REVIEW ARTICLE

See no evil: Cognitive challenges of security surveillance and monitoring

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Abstract

While the development of intelligent technologies in security surveillance can augment human capabilities, they do not replace the role of the operator entirely; as such, when developing surveillance support it is critical that limitations to the cognitive system are taken into account. The current article reviews the cognitive challenges associated with the task of a CCTV operator: visual search and cognitive/perceptual overload, attentional failures, vulnerability to distraction, and decision-making in a dynamically evolving environment. While not directly applied to surveillance issues, we suggest that the NSEEV (noticing – salience, effort, expectancy, value) model of attention could provide a useful theoretical basis for understanding the challenges faced in detection and monitoring tasks. Having identified cognitive limitations of the human operator, this review sets out a research agenda for further understanding the cognitive functioning related to surveillance, and highlights the need to consider the human element at the design stage when developing technological solutions to security surveillance.

Key words: visual search, dynamic decision-making, information overload, attentional failures, distraction

General Audience Summary

High expectations are placed upon surveillance technologies to protect infrastructure and public places. While technological systems can automate some aspects of the surveillance process, the human operator is still ultimately responsible for detection of suspicious activities and decision-making. Thus, the optimal design and development of new technology should not focus solely on the capabilities of the system itself, but on supporting the operator's cognitive vulnerabilities. Observations and interviews with closed-circuit television personnel have previously highlighted several challenges with the task and control room environment – including information overload, distraction, and long work shifts – which we review in terms of the cognitive science literature. We set out a research agenda to investigate these issues in relation to a recent psychological theory of detection, and suggest ways in which progress can be made regarding training of operators, visualization and workspace design, and the use of intelligent and automated systems.

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What Is Surveillance?

Surveillance can take many forms, such as monitoring of crowds (e.g., riots, lifeguarding), a particular individual (shoplifter, terrorism suspect, drug dealer), objects (vehicles, unattended baggage), infrastructure (both public and remote; e.g., government buildings, railways, hydroelectric dams), or computer systems (cyber-attacks), as well as radar-based monitoring and risk assessment such as that required by air traffic controllers or military personnel. These supervisory monitoring tasks are all similar in that they involve concentration for long periods on a complex and dynamically evolving situation, whereby particular rules are kept in mind to identify visual threats in the environment. Given the potential high cost of a detection failure (e.g., bomb explosion, drowning, mid-air collision, cyber-attack), high expectations are placed upon surveillance personnel to ensure safety and security. As such, a burgeoning area of research in a number of surveillance domains is the development of intelligent technologies to automate aspects of the detection process and augment the capabilities of the human operator. Nevertheless, the human operator retains a critical role in the process of detection and decision-making and thus it is imperative that any developments in surveillance technology take into account the limitations of the human cognitive system. Effective surveillance support must consider the cognitive fit between three elements: the task, the technological system, and the human operator. Yet, efforts so far to develop human factors guidelines for surveillance system design have mainly focused on technology- and task-related issues (see, e.g., de Bruijn, Jansen, Lenior, Pikaar, & Schreibers, 2016; Pikaar, Lenior, Schreibers, & de Bruijn, 2015; but see Stainer, Scott-Brown, & Tatler, 2017), thereby leaving the influence of human cognition underestimated. Towards filling this gap, the current article reviews the cognitive challenges faced by the human operator in relation to supervisory monitoring tasks – with particular focus on urban security surveillance – and evaluates ways in which these processes could be augmented through technology and training.

Surveillance Technologies

Surveillance technologies are essential to protecting a country's critical infrastructure and public places (e.g., city centres, airports, metro, major sport/entertainment events, information technology facilities) against the threat of terrorism, civil unrest, criminal activity, and cyber-attacks. Urban security surveillance relies heavily on closed-circuit television (CCTV) for two purposes: First, it is a means to monitor evolving activity in real-time with the possibility for intervention. During the 2011 London riots for example, CCTV facilitated the monitoring of evolving situations in multiple locations in real-time, allowing for higher order organization, prioritization, and the deployment of officers to specific sites. Increased security surveillance is also required for any high-profile events that draw large crowds (e.g., royal family, sports events, political rallies), in the hope that any potential threats might be detected and eliminated before an incident occurs. In these cases it is important to take advantage of human perception and intuition for the early identification of behaviours that might lead to adverse events (Brunyé, Howe, & Mahoney, 2014; Kaplan, Mintz, & Mishal, 2006). A second purpose is to provide an important visual record of a public space at any given time, so that it may be viewed retrospectively to detect the presence of a particular person/object in a particular place, or to trace the onset/development of an event that has already occurred. For example, one Scotland Yard review found that CCTV footage was used in 86 of 90 murder cases over a one-year period, and was key to solving 65 of these (Foy, 2010). A number of major incidents have also relied heavily upon retrospective CCTV footage to identify suspect persons/vehicles and to help piece together the time course of events (e.g., the 2013 Boston Marathon bombing, the 2015 Paris attacks).

With the increasing coverage of surveillance cameras, there is a greater workload placed upon control centre operators to adequately monitor and detect incidents from the wealth of footage available. By 2011, the UK's Association of Chief Police Officers (ACPO) estimated that there were 1.85 million cameras in the UK, with the government having invested £500 million in such equipment over the preceding decade. In order to ease the burden on the human operator, a burgeoning area of research is the development of intelligent video surveillance systems that aim to automatically identify/interpret the visual scene. This may take the form of alerts to direct the operator in a timely manner towards suspicious objects/behaviour that might require further attention and/or intervention; and can also be used in retrospective investigations to filter through hours of footage and pinpoint critical events, suspects, or locations. For example, background/foreground subtraction or temporal differencing techniques can be used to detect particular objects or changes in a visual scene (Valera & Velastin, 2005), and filtering mechanisms are used to track and predict movement (e.g., Nguyen, Venkatesh, West, & Bui, 2003).

Despite such advances, intelligent multi-camera surveillance faces many challenges. In terms of inter-camera tracking, it can be difficult to match the appearance of objects across different camera feeds due to differences in illumination, viewpoints, and camera settings (Wang, 2013). In some cases – for example, if a tracked suspect discards his/her black sweatshirt to then reveal a white t-shirt underneath – a human operator may prove superior to a computer algorithm in determining constancy in the face of a change in appearance. Tracking performance tends to be reduced markedly when people are wearing similar colours (Krumm et al., 2000) as image algorithms are often not robust enough to cope with more fine-grained differences of appearance. Furthermore, given that areas in need of high security such as airports and stations are also highly populated, occlusion is a major problem for tracking algorithms. Intelligent systems can alert and advise the operator but are still subject to misses and false positives. Even when visual changes are correctly identified, a judgement needs to be made regarding how important such a change is. For the time-being certainly, intelligent systems cannot replace the critical role of the human to oversee, evaluate, and prioritize software-generated options (Dadashi, Stedmon, & Pridmore, 2013); rather such systems may be used to help augment the human's capabilities (e.g., Atrey, El Saddik, & Kankanhalli, 2011; Parasuraman & Galster, 2013). Advancement in this area will not necessarily be achieved just by introducing intelligent systems within the operators' current role, but rather by assessing – during the design process – how automation and the human can operate as coagents (Suss, Vachon, Lafond, & Tremblay, 2015). In so doing, it is therefore important to fully analyse the task environment and cognitive limitations of the CCTV operator in order to suggest the nature of support tools and design features that might best fit with the human agent.

The Task of a CCTV Operator

CCTV operations involve both "reactive" and "proactive" surveillance (Keval & Sasse, 2010), each of which employ slightly different cognitive processes. *Reactive surveillance* (response to a specific incident, either retrospectively or in real time) is mostly driven by top-down guidance whereby the operator must identify, amongst other potential distractors, particular individual(s), groups, vehicles, etc., from a given description and then track their movement. For example, operators may be asked to identify and track a potential shoplifter who has left the premises; or may need to be alert to a missing person who is believed to have travelled to that particular city. *Proactive surveillance* (anticipation of an incident) is a search for suspicious activity based on given rules or subjective heuristics, involving vigilance over time so that critical behaviours or events are not missed (e.g., it might be necessary to monitor for potential trespassers in a prohibited area, or for indications of unrest in a night-time city centre). This likely involves a combination of attentional processes; for example, top-down control may play a role in bottom-up search after attention has been captured by a salient element (see, e.g., Theeuwes, Atchley, & Kramer, 2000). Furthermore, it is possible that in the absence of a specific search target, proactive surveillance may be driven by multiple top-down search templates of potential target events (e.g., pickpocketing, an escalating altercation, or loitering; Howard, Gilchrist, Troscianko, Behera, & Hogg, 2011), thus proactive search is unlikely to be purely stimulus-driven but guided by expectation also.

The frequency of events occurring during proactive surveillance can vary greatly: On the one hand, the frequency of incidents may be very low (e.g., monitoring a store at night), and on the other hand, the frequency can be overwhelmingly high (e.g., riots). Unlike reactive surveillance, which has a well-defined goal, proactive surveillance is an ongoing search for items or events that may not necessarily occur. Furthermore, events may occur that fall outside of a pre-established search set, but which may nevertheless pose an unexpected threat. Thus decision-making is a key feature of the task; that is, not only “seeing” an incident, but interpreting its significance and determining an appropriate level of response. This continuous visual search for low-probability potential incidents shares some similarities with other surveillance tasks such as baggage screening or air traffic control, although there are also notable differences: Unlike the static screen shots used in luggage monitoring (see Biggs & Mitroff, 2015), urban security surveillance involves dynamic, evolving crowd scenes which place greater demands on visual search processes; and unlike for example, an air traffic controller who observes and actively manipulates aircraft within a flight space (e.g., Metzger & Parasuraman, 2001), the job of a CCTV operator is passive with no interaction or influence over the movement of targets.

