best by selectively acquiring information from up to 4 sources. Each source costs time to acquire and the validity of information from each source varies. This task has been studied extensively in cognitive psychology (Newell and Shanks, 2003). The probabilistic inference task is related to the traffic control operator's task in the following way: The observations which an operator makes are noisy; and sometime this information is from multiple sources (e.g., different devices), and the reliability of these sources differs. In a probabilistic inference problem, the key questions concerned are, for example, how people integrate the noisy observations, or how people weigh different sources of information.



**Figure 20: An overview of the optimal control model for the road traffic case study**

The model aims to predict the operators' behaviours given theoretical assumptions about utility (e.g., a measure of the goal), psychological mechanisms (e.g., human eye-head coordination mechanism) and environment (e.g., the interaction between the operator and the interface). To achieve this goal, a state estimation and optimal control approach is used, as shown in Figure 20. In the task environment (bottom left), the operator moves head and eyes to acquire information from the displays, enter data, and execute traffic flow actions. The state estimator (the bottom right) encodes a percept from the interface, which is then integrated with previous state to generate a new state representation. Subsequently, the optimal controller chooses an action on the basis of the available state estimate and the current policy (which determines a state-action value function). State-action values are updated incrementally (learned) as reward and cost feedback is received from the interaction.

## Psychological Constraints

When human beings inspect a visual scene, frequent gaze shifts are required. The gaze shifts occur at an average rate of three to five times per second (Doshi & Trivedi, 2012). Studies have found that when shifting gaze to foveate a new target, humans mostly choose a unique set of eye and head movements from an infinite number of possible combinations (Proudlock, & Gottlob, 2007; Doshi & Trivedi, 2012;). Particularly, studies of eye-head coordination for gaze shifts have suggested that the degree of eye-head coupling could be determined by an unconscious weighing of the motor costs and benefits of executing a head movement (Nakashima & Shioiri, 2014). Some studies show that minimizing the impact of uncertainty, i.e., noise affecting motor performance, can account for the choice of combined eye-head movements (Saglam, Lehnert, and Glasauer, 2011). For example, in the road traffic control task, we also consider that pop-up warnings may appear on the screen. Research has found that sudden, bottom-up visual cues in the periphery evoke a different pattern of eye-head movement latencies as opposed to those during top-down, task-oriented attention shifts (Doshi & Trivedi, 2012).

## States and Actions

The state consists of decision relevant cues. For example, in order to decide whether an accident happened, several cues could be examined such as inner lane blocked, all lanes blocked, slow traffic flow, clear road at location x. Each of these cues would have a different indication of whether an accident happened. The state is then represented as all or some of the answers to these cues. To obtain information for these decision related cues, the model selects both eye movements and head movements (actions). The different arrangements and scales of the displays result in different time costs and reliabilities of the information obtained a certain device. During this process, the operators/model need to decide which cue to access, which device to look at, and when to stop information searching and make a decision.

This is similar to a probabilistic inference task (Gigerenzer & Gaissmaier, 2011; Newell & Shank 2003, 2004). For example, consider the following problem: given information about shares in two companies, you have to choose which company's share will be the most profitable. To support this choice, you might use information gained from reading a range of different cues (e.g., positive/negative share history, or whether there has been recent investment in the company's R & D). These cues can vary in the reliability of the information provided. The more cues examined, the more information gathered thus more likely to make a correct decision. However, extra time cost and/or financial cost would be required. The *probabilistic inference* task has been used in cognitive science in efforts to discover the decision-making heuristics used by people (Gigerenzer & Goldstein, 1996; B. Newell, Weston, & Shanks, 2003; Bröder & Schiffer, 2006; Rieskamp & Otto, 2006; Rieskamp, 2008; Rieskamp & Hoffrage, 2008).

## Learning

Crucially, the advantage of the optimal control approach is that the optimal control policy is learned rather than programmed by the modeler. This is achieved through Q-learning and leads to emergent skill-based and rule-based behaviour.

## 8 Case Study 2: Credit Card Fraud

### 8.1 A role for human analysts in credit card fraud detection?

In the report on the Credit Card Fraud Use Case (D7.1), there is no explicit role outlined for humans in the analysis process. This reflects the desire to have an automated screening and detection system which requires little or no human intervention. Given the enormous volume credit card transactions, it is clearly imperative that detection is performed automatically. *“Automatic systems are essential since it is not always possible or easy for a human analyst to detect fraudulent patterns in transaction datasets, often characterized by a large number of samples, many dimensions and online updates.”* (Dal Pozzolo et al., 2014). From this perspective, the notion of a user interface would appear contradictory and inappropriate. On the other hand, D7.1 notes that the credit card transaction process involves several stakeholders, i.e., cardholder, merchant, acquiring (merchant’s) bank, issuer (cardholder’s) bank, processor. Understanding the relations between these stakeholders is important for the socio-technical system.

D7.1 points out that the detection of financial fraud involves determining whether a given activity differs from what might be deemed ‘normal’ and acceptable behavior in a given system. The implication is that it is necessary to detect an activity which is counter to normal behavior. The role of the human analyst thus becomes either one of defining what constitutes deviation from normal (i.e., the rule set used in automated detection) or one of interpreting the results of the detection process. For the purposes of this section, we consider that latter activity. Broadly speaking, we are assuming that an automated detection process is running and that this process has flagged a given transaction (or set of transactions) as ‘suspicious’ and the analyst will engage in some form of investigation to decide how to respond to the flag.

