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Novice to Expert Real-time Knowledge Transition in the Context of X-ray Airport Security

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Abstract: The X-ray screening task is one of the most critical parts of the security processes at airports. Improving this task is related to the knowledge of the screeners directly. This paper describes an investigation on real-time knowledge transition during security screeners' performance of the x-ray screening task at the airports. Using eye-tracking glasses, behaviours of 10 x-ray screeners, including novices and experts, were observed during the regular screening task. Results show that there is a direct relationship between expertise and the amount of knowledge gained by and transferred to security employees. Experts demonstrated a superior ability to transfer knowledge to other security employees than novices.
Given the evidence of real-time knowledge transition that occurs during the screening task, this research proposed an intelligent interface to better facilitate the process of real-time knowledge transition. The interface should assist novices' learning process and their faster transition to becoming experts.

Keywords: novice to expert knowledge transition; x-ray screening task; expertise; intelligent interfaces

1. Introduction

The airport is a context in which many complex tasks are occurring. Security of airports is an issue that should be improved in the airports of the future. Security screening processes and security screeners are playing significant roles there. The high number of passengers and people in this environment make it challenging to manage security issues. In order to address this issue, a wide range of security measures have been applied since the 1960s (Figure 1).

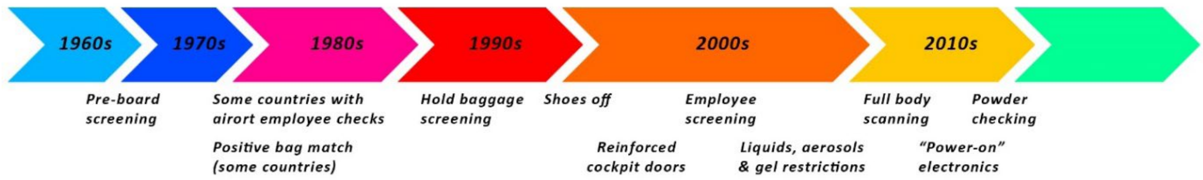

Figure 1 Security measures (Nugraha & Choi, 2016; Wong & Brooks, 2015)

Despite increasing security measures, the Federal Aviation Administration of America has found that more than 20% of prohibited objects were being missed by security screeners in 2000. Another compelling argument indicates that weak security controls result in the allowance of weapons and other prohibited objects (Seidenstat, 2004). Although security technologies have several direct effects on airports' security, the environment and training of operators play a critical role to increase the efficiency of the process (Harris, 2002). Today, it is inevitable that many of the security technologies should be operated by humans. It is accepted that security operators are an essential part of the airport security system, who provide the air travelling security (Swann, 2016). It is obvious that technologies assist human operators during the screening task, but using these devices requires a high level of knowledge. Achieving the highest performance from up-to-date and advanced security screening technologies is impossible without the human operators (Graves et al., 2011).They make the ultimate and the most important decisions during the screening process (Graves et al., 2011; Swann, 2016).

Knowledge and experience of screeners are known as vital factors which can affect the process of security screening. To successfully detect threat objects, it is essential for the screeners to possess specific knowledge of different objects and their appearance when represented by X-ray devices (Schwaninger et al., 2005). Studies indicate that experts possess superior visual knowledge, which improves the speed and accuracy of their threat detection compared to novices (Liu & Gale, 2011; Schwaninger et al., 2005; Swann et al., 2014). Graves et al. (2011) asserted that novice screeners are exposed to missing prohibited objects. These mistakes occur because of the mismatch between threats and harmless objects (Schwaninger et al., 2004). This happens due to using a lower amount of knowledge than the experts and thus decreases their effectiveness (Cokely et al., 2018). Although human errors are unavoidable in this context, high numbers of mistakes must be avoided (Babu et al., 2006). As screeners' performance is correlated with their knowledge, interface and equipment, security interfaces can assist the screeners, but extensive training and experience are required to achieve high performance (Cockburn et al., 2015). Gaining this experience sometime takes a long period of time.