Cognitive Challenges for the Human Operator

A heavy reliance is placed upon CCTV operators to detect potential incidents and maintain public safety and security, but studies show that effectiveness is less than optimal (e.g., Gill et al., 2005; Webster, 2009). Some of the factors impacting CCTV effectiveness are equipment-related, such as the positioning of the camera (field of view, obstructions), its manoeuvrability (presence of pan, tilt and zoom functions), and the quality of the video footage (lighting, frames per second). Yet many issues represent cognitive challenges faced by the human user, and must equally be addressed to ensure the high level of effectiveness that we assume of our surveillance networks (van Voorthuijsen et al., 2005). Previous studies conducted within surveillance control rooms have raised a number of human factors issues. In particular, we consider the studies of Keval & Sasse (2010), who conducted 4-6 hour observations and interviews with operators and managers across 13 control rooms; Gill et al. (2005) who also used observation and semi-structured interviews across 13 control rooms; and Smith (2004) who conducted observations and informal interviews with CCTV operators based on a UK college campus. Here we review the issues raised in these studies in relation to cognitive theory and experimental psychological literature, before setting out a research agenda and considering possible solutions that might address the current barriers to effectiveness.

One key obstacle in effective CCTV monitoring is the sheer volume of information for which operators are responsible. A major problem in many control rooms is the high camera-to-person ratio (e.g., Gill et al., 2005) with sometimes up to 50 screens to be monitored at once

(Troscianko et al., 2004). Operators report feeling overwhelmed by the sheer amount of information that must be attended and processed (Keval & Sasse, 2010). This is supported by experimental studies of divided visual attention, whereby the visual system becomes noticeably stretched and performance declines when monitoring four scenes concurrently (Rousselet, Thorpe, & Fabre-Thorpe, 2004; van Voorthujsen et al., 2005). Moreover, the number of potential camera feeds to select from often greatly exceeds the number of available screens on which to view them (e.g., a single operator may be responsible for up to 175 cameras at one time; Gill et al., 2005). Given that switch costs are well-documented in basic cognitive research (e.g., Monsell, 2003), the act of switching itself may introduce inefficiencies in monitoring. When constantly shifting attention between multiple camera views, situation awareness (SA) – that is, the ability of an operator to perceive the elements and events of his or her work environment with respect to time or space, to understand their meaning in relation to the tasks at play, and to foresee how they may change over time – will be reduced each time until the operator has reassessed the new scene and updated their situational model (Endsley, 1995; see also Bedny, Karwowski, & Jeng, 2004).

Given the impossibility of monitoring all screens and camera feeds concurrently, the operator must make decisions on which areas and individuals to fixate, and often these are based on heuristics, recent experience, and personal biases (Smith, 2004). For example, it might be prudent to devote more attention to a camera positioned on a parking lot if car crime has been a particular concern. The movement patterns of individuals may render them more likely targets for surveillance if they are moving too quickly, not moving (i.e., loitering), or appearing to have no particular direction (Smith, 2004). Also, eye-movement patterns may be deemed suspicious if a person is either looking around a lot, or staring at someone or something in particular for an extended period (Stedmon, Harris, Carse, Sharples, & Wilson, 2008). Operator personal prejudice is also apparent in the frequent targeting of young males (Norris & Armstrong, 1997), particularly those wearing hooded sweatshirts, baseball caps, or puffer jackets, who may be deemed as having subcultural, criminal affiliations (Smith, 2004). This heuristic processing can potentially introduce error (e.g., fixating for a long time on a youth wearing a hooded sweatshirt, at the risk of missing a potentially more serious incident on another screen). Attention is important for understanding the intent and action aspects of threat detection, but this can be more greatly influenced by top down factors the more demanding the situation (Parasuraman & Galster, 2013). As such, cognitive overload can give rise to more heuristic processing and personal biases may become more apparent. Stainer et al. (2013) showed that trained CCTV operators tend to spend more time monitoring a single camera feed of their choice on an isolated screen than a multiple-scene display. Such findings suggest that experts in CCTV surveillance may favour the use of a search strategy based on their prediction of where crime is likely to occur in order to reduce the demands of multiple-screen monitoring.

A recent study by Stainer et al. (2017) revealed that detection performance on a multiple-scene display is not exclusively driven by the number of scenes in the display. The authors showed that more visual information was associated with poorer detection performance regardless of whether this information was presented in a single scene or across multiple scenes. They also observed that the detection of relevant targets was improved compared to the detection of less important targets, with the magnitude of the difference increasing with the number of scenes to monitor. Such findings suggest that the amount of information available and its level of importance in relation to the surveillance task are in fact the key factors determining detection performance in multiple-screen surveillance, rather than the mere number of feeds to monitor.

Another difficulty noted in interviews/observational studies of proactive surveillance is that in many cases there is a fair amount of uncertainty regarding the specific nature of to-be-detected critical events, which is why personal biases come into play (Gill et al., 2005; Smith, 2004). Although in some work environments (e.g., airports) specific guidance is provided regarding the identification of suspicious items or unusual behavioural patterns, in other cases operators are simply told to “do surveillance” or to “look out for incidents” (Donald, 1998), meaning that the operator must make decisions about potential criminal activity based upon quite ill-defined and subjective criteria. Many operators report just having a “sixth sense” for when an incident may occur (Keval & Sasse, 2010), a concept that may be linked to intuition or intuitive decision-making. As opposed to analytical decision making, intuitive decision making relies upon a holistic approach to processing information and places more importance on feelings than facts and details (Sauter, 1999; see also Bryant, 2007). According to contemporary cognitive scientists, intuition is viewed as a cognitive state that is the end product of an implicit learning experience (e.g., Reber, 1989): Through experience, operators acquire expertise by implicitly internalizing certain activities and making them automatic. This enables the development of an overview approach to problem solving that guides information gathering and helps linking information in nonobvious ways. In the context of surveillance, intuition can help, for instance, identifying events that seem unrelated but, in reality, have a meaningful relationship. While this ability may develop with experience, it is hardly an ideal foundation for maintaining the safety of public spaces given that the efficiency of visual search is reduced with less detailed information (Biggs & Mitroff, 2014; Vickery, King, & Jiang, 2005).

One difficulty with defining suspicious activity is that it can rarely be identified by a single criterion, and often no given behaviour is either necessary or sufficient to determine malicious intent. The decision of whether or not to investigate a particular activity further is generally based upon multiple factors, including the context in which the behaviour is occurring. For example, looking around widely in a large, bright, shopping centre environment would seem quite natural, but may appear strange at an airport screening desk where people generally face forwards in a single file; however, looking around in itself would not necessarily be deemed suspicious unless other factors were also present, such as fixating on camera locations, attempting to conceal something, and looking nervous. One recent experimental paper found that crowd size and density were important cues in inferring level of threat, perhaps because participants take into account the perceived intention of suicide bombers to maximize the number of casualties (Brunyé et al., 2014). Other factors also had high predictive value of perceived threat including the proximity of entities to buildings, and whether or not individuals followed the common movement direction or showed erratic headings. Interestingly though, subjective reports showed that participants had little awareness of the parameters they were using to gauge threat level in the simulations viewed. This fits with the anecdotal idea that operators develop a “sixth sense” for behaviours or combinations of behaviours that seem out of place in a particular context, but are not necessarily able to articulate the parameters used (Keval & Sasse, 2010). Tracking and eliciting such tacit knowledge – and so-called intuitive decision-making – have proven quite difficult (see Sauter, 1999) despite the availability of a range of knowledge elicitation techniques (Hoffman, 2008). One potential avenue is the use of policy capturing and process tracing techniques in order to extract the decision path that leads to investigating an event further (or not) (see Kim, Chung, & Paradice, 1997; Lafond et al., 2009; Lafond, Vallières, Vachon, & Tremblay, in press).

Where training courses are provided, guidelines may still not deliver a definitive checklist of rules that can be taught and learnt. The UK's Centre for the Protection of National Infrastructure (CPNI) offers a general e-learning course for CCTV personnel and emphasizes the importance of knowing the specific environment in question and considering how particular behaviours may seem incongruent. Furthermore, operators are encouraged to take note of their "gut instinct", even if they are unable to verbalize what makes them feel suspicious about a particular behaviour. This feeling of "just knowing" when a behaviour does not seem right is likely the product of many subtle factors, and also driven by a high level of SA. Interpreting the degree of threat presented by a particular individual or object often depends on a broader appreciation of the situation: For example, an awareness of how long a solitary bag has been unattended, and whether or not the owner is still in the vicinity (e.g., have they just moved away to check the departures board, or left the station completely?). It is likely that this gut instinct does develop with experience, with the suggestion that experts are better able to anticipate upcoming visual events. Experienced CCTV operators have been found to process scenes more efficiently than untrained observers (Howard, Troscianko, Gilchrist, Behera, & Hogg, 2013), with less eye movement variability and a greater ability than non-experts to move their eyes to goal-relevant areas of the scene (i.e., "knowing what to look for", a finding that has also been applied to sport; Howard, Troscianko, & Gilchrist, 2010; Vickers, 2009). When ambiguous but potentially suspicious events occurred (e.g., loitering in a car park/urban underpass/outside a nightclub), experts' attention tended to be more drawn to "suspiciousness", with greater between-operator consistency in gaze location than with untrained individuals.