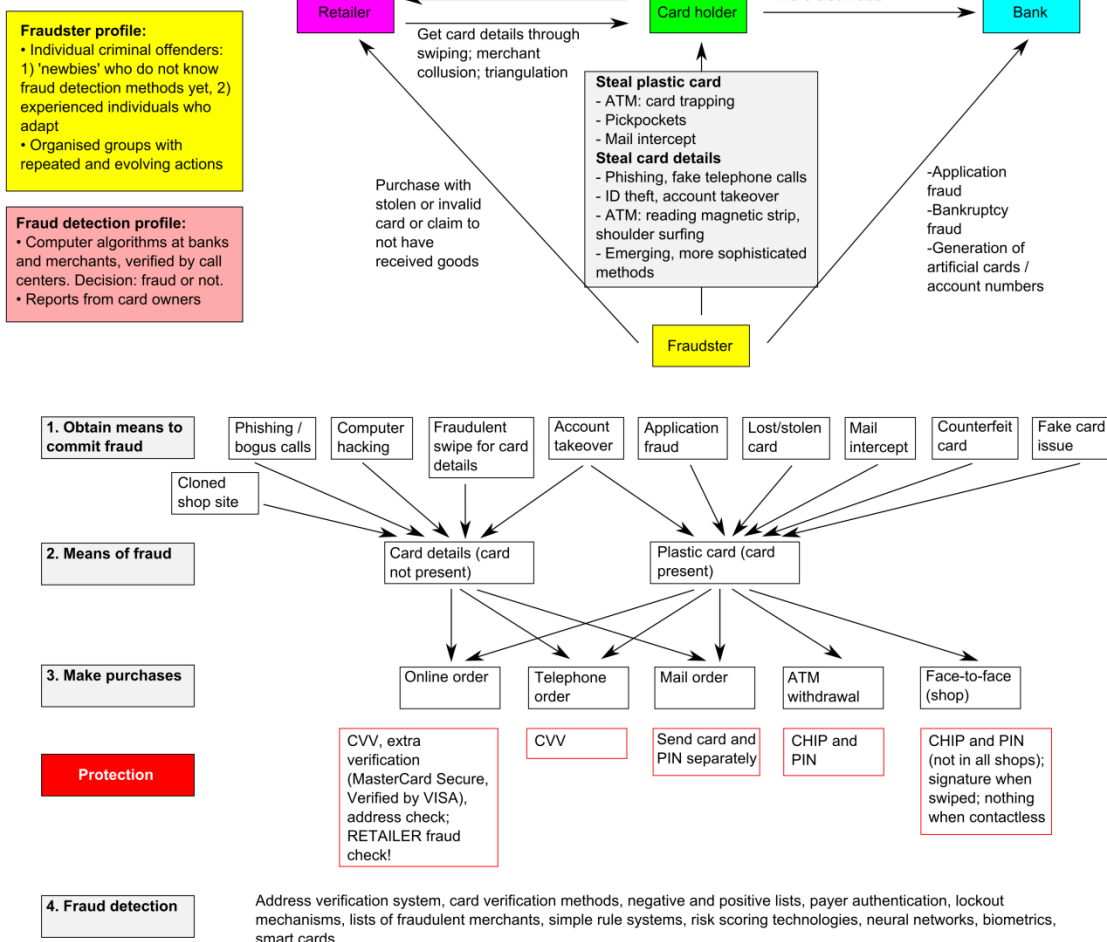
While the percentage of credit card transactions undergoing human review amongst average-sized retailers in the US is estimated at approximately 25% (CyberSource, 2014), this figure is expected to be substantially lower at the banking level due to the high number of transactions per day. If the bank fails to identify fraud, it relies on the customer to spot an illegitimate transaction (Krivko, 2010). In some instances, banks may also have an intermittent automatic step in which the user is asked to pass further authentication steps such as providing personal information (Pandey, 2010).

Fraud can be subdivided into first-party fraud (performed by a consumer) and third-party fraud (performed by a criminal using someone else’s details) (Experian, 2014). In terms of investigating fraud, approaches are either at the transaction level or at the account level. A transaction classification system (e.g., defined in terms of a set of ‘rules’ which are proprietary to that bank) will raise alerts on individual transactions which are tagged as suspicious (Brause et al., 1999; Dorronsoro et al., 1997; Krivko, 2010). Typically, the model will compare transactions against a notion of ‘normal’ and flag anything which lies outside this notion of normal. Figure 21 summarises our understanding of this process. As well as considering anomalous transactions, rules could describe transaction behavior for a given account over a period of time. In this way, ‘fraud’ could be

indicated by a change in behavior. In both cases, given the volume of transactions, it is essential for banks to use automated systems to apply the rules in order to produce timely detection of potential fraud. Once a transaction has been flagged as fraudulent, it might be necessary for human intervention to confirm or to determine what action to take. Thus, human analysts play several roles in the credit card fraud analysis process but it is not clear which of the roles are common to all banks. Nor is it clear how analysts perform their work, and there are few, if any, published accounts of credit card fraud analysis. The most comprehensive work has been carried out in insurance fraud, where researchers spent months understanding analyst behaviour using an ethnographic approach (Ormerod et al., 2003, Ormerod et al., 2012).

In credit card fraud, humans perform the final review stage based on the information filtered out by an automatic system. In some instances, the review could involve direct contact with the cardholder, in which the caller follows a pre-defined script and protocols that do not involve investigative capabilities. In this case, one might anticipate the caller to have access to account details for that specific card holder, such as the statement of transactions on that card over a period of time, together with some indication as to why that card is deemed suspicious, such as a score that was output from the automated system. In some cases, the review could involve the analysis of a set of transactions on an account, with the analyst seeking to decide whether or not to block the card. In this instance, the analyst would take a more forensic approach to the behaviour of the card holder and the use of the card, relative to some concept of 'normal' activity. In some cases, analysis could be at the level of transactions, in which the analyst seeks to identify patterns of criminal activity involving several cards. In this instance, the analysis would be looking for evidence of stolen details or unusual patterns of use of several cards, say multiple transactions in different locations within a short timeframe. In other cases, the role of the human would be to define, develop and refine the 'rules' that the automated systems use. Other functions that human operators can take on in the fraud detection process have been suggested as the following: risk rank alerts and prioritisation, fast closure of low risk cases, investigation and documentation of false positives and incorporation in future rules, understand how fraud is captured, training session and rotation for staff to understand all processes involved in fraud detection, as well as creating good quality control and review processes (Pandey, 2010). There also have been attempts to identify risk profiles / fraud likelihood and patterns (Sánchez et al., 2009, Jha and Westland, 2013), although some of the conclusions drawn from the evidence appear questionable and may not translate between different countries or cultures. In Insurance Fraud, Human assessors can work in 'Special Investigation Units' (SIUs) (Viaene et al., 2002, Dionne et al., 2003). Their role is to 'red flag' suspicious claims based on the above informal training in feature recognition (Viaene et al., 2002, Dionne et al., 2003, Morley et al., 2006).