Most of the time, novices are faced with a large amount of information which makes it hard for them to make correct decisions. They often experience difficulty because of their inadequate attention, as they are not able to interpret the required information and choose among different pieces of perceived data. It is also probable that novices use irrelevant information for a specific task instead of the key required knowledge (Endsley, 2018). The problems might exist during an interaction with unfamiliar devices. Failure of x-ray screeners in recognising threat objects reveals the importance of human operators' role even if the most expensive and up-to-date equipment is in use (Schwaninger, 2011b). The performance of expert operators also can diminish to novices when they use unknown equipment. It is argued that the interfaces are designed for experts which enable them to achieve a high level of performance but only after extensive training (Cockburn et al., 2015). Even when the equipment is used correctly, it is difficult to recognise the prohibited objects using security screening devices, such as x-ray, due to image-based factors such as unusual viewpoint, superposition effects, and bag complexity (Schwaninger, 2011a, 2011b). This presence of image-based factors can lead to further errors in the interpretation of threat objects.

The complexity of the screening task for novice screeners shows the importance of focusing on the learning approaches. By improving their knowledge and experience, they may make fewer mistakes, especially in uncertain and complex situations. Therefore, it is important to understand how the learning that facilitates novice to expert knowledge transition process occurs. The significance of training to expertise development is overviewed in Section 2.

2. Expertise

'Expertise' is defined as 'a high level of knowledge or skills' (Cambridge, 2018). The advanced ability and performance that enables someone to master a set of specific skills in order to surpass others, can be defined as expertise (Ericsson, 2014; Winegard et al., 2018). Bilalić and Campitelli (2018) believe that experts have a wider point of view than novices, which facilitates predicting results as well as improving and adapting themselves, in unpredictable situations. In complicated situations, experts demonstrate higher performance in thinking and identifying the best solution compared to novices (Kahneman & Klein, 2009).

A key aspect of expertise is knowledge development. Knowledge is a dynamic mechanism which can be developed by experiential learning (Orlikowski, 2002). It can be classified into two categories, tacit and explicit knowledge. Explicit or codified knowledge can be transmitted in formal and systematic language, which does not rely on experiencing of knowledge (Howells, 2002). So, the process of codifying and transferring explicit knowledge can be performed using systematic language tools, such as written materials (O'Dwyer et al., 2019). In comparison, tacit knowledge is acquired from experience in the environments where it will be needed later (Horvath et al., 1999; Sternberg, 2003). It is hard for users to quantify the exact content of their tacit knowledge and, therefore, this type of knowledge is hard to articulate (Collins, 2010; Grasseni, 2008; Horvath et al., 1999; Howells, 2002; Pérez-Luño et al., 2019), which can result in difficulty codifying and transferring it (O'Dwyer et al., 2019).Tacit knowledge is necessary for expertise development due to its critical role for intelligent behaviour in practical situations (Horvath et al., 1999). It is believed that tacit knowledge can be understood by differences between problem-solving efficiency of users, before and after of education (Ackerman & Lakin, 2018). It plays a critical role in predicting the competent performance in real practical situations (Sternberg et al., 1993), and is considered as one of the influential but not sufficient factors for efficient performance (Horvath et al., 1999). This shows the importance of training and skilled practice by means of everyday experience in each field of expertise.

Skilled practice is one of the influential factors in gaining knowledge and experience. The significance of training to develop expertise is undeniable (Baker et al., 2018). It is almost impossible to become an expert in any specific domain without concentrated training for thousands of hours (Cokely et al., 2018; Ericsson, 2018; Ericsson, Prietula, & Cokely, 2007). When these practice efforts happen carefully and consistently, changes in knowledge, abilities and skills will appear (Cokely et al., 2018). Users' skills can be developed by training and experience when combined with guidance of professionals (Grasseni, 2008).

Experts are often able to overcome many difficulties, such as decision making in complex tasks and uncertain environments, which they might be faced with (Ericsson & Towne, 2010). Their high level of knowledge, when combined with their experiences, demonstrates their ability to solve complex problems (Chi, 2006; Popovic, 2000). The performance of experts is superior to that of novices as they are able to use and encode the required information in a shorter period of time (Cokely et al., 2018; Moxley et al., 2012). Furthermore, novices use lower amounts of information than those of experts', which makes them less effective in complex tasks (Cokely et al., 2018). Cokely et al. (2018) believed experts can use a wider range of solutions when confronting a complex problem compared to those of inexperienced users. This can result in low efficiency of novices. For example, in security screening, task complexity can deteriorate a screeners' efficiency and accuracy (Swann et al., 2014). Hall (2002) argued that the complexity of the tasks in complex systems can increase the probability of failure. Given the complexity of the airport screening task, the effective transfer of knowledge to x-ray screeners is critical for the development of skilled expertise within this domain.