A further issue highlighted in the qualitative studies reviewed was noise and concentration difficulties within the control room (Keval & Sasse, 2010). Security centre control rooms are often shared with a number of security personnel meaning that continuous background sound from colleagues' conversations, telephones ringing, and radio calls (e.g., police, ground security) can be distracting, as well as more explicit task interruptions that require the operator to temporarily suspend the ongoing task so as to engage in another activity. Although background sound itself does not require any explicit response on the part of the operator, it can be disruptive by capturing attention: Auditory distraction paradigms show that when we perceive a loud, new or incongruent sound, attention necessarily orients towards that sound, momentarily diverting resources away from the task in hand (e.g., Hughes, Vachon, & Jones, 2007). Fragmented conversation that has frequent onsets and offsets (e.g., hearing just one side of a colleague's telephone conversation, interspersed with quiet), is known to be particularly disruptive (e.g., Emberson, Lupyan, Goldstein, & Spivey, 2010) since attention is particularly captured by the onset of sound (e.g., Hughes et al., 2007). Higher levels of concentration (i.e. the degree of attentional engagement) are known to reduce distraction from irrelevant stimuli (e.g., Halin, Marsh, Hellman, Hellström, & Sörqvist, 2014; Hughes, Hurlstone, Marsh, Vachon, & Jones, 2013), and so auditory attentional capture may have less of an impact under conditions of high than low concentration (see Sörqvist & Marsh, 2015). On the other hand, operators are likely to be more susceptible to conditions of distraction under increased cognitive load (Lavie, 2005). There is evidence showing that individuals with higher working memory capacity may be more resistant to external distraction (e.g., Hughes et al., 2013; Sörqvist, 2010) as well as internal distraction (mind-wandering; e.g., Robinson & Unsworth, 2015), which is likely to be an issue for surveillance given the monotonous nature of the task.

Another body of research demonstrates that even continuous background speech, without distinct onset/offsets, can be disruptive to a range of mental activities in the workplace, such as reading, writing, mental arithmetic, and memory processes (see Banbury, Macken, Tremblay, & Jones, 2001). Although we may think that we can simply “block out” background sound after a while, research shows that it is not something we are able to habituate to over time (Tremblay & Jones, 1998), and disruption occurs despite efforts to ignore the sound, and regardless of its volume (Ellermeier & Hellbruck, 1998). Furthermore, it is not just verbal tasks that are vulnerable to interference from background speech but visuo-spatial processes too (Jones, Farrand, Stuart, & Morris, 1995). One view is that interference arises due to a conflict of process between the background sound and the focal task, for example, a conflict between the automatic perceptual organization of speech sounds, and any “seriation” (memory for the order of events) required by the focal task (see Hughes, 2014). In the case of surveillance, acoustic changes present in the background speech may interfere with an operator’s ability to process and commit to memory the order of a series of actions observed on the screen or between screens. In turn, the inability to retain information about the actions and movements of various individuals could impact upon SA and the operator’s interpretation of the situation.

Alternatively, a conflict of process may occur beyond perceptual features to a conflict at the semantic level. Although operators will attempt to block out background sound, the meaning of speech may still be registered relatively automatically and this can conflict with semantic properties of information that he/she is making a conscious effort to retain. This could particularly be the case if the background sound contains information that is similar (but irrelevant to) the operator’s current task (Marsh, Hughes, & Jones, 2009; Marsh, Perham, Sörqvist, & Jones, 2014). For example, even if not attending to a colleague’s conversation, semantic information regarding an individual’s appearance may nevertheless be processed and then inadvertently conflict with information held in working memory regarding the operator's current search task, potentially increasing false alarms and suspect identification errors.

Aside from background sound, monitoring effectiveness may be affected by more explicit distraction in the form of task interruptions, such as requests for information from an external authority (e.g., Hodgetts, Vachon, & Tremblay, 2014), or from dynamic team communication within the control room itself (e.g., Tremblay, Vachon, Lafond, & Kramer, 2012). Just a 20-s phone call for example, will take participants' attention away from the screens while events continue to unfold, which then requires time to reconfigure and update a mental model of people/activities that have continued to evolve. Interruptions can thus impede task flow and reduce SA (Endsley, 1995; see St. John & Smallman, 2008). In a dynamic military surveillance task, eye fixations were found to be quicker following interruption (Hodgetts et al., 2014), supporting the idea of a rapid re-encoding and updating of the situation upon return. In this task, interruptions were found to slow decision-making time during the post interruption period, and this cost persisted for longer under conditions of divided attention or higher workload (Hodgetts, Tremblay, Vallières, & Vachon, 2015). The process of recovering SA after very brief interruptions is thought to involve the automatic reactivation of task goals (Altmann & Trafton, 2002), while a more effortful process of reconstruction will be necessary if attention has been diverted for a longer period (Salvucci, 2010). If a critical change occurs during the interruption it can be difficult for the visual system to capture and compare pre- and post-interruption visual transients, thus exacerbating the problem of change detection (St. John & Smallman, 2008).

Although interruptions are generally found to have a negative impact on performance, an interesting possibility is that interruption may actually improve incident detection in longer scenarios by heightening arousal and reducing the vigilance decrement (Ariga & Lleras, 2011).

The suggestion here is that a vigilance decrement occurs not because of depletion in attentional resources, but due to a difficulty in maintaining the activation of the vigilance goal which then habituates over time (c.f. Hopstaken, van der Linden, Bakker, Kompier, & Leung, 2016). In this case, interruption may serve a useful purpose in terms of momentarily deactivating the goal so that it does not habituate, and thus vigilance performance may be maintained for longer.

Another important issue highlighted by observational studies and interviews is the length of shifts and unsociable hours that operators are subjected to, making fatigue and boredom a key concern. A typical shift pattern can involve four consecutive 12-hour day shifts, a two-day break, and four consecutive 12-hour night shifts (Keval & Sasse, 2010). Due to circadian rhythms, performance on a range of tasks is known to be impaired during night time hours as our internal biological clock is willing us to sleep. There is a trough of efficiency between 01:00 to 07:00, and the onset of fatigue occurs sooner if the period of work begins in the trough, or at the onset of the trough (Rosa, Colligan, & Lewis, 1989). If sleep is not adequately caught up upon, then frequently working unsociable hours may also result in sleep deprivation which can affect visual perception (Quant, 1992), reaction time and sustained attention (Davies & Parasuraman, 1982), and short- and long-term memory (Polzella, 1975; Idzikowski, 1984).

Proactive security surveillance requires active visual search throughout these long shifts; however, vigilance is largely motivational and can be hard to sustain when incidents seldom occur. For example, in Smith’s (2004) study, despite 24-hour monitoring not a single incident was detected on any of the 11 cameras in three weeks (Smith, 2004). Surveillance personnel report the need to take frequent breaks to prevent them from “going wappy” (Gill et al., 2005), while newspapers, crosswords, and other distractions are used in CCTV control rooms as a way to cope with the monotony of the job (Smith, 2004). In visual search, there is accumulating evidence that the probability of detecting a target is influenced by the prevalence of target presentation. Recent studies have shown that high-prevalence targets are detected more often than low-prevalence targets (the so-called prevalence effect; Fleck & Mitroff, 2007; Wolfe, Horowitz, & Kenner, 2005). The increased probability of detecting a high-prevalence target has also been demonstrated in more realistic environments such as airport X-ray screening (e.g., Godwin, Menneer, Cave & Donnelly, 2010; Godwin, Menneer, Cave, Helman et al., 2010) and has been found to influence detection performance by increasing the time spent examining objects in the display (Godwin, Menneer, Cave, Thaibsyah, & Donnelly, 2015). The low prevalence of incidents in CCTV security surveillance may therefore impair detection performance. When attention must be sustained for long periods of time, and when the occurrence of critical events are rare, a “vigilance decrement” can occur (Parasuraman, Warm, & See, 1998; Stearman & Durso, 2016); that is, the likelihood that a critical event will be noticed, or the speed with which it is detected, is reduced. One misperception is that the vigilance decrement occurs only after hours of observation; while it may be increased over longer periods (e.g., Meuter & Renata, 2016), a reduction in performance has been demonstrated with tasks as short as 10 or 12 min (Temple et al., 2000). Furthermore, although vigilance tasks are typically associated with low-workload and understimulating assignments, the need to maintain alertness over prolonged periods is also required in high-demand sustained attention tasks, and so surveillance of dynamic and complex situations may also be vulnerable to a vigilance decrement. One suggestion is that fatigue from focused attention reduces sensitivity to events so that they are less likely detected (Wickens & Hollands, 2000). Another viewpoint is that reduced vigilance performance does not arise from a reduction in mental capacity or energy over time, but an active disengagement from the task so as to save costly cognitive resources for more beneficial activities at a later point. That is, during mental fatigue, people do not become less able to perform the task but just less inclined to do so (Hopstaken et al., 2016).