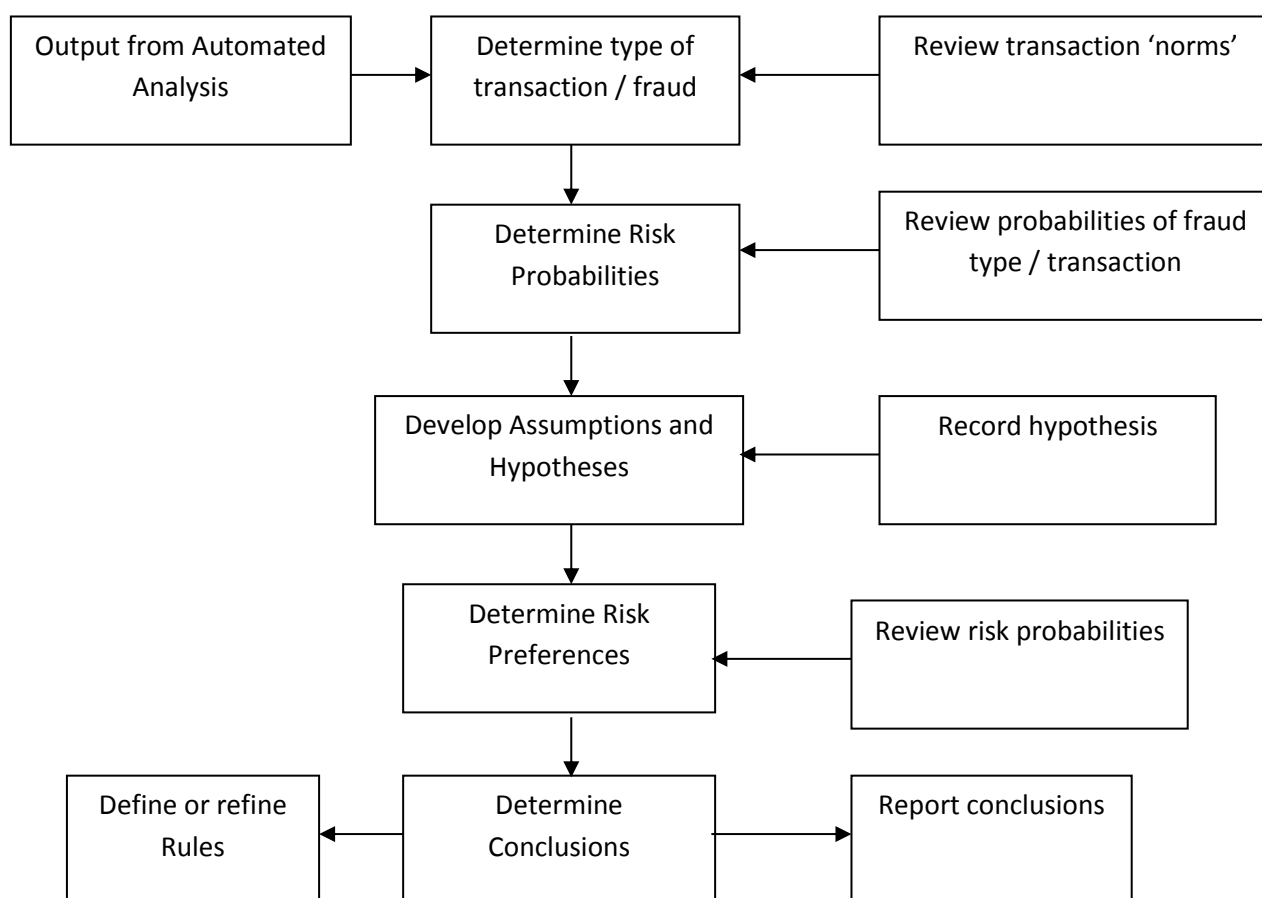
## Credit Card Fraud



	Fraudster spending profile	Detection: cardholder	Detection: bank
<b>Medium</b>			
Counterfeit card	'Slipping in' occasional, non-suspicious looking purchases of lower value.	Slow, cardholder notices illegitimate purchases on statements when looking carefully.	Slow to undetectable unless purchases deviate from customer profile.
	Large purchases, potentially several in a row up to credit limit.	Medium, cardholder notices substantial difference in account balance.	Medium to fast, algorithm detect abnormality in spending behaviour.
Mail intercept	Purchases are made while missing card has not been noticed.	Medium, cardholder notices that card did not arrive.	Medium, 100% relies of report from card owner.
Stolen card	Purchases are made fast due to risk of stolen card being reported (~1 day)	Fast, cardholder notices missing card.	Medium to fast depending on spending pattern and card owner alert.
Stolen card details	Paired with assault (PIN) or trapped card: fast purchases due to short reporting window	Immediate (assault) or near-immediate (trapped card); cardholder reports to police/issuer.	Fast following owner alert or detection of unusual spending pattern.
	Details taken without notice: potential waiting period followed by single or multiple purchases, varying patterns	Slow to medium, cardholder notices illegitimate purchases on statements.	Medium to fast depending on spending pattern and card owner alert.
Bankruptcy fraud	New customer spends full allowance with intention to never pay back.	N/A	Medium, relies on databased of known fraudsters and background checks at application stage.
Fake card generation	Likely small test amount followed by large amount after card details work.	No 'real' card holder or real person following ID theft. In case of ID theft, slow in finding out.	Slow.
Application fraud	Varies, can be a fast spent due to fear of detection or slow flying under radar.	No 'real' card holder or real person following ID theft. In case of ID theft, slow in finding out.	Slow, unless bank detects fraud at application stage based on database/background checks.

Figure 21: Opportunities for Fraud – a summary from the literature

Johnson et al. (2001) describe a process in which ‘cues’ (drawn from financial statements) lead to a comparison of these cues with the analyst’s expectations. This requires the analyst to have some sense that the ‘cues’ themselves are noteworthy and that the analyst has a model, or set of expectations, of what would constitute ‘normal’ in this activity. Any ‘inconsistencies’ are then explained through hypotheses that the analyst develops, and the hypotheses are tested through the collection of additional evidence. This process is similar to the Compliance evaluation that we have observed in a bank involved in share trading. Johnson et al. (2001) conclude their model with a ‘global assessment’ which we suggest could lead to the development of rules which could be given to the automated reasoning systems. In a review of applications of Visual Analytics to Financial Decision-making, Savikhin (2013) offered a three-stage model of the analyst’s decision process as: (1) retrieve and process information (from heterogenous sources); (2) developing subjective assumptions (from prior experience) of the likely cause of an activity and the likely outcome of an intervention; (3) select course of action, taking into account likelihood of success, constraints and benefits. He then proposes that each stage will involve particular types of activity and can be supported by particular forms of Visual Analytic. On the basis of these descriptions we offer an tentative description of the credit card fraud analyst’s decision process in figure 22.



**Figure 22: Initial Process Model of Credit Card Fraud Analysis**

## 8.2 Abstraction Hierarchy

In figure 23, we have used the phrase ‘effective management of credit card transactions’ as the Functional Purpose of the system. This implies that the purpose of the system as a whole is not to detect fraud, but rather that the system is geared towards managing the use of credit cards in transactions. This indicates that the detection of fraud is a subset of this broader purpose and that there might be potential for fraud detection to conflict with some of the priorities of the system.

Having defined a Functional Purpose, the Value and Priority Measures of the system (the second row of figure 22) represent those aspects of performance that the system could use to indicate how well it is performing. Through the literature review and initial interviews with bank staff involved in compliance and fraud detection, we defined the foci of the system in terms of the following aspects:

- To ensure minimal fraud in the system
- To endure minimal financial loss to any party in the system
- To protect the card holder
- To ensure maximal confidence of the customers in the credit card system
- To maintain positive reputation of credit card issuer, merchants, customers etc.
- To support the definition of patterns of fraudulent activity which can be used by machine learning (ML) algorithms
- To ensure that decisions (identifying fraudulent activity) are accurate, i.e., high hit rate and low false alarms
- To ensure that decisions (identifying fraudulent activity) are made in a timely manner, i.e., to limit financial risk associated with prolonged conduct of a fraud, or to ensure resolution of investigation leads to speedy restitution for stakeholders

In terms of potential for conflict or trade-off in these priorities, one might expect accurate and fast decisions to imply some form of trade-off, e.g., given sufficient time, it might be possible to have more accurate decisions.