In order to understand how knowledge transition occurs in the process of x-ray screening at airports, it is essential to investigate knowledge utilisation and development in this context. To this end, it is necessary to focus on the behaviours of screeners and the learning approaches they use to become expert. Technologies can assist screeners to achieve this goal. Interfaces can act as a bridge between human and computers to facilitate the knowledge-based processes.

3. Intelligent interface, the bridge to knowledge transition

Intelligence can be defined as the capability of learning and understanding different phenomenon to make decisions and solve problems (Negnevitsky, 2005). The intriguing viewpoint of Artificial Intelligence (AI) indicates that computers can be intelligent. This intelligence enables computers to make decisions, learn, plan, and analyse information (Phillips-Wren, 2012), which provide the opportunity for machines to find the most appropriate results (Buchanan et al., 2018).

One area of research in AI is focusing on the systems which are related to human knowledge.

The AI enables computers to learn and to analyse an enormous amount of information as well as to recognise patterns for increasing efficiency beyond the human ability (Abu-Mostafa, 2012; Harari, 2017). Focusing on human expertise provides the possibility to design intelligent systems which are able to explain the human reasoning process (Buchanan et al., 2018). It is worthwhile for a machine to learn about each user and modify its functions to users (Jameson, 2008). To this end, a wide range of research has been conducted based on developing computer systems and interfaces to recognise human states and behaviours (Liao et al., 2006; Nasoz & Bayburt, 2009; Nasoz et al., 2010; Scheirer et al., 2002). Suchman (2006) argued that machines can assess situated actions by prediction of a user's actions and finding out the results of the actions taken. When a user performs an action, its effects can be mapped to the desired plan, which can result in an appropriate response by the system. For example, an intelligent machine can learn from the experts' actions when facing uncertain situations, then predict similar situations and support the novice users by representing prompts or some probable solutions.

This research focuses on the need to find an appropriate solution to transfer knowledge and experience from expert to novice x-ray screeners at an airport. The information and advice provided to users on how to use applications or perform a task is a challenge of an interface design (Jameson, 2008). Therefore, AI and its related tools can facilitate this process. Numerous investigations exist on how to design interfaces for both the novices and experts; however, designing an interface that is able to make the transition from novices to experts is still not developed (Cockburn et al., 2015). Using the results of this research, an intelligent (collaborative) interface can be proposed to help the novice x-ray screeners to perform similar to experts and to make a quick novice to expert transition.

4. Method

A reasonable amount of research has been conducted on the factors effective for developing the security screening process at airports (Graves et al., 2011; Swann, 2016; Swann et al., 2019; Swann et al., 2015). However, the knowledge transition from novice to expert during performing the real task has not been well investigated. This research addresses the following research question:

Research Question: What are the real-time learning approaches that could facilitate the novice to expert x-ray security screeners' transition?

Therefore, this research aims to find out the importance of real-time knowledge transition in the context of airport security. To do this, ten x-ray security screeners were observed while performing the x-ray screening task under normal conditions at the departure's security checkpoint of an International Airport. Participants were selected based on their experience. Five novice screeners were observed during this study who have the screening experience equal to 1 to 12 months. Five experts also participated in this research who have the screening experience between 36 and 108 months.

The duration of observations was between 10 to 20 minutes. Participants were asked to perform their normal screening task using visual stimuli consisting of x-ray images of real passengers' carry-on baggage. The participants were asked to wear Tobii eye-tracking glasses during the observation sessions (Tobii AB, 2014). Tobii eye-tracking glasses collected eye movement data, recorded video from the observers' visual perspective, and recorded audio of their verbal interactions. Eye movement data, in the form of saccades and fixations, was captured as an overlay on the recording video. This data facilitated the analysis of different actions and the knowledge of participants during the screening task.

5. Analysis

Video and verbal recorded data collected using Tobii eye-tracking glasses were coded in Noldus Observer XT v14 (Observer, 2013). A coding scheme, consisting of key behaviours and knowledge, was developed to analyse the data. The coding scheme identifies twelve behaviour categories and four knowledge categories. Behaviour categories include all the screeners' activities during the screening task (Table 1). The coding scheme is based on previous research conducted analysing activities and knowledge in airport security screening (Swann, 2016), and has been modified to analyse knowledge transition.