Given the long shifts and number of camera feeds to monitor, it is perhaps not surprising that some incidents are missed especially if on screen for only a brief amount of time; however, it is curious that seemingly prominent objects or events can also remain undetected for a prolonged period. Fathers 4 Justice campaigners for example, despite wearing conspicuous superhero costumes, have managed to evade security surveillance to achieve several high-profile stunts at key London landmarks (e.g., Buckingham Palace, House of Commons, Tower Bridge). This phenomenon is known as inattentional blindness (Mack & Rock, 1998; Most, Scholl, Clifford, & Simons, 2005) and poses a problem for security surveillance due to the cognitive challenges associated with the task of a CCTV operator (e.g., cognitive/perceptual overload, dynamic evolving environment). Research into inattentional blindness demonstrates that the phenomenon is more likely to occur when attentional demands of the task are high (Simons & Chabris, 1999) and when the expectancy of events is low (Steelman, McCarley & Wickens, 2013). Moreover, failures to notice obvious objects or events become more likely as screen quantity increases (Finnegan, 2011). These are conditions characteristic of CCTV surveillance, whereby operators must monitor for multiple threats on multiple screens (high attentional demands), yet the occurrence of actual incidents are few and far between (low expectancy). On the other hand, surveillance during times of civil unrest may give rise to a high number of incidents, but still the vulnerability to detection failure remains. Studies show that inattentional blindness can be exacerbated during periods of high tempo activity when there are competing visual demands (Nikolic & Sarter, 2001; Sarter & Woods, 1994), and when visuo-spatial information must be maintained in memory (Todd, Fougnie, & Marois, 2005), as might be the case when keeping track of the evolution of several potential incidents across multiple camera feeds. Inattentional blindness has been found to increase with greater working memory load (Fougnie & Marois, 2007), with some evidence to suggest that individuals with higher working memory capacity might be less vulnerable (Hannon & Richards, 2010), although this may only be the case at high loads (Calvillo & Jackson, 2014).

Research Agenda

Interviews and observational studies have identified key problems in CCTV operations that could be better understood – and hopefully to some extent alleviated – through further investigation using psychological theory as a framework to guide predictions and interpretation. Applying an experimental approach, the research we propose will use the Cognitive Solutions for Surveillance in Security (CSSS) microworld; a dynamic and realistic monitoring task that simulates CCTV operations within a city centre setting (see Vachon, Vallières, Suss, Thériault, & Tremblay, 2016). While previous experimental research into surveillance has tended to rely upon existing unscripted CCTV footage (Dadashi et al., 2013) or scripted actions carried out by actors in public places (van Voorthuijsen et al., 2005), the use of a microworld can circumvent many of the issues that these approaches entail. There are limitations to the types of activities that can be staged (or limitations to the existing footage available), but a microworld allows inclusion of events such as explosions/fires that might otherwise be unethical or expensive to stage. Another issue is extraneous variables and experimental control: Use of a microworld allows precise control over scripting such as the location, timing, duration, frequency and nature of incidents, so that direct comparisons can be made between experimentally manipulated conditions.

The CSSS microworld provides a complex and realistic simulation of operations in a CCTV control room. The participant monitors a large video display wall comprising six camera feeds; they must switch regularly between available camera viewpoints, keep abreast of intelligence updates, and communicate with external colleagues (e.g., police, store security). The types of events scripted might be location-specific and relate to a pre-task briefing (e.g., look out for intrusions into the Parliament building), or person-specific whereby the participant must look for a suspect fitting a particular description. Other unanticipated events might also occur (e.g., street fight, graffiti) for which participants must also be alert. In addition to investigating detection rates and times, eye-tracking measures can be taken to understand the deployment of attention across displays.

In setting out a research agenda, we turn to a recent model of attention to gain insight into why certain features of the control room environment might exacerbate the challenges of proactive security surveillance and the detection of critical events. NSEEV (noticing – salience, expectancy, effort, value; Steelman, McCarley, & Wickens, 2011) is a recent model of attention behaviour, and although not directly applied to surveillance issues, it could provide a useful theoretical basis for understanding the challenges faced in detection and monitoring tasks. It combines aspects of basic visual perception such as visual search and attentional capture, with a broader engineering approach that also takes into account the working environment. The model can be used to estimate detection rates and response times to dynamic events using heuristic parameter values, and has been validated against empirical data on the detection of visual alerts (Steelman et al., 2011; Wickens, Hooey, Gore, Sebok, & Koenicke, 2009).

The model predicts that on account of bottom-up attentional features, the greater the *salience* of an incident, the greater the likelihood of detection and the faster the response time.

Experimental studies show that dynamic visual search in evolving realistic scenes is more effortful with increasing visual clutter (Neider, Brotzen, & Zelinsky, 2010), and so large crowds or cluttered displays can reduce the efficiency with which incidents are located (e.g., Boot, Kramer, Becic, Wiegmann, & Kubose, 2006). Higher rates of detection have been found when the target/incident is visually salient and when present on screen for a longer period; while detection is reduced when the scene is complex, dynamic, and in need of deeper visual analysis (Donald, Donald, & Thatcher, 2015). One way to compare saliency could be the size of the incident on the screen; for example, a street fight involving a large group of people would perhaps be more salient (and thus more likely detected) than an incident involving a solitary individual. When perceptual load is increased, the NSEEV model would predict that with more visual clutter, each individual or event would have reduced salience, particularly if there are similar distractors. Generally, the perpetrators of crime try to conceal their illegal activity and thus minimize saliency; as such, it may be difficult to notice the covert actions of a shoplifter who integrates amongst other regular shoppers. On the other hand, an event such as a large explosion would presumably be more salient due to, for example, its sudden onset (which may help capture attention even in the periphery; see Remington, Johnston, & Yantis, 1992; Theeuwes, 1994), the social attention of others (e.g., reaction of bystanders; see Langton & Bruce, 1999), and its impact on other activity in the vicinity (e.g., damage to property) increasing the size of the area affected on screen.

According to the model, top-down attentional settings can also influence the speed and likelihood of detection; in particular, an event that is perceived as being more likely to occur should have a greater level of attentional activation and thus be more likely fixated (and consequently detected) than one that is not anticipated (*expectancy*). Following a sports event for example, surveillance personnel might be on particular alert for fighting between rival fans, but due to this bias in the allocation of focused attentional resources, they might be relatively less sensitive to other types of incident (e.g., pickpocketing, fire). Thus if both occurred, the fight might be more likely detected due to greater expectancy and attentional activation. We intend to test the effect of expectancy on detection through our manipulation of incident type: 1) looking for a specific incident on a specific screen (e.g., trespassing in a forbidden area), 2) a specific incident on a non-specific screen (e.g., looking for a missing child), and 3) a non-specific incident in a non-specific location (other illegal activity for which the participant has not been forewarned). One might find that detection rates are higher for those incidents for which the participant is specifically forewarned through pre-task briefing, rather than for those incidents that are not anticipated. The expectancy component of the model can also help to explain why it is difficult to maintain vigilance over long periods when incidents are few and far between; as time goes by without any incidents, expectancy of a future event declines and makes detection less likely if it does occur.

Another factor to be tested is the impact of *effort* needed to shift attention towards the event. One might expect that an incident occurring closer to the current point of gaze would be more likely – and more quickly – detected than one occurring in the periphery. Thus an increase in cognitive load (i.e., a greater number of screens to monitor) would likely mean a greater chance of missing a relevant event (especially if brief in duration) by virtue of not looking in the right place at the right time, and by requiring greater effort to switch attention towards a different screen. Finally, the model emphasizes the influence of incident *value*; the criticality/consequences of that event being missed should it occur. This would be tested by comparing detection rates and times between those incidents rated as more severe (e.g., a car on fire; individual with a gun) with less critical incidents (e.g., graffiti; dropping litter; petty theft).

As well as testing the basic parameters of the model within a security setting, we would also look to examine the impact of other control room stressors on operator performance, taking into account the NSEEV framework. In terms of background sound and interruptions, one might expect that attentional resources are diverted towards these environmental distractions leaving fewer resources to detect on-screen occurrences. Currently, the NSEEV model does not include any detection threshold; it is the case that all fixated items are detected, with the probability of fixating an item proportional to its relative level of attentional activation. It is possible that a detection threshold could be implemented into the model, such that any item with overall attentional activation above a certain level would be detected, irrespective of the source of that attentional activation. To reach thresholds for detection under conditions of distraction, incidents might need to be particularly important, visually salient, already anticipated, or occurring close to the focal point of gaze.

Potential Solutions to Cognitive Limitations

Automated systems. Given the critical importance to public safety of detecting potential threats—and the human vulnerability to detection failure—the development of intelligent surveillance systems to automate aspects of the detection task is perhaps not surprising. For example, police in London used facial recognition software to help identify those involved in the 2011 riots (Dillow, 2011). Security organizations offer functions such as people/vehicle counters and object, intrusion and queue detector software (e.g., see www.kiwisecurity.com), while algorithms can be used to track movement and analyse behaviour (Valera & Velastin, 2005). Although there continue to be advances in CCTV technology, such systems will always require a human operator at least in a supervisory capacity (Dadashi et al., 2013; Norris & Armstrong, 1997), thus retaining some vulnerability to the cognitive limitations discussed previously. In such context, it would be remiss to spend excess time and resources perfecting the system itself, at the expense of understanding the interaction between the system and the human agent (Dadashi et al., 2013; Stedmon, King, & Wilson, 2007). Like any co-ordinated teamwork, a joint human-automation system is most effective when participants are mutually predictable, responsive to each other's influence, and are able to communicate their status and intentions in a way that is obvious and interpretable by the other(s) (Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004). In essence, technology does not so much replace the human as change the nature of the work that the human does so that the two can work in harmony together towards a common goal.