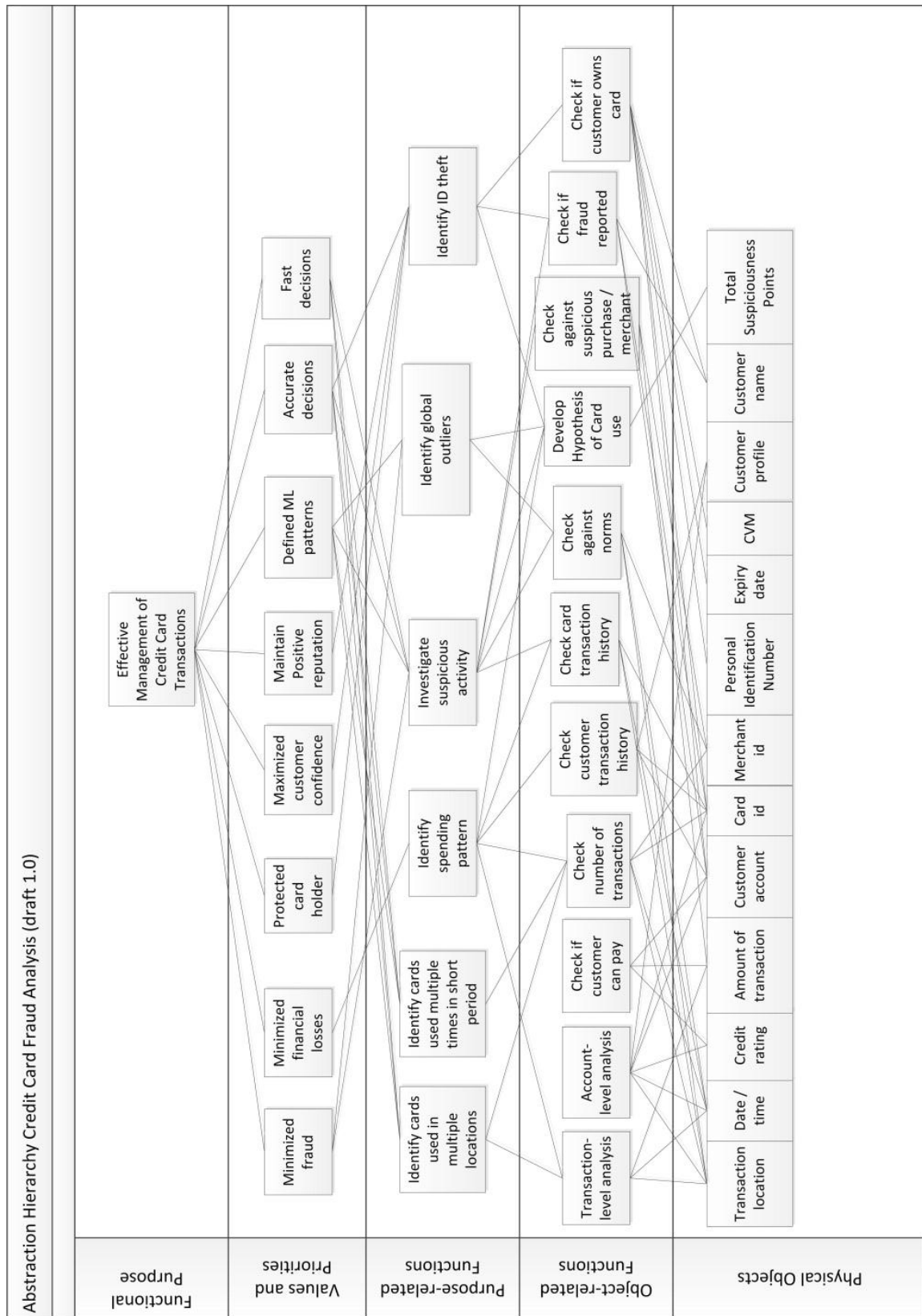


Figure 23: Abstraction Hierarchy for Credit Card Fraud Case Study

### 8.3 Social Organisation and Cooperation Analysis

D7.1 identified the following Stakeholders in the Credit Card Fraud Use Case:

- The acquirer (the acquiring bank) which holds the merchant's accounts
- The issuer (the issuing bank) which issued the card to the cardholder
- The processor "which serves as a bridge between the acquirer and the issuer"
- The cardholder
- The merchant

We assume that there are at least four types of people involved in credit card fraud analysis, and each type has different information requirements. These people are identified (in the SOCA, figure 24) are the cardholder, the merchant, the acquirer, the analyst (who is tasked with developing and implementing models for the system to apply), the issuer / card manager (who manages relations with the customer, perhaps making an initial call to check if the cardholder is aware of the activity which is being investigated), and the automated system(s) which monitor and analyse card use. We are aware that the names that we have used for these roles might differ from those used in industry, and that some of the roles (particularly fraud investigator and analyst) are likely to be performed by individuals in more than one organization, e.g., the merchant's bank, the cardholder's bank and the card issuer. As with the SOCA in the Road Traffic Management Use Case (figure 19) the point of this diagram is to illustrate possible relationships between different actors involved in the analysis activity. This highlights a potential need to better understand how information might be shared between actors or how Situation Awareness might vary between actors.