Four types of knowledge derived from the literature were included in the coding scheme (Table 2). In the analysis, each knowledge type was coded based on whether it was used by screeners, gained by screeners, gained by searchers, and if there was evidence of it being deficient knowledge. Each of these distinctions describes different applications of knowledge during the screening process.

Table 1 Behaviour categories

Behaviours	Description
Search	Visual interaction with stimuli displayed on the screen for the purpose of finding threats. Characterised by visual scanning and attention that was distributed to a number of areas within the visual stimuli.
Examine	Visual interaction with stimuli displayed on the screen for the purpose of inspecting the nature and quality of objects or areas of interest. Characterised by attention and focus on a specific object or area within the visual stimuli.
IEFs or Zoom	Interaction with stimuli displayed on the screen using Image Enhancement Functions (IEF) or zooming in and out the display for the purpose of better clarity in some areas of interest.
Object Glance	A quick look at the carry-on baggage.
Object Touch	Touching the carry-on baggage.
Object Manual Search	Manual search the baggage by the screener for the purpose of finding the threat which observed on the screen.
Ask Questions	Asking questions from searchers about the process or the probable threat.
Discuss	Discussing with other searchers for the purpose of solving a problem in finding a threat which was displayed on the screen.
Request Removal or Manual Search	Asking searchers to manual search the baggage or removing the threats which were displayed on the screen.
Request Re-run	Making a request for re-run the objects for the purpose of implementing X-ray in another angle to have better clarity.
Talking with Passengers	Talking with passengers with the purpose of finding out what they are carrying or informing them about the process of screening.
Downtime	Activities that are performed while not actively screening. For example, waiting for the machine to resume or socialising.

Table 2 Knowledge types

Knowledge Modifiers	Descriptions
Perceptual	Explicit knowledge about objects and concepts (Millar, 2000).
Procedural	Knowledge of actions and processes in a specific domain (De Jong & Ferguson-Hessler, 1996).
Situational	Knowledge of problem situations or knowledge of when and where to access some specific facts (De Jong & Ferguson-Hessler, 1996; Popovic, 2003).
Strategic	Knowledge used during problem solving and knowledge acquisition processes (De Jong & Ferguson-Hessler, 1996; Popovic, 2003).

6. Results

The analysis was performed on the data gathered during observations on five novice and five expert x-ray screeners at the airport. The results focused on different types of knowledge applied during the twelve types of behaviour.

Collected data has been analysed during problem-solving phases. Problem-solving phases are comprised of activity used to support search and decision making. This includes the examination of unknown objects as well as interactions with other staff and the interface functions to gain more information (Swann et al., 2019). All the behaviours and knowledge during the problem-solving process may be interspersed with each other while search and downtime (periods of inactivity) are usually performed as isolated activity (Figure 2).