Automated systems do not necessarily provide a failsafe solution and in fact come with their own issues. An overreliance on automation (misuse) can create a "false sense of security" (Wickens, 1984), whereby operators become complacent and offload to the intelligent system in the belief that all incidents will be detected. However, an automated system can only alert the operator to the specific incidents that it has been programmed to detect, and there may be cases that are not picked up by the particular algorithm, or other unexpected threats that had not been anticipated. Furthermore, software may fail if conditions are sub-optimal, for example, if a suspect's face is hidden from camera or if a potential threat is partially occluded. In these cases, there may need to be some judgement and flexibility on the part of the human operator. An overreliance on the software system and complacent attitude may lead to a decline in SA, meaning a reduced ability to gauge the presence of threat in evolving situations.

On the other hand, neglect (disuse) of the system often occurs when there is a high false-alarm rate. Automated software is more likely to "detect" a high number of possible threats for filtering by the human operator, rather than risk missing an incident that could be catastrophic. However, this runs the risk of a “cry-wolf effect” whereby the operator deliberately chooses to ignore automated alerts believing that they too are most likely a false alarm (Breznitz, 1983; although see Wickens, Rice et al., 2009). Beyond the mere detection of problematic behaviour is also the need to distinguish benign behaviours from those that have a malicious or malevolent intention, and to determine what level of resources should be allocated. Even with the increase in automated systems, reliability and frequency of false alarms is still an issue, thus a lot of the responsibility for “detection” (filtering, prioritizing, and decision of response) is still placed firmly with the human operator.

Automated systems developed within other supervisory and monitoring tasks demonstrate that even when critical events are detected automatically by the system, the human operator is still vulnerable to detection failures. Within the context of military operations, the Change History EXplicit (CHEX) tool (Smallman & St John, 2003) has been developed to circumvent the problem of change blindness by displaying a record of all changes occurring on the radar system. This table provides a cross reference or a “second chance” to detect changes that may have been missed if attention was directed elsewhere at the time of the event (e.g., during an interruption). However, one drawback of this system in its current form is that it records all changes, leaving the analysis and prioritization decisions to the human operator. Consequently, the table of recent changes can quickly become cluttered and such a high number of false alarms to filter through may even detrimentally increase workload relative to no support tool (Vallières, Hodgetts, Vachon, & Tremblay, 2016). Thus, the introduction of an automated detection system does not eliminate error, and the fallibilities of the human cognitive system must be taken into account during the design process.

While, on the one hand, it may be desirable for automated systems to minimize the number of false alarms generated, on the other hand, a certain number of false alarms may even improve detection performance. Within the context of baggage screening, one solution to the vigilance challenge has been Threat Image Projection (TIP) software. Essentially the reporting of threats decreases when there is a low probability, and so the idea is to increase the base rate through inserted graphic objects added to the images viewed. This maintains a higher level of vigilance (see Hopstaken et al., 2016) and increases reporting of items that are marginally suspect but which might have previously been dismissed on account of the low probability of risk. It is possible that a similar idea could be implemented within CCTV surveillance (e.g., inserting unattended baggage images) with the aim of increasing expectancy and thus shifting decision-making criterion to increase the likelihood of detection (Neil, Thomas, & Baker, 2007). However, the benefits of TIP software observed within a static detection task may not translate so well to a dynamically evolving surveillance environment.

Attention Aware Systems. Such support systems take into account a user's current focus and goals as well as environmental factors in order to update task information dynamically so that the most relevant information is displayed at the most appropriate time and in the most appropriate manner (e.g., Roda & Thomas, 2006). The aim is to avoid information overload and unnecessary mid-task distractions, while ensuring the timely receipt of the most pertinent information in a manner that is most easily processed. To do so, the system must detect the user's current attentional state as well as alternative states, and establish the available attentional capacity of the user. Attentional focus can often be inferred through gaze tracking (although this is by no means a certain indicator; Rayner, 2009; Marshall, 2007; Simons & Rensink, 2005), while physiological measures have also been used (e.g., heart rate variability and electroencephalogram [EEG] analysis; Chen & Vertegaal, 2004; see also Lieberman, Kramer, Montain, & Niro, 2007, for a wrist-worn system applied to monitor the level of vigilance in aviation). In some cases, the attention aware system may establish that the current goal has changed and adapt the nature of available information accordingly (e.g., content, depth, presentation), or it might establish that an alternative (better) focus is available and guide a goal change (interruption) within the current activity. Furthermore, the system may then later deliver reminders about previously unfinished tasks (e.g., providing context information necessary for resumption). The ability to monitor and adapt to the user's current attentional state may be particularly useful for keeping operators on task and goal-focused during the long shifts that are characteristic of CCTV surveillance. Such a research and development endeavour – that is, to develop intelligent systems that adapt their intervention to the cognitive and affective functional state of its user – is long standing and requires measurements that capitalize on the online monitoring of multiple physiological sensors used as proxies to psychological dimensions (such as attention, stress, engagement and workload; see Durantin, Gagnon, Tremblay, & Dehais, 2014), and conceptually valid metrics capable of providing diagnostic information about the variability in the functional state of the operator (Gagnon, Lafond, Rivest, Couderc, & Tremblay, 2014). Promising results have identified physiological markers for attentional tunnelling (Dehais, Causse, & Tremblay, 2011) and the level of fun in video games (Chamberland, Grégoire, Michon, Gagnon, Jackson, & Tremblay, 2016), as well as methods to approximate mental models of decision makers (Lafond, Tremblay, & Banbury, 2013) that are the core of adaptive systems and individually-tailored cognitive assistants.

Visualization. The manner in which information is displayed has the potential to either help or hinder the success with which the surveillance task is performed, however there is a dearth of studies looking into this aspect of surveillance. Typically, a single operator is responsible for a large number of screens displayed on a media wall. Often the number of CCTV cameras to be monitored exceeds the available screen space, meaning that operators need to switch between camera feeds at regular intervals rather than having all viewpoints available at any one time. One recent paper combining Cognitive System Engineering and User Experience Design considered how best to display all this available information and proposed three new designs to optimize the surveillance interface (Pelletier, Suss, Vachon, & Tremblay, 2015). Although there is perhaps an assumption that displaying all information at once is best (there then being the chance that attention could be captured in the periphery if something significant is happening), the authors suggest that this type of organization does not necessarily work in synchrony with the human's natural mode of processing. They argue that visual processing occurs in a serial manner and propose a seemingly counterintuitive serial browsing design whereby operators flip sequentially through camera feeds, attending to each in turn. Other feeds are partially available in the background (similar to the iTunes cover flow design), but focal attention is concentrated on one scene at a time in a sequential rather than simultaneous manner. Other designs included a "carousel" with a main display and the opportunity to flip through others in the periphery, and a hybrid design that incorporated serial browsing of the main display with a multiplex display of other feeds available simultaneously. These designs could be considered more "cognitively ergonomic", encouraging the operator to attend to one view at a time in a focused manner, rather than inefficiently attempting to divide attention between several at once. Improving the design and layout of control centre screens is a relatively neglected aspect of surveillance, yet careful design could offer a user experience that is more in harmony with human perceptual affordances and cognitive limitations, thus improving visual search efficiency and detection rates.

Training solutions. In the wake of the 2015 Paris attacks, the UK's CPNI offered security advice and an e-learning course for CCTV operators. The course discusses human factors aspects of the job (e.g., memory, visual attention, personal biases), to make operators aware of their cognitive limitations and ways around them (e.g., noting down features of an incident so it is not forgotten, or asking colleagues open-ended questions about a situation so as not to influence others' opinions with personal stereotypes). Inclusion of human factors aspects would seem to be good practice for training surveillance personnel in general (whether store security, control centre operators, cyber security), as optimal job performance extends beyond the mere technical know-how of operating equipment.

As noted previously, experienced CCTV operators often report having a "sixth sense" for when an incident will occur; it would therefore be useful for training purposes to somehow capture the features that operators most frequently use in order to detect criminal activity. While it may be difficult for operators to verbalize the precise cues that they are picking up on (see, e.g., Cooke, 1999), as mentioned before, it might be possible to employ a policy capturing approach – a judgement analysis method using statistical models or machine learning algorithms to estimate expert judgements (e.g., Lafond et al., in press) – to help begin to understand a little more about the subjective decision criteria that are used for identifying suspicious activity in such cases. Eye-movement data could enable tracing the areas most recently fixated leading up to a decision, as well as those areas fixated most frequently and for the longest (see Rehder & Hoffman, 2005). From this it might be possible to infer which factors are most important in the assessment of suspicious activity, and specify the subjective heuristics that operators use (e.g., target's posture, direction of gaze, speed/direction of movement, interaction with others), and also whether these criteria shift under different conditions (e.g., load, distraction, boredom). The knowledge gleaned could greatly benefit the speed and success of both real-time and archival incident detection.