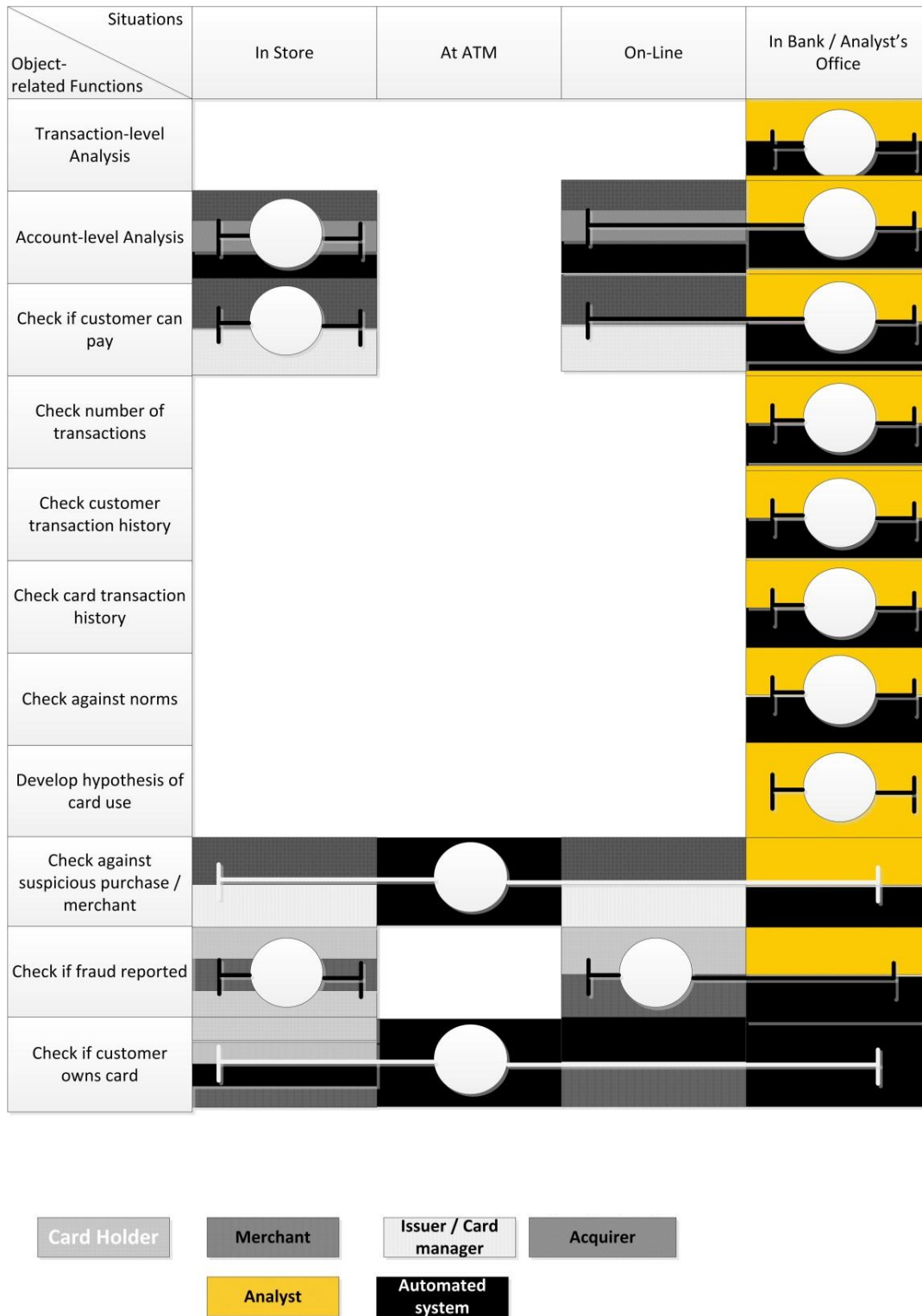


Figure 24: SOCA for Credit Card Fraud

## 8.4 Control Task Analysis ('decision ladder')

The initial description of fraud analysis that we have derived from our literature reviews, suggest a series of actions that the analyst will seek to perform. These are illustrated by figure 25, which is intended to be a generic description of how analysis *might* be performed. The key points to note here are that we suggest that there are various 'short-cuts' that the experienced analyst might seek to apply (indicated by dotted lines), perhaps in light of particular patterns of data or reports from previous analysis.

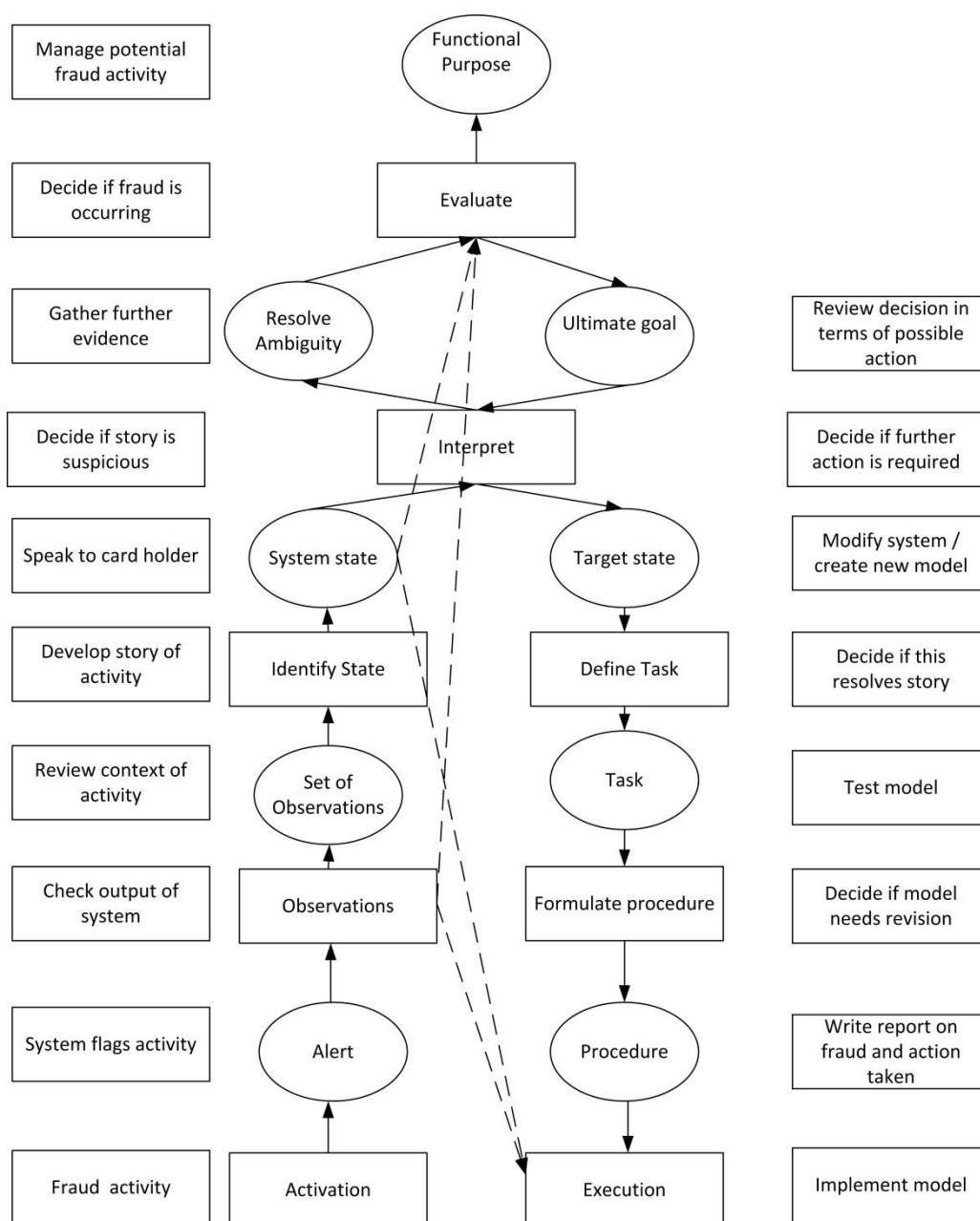
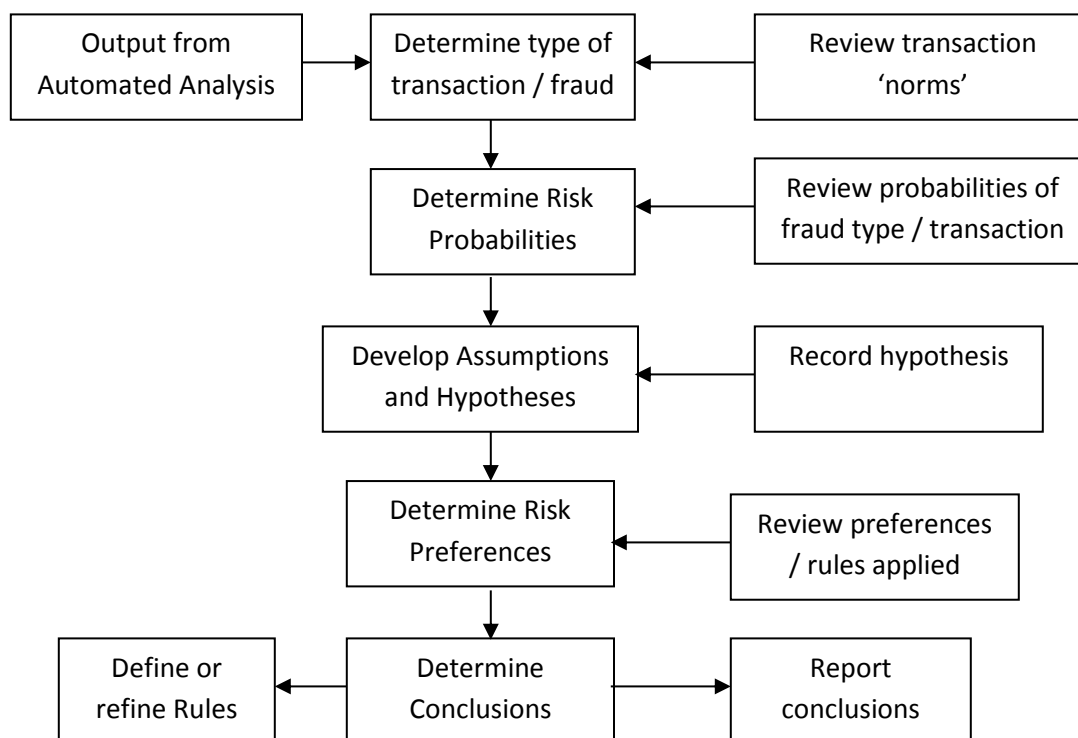