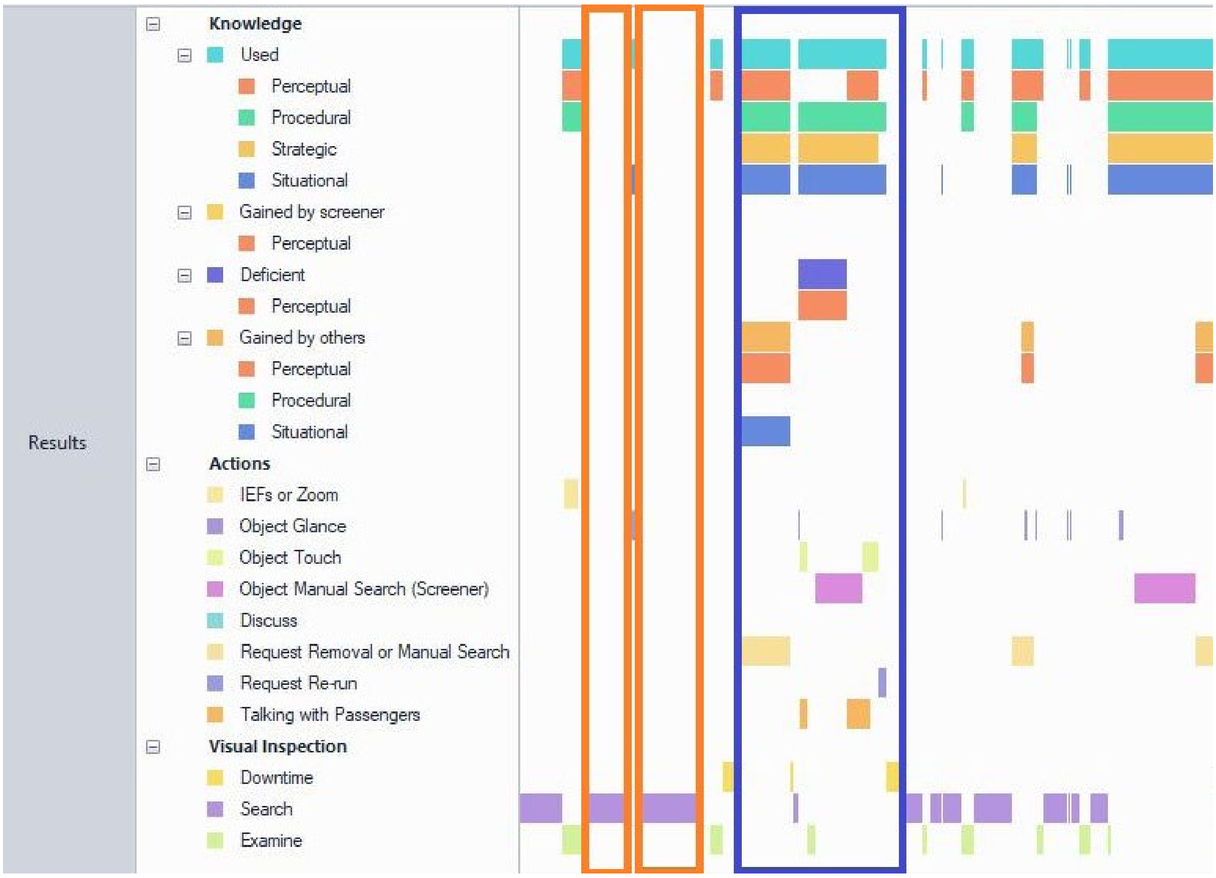

Figure 2 Participants behaviours and their knowledge application during different activities. The orange box shows isolated activities which are not interspersed with other activities or knowledge. The blue box shows problem-solving activities and application of knowledge that may happen simultaneously.

Different types of knowledge have been coded during the screening task for both the novices and experts. Collected data has been analysed based on the total problem-solving time (time of all the activities excluding search and downtime) and knowledge application. Therefore, the reported percentages express the average percentage of time each action or knowledge was used during problem-solving activity. The findings focus on the knowledge that can be gained by the screeners and the knowledge screeners transfer to the searchers, the security employees who performs baggage manual search, both during the screening task. Here, a searcher is a security employee who performs baggage manual search and other actions at the instruction of the x-ray screener.

Data reveals that during problem-solving phases, novices gained perceptual, procedural, situational and strategic knowledge, whereas experts only gained perceptual and situational knowledge. The highest amount of knowledge gained by the novice screeners is allocated to situational knowledge, which occurred during 4.10% of problem-solving activity. It was followed by perceptual knowledge, which was 3.12%. The results show lower percentages for these two categories for the expert screeners which were 1.04% and 2.14% respectively. Also, novices gained 0.75% of procedural and 0.32% of strategic knowledge when experts gained none of these types of knowledge during problem-solving phases (Figure 3).