Improved surveillance performance might also be achieved through the training of non-technical skills; that is, general skills that are not specific to the equipment or procedures used within a particular work environment. Depending on the focus of the non-technical skill training, its content can be fed by knowledge elicitation methods such as Cognitive Task Analysis (CTA; see Crandall, Klein, & Hoffman, 2006) and Goal-Directed Task Analysis (GDTA; Endsley, Bolte, & Jones, 2003). CTA centers its analysis on addressing the knowledge structure and information processing strategies involved in task performance, and the underlying mental processes that give rise to errors, while GDTA focuses on situational awareness requirements associated with a task, and how that information must be used to support decision-making in dynamic environments. For instance, Adams et al. (2009) used these techniques to guide the development of support systems and training procedures for the use of Unmanned Aerial Vehicle (UAV) in search and rescue missions.

At the level of information processing capacity, one possibility regards improving the operator's Useful Field of View (UFOV); that is, the size of the area around each fixation from which information can be extracted. UFOV narrows under stress and high cognitive workload (Ball, Beard, Roenker, Miller, & Griggs, 1988), which are key concerns for surveillance operators. However, the implication is that it can be trained; it tends to be wider in experienced drivers, and UFOV training improves the visual processing of older adults with benefits even at five-year follow-up (Willis et al., 2006). It seems plausible to suggest that such training could benefit surveillance operators; by allowing more efficiency with each fixation, operators may be able to regain SA quicker whenever switching between screens or tasks.

Summary

Surveillance is necessary to detect and prevent the occurrence of dangerous incidents (e.g., drowning, aircraft collision) or deliberately malicious acts (terrorism, cyber-attacks, civil disobedience). In terms of the latter, governments have invested heavily in CCTV cameras with the intention to improve the safety and security of public spaces and infrastructure. At the same time, existing research on CCTV surveillance from a human factors perspective has tended to focus on technological and operational aspects (e.g., Pikaar et al., 2015). However, the very nature of CCTV control centres can leave operators vulnerable to cognitive failures during proactive security surveillance. Cognitive and perceptual overload is likely when information is displayed across numerous screens on a large media wall, with each displaying busy public places. This susceptibility is compounded by the dynamic nature of the task, the use of long shifts or unsociable hours, and visual/auditory distractions and interruptions. In the current paper we aim to stimulate research by pinpointing different human-related aspects of surveillance that deserve further investigation, and in turn greater knowledge may lead to recommendations for work policies or support systems. Although the development of automation represents advancement in the field, we must first understand the limitations and vulnerabilities of the cognitive system so that automated systems can work in harmony with the human operator.

Author Contributions

All authors contributed to reviewing the literature and writing the paper.

Conflict of Interest Statement

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References

Adams, J. A., Humphrey, C. M., Goodrich, M. A., Cooper, J. L., Morse, B. S., Engh, C., & Rasmussen, N. (2009). Cognitive task analysis for developing unmanned aerial vehicle wilderness search support. *Journal of Cognitive Engineering and Decision Making*, *3*, 1-26.

Altmann, E. M. & Trafton, J. G. (2002). Memory for goals: An activation-based model. *Cognitive Science*, *26*, 39-83.

Ariga, A., & Lleras, A. (2011). Brief and rare mental "breaks" keep you focused: Deactivation and reactivation of task goals preempt vigilance decrements. *Cognition*, *118*, 439-443.

Atrey, P. K., El Saddick, A., & Kankanhalli, M. S. (2011). Effective multimedia surveillance using a human-centric approach. *Multimedia Tools and Applications, 51*, 697-721.

Ball, K., Beard, B., Roenker, D., Miller, R., & Griggs, D. (1988). Age and visual search: Expanding the useful field of view. *Journal of the American Optical Society A: Optics and Image Science, 5,* 2210-2219.

Banbury, S., Macken, W. J., Tremblay, S., & Jones, D. M. (2001). Auditory distraction and short-term memory: Phenomena and practical implications. *Human Factors, 43,* 12-29.

Bedny, G. Z., Karwowski, W., & Jeng, O. J. (2004). The situational reflection of reality in activity theory and the concept of situation awareness in cognitive psychology. *Theoretical Issues in Ergonomics Science*, *5*, 275-296.

Biggs, A. T., & Mitroff, S. R. (2015). Improving the efficacy of security screening tasks: A review of visual search challenges and ways to mitigate their adverse effects. *Applied Cognitive Psychology*, *29*, 142-148.

Boot, W. R., Kramer, A. F., Becic, E., Wiegmann, D. A., & Kubose, T. (2006). Detecting transient changes in dynamic displays: The more you look, the less you see. *Human Factors, 48*, 759–773.

Breznitz, S. (1983). *Cry-wolf: The psychology of false alarms.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Brunyé, T. T., Howe, J. L., & Mahoney, C. R. (2014). Seeing the crowd for the bomber: Spontaneous threat perception from static and randomly moving crowd simulations. *Journal of Experimental Psychology: Applied, 20*, 303-322.

Bryant, D. J. (2007). Classifying simulated air threats with fast and frugal heuristics. *Journal of Behavioral Decision Making*, *20*, 37-64.

Calvillo, D. P. & Jackson, R. E. (2014). Animacy, perceptual load, and inattentional blindness. *Psychonomic Bulletin & Review, 21*, 670–675.

Chamberland, C., Grégoire, M., Michon, P. E., Gagnon, J. C., Jackson, P. L., & Tremblay, S. (2015). A cognitive and affective neuroergonomics approach to game design. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *59*, 1075-1079.

Chen, D., & Vertegaal, R. (2004). Using mental load for managing interruptions in physiologically attentive user interfaces. In *CHI'04 extended abstracts on Human Factors in Computing Systems* (pp. 1513-1516). ACM.

Cooke, N. J. (1999). Knowledge elicitation. In F. T. Durso (Ed.), *Handbook of applied cognition* (pp. 479-509). New York: Wiley.

Crandall, B., Klein, G., & Hoffman, R. R. (2006). Working Minds: A practitioner's guide to cognitive task analysis. London: MIT Press.

Dadashi, N., Stedmon, A. W., & Pridmore, T. P. (2013). Semi-automated CCTV surveillance: The effects of system confidence, system accuracy and task complexity on operator vigilance, reliance and workload. *Applied Ergonomics, 44,* 730-738.

Davies, D. R., & Parasuraman, R. (1982). *The psychology of vigilance.* London: Academic Press.

de Bruijn, D., Jansen, J., Lenior, D., Pikaar, R., & Schreibers, K. (2016). Human factor guidelines and workload in CCTV design. In D. de Waard, K. A. Brookhuis, A. Toffetti, A. Stuiver, C. Weikert, D. Coelho, D. Manzey, A.B. Ünal, S. Röttger, and N. Merat (Eds.) *Proceedings of the Human Factors and Ergonomics Society Europe Chapter 2015 Annual Conference* (pp. 209-219).

Dehais, F., Causse, M., & Tremblay, S. (2011). Mitigation of conflicts with automation: use of cognitive countermeasures. *Human Factors*, *53*, 448-460.

Dillow, C. (2011). London cops are testing out facial recognition tech to identify rioters. *Popular Science.* Retrieved from http://www.popsci.com/technology/article/2011-08/london-cops-are-testing-out-facial-recognition-tech-identify-rioters

Donald, F. M. (1998). Providing a Focus for Observation. *Focussing CCTV Operator Performance (Part 1).* Retrieved from http://www.leaderware.com/Hitech/focussing%20operators.htm

Donald, F., Donald, C., & Thatcher, A. (2015). Work exposure and vigilance decrements in closed circuit television surveillance. *Applied Ergonomics, 47,* 220-228.

Durantin, G., Gagnon, J. F., Tremblay, S., & Dehais, F. (2014). Using near infrared spectroscopy and heart rate variability to detect mental overload. *Behavioural brain research*, *259*, 16-23.

Ellermeier, W., & Hellbruck, J. (1998). Is level irrelevant in "irrelevant speech"? Effects of loudness, signal-to-noise ratio, and binaural unmasking. *Journal of Experimental Psychology: Human Perception and Performance, 24,* 1406-1414.

Emberson, L. L., Lupyan, G., Goldstein, M. H., & Spivey, M. J. (2010). Overheard Cell-Phone Conversations: When Less Speech Is More Distracting. *Psychological Science, 21,* 1383-1388.

Endsley, M. R., Bolte, B., & Jones, D. G. (2003). Designing for situation awareness: An approach to user-centered design. Boca Raton, FL: CRC Press.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic system. *Human Factors, 37,* 32-64.

Finnegan, S. (2011). *Smile, you're on camera: The influence of screen arrangement with regard to inattentional blindness, surveillance detection confidence and eye fixations, in CCTV (Unpublished honours thesis).* University of Abertay, Scotland.

Fleck, M. S., & Mitroff, S. R. (2007). Rare targets are rarely missed in correctable search. *Psychological Science*, *18*, 943-947.

Fougnie, D., & Marois. R. (2007). Executive working memory load induces inattentional blindness. *Psychonomic Bulletin & Review*, *14*, 142-147.

Foy, S. (2010). *CCTV in homicide investigations.* Scotland Yard report, UK.

Gagnon, J.-F., Lafond, D., Rivest, M., Couderc, F., & Tremblay, S. (2014). Sensor-Hub: A real-time data integration and processing nexus for adaptive C2 systems. *Proceedings of the Sixth International Conference on Adaptive and Self-Adaptive Systems and Applications,* 63-67.

Gill, M., Little, R., Spriggs, A., Allen, J., Argomaniz, J., & Waples, S. (2005). *Assessing the impact of CCTV: The Hawkeye case study*. Home Office Online Report. London: Home Office.