Figure 25: Decision Ladder for Credit Card Fraud Case Study

In order to develop the User Interface, we summarise figure 25 in terms of a particular strategy which reflects one way in which analysis could be performed. This strategy is illustrated by figure 26. We make no claims for the veracity of this strategy because we have not had the opportunity to validate this with Subject Matter Experts. However, this presents a 'best-guess' description of how analysis might be undertaken.



**Figure 26: Possible strategy for fraud analysis**

## 8.5 User Interface Concept for Credit Card Fraud Use Case

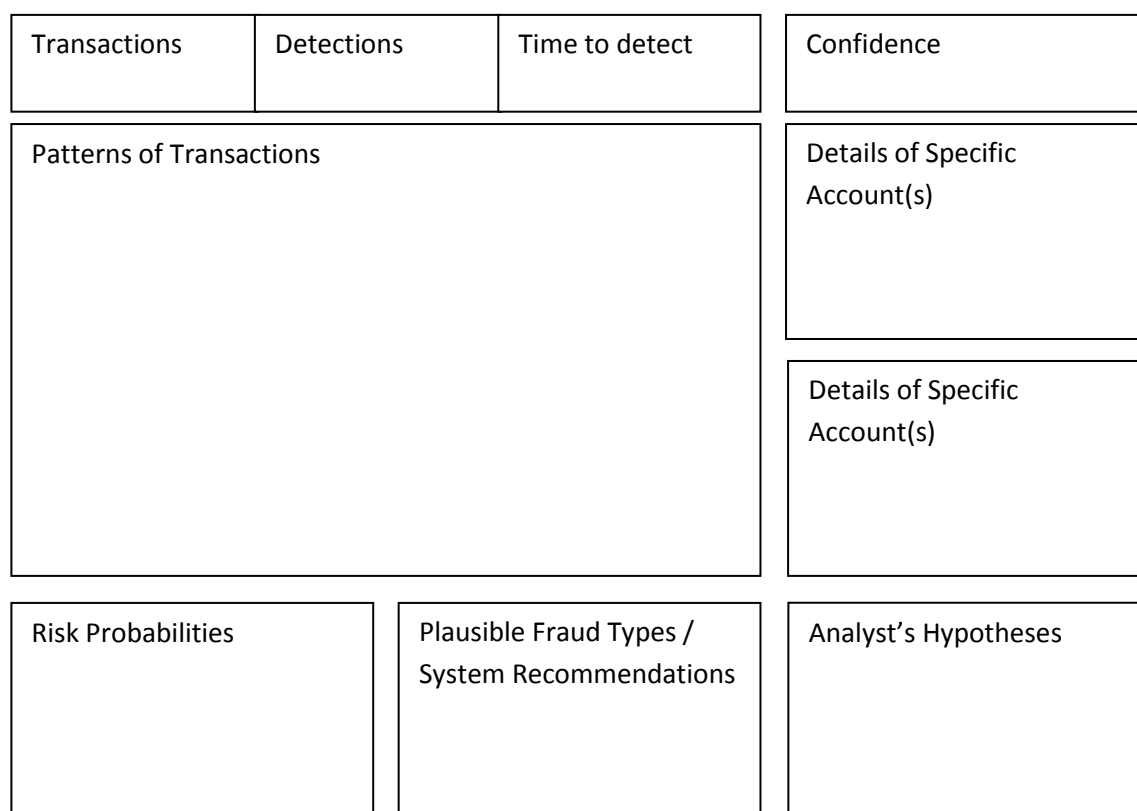
Mapping between entries for Values and Priorities from figure 23 allows table 4 to be developed. This implies key information that might need to be presented to the analyst.

	Fraud	Loss	Protect	Confidence	Reputation	Patterns	Accurate	Fast
Fraud	-	Increase loss		Reduce confidence	Adverse publicity	Improve knowledge	Confidence detection	Rapid detection
Loss		-		Reduce confidence	Adverse publicity			
Protect			-	Improve confidence				
Confidence				-	Recommend to friends	False alarms	False alarms	Limited activity
Reputation					-	Confidential	False alarms	
Patterns						-	Discriminability	Process time
Accurate							-	
Fast								-

Table 4: Relations between Values and Priorities for Credit Card Fraud Case Study

## 8.6 Sketch of Interface Concept

From table 4, and the decision ladder in figure 25, we propose a set of elements in the User Interface which will need to be presented to the analyst.