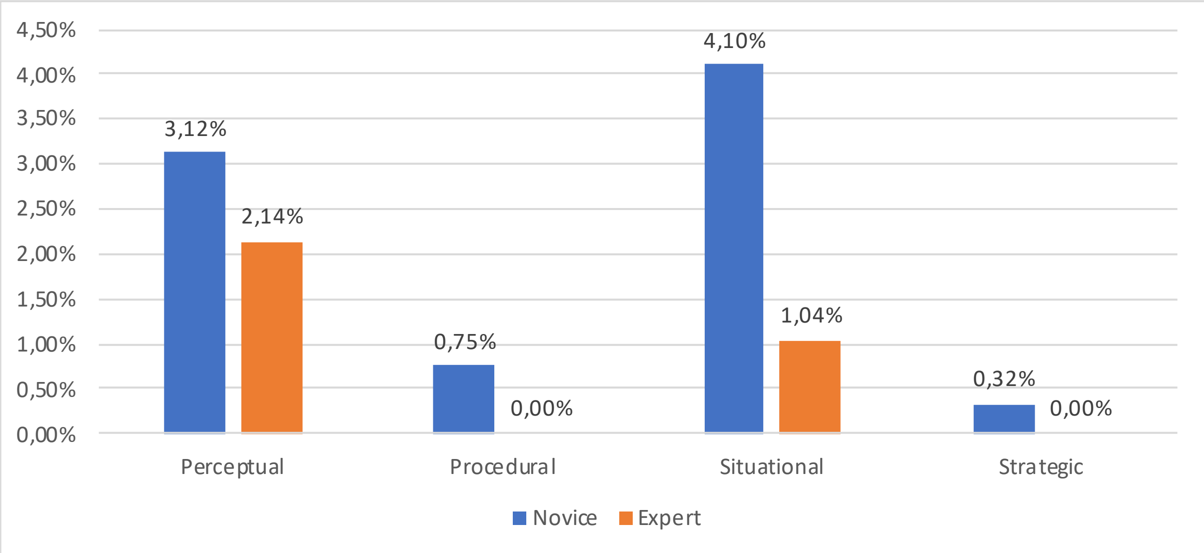

Figure 3 Knowledge gained by screeners

Screeners interact with other staff, primarily with searchers, during problem solving. Therefore, it is possible for the screeners to transfer knowledge to the searchers by explaining a task or a process. Figure 4 illustrates the knowledge transferred to searchers by screeners. The results show higher transferring rate for perceptual, procedural and situational knowledge when an expert was performing the screening task. Experts transferred perceptual knowledge in 11.71% of problem-solving activity, whereas the rate for novices was 10.63%. Results also show 3.31% and 2.22% of procedural knowledge transfer by the experts and novices respectively. Although results indicated that experts also transfer situational knowledge in 11.73% of their problem-solving activity, novice screeners did not transfer of this type of knowledge.

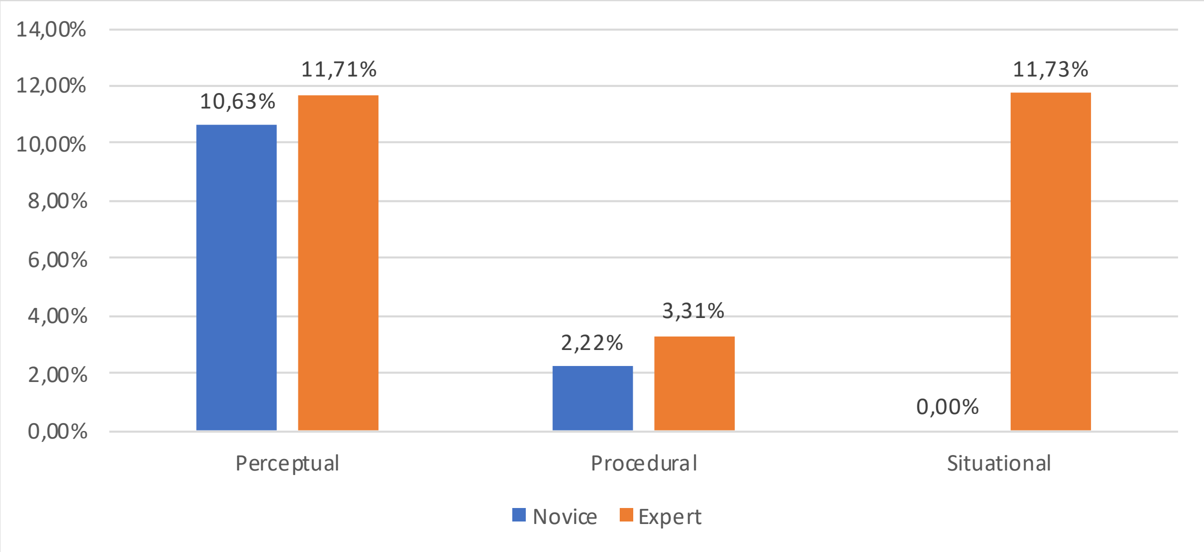

Figure 4 Knowledge transferred to searchers by screeners

Figure 5 shows human interaction during real-time knowledge transfer. These interactions include asking a question from a searcher, discussing, requesting removal or manual search, as well as requesting re-run of bags through the X-ray. These interactions provide important instances for knowledge transfer for screeners.