Godwin, H. J., Menneer, T., Cave, K. R., & Donnelly, N. (2010). Dual-target search for high and low prevalence X-ray threat targets. *Visual Cognition*, *18*, 1439-1463.

Godwin, H. J., Menneer, T., Cave, K. R., Helman, S., Way, R. L., & Donnelly, N. (2010). The impact of relative prevalence on dual-target search for threat items from airport X-ray screening. *Acta Psychologica, 134*, 79-84.

Godwin, H. J., Menneer, T., Cave, K. R., Thaibsyah, M., & Donnelly, N. (2015). The effects of increasing target prevalence on information processing during visual search. *Psychonomic Bulletin & Review*, *22*, 469-475.

Halin, N., Marsh, J., Hellman, A., Hellström, I. & Sörqvist, P. (2014). A shield against distraction. *Journal of Applied Research in Memory and Cognition, 3,* 31-36.

Hannon, E. M., & Richards, A. (2010). Is inattentional blindness related to individual differences in visual working memory capacity or executive control functioning? *Perception*, *39*, 309-319.

Hodgetts, H. M., Vachon, F., & Tremblay, S. (2014). Background sound impairs interruption recovery in dynamic tasks: Procedural conflict? *Applied Cognitive Psychology, 28,* 10-21.

Hodgetts, H. M., Tremblay, S., Vallieres, B., & Vachon, F. (2015). Decision support and vulnerability to interruption in a dynamic multitasking environment. *International Journal of Human-Computer Studies, 79,* 106 –117.

Hoffman, R. R. (2008). Human factors contributions to knowledge elicitation. *Human Factors*, *50*, 481-488.

Hopstaken J. F., van der Linden D., Bakker A. B., Kompier M. A., & Leung, Y. K. (2016). Shifts in attention during mental fatigue: Evidence from subjective, behavioral, physiological, and eye-tracking data. *Journal of Experimental Psychology: Human Perception and Performance, 42*, 878-889.

Howard, C. J., Gilchrist, I. D., Troscianko, T., Behera, A., & Hogg, D. C. (2011). Task relevance predicts gaze in videos of real moving scenes. *Experimental brain research, 214*, 131-137.

Howard, C. J., Troscianko, T., & Gilchrist, I. D. (2010). Eye-response lags during a continuous monitoring task. *Psychonomic Bulletin & Review, 17*, 710-717.

Howard, C. J., Troscianko, T., Gilchrist, I. D., Behera, A. & Hogg, D. C. (2013). Suspiciousness perception in dynamic scenes: A comparison of CCTV operators and novices. *Frontiers in Human Neuroscience, 7*, 441.

Hughes, R. W. (2014). Auditory distraction: A duplex-mechanism account. *PsyCH Journal, 3*, 30-41.

Hughes, R. W., Hurlstone, M., Marsh, J. E., Vachon, F., & Jones, D. M. (2013). Cognitive control of auditory distraction: Impact of task difficulty, foreknowledge, and working memory capacity supports duplex-mechanism account. *Journal of Experimental Psychology: Human Perception and Performance, 39*, 539-553.

Hughes, R., Vachon, F., & Jones, D. M. (2007). Disruption of short-term memory by changing and deviant sounds: Support for a duplex-mechanism account of auditory distraction. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 33*, 1050-1061.

Idzikowski, C. (1984). Sleep and memory. *British Journal of Psychology, 75,* 439–449.

Jones, D. M., Farrand, P., Stuart, G., & Morris, N. (1995). Functional equivalence of verbal and spatial information in serial short-term memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21,* 1008-1018.

Kaplan, E. H., Mintz, A., & Mishal, S. (2006). Tactical prevention of suicide bombings in Israel. *Interfaces*, *36,* 553–561.

Keval, H., & Sasse, M. A. (2010). "Not the Usual Suspects": A Study of Factors Reducing the Effectiveness of CCTV. *Security Journal, 23*, 134-154.

Kim, C. N., Chung, H. M., & Paradice, D. B. (1997). Inductive modeling of expert decision making in loan evaluation: A decision strategy perspective. *Decision Support Systems, 21*, 83-98.

Klein, G., Woods, D. D., Bradshaw, J. M., Hoffman, R. R., & Feltovitch, P. J. (2004). Ten challenges for making automation a "Team Player" in joint-agent activity. *IEEE Intelligent Systems, 19*, 91-95.

Krumm, J., Harris, S., Meyers, B., Brumitt, B., Hale, M., & Shafer, S. (2000). Multi-camera multi-person tracking for EasyLiving. In *Proceedings of Third IEEE International Workshop on Visual Surveillance (*pp. 3-10). IEEE.

Lafond, D., Champagne, J., Hervet, G., Gagnon, J.-F., Tremblay, S., & Rousseau, R. (2009). Decision analysis using policy capturing and process tracing techniques in a simulated naval air-defense task. In *Proceedings of the Human Factors and Ergonomics Society 53th Annual Meeting* (pp. 1220–1224) Santa Monica, CA: Human Factors and Ergonomics Society.

Lafond, D., Tremblay, S., & Banbury, S. (2013). Cognitive shadow: A policy capturing tool to support naturalistic decision making. In *2013 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)* (pp. 139-142). IEEE.

Lafond, D., Vallières, B. R., Vachon, F., & Tremblay, S. (in press). Judgment analysis in a dynamic multi-task environment: Capturing non-linear policies using decision trees. *Journal of Cognitive Engineering and Decision Making*.

Langton, S. R., & Bruce, V. (1999). Reflexive visual orienting in response to the social attention of others. *Visual Cognition*, *6*, 541-567.

Lavie, N. (2005). Distracted and confused? Selective attention under load. *Trends in Cognitive Science*, *9*, 75-82.

Lieberman, H. R., Kramer, F. M., Montain, S. J., & Niro, P. (2007). Field assessment and enhancement of cognitive performance: Development of an ambulatory vigilance monitor. *Aviation, Space, and Environmental Medicine, 78,* B268-B275.

Mack, A., & Rock, I. (1998). *Inattentional blindness.* Cambridge, MA: MIT Press.

Marsh, J. E., Hughes, R., & Jones, D. (2009). Interference by process, not content, determines semantic auditory distraction. *Cognition, 110,* 23-38.

Marsh, J. E., Perham, N., Sörqvist, P., & Jones, D. M. (2014). Boundaries of semantic distraction: Dominance and lexicality act at retrieval. *Memory & Cognition*, *42*, 1285-1301.

Marshall, S. P. (2007). Identifying cognitive state from eye metrics. *Aviation, space, and environmental medicine*, *78*, B165-B175.

Metzger, U., & Parasuraman, R. (2001). The role of the air traffic controller in future air traffic management: An empirical study of active control versus passive monitoring. *Human Factors, 43*, 519-528.

Meuter, R., & Renata, P. (2016). When and why threats go undetected: Impacts of event rate and shift length on threat detection accuracy during airport baggage screening. *Human Factors, 58*, 218-28.

Monsell, S. (2003). Task switching. *Trends in Cognitive Science, 7,* 134-140.

Most, S. B., Scholl, B. J., Clifford, E. R., & Simons, D. J. (2005). What your see is what you set: Sustained inattentional blindness and the capture of awareness. *Psychological Review, 112,* 217-242.

Neider, M., Brotzen S., & Zelinsky, G. (2010). Cutting through the clutter: Searching for targets in evolving realistic scenes. *Journal of Vision, 7*, 1-16.

Neil, D., Thomas, N., & Baker, B. (2007). Threat image projection in CCTV. In *Proceedings of the 41st Annual IEEE International Carnahan Conference on Security Technology* (pp. 272-280). IEEE.

Nguyen, N. T., Venkatel, S., & West, G., & Bui, H. H. (2003). Multiple camera coordination in a surveillance system. *ACTA Automatica Sinica 29*, 408-422.

Nikolic, M. I., & Sarter, N. B. (2001). Peripheral visual feedback: A powerful means of supporting attention allocation and human-automation coordination in highly dynamic data-rich environments. *Human Factors, 43,* 30-38.

Norris, C., & Armstrong, G. (1997) *The Unforgiving Eye: CCTV Surveillance in Public Space.* Hull: Centre for Criminology and Criminal Justice, University of Hull.

Parasuraman, R., & Galster, S. (2013). Sensing, assessing, and augmenting threat detection: Behavioral, neuroimaging, and brain stimulation evidence for the critical role of attention. *Frontiers in Human Neuroscience, 7,* 1-10.

Parasuraman, R., Warm, J. S., & See, J. E. (1998). Brain systems of vigilance. In R. Parasuraman (Ed), *The attentive brain* (pp. 221-256). Cambridge, MA: MIT Press.

Pelletier, S., Suss, J., Vachon, F., & Tremblay, S. (2015). Atypical visual display for monitoring multiple CCTV feeds. *Proceedings of the 33rd Annual ACM (CHI) Conference on Human Factors in Computing Systems*, 1145-1150. New York, NY: ACM.

Pikaar, R., Lenior, D., Schreibers, K., & de Bruijn, D. (2015). Human factors guidelines for CCTV system design. In G. Lindgaard and D. Moore (Eds), *Proceedings 19th triennial congress of the International Ergonomics Association* (pp. 837-844).

Polzella, D. J. (1975). Effects of sleep deprivation on short-term recognition memory. *Journal of Experimental Psychology: Human Learning and Memory, 104,* 194-200.