**Figure 27: initial sketch of credit card fraud interface**

## 8.7 Graphic Options for the Different Regions of the User Interface

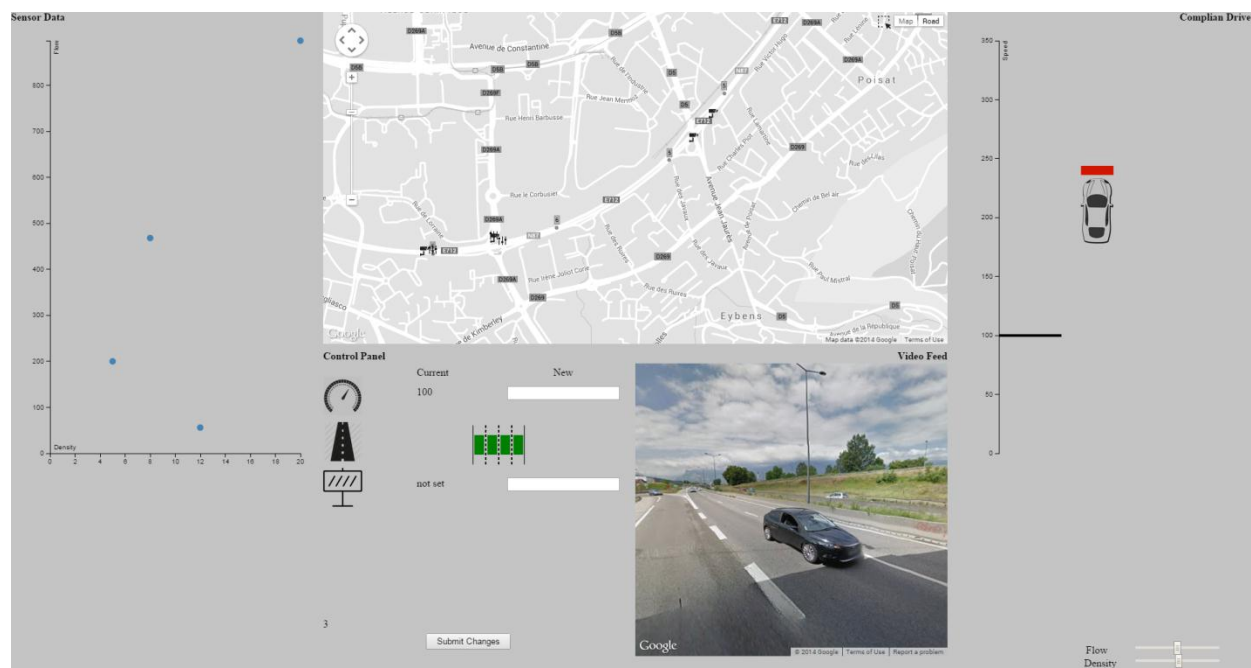
The top of the screen would present a 'dashboard' to the analyst, reflecting the values and priorities (from figure 23). Below this, the main panel would present 'patterns of transactions'. This would present a view of transactions, per unit time (say, in the past hour) which show 'norms' for specific regions (say in terms of average transaction value) and any transactions which violate 'rules'. For instance, partitioning the display by longitude and shading regions by transaction value, it is possible to highlight variation in transactions across the world at the current time. We might also adjust the width of the 'regions' to reflect the number of transactions being processed. This would show the busy parts of the world, in terms of transactions, at this time. It might also help the analyst to spot regions which seem disproportionately busy, e.g., because merchants in that region are processing high numbers of internet orders. The display might also link instances in which a single card is used for multiple transactions, or in multiple regions during that time period.

# 9 Fit with Requirements

## 9.1 Introduction

In this section, we compare our initial design concepts with the requirements outlined in deliverables 7.1 and 8.1. The aim is not to validate the designs so much as to provide an initial 'sanity' check of these concepts in order to ensure that these design concepts align with the initial set of requirements.

## 9.2 Interface Designs for Road Traffic Management Use Case



**Figure 28: SPEEDD User Interface for Road Traffic Management Use Case v1.0**

## 9.3 Requirements for Traffic Management Use Case

Deliverable 8.1 identified several stakeholders in the traffic management use case, i.e., not only the control room staff but also emergency services personnel, traffic management or road maintenance staff, road users etc. An interesting question for the development of a socio-technical view of the system, therefore, lies in identifying the relationships between, and information requirements of, these different stakeholders.

In terms of user requirements, deliverable 8.1 highlighted the following:

- Allow Operator to clarify and query notification
- Allow Operator to draw on experience of previous incidents
- Allow Operator to select Incident Type option
- Allow Operator to draw on several sources of information to confirm location

- Support Operator Situation Awareness
  - Of current incident
  - Of future conditions
- Allow Operator selection of response
- Allow Operator to challenge or negotiate response
- Support Operators in gaining Global and Local Situation Awareness of road user behaviour
- Supporting Operators in determining that the incident has no unexpected consequences

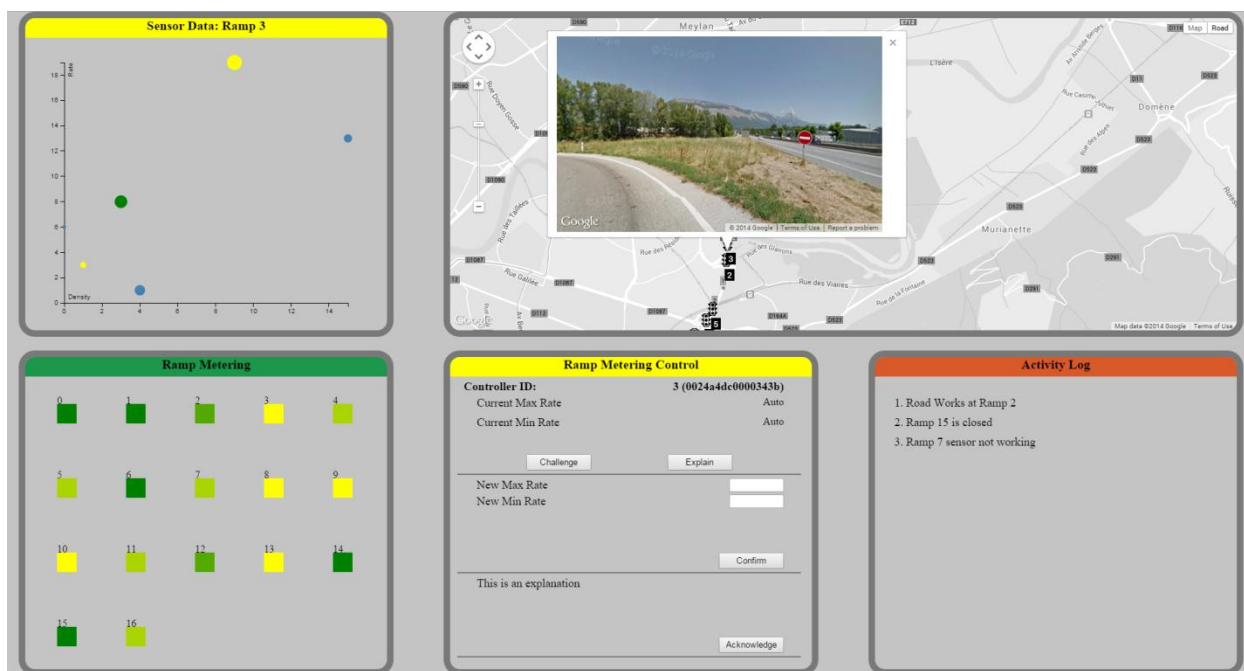
## 9.4 User Interface for First Prototype Trials

While figure 28 presents the User Interface derived from our analysis of operator activity and information requirements, the first prototype for the SPEEDD demonstration focuses on a specific subset of this use case. In the demonstration, the operator needs to monitor ramp metering and to accept (or challenge) the automated systems control of ramps around the city. The User Interface for this task is presented in figures 29 and 30. In addition to the User Interface supporting the operator task, it also provides an opportunity for controlled experiments which will allow testing of the decision models and the eye-tracking metrics. For these experiments, participants will be presented with a series of ramp metering scenarios and will need to respond as quickly as possible to the automated system's recommendations. Using reaction time, it is possible to distinguish between different levels of performance, e.g., when all windows in the display contain corresponding information versus situations when information in one window or multiple windows conflicts with the others. In addition to reaction time, the experiments will also employ eye-tracking to ascertain which information sources participants tend to focus on under the different conditions.