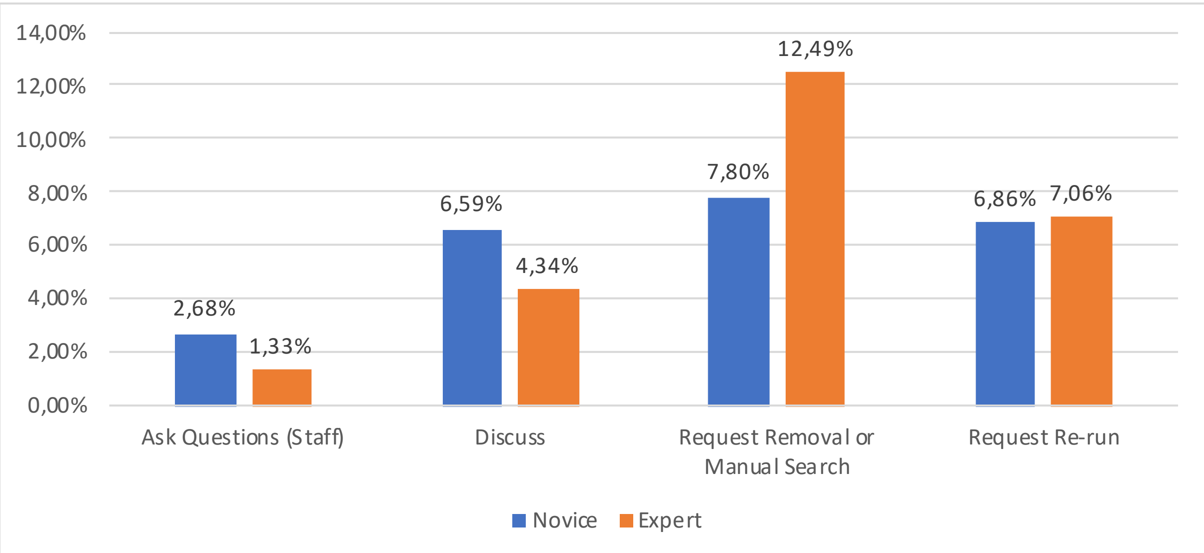

Figure 5 Human interactions between screeners and searchers

Results show that novices experienced higher percentages when asking questions (2.68%) and discussing (6.59%) than experts who spent 1.33% and 4.34% of their problem-solving time on these interactions (Figure 5). In contrast, experts spend more of their interactions with searchers requesting manual search or removal of objects (12.49%) than novices do (7.80%). Both the novices and experts allocate most of their interaction time with searchers requesting removal or manual search.

The results of this investigation can be used in designing an intelligent interface to make a transition from novices to experts and enhance the learning process. This is discussed further in sections 7 and 8.

7. Discussion

It is understood that experts are better at solving problems than novices because of their accessibility to a higher amount of knowledge. Their knowledge enables them to identify patterns and perform specific actions when they confront a problematic situation (Salas et al., 2010). On the other hand, novices have access to a lower amount of knowledge. Novice and expert accessibility to a different type of knowledge has been investigated previously (De Jong & Ferguson-Hessler, 1996; Friege & Lind, 2006; Swann et al., 2014). This paper has expanded on this understanding by looking at real-time learning approaches for developing knowledge.

Specific knowledge categories were analysed. They were defined to understand the knowledge gained and transferred during real-time learning, which could be a facilitator of the novice to expert transition. Results indicate the importance of real-time learning approaches for security screeners when performing a real screening task. It can be understood from the results of this study that novice screeners can gain a higher amount of knowledge during the screening process. According to the results, experts have a higher capability to transfer knowledge to other searchers compared to novice screeners. Another compelling argument is that collaborative interactions between screeners and searchers play an important role in knowledge transfer. Both the novice and expert screeners allocate almost a quarter of their problem-solving time to communicate with searchers for the purpose of asking questions, discussing, requesting removal or manual search, and requesting re-run. Therefore, it is an important part of the problem-solving process to focus on a solution to improve the real-time knowledge transition during human interactions.