Quant, J. R. (1992). The effect of sleep deprivation and sustained military operations on near visual performance. *Aviation, Space, and Environmental Medicine, 63,* 172-176.

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *The Quarterly Journal of Experimental Psychology*, *62*, 1457-1506.

Reber, A. S. (1989). Implicit learning and tacit knowledge. *Journal of Experimental Psychology: General*, *118*, 219-235.

Rehder, B., & Hoffman, A. B. (2005). Thirty-something categorization results explained: Selective attention, eyetracking, and models of category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*, 811-829.

Remington, R. W., Johnston, J. C., & Yantis, S. (1992). Involuntary attentional capture by abrupt onsets. *Perception and Psychophysics, 51*, 279-290.

Robinson, M. K., & Unsworth, N. (2015). Working memory capacity offers resistance to mind-wandering and external distraction in a context-specific manner. *Applied Cognitive Psychology*, *29*, 680–690.

Roda, C. & Thomas, J. (2006). Attention aware systems: Theories, applications, and research agenda. *Computers in Human Behavior*, *22*, 557–587.

Rosa, R. R., Colligan, M. J., & Lewis, P. (1989). Extended workdays: Effects of 8-hour and 12-hour rotating shift schedules on performance, subjective alertness, sleep patterns, and psychosocial variables. *Work & Stress: An International Journal of Work, Health & Organisations*, *3*, 21-32.

Rousselet, G. A., Thorpe, S. J., & Fabre-Thorpe, M. (2004). Processing of one, two or four natural scenes in humans: The limits of parallelism. *Vision research 44*, 877-894.

Salvucci, D. D. (2010). On reconstruction of task context after interruption. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 89-92). New York: ACM Press.

Sarter, N. B., & Woods, D. D. (1994). Pilot interaction with cockpit automation II: An experimental study of pilots' model and awareness of the Flight Management System (FMS). *International Journal of Aviation Psychology*, *4*, 1-28.

Sauter, V. L. (1999). Intuitive decision-making: Combining advanced analytical tools with human intuition increases insight into problems. *Communications of the ACM*, *42*, 109-115.

Simons, D. J., & Chabris, C. F. (1999). Gorillas in our midst: Sustained inattentional blindness for dynamic events. *Perception*, *28*, 1059-1074.

Simons, D. J., & Rensink, R. A. (2005). Change blindness: Past, present, and future. *Trends in cognitive sciences*, *9*, 16-20.

Smallman, H. S., & St. John, M. (2003). CHEX (Change History EXplicit): New HCI concepts for change awareness. In *Proceedings of the 47th Annual Meeting of Human Factors and Ergonomics Society* (pp. 528–532). Santa Monica, CA: Human Factors and Ergonomics Society

Smith, G. J. D. (2004). Behind the Screens: Examining Constructions of Deviance and Informal Practices among CCTV Control Room Operators in the UK. *Surveillance & Society*, *2*, 376-395.

Sörqvist, P. (2010). High working memory capacity attenuates the deviation effect but not the changing-state effect: Further support for the duplex-mechanism account of auditory distraction. *Memory & Cognition*, *38*, 651-658.

Sörqvist, P., & Marsh, J. E. (2015). How concentration shields against distraction. *Current Directions in Psychological Science, 24*, 267-272.

Stainer, M. J., Scott-Brown, K. C., & Tatler, B. W. (2017). On the factors causing processing difficulty of multiple-scene displays. *i-Perception*, 1-26.

Stearman, E. J., & Durso, F. T. (2016). Vigilance in a dynamic environment. *Journal of Experimental Psychology: Applied, 22*, 107-123.

Stedmon, A., Harris, S., Carse, A., Sharples, S., & Wilson, J. (2008). Tracking a suspicious person using CCTV: But what do we mean by suspicious behaviour? *Contemporary Ergonomics*, 139-144.

Stedmon, A. W., King, M., Wilson, J. R. (2007). Observing 'normal' behaviour: Cueing methods for CCTV. *Contemporary Ergonomics*, 178-183.

St. John, M., & Smallman, H. S. (2008). Staying up to speed: Four design principles for maintaining and recovering situation awareness. *Human Factors*, *2*, 118–139.

Steelman, K. S., McCarley, J. S., & Wickens, C. D. (2013). Great expectations: Top-down attention modulates the costs of clutter and eccentricity. *Journal of Experimental Psychology: Applied*, *19*, 403-419.

Steelman, K. S., McCarley, J. S., & Wickens, C. D. (2011). Modeling the control of attention in visual workspaces. *Human Factors, 53*, 142-153.

Suss, J., Vachon, F., Lafond, D., & Tremblay, S. (2015). Don't overlook the human! Applying principles of cognitive systems engineering to the design of intelligent video surveillance systems. In *Proceedings of the 12th IEEE International Conference on Advanced Video and Signal Based Surveillance* (pp. 1-6). IEEE.

Temple, J. G., Warm, J. S., Dember, W. N., Jones, K. S., LaGrange, C. M., & Matthews, G. (2000). The effects of signal salience and caffeine on performance, workload, and stress in an abbreviated vigilance task. *Human Factors, 42*, 183-194.

Theeuwes, J., Atchley, P., & Kramer, A. F. (2000). On the time-course of top-down and bottom-up control of visual attention. In S. Monsell and J. Driver (Eds.), *Control of cognitive processes: Attention and performance XVIII* (pp. 105-124). Cambridge, MA: MIT Press.

Theeuwes, J. (1994). Stimulus-driven capture and attentional set: Selective search for colour and visual abrupt onsets. *Journal of Experimental Psychology: Human Perception and Performance, 20*, 799-806.

Todd, J. J., Fougnie, D., & Marois, R. (2005). Visual short-term memory load suppresses temporo-parietal junction activity and induces inattentional blindness. *Psychological Science, 16*, 965-972.

Tremblay, S., & Jones, D. M. (1998). Role of habituation in the irrelevant sound effect: Evidence From the effects of token set size and rate of transition. *Journal of Experimental Psychology: Learning Memory and Cognition, 24*, 659-671.

Tremblay, S., Vachon, F., Lafond, D., & Kramer, C. (2012). Dealing with task interruptions in complex dynamic environments: Are two heads better than one? *Human Factors, 54*, 70–83.

Troscianko, T., Holmes, A., Stillman, J., Mirmehdi, M., Wright, D., & Wilson, A. (2004). What happens next? The predictability of natural behaviour viewed through CCTV cameras. *Perception, 33,* 87-101.

Vachon, F., Vallières, B. R., Suss, J., Thériault, J.-D., & Tremblay, S. (2016). The CSSS microworld: A gateway to understanding and improving CCTV security surveillance. In *Proceedings of the Human Factors and Ergonomics Society 60th Annual Meeting* (pp. 265-269). Santa Monica, CA: Human Factors and Ergonomics Society.

Valera, M., & Velastin, S.A. (2005). Intelligent distributed surveillance systems: A review. *IEE Proceedings-Vision, Image and Signal Processing, 152,* 192-204.

Vallières, B., Hodgetts, H. M., Vachon, F., & Tremblay, S. (2016). Supporting dynamic change detection: Using the right tool for the task. *Cognitive Research: Principles and Implications, 1*, 32.

van Voorthuijsen, G., van Hoof, H., Klima, M., Roubik, K., Bernas, M., & Pata, P. (2005). CCTV effectiveness study. In *Proceedings of the 39th IEEE Annual 2005 International Carnahan Conference on Security Technology* (pp. 105-108). IEEE.

Vickers, J. N. (2009). Advances in coupling perception and action: The quiet eye as a bidirectional link between gaze, attention, and action. *Progress in Brain Research*, *174*, 279-288.

Vickery, T. J., King, L. W., & Jiang, Y. (2005). Setting up the target template in visual search. *Journal of Vision, 5,* 81-92.

Wang, X. (2013). Intelligent multi-camera video surveillance: A review. *Pattern Recognition Letters, 34,* 3-19.

Webster, C. W. R. (2009). CCTV policy in the UK: Reconsidering the evidence base. *Surveillance and Society*, *6*, 10-22.

Wickens, C. D. (1984). Processing resources in attention. In R. Parasuraman and D. R. Davies (Eds), *Varieties of Attention* (pp. 63-102). New York: Academic Press.

Wickens, C. D., & Hollands, J. G. (2000). *Engineering psychology and human performance* (3rd ed.). Upper Saddle River, NJ: Prentice Hall

Wickens, C. D., Hooey, B. L., Gore, B. F., Sebok, A., & Koenicke, C. S. (2009). Identifying black swans in NextGen: Predicting human performance in off-nominal conditions. *Human Factors*, *51*, 638-651.

Wickens, C. D., Rice, S., Keller, D., Hutchins, S., Hughes, J., & Clayton, K. (2009). False alerts in air traffic control conflict alerting system: Is there a "cry wolf" effect? *Human Factors*, *51*, 446–462.

Willis, S. L., Tennstedt, S. L., Marsiske, M., Ball, K., Elias, J., Koepke, K. M., ... & Wright, E. (2006). Long-term effects of cognitive training on everyday functional outcomes in older adults. *Journal of the American Medical Association*, *296*, 2805-2814.

Wolfe, J. M., Horowitz, T. S., & Kenner, N. M. (2005). Rare targets are often missed in visual search. *Nature*, *435*, 439-440.