Figure 29: User Interface for first SPEEDD demonstration

The User Interface for the ramp metering task (figure 29) shows the operator which ramp is being controlled (in terms of the graph on the top left of the screen), the fact that the map centres on this specific ramp, and the text in the 'ramp metering control' box. In the operator wishes to check the output of the CCTV for this ramp, then clicking on the camera icon (on the map) will cause a video window to pop up (figure 30). If the operator wishes to know more about the rationale for a specific ramp metering setting, then the 'Explain' button (in the 'ramp metering control' box) will cause additional information to be presented (figure 30).



**Figure 30: Selecting a CCTV view or selecting Explain or Challenge on the User Interface**

If the operator feels that a setting is not appropriate, then the ramp being controlled can be selected and the decision can be queried, using the <challenge> button. This then allows the operator to either <reset parameters> or engage in some other form of intervention (figure 30).

While this is a simple example, it highlights how the User Interface can be used to indicate the constraints under which the operator can act (where 'constraint' is seen as a positive means of shaping operator activity and indicating which function the operator is expected to perform).

## 9.5 Requirements for the Credit Card Fraud Use Case

In previous correspondence within the consortium, it was suggested that there is a need to support decision-making (by analysts) through "explaining the results of the models in a human-friendly way", "reducing false alarms to reduce alert fatigue", and, in terms of Visual Analytics, the "ability to move from explanation visuals (what is happening now) to exploration visuals (why something happened)", and "dealing with time-changing results and dealing with many dimensions and variables."

## 9.6 Interface Designs for the Credit Card Fraud Use Case

The interface design for the Credit Card Fraud use case is less well developed than those for the Road Traffic Management use case. In part this reflects the challenge of gaining understanding of analyst activity, and in part this reflects the development of the Fraud use case for SPEEDD (particularly in terms of the data which can be fed into the SPEEDD architecture). Consequently, the User Interface design currently reflects the sketch presented in figure 27. The layout (figure 32) is based on the following principles:

- Boxes in the top ribbon will contain global information (some digested transaction statistics over a period of time).
- Physical locations will be mapped to the treemap, colour and size will be determined by transaction statistics in the region.
- On the right of the treemap, boxes with headings “Selection Info Type” will contain specific information about any selected account, merchant, cardholder, ATM, etc.
- CEP outputs regarding the selected transaction will be displayed under “Recommendations”
- “Analysts’ Workspace” will contain tools for submitting data queries
- Under “Notebook”, the analysts will be able to log hypotheses and decisions regarding the investigations process
- “Flagged Transactions” will be the list of suspicious transactions

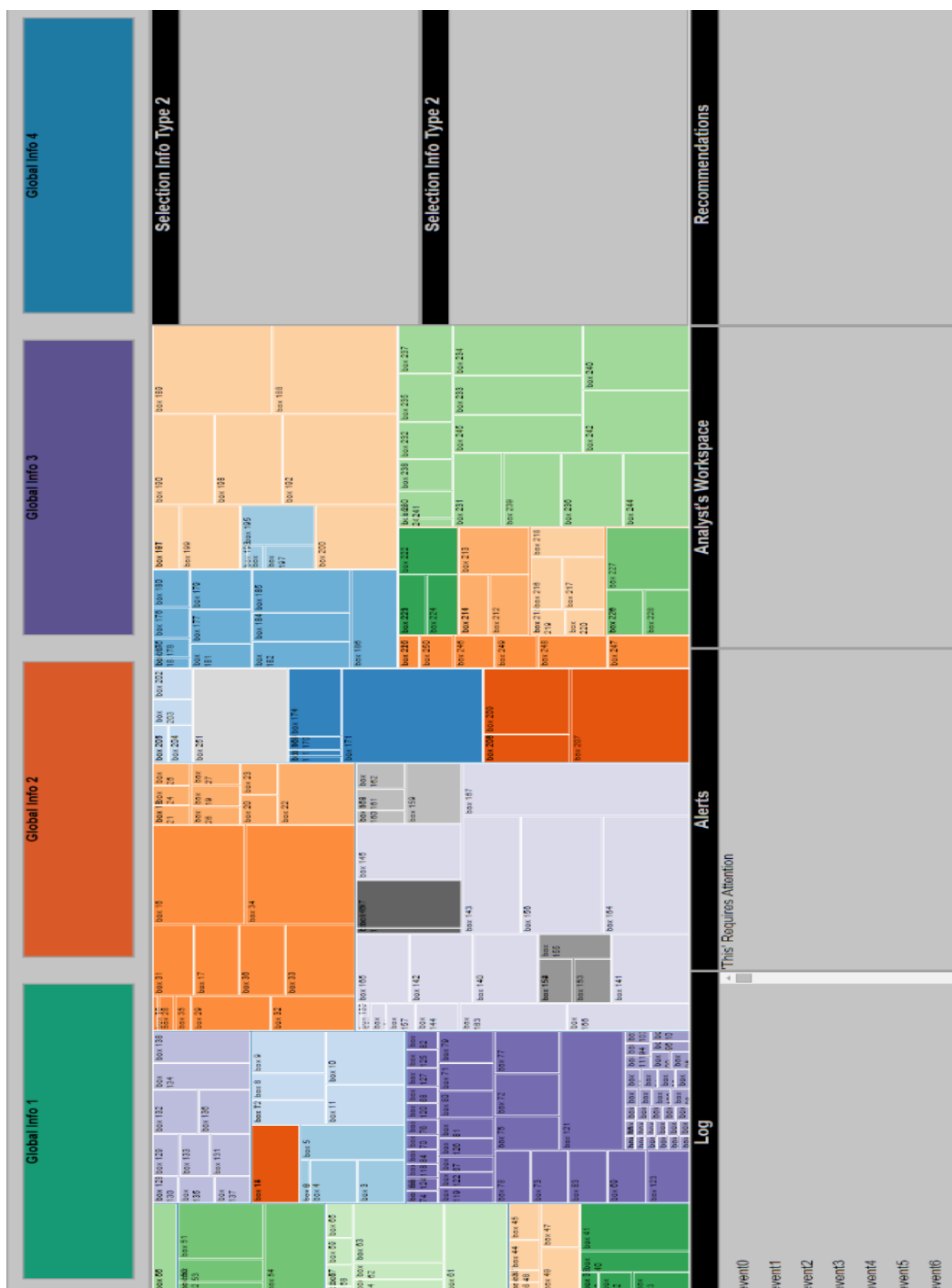


Figure 31: User Interface Design for Credit Card Fraud use case.

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