We argue that understanding and emphasising real-time learning could accelerate novice to expert transition. An intelligent collaborative interface could be a way of achieving this goal. Problem solving and decision making are considered as one of the most complex tasks which can be facilitated using intelligent collaborative interfaces. Interfaces could help novice operators to gain the required knowledge in a very short time.

8. Intelligent interface - future scenario

Airport security screeners should possess sufficient knowledge and skills that are suited to the systems they are using (Harris, 2002). This research has contributed new knowledge about real-time learning, in the context of airport x-ray security screening. The transfer of situational knowledge from experts was identified to be of particular importance. It is essential for understanding encountered situations and acting effectively. Understanding this knowledge transfer can be applied in the design of an intelligent interface to facilitate fast novice to expert knowledge transition. Enhancing the process of knowledge transition has the potential to improve the screening process by better equipping screeners to deal with problem solving situations and improving identification of threat objects. We propose an intelligent interface, which is expected to assist the novice screeners during problem-solving activities. To foster the efficiency of x-ray screening and training, the proposed interface focuses on providing real-time training. The interface would learn from the actions of experts when interacting with unpredictable or uncertain situations. Then, the system could suggest relevant actions to the novice screeners who encounter similar situations when using the interface without any necessity to ask from other employees. For example, when a novice screener faces a cluttered bag, improving the clarity of the contents is desirable. Similar pattern is being used in chess computer programs in which searching millions of position can be resulted in offering the most optimal solution for the candidate moves (Cokely et al., 2018). The intelligent collaborative interface could suggest relevant actions based on those typically performed by experts in similar situations. This indicative functionality is demonstrated in the following scenario.

8.1 Scenario: Expertise transfer- expert to novice screeners

James, an expert screener with seven years of experience, is using an intelligent interface to detect threats and transfer his knowledge and experience to other screeners with a lower level of expertise. During screening passengers' baggage, he suspects a sharp object among within baggage characterised by medium density clutter. He calls a searcher, describes the situation and requests the baggage to be re-run at a specific angle to improve the clarity of the image. When the baggage comes through at a new angle James is easily able to confirm that the object is a sharps threat. He calls the searcher to have the object removed and disposed. This process is automatically captured by the intelligent interface and transferred to the system database. This includes cataloging details of image context (sharps, medium density clutter) as well as procedure applied (re-run, request for removal). Catalogued information and images are used as learning material to assist identifying similar situations.

Madeline, a novice screener, frequently encounters similar situations as cluttered bags are common in airport screening. She has difficulty with these, often asking for object removals resulting in false decisions and delays as each bag requires manual search. The system recognises baggage with similar characteristics as those stored in memory. When Madeline experiences difficulty with luggage of medium or lower density clutter, it draws on examples of experts problem-solving strategies, such as re-running at a new angle, and prompts Madeline to use these. This enables Madeline to gain experience applying strategies to better overcome baggage, and it reduces delays caused by frequent manual searches. This enables Madeline to gain experience applying effective strategies and facilitate faster transition to an expert. She is better able to independently overcome difficult situations and reduce delays caused by frequent manual searches.

The findings and implications of this research can also be applied to other complex domains which need transferring knowledge to novice users in a very short time. Utilising this system can eliminate long and expensive training sessions before starting any task. The scenario of this collaborative interface supports this vision.

9. Conclusion and future work

The focus of this research is finding out the real-time learning approaches which can facilitate the novice to expert x-ray security screeners' transition. To this end, this research focused on the behaviours of screeners and their application of knowledge during the screening task.

Results of this research show the knowledge gained and transferred in real time for the novice and expert x-ray screeners during problem-solving phases in the screening task. Accessibility to a higher amount of knowledge and experience by experts resulted in transferring a higher amount of knowledge to the searchers. However, novice screeners gained more knowledge compared to the expert screeners during problem-solving phases. Based on these findings, our future work will focus on an intelligent interface design to facilitate the process of knowledge transition from novice to expert x-ray screener. In addition, methods, findings and the future interface can be used in many other domains, especially group working tasks, which have a correlation with knowledge. Activities and cognitive processes in every context can be visualised and the relationships between interactions and knowledge transitions can be realised. This research is significant as it opens a vision for a design of a novel collaborative interface to support faster novice to expert transition and their operations in complex and uncertain environments.

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